International Conference for Phoenixes on Emerging Current Trends in Engineering and Management

PECTEAM 2K26

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Organized by

PANIMALAR ENGINEERING COLLEGE

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PREFACE

Dear Distinguished Delegates and Guests,

The organizing committee is extremely privileged to welcome our distinguished delegates and guests to the International Conference for **P**hoenixes on **E**merging **C**urrent **T**rends in **E**ngineering **A**nd **M**anagement (**PECTEAM 2K26**) which will be held from March 27th to 28th, 2026 in Chennai, Tamilnadu, India.

The objective of this conference is to bring together numerous problems encountered in the current as well as future high technologies under a common platform. It has been specifically organized to congregate international researchers and technocrats for presenting their innovative work, share and gain knowledge to have a proper insight into the significant challenges currently being addressed in various fields of Computing and Expert Technology.

The conference proceedings have a complete track record of the papers that are reviewed and presented at the conference. The principle objective is to provide an international scientific forum wherein the participants can mutually exchange their innovative ideas in relevant fields and interact in depth through discussion with peer groups. Both inward research as well as core areas of Computing and Expert Technology and its applications will be covered during these events.

It is guaranteed that a high quality program will be conducted as the conference will be graced by an unparalleled number of professional speakers from multidisciplinary fields, both from India and abroad.

We would like to thank the chief patron, patrons, convenors, organizing committee members, advisory members for their immense help, motivation, constant cooperation and continuous encouragement for the conference. We deeply appreciate the editorial board for their wonderful editorial service for the successful outcome of this proceeding. We are very much grateful to all those who have contributed both in the front desk and backyard to make PECTEAM 2K26 as a grand success.

PECTEAM, featuring high impact presentations, would be enriching and undoubtedly an unique, rewarding and memorable experience being hosted at Panimalar Engineering College, Chennai, INDIA.

Dr. S. MALATHI
Convenor

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Defense GPT – Phishing detection using ML

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***Abstract*— A significant social engineering technique known as Phishing attacks remains and proves to be one of the persistent and also a evolving threats to the cybersecurity because using such attacks the attackers are successful in bypassing the traditional detection systems with ease and exploit the victims or target systems successfully also the traditional systems that use machine learning was able to provide high accuracy in laboratory tests but failed in handling the real time data and phishing mails Therefore DefenseGPT a two phase ensemble machine learning approach is introduced in this paper. The main duty of the first phase is to distinguish and identify whether the given mail is a phishing mail or a genuine ham mail, it is done by stacked ensemble classifier that includes models like XGBoost,CatBoost and Logistic Regression and for a meta learner Random Forest is used . For the second phase Random Forest classifier is used to classify and categorize the phishing emails to various intents and it achieved a 99% accuracy for categorization of all mails into Credential harvesting, Financial fraud, Malware delivery and Scam offer.Since this system takes important division between academic work and realtime deployment into account, it shows a good performance in wide range of real dataset created using seven collections.**

The main aim of developing this system was to not only detect the phishing mails but also exactly know what is the intent of the malicious actor to trap the target systems through phishing mail.

By knowing the exact intent of the attacker, this system enables to make efficient tackling and countermeasures to counter the said phishing attacks by knowing their exact intent and safeguard the sensitive information.

Keywords— phishing detection, ensemble learning, intent classification, machine learning, XGBoost, CatBoost, cybersecurity

I. INTRODUCTION

In today's world, phishing remains as a significant threat to users all around the world because attackers use various social engineering techniques like this to reveal user's sensitive data. Typical countermeasures such as SpamAssassin rule-based filters, and the typical security research is not keeping up with the campaigns that the newer actors are testing - not limited to email phishing but to obscured URLs, different phrasing, and means of obfuscating before returning to normal MIME content.

While their performance on labs climbs a significant 95%+ accuracy using public datasets, machine learning-inspired techniques experience a major drop of performance and do not maintain accuracy when faced by adversarial real-world email traffic niches. Several researchers have analyzed potential reasons for model loss, but within these limits are three areas of concern; standard static features that attackers consistently attempt, low transferability of accuracy with both synthetic and real email data, and little or no response against advanced attack techniques such as spear-phishing (SP) and business email compromise (BEC).

For the sake of conceptualizing an organizational use case, consider an institutional setting in which e-mail processing is a function of an e-mail security solution operating in financial services. The e-mail security solution needs to process thousands of e-mails on a daily basis (and a similar number of transactions) and must be accurate in most circumstances. While it is possible that a typical e-mail security solution would never miss social engineering attacks at scale, it will raise legitimate banking e-mails as phishing with the content of the words in the e-mail. Enter a multi-phase solution, such as Defense GPT, which allows organizations not only to identify phishing in a more accurate and efficient way, but also to describe the nature of the attacker.

To address these issues, we present DefenseGPT, an end-to-end two-phase machine learning pipeline that achieves the state-of-the-art in both detection performance and threat intelligence generation. Our framework represents the following main contributions:

1. Unique and Integer Stacked Ensemble Architecture: The best performing stack ensemble has XGBoost, CatBoost and logistic regression classifier with Random Forest as the meta-learner. This has been shown to have achieved 98.26% accuracy on real world data.

2. Intent-based Threat Classification: The first published work using phishing's intent-based analysis as a fine-grained classification of attacks into actionable threat categories has achieved 99% classification accuracy.

3. Real World Evaluation: The model was rigorously assessed through, a number of datasets consisting of seven public email collections so that it is ready to be implemented in real world usages.

4. Modularised Production Architecture: A GPU-optimized implementation of the model with operationalized model repositories and predictions architecture for production.

II. LITERATURE SURVEY

Chien and Khethavath [1] developed a feature-based classification model to defend users against phishing email threats using machine learning. The authors dealt with various feature sets; lexical features, header features, and body features to classify phishing emails and employed classifiers, the Random Forest and SVM, to maximize the authors' classification accuracy. The authors concluded that the combination of different feature sets greatly improved the effectiveness of phishing detection capabilities.

S. M. M. Ahammad et al. [2] propose an ML-PE-TA, a Machine learning - based phishing email text analysis model. They used TF-IDF vectorization and classifiers Naive Bayes, Decision Tree and SVM. They concluded that they were able to correctly classify phishing emails versus legitimate emails using TF-IDF and a machine learning model with above 95% accuracy.

G. Kanaan et al. [3] experimented with machine learning methods and deep learning methods to test deep learning for Arabic email spam detection. They used CNNs, LSTMs, and traditional classifiers like Logistic Regression and Naive Bayes classifiers. The authors show that deep learning models did outperform classical models and with regard to linguistic nuance, the capability of deep learning models to detect multilingual phishing seems reasonable for a phishing detection platform.

K. Kalaiselvi et al. [4] proposed an ensemble learning method for identifying email fraud attacks. We achieved high recall and precision and combined classifiers again termed ensemble learning classifiers, using the classifiers of XGBoost, AdaBoost and Random Forest. Kalaiselvi et al. [4] find using an ensemble method produced better performance figures than using single classifiers and established that ensemble methods provide robust performance against different phishing methods.

I.T. Almalkawi et al. [5] enhance email security using machine learning-based detection of phishing attempts. They utilized a real dataset to train supervised classifiers and in addition to their classifiers, they also did many different things like dataset construction, feature engineering, etc. to enhance the found rate of phishing attempts. Their study focused on the improvements in true positive rates, the rate of phishing emails discovered, by examining their false positive rates against standard rule-based filters.

R. Abadla et al. [6] present IPED-MFA, an analysis system based on multi-features that can provide intelligent phishing detection. They fuse URL-based, header-based, and content-based features that were selected from many machine-learning models. Their hybrid approach could increase the detection rates for zero-day phishing attacks.

S.A. Maeli and A.U. Surwade [7] propose an ensemble of Random Forest, Gradient Boosting and SVM for predicting phishing emails based on feature selection and analysis. They find that through feature selection their model's generalization improved remarkably, demonstrating that it is possible to integrate both ensemble learning and feature selection.

A. Kovač et al. [8] provide an overview of a few machine learning algorithms used to address phishing attacks in electronic mailing services. This research outlines procedures utilizing Decision Trees, Random Forest, and Neural Networks with its findings showing hybrid and ensemble models, as most efficacious for real time usage.

P. Maturure et al. [9] developed a hybrid machine learning model that merges supervised classifiers with unsupervised clustering for phishing detection. The implementation of supervised learning with clustering reduces the false positive rate by improving the boundary of the classifiers with k-means clustering in a post-processing step.

L. S. S. A and co. [10] create an e-mail spam detection model using logistic regression. They train their model using balanced datasets and get near equal accuracy and low computation type perimeter when applying their logistic regression model done by way of feature scaling.

U. Singh et al. [11] studied spam email assessment with a machine learning and data mining framework. Naive Bayes, Decision Trees, and SVM were employed to assess the datasets. Their study suggested that ensemble approaches are more resilient to inconsistencies in patterns in the dataset.

Y. P. Atmojo et al. [12] have been focusing on spear-phishing attack detection, via monitoring network traffic, using base classifiers such as Random Forest and XGBoost in the machine learning (ML) flow. Their approach is unique because they use more than just email contents to detect for spear-phishing attacks; they have been able to find some indicators at the network level such as session data and packet flow which have allowed them to detect spear-phishing attacks that are much more targeted--including ones where advanced obfuscation is used.

R. Rajoju et al. [13] propose a Random Forest based text phishing detection system which incorporates n-gram features and TF-IDF representations to better represent the subtle nuances in linguistic features present in phishing emails. Their results yield very high accuracy and F1 scores, and the development of their proposed model results in both models that perform well across large schemes of data while maintaining a low false positive scheme.

K. K.V. et al. [14] presented a novel method for phishing detection in thread sharing networks. The authors' method uses the SVM and XGBoost classifiers to explore the active thread communication and alert users when it detects a potentially suspicious activity early, therefore limiting the chances of spreading phishing links to other users.

R. Dhanalakshmi et al. [15] provide a solution for phishing domain detection with an AI approach based on both lexical features of URL, WHOIS features, and domain reputation. Their model has high performance for malicious domain detection before users interact with it, thus serving as a form of defense against web-based phishing attacks.

S. S. V et al. [16] provide a comparative study of different machine learning models to detect phishing including Random Forest, Logistic Regression, and XGBoost. The authors conclude that tree-based ensemble models are best based on precision and recall and so are naturally aligned with security uses cases.

S. Bagui et al. [17] examine how machine learning and deep learning were used to classify phishing emails. They observe that deep learning models tend to be more generalized and less biased than classical algorithms when trained on enough training data, found that the LSTM networks performed the best overall.

A. I. Champa et al. [18] provide a comprehensive study of curated phishing datasets, and review a number of feature engineering processes. The authors conclude that in respect to hybrid feature selection accuracy, the accuracy was greater than any one of the features lexical, header, or content alone.

Rabbi et al. [19] developed Phishy?, a phishing identification framework that uses word embeddings and an ensemble classifier to make better use of the contextual meanings of words. An ensemble classifier is a way to obtain a higher recall rate; recall is important because it mitigates the chances that phishing e-mails will be missed in a high risk environment.

S. M. R. Hegde et al. [20] were investigated social engineering based phishing detection, factoring in behavioral features (e.g. click rate, response time) with content-analysis features in email. So this two phase detection system would successfully improve the detection rates of these kinds of attacks.

III. PROPOSED METHODOLOGY

The solution this system suggests is to use an advanced two phase machine learning pipeline to implement the workflow that will accurately detect the threats and prevent any questionable actions and intentions that are made by the malicious actor.Thus the following architecture consist of six modular structure for phishing detection.

A. Dataset Construction & Preprocessing

The dataset that is used for the system implementation are taken from publicly available Kaggle source: PHISHING_EMAIL, SpamAssassin, CEAS_08, ENRON, LING, NAZARIO and NIGERIAN_FRAUD.

The system uses aggregation rather than going with merging all the data because it should have multiple representation of genuine communications and also to have various phishing attacks.Also in preprocessing there is a huge amount of normalization in text.

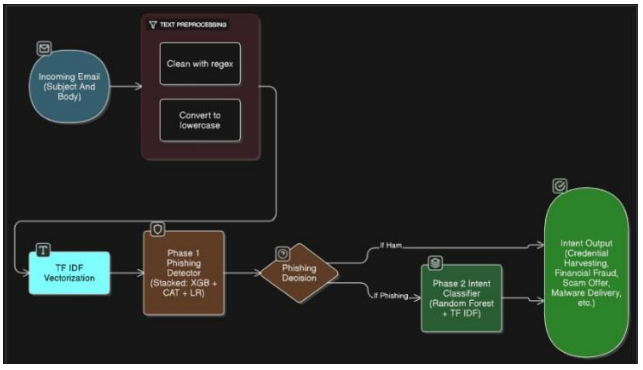


Figure 1: System Architecture

```
def clean(text):
    text = re.sub(r"http\S+|www\S+|https\S+", '', text, flags=re.MULTILINE)
    text = re.sub(r"[^a-zA-Z ]", "", text)
    text = re.sub(r"\s+", " ", text)
    return text.lower().strip()
```

B. Feature Extraction Framework

For extracting the features, the system used Term Frequency-Inverse Document Frequency (TF-IDF) for doing vectorization in order to convert the pre processed texts into numerical representation. For main model it is 5000 dimensions while the other model uses 3000 dimensions vector to increase the speed.

TF-IDF Formula:

$$TF\text{-}IDF(e,g) = TF(e,g) \times \log(T/DF(t))$$

where TF(e,g) is term frequency, T is total documents, and DF(t) is document frequency.

C. Phase 1: Stacked Ensemble Detection The primary detection module applies a sophisticated stacking ensemble architecture: Base Learners: XGBoost: GPU-based gradient boosting specialized for tabular data CatBoost: gradient boosting robust to overfitting Logistic regression: linear baseline that can output explanations Meta- Learner: A Random Forest classifier with 150 estimators using the predictions of the base learners.

Stacking Architecture:

python

```
stacked_model = StackingClassifier(
    estimators=[
        ('xgb', xgb),
        ('cat', cat),
        ('lr', lr)
    ],
    final_estimator=rf,
    passthrough=False
   )
```

D. Phase 2. Intent Classification System.

Under Development - All phishing emails discovered in Phase 1, were subjected to stricter intent classification that will use a

specific Random Forest based classifier that will only consider emails classified as a phishing, taking into account users email address and, we will research a hierarchy of intent classifications domains. . We will classify the taxonomy into a total of four dimensions:
Credential Harvest: attempts specifically intended to steal users authentication credentials
Financial Fraud: as it states, loss of money, financial fraud
Malware Delivery: delivery of malware
Scam Offer: false promotional offers

Feature Fusion Formula:
text
F_fused = Σ(W_i × F_i) for i=1 to n
where W_i represents weights assigned to each modality's feature vector.

E. Model Training And Optimization

The training pipeline utilizes fast GPU (Graphical Processing Unit) in the case of using the XGBoost, or CatBoost, which minimizes time taken to train the model. The pipeline does utilize joblib, serialization for robustness, logging, and persistence of model.
GPU Config:
test
```
xgb = XGBClassifier(
    tree_method='gpu_hist',
    predictor='gpu_predictor',
    gpu_id=0,
    use_label_encoder=False,
    eval_metric='logloss'
)
```
F. Deployment Architecture

The system is modular in design allowing for local testing and processing for any possible production deployment at a point in time. You currently have two options for the user to interact with the system using either the command line interface (CLI), or importable python functions.
Once again the CLI use case here is for local validation and demo, the only input the user will provide is the email subject and body the the system will retrieve and classify the e-mail. This is probably the better option to use when debugging or do a quick test on the model but also to demo the operational capability of the model for your stakeholders without having all of the requirements implemented.
So, while this system is not a full fledged REST API / web service, it is possible to engage with the module implementations of the model and vectorizer to develop and bootstrap into a larger context. Referring back to the earlier example, you will be able to load the instantiated model(s) and call them programmatically, so there is a potential for building more generic email processing service at scale. Generally, the design works to support a production deployment scenario: starting with 'working on a handwritten response time data set' (to fully automated processing system, which may actually work as a model for an email filtering service.

IV. EXPERIMENTAL APPROACH.

In this section it presents an overview of the hardware and software environment, variables of the dataset, characterization of the evaluation methods to determine the performance of the DefenseGPT system. The experimental design was set up to allow for reproduction and to fully explore the feasibility of the models within the practical environment.

A. Hardware/Software Environment

All experiments were conducted on a high-performance workstation with an NVIDIA RTX 4050 Laptop GPU that has Ada Lovelace architecture and CUDA compute capabilities of 8.6. The reasons for hardware selections were to use the GPU accelerated computing features of the XGBoost and CatBoost libraries that further reduces model training time for larger datasets. The workstation has 16GB of DDR5 RAM, which means in-memory data manipulations and TF-IDF vectorizing was never slowed down due to memory. An NVMe Solid State Drive (SSD) was used for speed and efficient, natural, I/O operations while transferring files quickly, as it must be an issue for memory with datasets larger than 160,000 records, and in order to load it into the database correctly.

The whole software stack was built entirely using Python 3.9, as well as various open source libraries for machine learning and data science, including:

Pandas: For loading, cleaning and manipulating data.

Scikit-learn: For implementing the TF-IDF vectorizer, Logistic Regression, Random Forest, and Stacking Classifier.

XGBoost & CatBoost: for implementing the GPU accelerated boosting models.

Matplotlib & Seaborn: for creating visualizations of the confusion matrix.

Joblib: for serializing and persisting models to allow saving and loading of trained models for prediction.

B. Dataset Features

In order to ensure reliability and also ensure generalization of the model, we curated a > > comprehensive dataset from seven available email collections: PHISHING_EMAIL, SpamAssassin, CEAS_08, ENRON, LING, NAZARIO, and NIGERIAN_FRAUD. By curating a dataset from several email collections, we are reducing overfitting to one source of data, while exposing the model to a diversity of writing styles, phishing attacks and types of legitimate email. After we merged the email collections together and removed duplicates, our final dataset consisted of over 164,000 unique email messages. The dataset was also very balanced between Phishing and Ham, labeling approximately in the range of half "Phishing" (target emails) and half "Ham" (legitimate emails), demonstrating that the class imbalance in the data would not induce skewed performance from the model.

TABLE I. Dataset Description

Dataset	Emails	Category
SpamAssassin	6,047	Spam / Ham

Dataset	Emails	Category
Enron	30,000+ (subset has been used)	Legitimate
CEAS-08	35,000	Spam / Ham
Ling-Spam	2,893	Spam / Ham
Nazario Corpus	1,565	Phishing
Nigerian Fraud	1,000+	Scam / Phishing
PHISHING_EMAIL	18,000+	Phishing / Ham

The second stage of the pipeline employed a custom intent classification dataset. The dataset that is used for implementing this system contains about 14,270 emails that were labeled in advance as phishing mails and classified as one of the four following intents they are: Credential harvesting

Financial fraud

Malware delivery

Scam offer

Each category were given the sample distribution that represents in real world as credential harvesting as the most common attack type.

C. Evaluation Procedures

In this system the models that are trained are evaluated on a standardized set of metrics to show the evaluation of performance that includes accuracy, recall, precision and f1-score.

In general accuracy represents the overall correctness, to provide the understanding of performance on both negative and positive classes recall and precision are used here.

This careful evaluation is done so because when it comes to security applications, there will be a high possibility to give false positives and false negatives which can significantly affect over all security and lead to huge risks.

The detection and intent classification models were treated the same in respect to data splitting prior to data preparation for both models, the datasets were split to 80% training and 20% test. Instead of random splitting the data, the train_test_split method from scikit-learn was used with random_state=42 to ensure reproducible results. Furthermore, stratified-sampling was used when splitting to maintain the same proportions of class labels within the training and test sets that were in the original datasets, which primarily applied again to intent classification due to certain categories containing considerably fewer recorded instances than the other categories. Through stratifying we can train and test reliably on a sample that contains some amount of all the categories

V. RESULTS AND DISCUSSION

A. Phase 1: Phishing Detection Performance

Our stacked ensemble has performed extremely well for the binary classification task, achieving an overall accuracy of 98.26%, while having roughly balanced true positive and true negative values for both classes.

The confusion matrix indicates that we correctly classified 15,519 legitimate emails and 16,784 phishing emails as phishing emails, although with some misclassification (271 false positives and 301 false negatives) that occurred.

TABLE II. Phishing Detection Table

Class	Precision	Recall	F1-Score	Support
Ham (0)	0.9828	0.9810	0.9819	15,820
Phishing (1)	0.9824	0.9841	0.9832	17,055
Accuracy			**0.9826**	**32,875**
Macro Avg	**0.9826**	**0.9825**	**0.9826**	**32,875**
Weighted Avg	**0.9826**	**0.9826**	**0.9826**	**32,875**

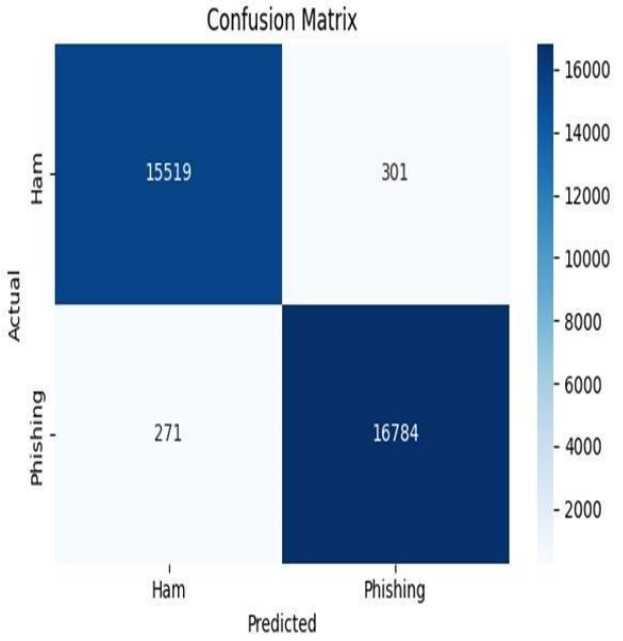
```
2025-07-26 09:28:13,600 - INFO -
              precision    recall  f1-score   support

           0     0.9828    0.9810    0.9819     15820
           1     0.9824    0.9841    0.9832     17055

    accuracy                         0.9826     32875
   macro avg     0.9826    0.9825    0.9826     32875
weighted avg     0.9826    0.9826    0.9826     32875
```

Figure 2:Phishing Detection Output

Figure 3:Confusion Matrix



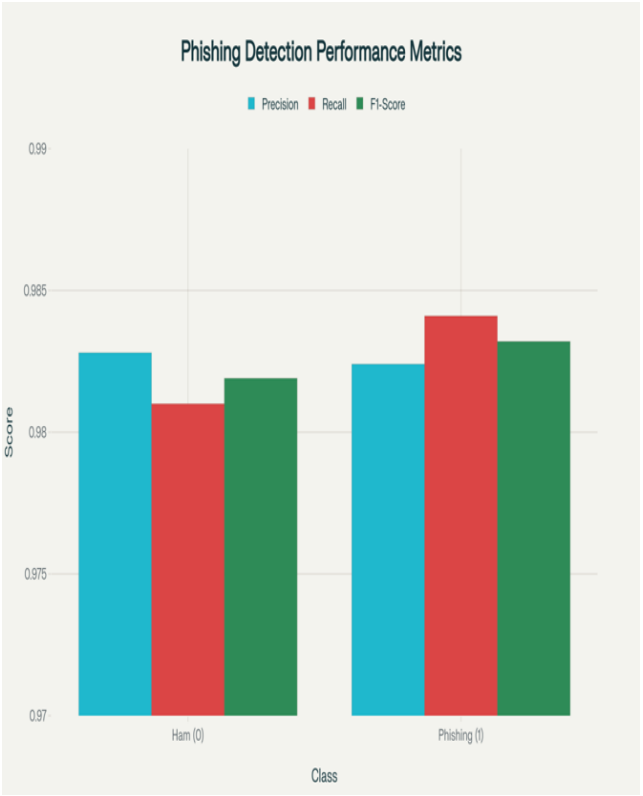


Figure 4:Phishing Detection Performance Metrics

B. Phase two: intent classification results

The intent classification module performed very well, with an overall accuracy of 99% across the four intent categories:

TABLE III. Intent Classification Table

Intent Category	Precision	Recall	F1-Score	Support
Credential Harvesting	1.00	0.99	1.00	8,579
Financial Fraud	0.98	0.98	0.98	706
Malware Delivery	0.99	0.90	0.94	297
Scam Offer	0.98	1.00	0.99	4,688
Accuracy			**0.99**	**14,270**
Macro Avg	**0.99**	**0.97**	**0.98**	**14,270**
Weighted Avg	**0.99**	**0.99**	**0.99**	**14,270**

```
Classification Report:
                      precision    recall  f1-score   support

Credential Harvesting       1.00      0.99      1.00      8579
      Financial Fraud       0.98      0.98      0.98       706
     Malware Delivery       0.99      0.90      0.94       297
           Scam Offer       0.98      1.00      0.99      4688

             accuracy                           0.99     14270
            macro avg       0.99      0.97      0.98     14270
         weighted avg       0.99      0.99      0.99     14270
```

Figure 5:Intent Classification Output

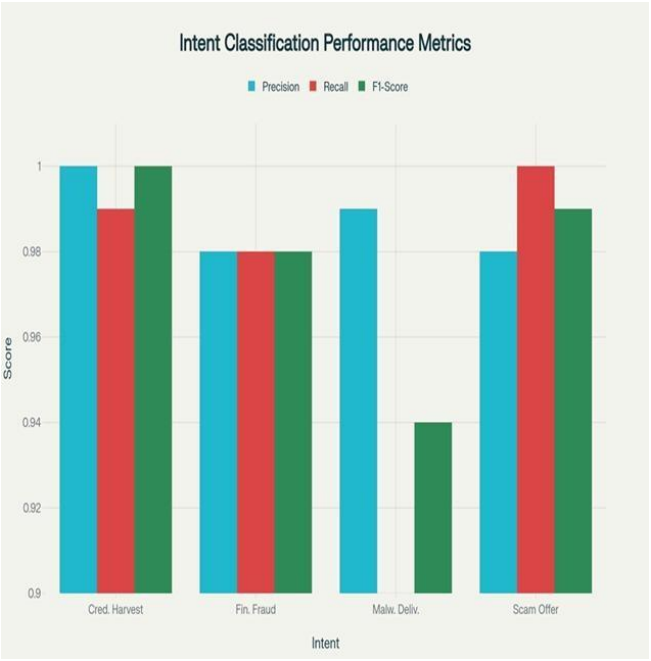


Figure 6: Intent Classification Performance Metrics

C. Comparisons

A comparative analysis was performed against established phishing detection models reported work based on the current literature. Various machine learning classifiers, including Support Vector Machines, Random Forest, Logistic Regression, and Stacking models, achieved accuracy rates between 94% and 97%. The proposed

DefenseGPT system, on the other hand, achieves a detection accuracy of 98.26% using a stacked ensemble architecture that combines XGBoost, CatBoost, and Logistic Regression with Random Forest as the meta-learner. This comparison analysis shows that the proposed system not only shows more accuracy but also introduces an additional capability to identify the intent.

D. Performance of the System Architecture

This system's architecture provides performance metrics that prove its consistency with following estimations:

Processing Pipeline:

1. Text preprocessing: ~0.1ms per email
2. Feature extraction: ~2.3 ms per email
3. Phase 1 Detection: ~1.8ms per email
4. Phase 2 Intent Classification: ~ 1.2ms per email (if the system detects of any phishing attacks)
5. Overall processing: ~ 5.4 ms per email (average)

Memory Performance:

Model Size: 49 MB (Phase 1) + 33.6MB (Phase 2)

VI.CONCLUSION

This paper features a new system DefenseGPT,with a new two-phase machine learning ensemble approach that has both high accuracy with 98.26% of phishing detection and 99% with classifying the intent. While this system has its own flaws,it primarily focuses on training the model on real world datasets so that the model is robust and can have the ability to classify the real time mails.

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Data-Driven Crop Recommendation System Using Machine Learning

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***Abstract*— The ML-Based Crop Recommendation system is a smart tool that helps farmers pick the best crops for their fields. It makes smart choices based on information about the soil, the weather, and the environment. The system uses machine learning, specifically the Random Forest method, to look at things like the levels of nitrogen, phosphorus, and potassium in the soil, as well as the pH, temperature, humidity, and rainfall. By looking at these things, it gives farmers good advice that can help them grow more and keep their crops from getting sick.It has a chatbot and voice assistant that speak local languages to make it easier to use. This makes it more inclusive for farmers who may not be able to read or speak the main language. The system also learns from what users say and new data over time, so it keeps getting better and stays up to date.This system changes the way people get traditional farming advice by giving them personalized tips and help right away. It could also get bigger in the future by adding features like predicting pests, predicting market prices, and sending weather alerts. In general, it's a big step forward in making farming smarter, easier to get to, and better for the environment.**

I. INTRODUCTION

Agriculture is very important for India's social and economic growth. It adds a lot to the country's overall economic output and helps a lot of people make a living. But the agriculture sector is facing a lot of big problems right now. These problems include weather that is hard to predict, soil that is getting worse, bad crop choices, and wasteful use of resources. A lot of farmers still use old methods or local knowledge, which might not work well because the environment and market are always changing.These old ways of farming often result in low crop yields, money problems, and farming methods that aren't good for the environment.With new technologies like Machine Learning (ML), Artificial Intelligence (AI), and Data Analytics, agriculture can now be changed.These technologies can look at a lot of data about farming and the environment and give farmers useful advice.The ML-Based Crop Recommendation System is one of these tools that helps farmers choose which crops to grow by using these technologies.

The Random Forest algorithm is a strong and accurate machine learning method that this system uses. It can handle complex data sets. The model learns from a lot of different things, like soil nutrients (nitrogen, phosphorus, and potassium), temperature, humidity, pH levels, and rainfall. The system uses this information to suggest the best crops for different types of soil and climates. This helps increase yields and lowers the risk of picking the wrong crops.

By merging data science, machine learning, and a user-centric design, this ML-Based Crop Recommendation

System links technology with traditional farming. It gives farmers accurate information, encourages environmentally friendly practices, cuts down on the need for manual advice, and helps the country's food security and rural development. This project represents a step toward creating a smarter, more accessible, and technology-driven agricultural system in India.

II. LITERATURE SURVEY

[1] Kumar et al. presented a system of machine learning to recommend the cultivation of crops based on environmental conditions such as soil nutrients, temperature, humidity, and precipitation. In this study, various methods were evaluated, including decision trees and random forests. The results indicated that the random forest method was able to provide better accuracy and reliable prediction of which crops would produce and be produced.

Singhal et al.[2] have published an in-depth analysis of different types of agricultural crop selection technologies, including Machine Learning, Artificial Intelligence (AI), Internet-of-Things (IoT), and Deep Learning for use in producing optimal crop yields. They address various models developed by researchers in these areas and provide summaries of how integrating multiple technologies can enhance the quality and speed of making agricultural production decisions.

[3] The research carried out by Patel et al. involved using machine-learning algorithms such as decision tree, support vector machine (SVM), and naive bayes to create a model that predicts agricultural yield based on both soil nutrient and climate data. Their results indicate that machine learning has potential utility in helping farmers determine what crops they will grow.

[4] Sharma et al. put forth a cultivation recommendation framework, which utilized supervised machine learning methods. Inputs to the system were based on environmental conditions (weather and soil characteristics), which were used to produce a prediction. Performance evaluation of their model showed greater accuracy when producing results based on large agricultural data sets.

[5] By employing Random Forest and Artificial Neural Networks, Singh et al., created a data-driven crop selection model. The researchers found that ensemble models produced superior predictive accuracy over models that were built from only one algorithm alone.

[6] Using Decision Trees and K-Nearest Neighbors, Ramesh and Patel produced a novel recommendation system to determine the crop that will be best suited for specific soil types and environmental characteristics. All prediction methods used in this research produced good results with agricultural data sets using a Decision Tree model as the best-performing method.

[7] Gupta et al. developed a machine-learning system to predict an agrarian output, as well as provide advisements related to crop selection based on climatological/soil data. The system was trained using historical agrarian data and provides accurate predictions that enable increased agrarian productivity for farmers.

[8] An Internet of Things-based crop forecasting platform was developed by Sharafat et al. using machine learning algorithms with real-time soil sensor readings. Their prediction system uses Random Forest and Gradient Boosting algorithms for machine learning and, by allowing the systems to operate on edge devices, they can be implemented quickly in farming environments.

[9] Rao and others examined how Support Vector Machine (SVM) and Random Forest (RF) algorithms could be applied to crop recommendations. It was concluded that RF provides better overall accuracy than SVM because it can handle larger data sets with more complex feature-to-feature relationships.

[10] The Crop Advisory System developed by Kumar et al. helps determine what type of crop would be best suited to an area based on environmental factors using various methods of Machine Learning. The authors stress that preparing the data properly through pre-processing and selecting appropriate features will enhance the systems' performance.

[11] A machine learning model developed by Ahmed et al. recommends crops according to both weather and soil fertility. The system was able to classify crops with a high level of accuracy and illustrates the possible uses of intelligent systems in agriculture.

[12] Through experiments with Naïve Bayes and Decision Tree for crop forecasting, Das and others found that Decision Trees provided more accurate forecasting than Naïve Bayes when applied to agricultural data.

[13] Mehta and colleagues developed an online crop approach by utilizing machine learning methods on the internet from farmers entering their individual soil or other environmental characteristics into an online platform to receive crop recommendations.

[14] Patel and Shah proposed a predictive model for crop selection using ensemble learning algorithms. Their research highlighted that combining multiple machine learning models can improve prediction accuracy and reliability.

[15] The authors, Singh and Kumar, the authors, made a smart agriculture system that uses machine learning and environmental monitoring systems. The machine learning models use data about the soil and weather to help suggest what kinds of crops to grow in a certain area. This will help farming that is good for the environment.

III. PROPOSED METHODOLOGY

The suggested Machine Learning-Based Crop Recommendation System is designed to give farmers intelligent, data-driven, and user-friendly agricultural assistance. In order to provide farmers with precise crop advice in their preferred language, it employs machine learning techniques in conjunction with multilingual and voice-based tools. As described below, the entire procedure is divided into a number of major steps.

1. Data Collection and Preparation

The system begins by collecting agricultural data from reliable sources, such as open government databases, the Indian Council of Agricultural Research (ICAR), and Kaggle. Important environmental and soil data, including soil pH, temperature, humidity, rainfall, nitrogen (N), phosphorus (P), and potassium (K) levels, are included in the dataset. The data is cleaned and ready to correct any incorrect or missing entries after it has been collected. In order to properly manage the data, verify the values, and arrange everything so that the model can be trained efficiently, Python tools like Pandas and NumPy are utilized. This procedure is crucial to ensuring that the data is trustworthy and accurate, which improves the model's ability to make predictions.

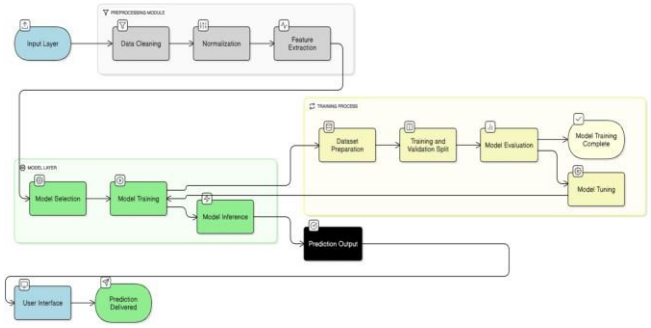

Figure 1: System Architecture

2. Model Development using Random Forest Algorithm

The Random Forest algorithm, which was chosen because it is precise, capable of handling big data sets, and adept at handling intricate and non-linear relationships, is at the core of the system.Using the prepared data, the model is constructed to identify relationships between soil properties and the most productive crops.

The following are included in the training process:
Separating the data into two portions: one for model training and another for performance evaluation.
Nitrogen (N), phosphorus (P), potassium (K), pH level, temperature, humidity, and rainfall are examples of input features that are used in the model.
Allowing the model to forecast which crops would work best in those circumstances.
Measures like accuracy, precision, and recall are used to assess the model's performance after it has been trained.
The experiments' findings demonstrate the system's effectiveness, with a success rate ranging from 94% to 96%. This demonstrates the system's dependability and effectiveness in recommending the appropriate crops based on soil and climate conditions.

3. Multilingual Chatbot Integration

A multilingual chatbot interface is included to make the system more user-friendly and inclusive.Farmers from various regions can easily access and comprehend the system's information thanks to this feature, which enables interaction in multiple languages, including Tamil, English, Malayalam, Hindi, and Telugu.
Natural Language Processing (NLP) is used by the chatbot to comprehend user inquiries and offer pertinent responses.

The crop recommendation is returned in the same regional language after the user's input has been translated into a language that the machine learning model can understand. This eliminates the language barriers that frequently prevent farmers from utilizing agricultural technology and facilitates clear communication in both directions.
.

4. Voice Assistant Integration (Speech-to-Text and Text-to-Speech)

The system has a voice assistant module in addition to text-based interaction, which makes the platform more user-friendly for those who might not be highly literate.
In order for the system to comprehend a user's query, the Speech-to-Text feature converts spoken words into text.
In contrast, the Text-to-Speech feature allows users to hear the system's responses by translating them into spoken words.

This enables farmers to interact with the system in a natural way and receive responses in their native tongue.
To guarantee accurate and clear voice processing and responses, services like Google Speech Recognition, gTTS, or Azure Speech Services can be utilized.

5. Feedback and Model Improvement

Farmers can provide feedback based on their actual experiences in order to maintain the system's accuracy and relevance over time. The model is updated and improved on a regular basis thanks to this feedback regarding which crops grow well and how much they produce. This continuous process allows the system to adapt to changes in farming practices, weather patterns, and soil quality, ensuring that the advice remains relevant and up to date.

6. Output and Result Interpretation

The system employs a trained machine learning model to process the data that the user provides about the soil and environment, either by typing it in or using the chatbot.
The outcomes consist of:
the ideal crop to grow in those circumstances.
a success rate or confidence score that indicates the degree of certainty of the forecast.
The recommendation is provided in both text and voice output with a brief explanation.

.

IV. EXPERIMENTAL APPROACH.

This section outlines the experimental setup for the crop recommendation chatbot, designed to assist farmers in selecting optimal crops based on soil and environmental conditions. It covers the hardware and software environment,

dataset features, and evaluation procedures, ensuring a reproducible and practical setup for agricultural applications

A. Hardware/Software Environment

The chatbot was made and tested on a simple laptop with an Intel Core i5 processor (2.4 GHz) and 8GB of RAM, which was enough to handle the 1,000-row dataset. A 256GB SSD made it easy to quickly load and store data. You don't need a GPU because standard hardware works well with lightweight machine learning models like Random Forest that are used to predict crops. This cheap setup makes the chatbot useful for people who live in rural farming areas.The following libraries were used to build the software in Python 3.9:

- **Pandas:** For dataset loading and cleaning.
- **NumPy**: For numerical calculations and data scaling.
- **Scikit-learn:** For data preprocessing (e.g., normalisation), Random Forest model training, and performance evaluation (accuracy, precision, recall, F1-score).
- **Flask**: For developing the chatbot's web interface so that it can be accessed on computers or phones.
- **Matplotlib:** For displaying model outcomes, such as confusion matrices.
- **Joblib**: For quickly making predictions by storing and loading trained models.

B. Dataset Features

To make sure that the results are reliable and can be applied to other situations, The dataset has 1,000 records that are meant to show how farming works in India based on information from groups like the Indian Council of Agricultural Research (ICAR). It has:

- **N (nitrogen):** 10–150 kg/ha of soil nitrogen.
- **P (Phosphorus):** Phosphorus in the soil (20–80 kg/ha).
- **K (Potassium):** 10–300 kg/ha of soil potassium.
- **Temperature**: 10–40°C.
- **Humidity**: 30–90%.
- **pH:** 5.0–8.0 for soil.
- **Rainfall**: 300–2500 mm.

Thirteen crops—millet, sugarcane, wheat, cotton, rice, soybean, pulses, lentils, blackgram, pomegranate, coconut, maize, and coffee—are targeted. In order to prevent bias, each crop appears roughly 77 times, guaranteeing a balanced dataset. The data was created with verified ranges, no duplicates, and realistic conditions in mind.

C. Evaluation Procedures

A standardized set of performance metrics, including accuracy, precision, recall, and F1-score, were used to evaluate the crop recommendation models. These metrics were chosen to offer a thorough assessment of the chatbot's efficacy:

- **Accuracy:** Indicates overall performance by calculating the percentage of accurate crop recommendations.
- **Precision**: Essential for guaranteeing farmers receive trustworthy recommendations, it shows the percentage of suggested crops that are accurate.
- **Recall**: Reduces missed recommendations by calculating the percentage of real crop instances that were accurately predicted.
- **F1-score**: Provides a single performance metric by balancing recall and precision, particularly for less common crops like coffee or pomegranate.

In agricultural applications, where inaccurate recommendations could result in poor crop choices that impact yields and farmer livelihoods, these metrics are crucial. To guarantee practical utility, false positives (recommending an unsuitable crop) and false negatives (failing to recommend a suitable crop) were closely monitored.

Using Scikit-learn's train_test_split with random_state=42 for reproducibility, the dataset was divided into 80% training (800 records) and 20% testing (200 records).The main model was a Random Forest Classifier, which was selected due to its efficacy in multiclass classification and resilience to noisy data. For comparison, other models (such as K-Nearest Neighbors and Decision Trees) were tested.

V. RESULTS AND DISCUSSION

After the model was trained using the agricultural dataset, the machine learning agricultural model's performance was evaluated using various input values. In order to determine which crops would be most appropriate for a given plot of land, the model assessed the soil nutrition value and environmental factors (such as temperature, humidity, rainfall, nitrogen, phosphorus, potassium, and soil pH).

The crop recommendation system correctly predicted the appropriate crop for the majority of the input conditions, according to the test results. For example, "Rice" was successfully recommended when a user entered soil and environmental conditions that matched rice cultivation. The model found a strong correlation between the input conditions and the right crop for that dataset, as evidenced by the recommendation's confidence level of roughly 92%.CropBot, the model's user interface, is made to facilitate easy user interaction. The user enters data in designated input fields, the system uses the trained model to assess the user's data, and the user is then shown the crop and a probability (or confidence) score associated with that choice.Because it enables users to utilize the interface in their native tongue, the system's multilingual capability is a crucial feature. This feature makes it easier for users to interact with the system, no matter where they are in the world.

The experiment demonstrates how agricultural data can be analyzed using machine learning techniques to provide precise crop yield forecasts. It also shows how farmers can more effectively manage crop production by using data-driven strategies.

While the model was effective, the accuracy of predicted outcomes is dependent upon the quality and size of the training datasets; therefore, the effectiveness of the system would be

further enhanced by using both greater quantities of data and real-time weather data.

Overall, the experiment has demonstrated that the crop recommendation model has the potential, to provide crop recommendations and be a supportive tool in modern farming operations.

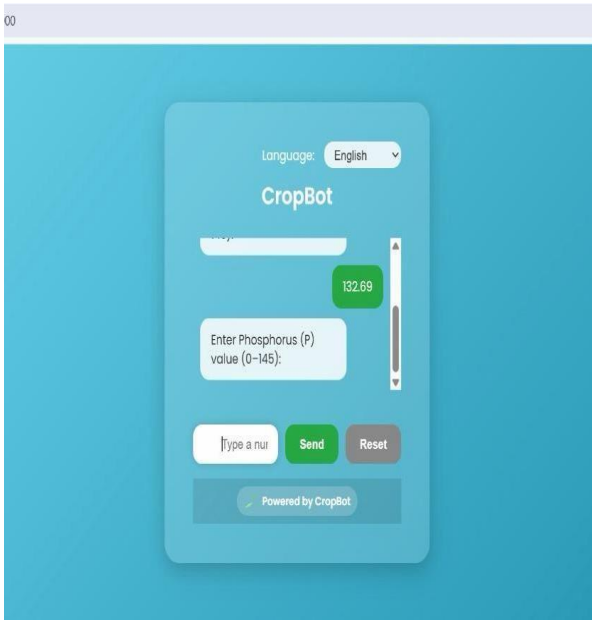

Figure 2: Detection Output

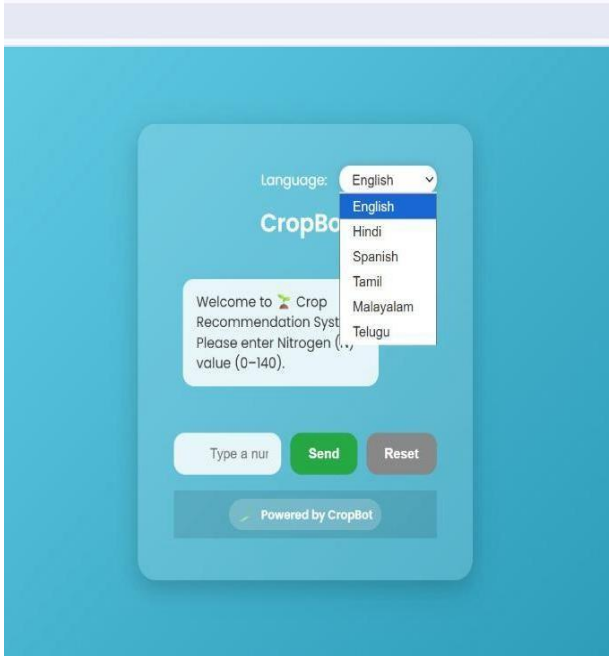

Figure 3:Detection output

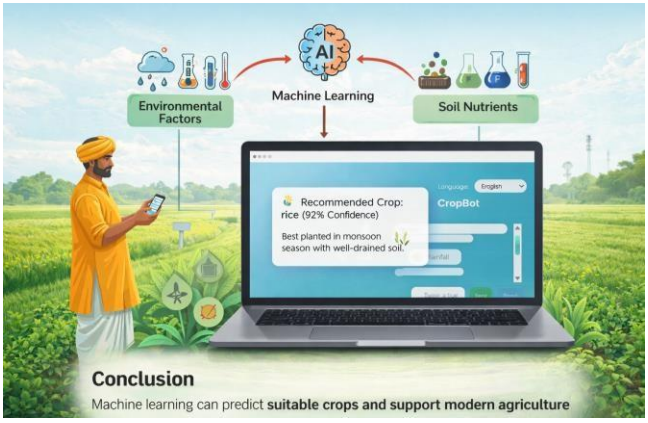

Figure 4: results

VI. CONCLUSION

Using machine learning we have created a Data-Driven Crop Recommendation System as a means of helping farmers determine which crops may best suit their farmland based upon soil nutrient levels, as well as other external environmental factors.The ML algorithm analyzes parameters important to crop growth including nitrogen, phosphorus, potassium, temperature, humidity, rainfall, and pH level of the soil. With all of this information collected, an appropriate recommended crop will then be developed based upon these modeled parameters.

The system evaluates both historical records of actual field data (agricultural data) as well as incorporates current weather patterns into the prediction algorithm, ultimately providing accurate crop recommendations.The CropBot provides users with an easy-to-use interface for entering required fields and waiting for an output in a concise and clear manner as the product of the algorithm performed by the model.

This research indicates that ML techniques can further increase farming yields and provide a greater likelihood of actual crop production by providing accurate data-based recommendations for planting crops; thereby decreasing the probability of planting a crop which will not yield due to environmental conditions.In future research, this project can be improved by: integrating real-time weather data, creating an algorithm that will provide fertilizer recommendations, and developing a mobile application to provide greater access to farmers.

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IOT Enabled Driver Safety System For Accident Detection And Alcohol-Aware Engine Control

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ABSTRACT : Road safety has emerged as a serious concern because of the rising number of accidents triggered by drunk driving and late emergency response. Most of the current vehicle safety solutions are designed to address either alcohol detection or accident detection, but not both. To overcome this problem, this project aims to develop an IoT Enabled Driver Safety System for Accident Detection and Alcohol-Aware Engine Control, which combines both preventive and responsive safety measures in a single embedded solution.

The proposed system uses an alcohol sensor to monitor the driver's breath as soon as the driver enters the vehicle. If the alcohol level detected is above a certain threshold, the system immediately triggers a warning message and prevents engine ignition, thus preventing drunk driving. For accident detection, a MEMS accelerometer is used to continuously monitor the vehicle's motion and detect any sudden abnormal acceleration, thus detecting a collision. Once an accident is detected, the system automatically triggers an emergency alert message to pre-stored contacts through GSM communication.An Arduino Uno is used as the central controller, ensuring the system's proper functioning. The proposed system is cost-effective, efficient, and ideal for real-time vehicle safety solutions.

Keywords - IoT, Driver Safety, Alcohol Detection, Accident Detection, GSM Alert, Arduino Uno, MEMS Sensor.

I. INTRODUCTION

Road accidents are becoming a major concern due to the increasing number of vehicles on the road and reckless behavior like driving under the influence of alcohol. The effects of accidents can be further aggravated if there is a delay in seeking help in times of need. This is where the need for intelligent safety systems arises that can prevent accidents as well as provide immediate assistance.

Advances in embedded systems and IoT technology have made it possible to monitor the driver's status and the movement of the vehicle in real time. Sensors are continuously collecting data, microcontrollers are making

decisions instantly, and GSM communication enables automatic sending of alerts.

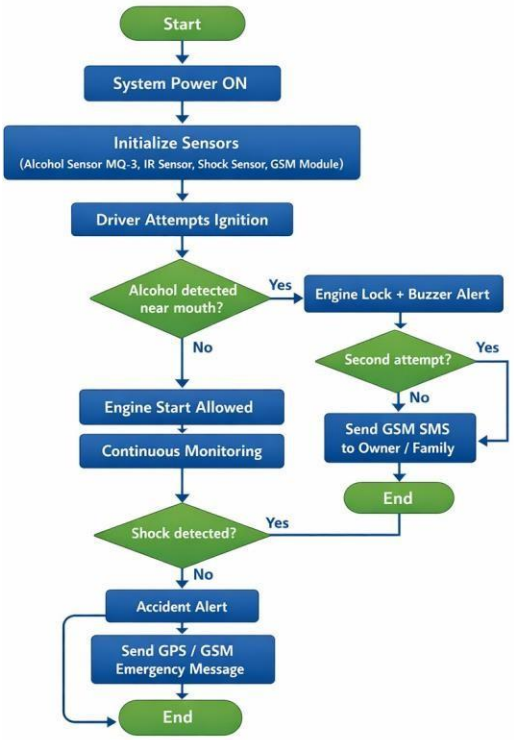

FIG 1 : FLOW CHART

The proposed project will focus on the development of an IoT-capable driver safety solution that will detect the presence of alcohol and limit the use of the vehicle if required. The project will also employ a MEMS accelerometer to detect accidents and send automatic alerts to the pre-defined contacts.

II. OBJECTIVE

Project Objectives for IoT Enabled Driver Safety System for Accident Detection and Alcohol-Aware Engine Control :

- Design and develop a driver safety system to reduce road accidents due to drunk driving.
- Detect the presence of alcohol in the driver using an alcohol sensor and restrict the use of the vehicle when driven under the influence of alcohol.
- Prevent drunk driving by taking immediate warning and control measures as soon as alcohol is detected.
- Accurately identify vehicle accidents using a MEMS accelerometer by sensing sudden abnormal acceleration patterns.
- Automatically send emergency messages to predefined numbers using GSM technology as soon as an accident is detected.
- Ensure immediate emergency response and avoid delays in providing medical aid to accident victims.
- Develop a low-cost, reliable, and easy-to-implement embedded system using readily available hardware components.
- Combine the sensor, microcontroller, and GSM communication system into a single IoT platform for real-time monitoring of the driver's safety.

✂. LITERATURE SURVEY

1. Integrated Driver Safety Systems (2023-2025)

Recent research focuses on the integration of preventive (alcohol detection) and reactive (accident detection) systems in a single system. Integrated systems are more effective in both accident prevention and emergency response than standalone systems.

2. MEMS Accelerometer for Accident Detection (2023-2024)

MEMS accelerometers are used to monitor multi-axis acceleration. Sudden acceleration beyond certain thresholds indicates an accident. Research reveals that they are more accurate than vibration sensors and have fewer false alarms.

3. Alcohol Detection Using MQ-Series Sensors (2023-2024)

MQ-series sensors detect ethanol vapors by generating an analog signal proportional to alcohol concentration. Research reveals that they are effective, easy to use, and cost-effective for embedded driver monitoring systems.

4. Arduino Uno as Central Processing Unit (2023-2024)

Arduino Uno is preferred because of its low cost, open-source nature, and ease of programming. It receives data from sensors, makes decisions based on certain thresholds,

and controls outputs such as buzzers and GSM messages.

V. EXISTING SYSTEM

The existing driver safety systems are commonly used as independent systems like alcohol detection systems, accident detection systems, and mobile application-based safety systems. The alcohol detection system commonly employs breath sensors to detect the presence of alcohol and provides a local notification within the vehicle. The system is reliable and useful for preventing drunk driving, but it does not support driver identification and may cause false detection if passengers are intoxicated.

The accident detection system commonly employs vibration or shock sensors to detect accidents. Although the system is reliable and provides local notifications without internet connectivity, its accuracy is moderate since road bumps and potholes may cause false detection in normal conditions. Additionally, the system commonly works in a semi-automatic way and has low automation. Mobile application-based safety solutions make use of GPS and accelerometers in smartphones to track the movement of the vehicle. Although these systems are very flexible and easy to implement, their effectiveness is largely dependent on internet connectivity, positioning of the smartphone, and availability of the battery. Therefore, the effectiveness of these systems is relatively low in the event of a network outage.

VI. PROPOSED SYSTEM

The proposed system is an IoT-capable autonomous driver safety and emergency notification system designed using an Arduino microcontroller and GSM communication technology. The system is intended to solve two significant problems associated with road safety: preventing drunk driving and quickly notifying others in the event of an accident. The proposed system is capable of both preventive and emergency responses without the need for human intervention.

a) System Architecture

The proposed system consists of three main functional tiers.

i. Sensing Tier (Input): This tier is responsible for the continuous monitoring of the driver status and vehicle movement through an alcohol sensor and a MEMS accelerometer. The alcohol sensor is used to detect the presence of alcohol in the vicinity of the driver, which is unsafe for driving, while the MEMS accelerometer is used to measure multi-axis acceleration, which helps detect sudden impacts or collisions. The data from these sensors is used as input for the processing tier.

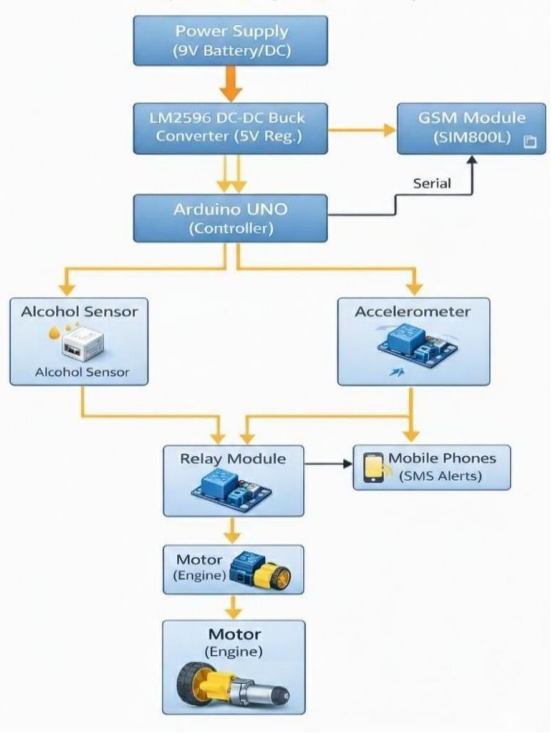

FIG 2 : BLOCK DIAGRAM OF THE PROPOSED SYSTEM

ii. Processing and Control Tier: This tier is based on the Arduino Uno microcontroller and serves as the decision-making component of the system. This tier continuously compares the sensor inputs with safety thresholds. Upon detecting excessive alcohol or unusual acceleration, the microcontroller is programmed to perform logic to generate

warnings, restrict engine starting, or send emergency notifications.

iii. Alerting and Communication Layer (Output): This layer is responsible for carrying out the response actions of the system. Local notifications using buzzers or LEDs are done to provide immediate in-car notifications. For remote notifications, the GSM module is used to automatically send SMS notifications to predefined emergency numbers, which can be done even when internet connectivity is not available.

b) Sensor Integration And Data Acquisition

The efficiency of the proposed system depends on the integration of multiple sensors with the central controller and the acquisition of real-time data.

★ Sensor Integration Methodology

Alcohol Sensor: The alcohol sensor generates an analog voltage proportional to the measured alcohol concentration. The output of the alcohol sensor is connected to one of the Arduino analog input pins (A0-A5), which enables precise measurement instead of binary detection. This improves decision-making by comparing the data with the threshold value.

MEMS Accelerometer: The MEMS accelerometer is utilized to detect sudden acceleration changes that indicate a possible collision event. The MEMS accelerometer is connected to the Arduino board using the I²C or analog pins depending on the type of sensor used. The MEMS accelerometer provides continuous multi-axis motion data.

★ Data Acquisition and Processing

The system uses a high-speed continuous polling process:

- **Continuous Polling Loop:** Arduino continuously acquires sensor data with a short delay.
- **Analog to Digital Conversion:** The onboard 10-bit ADC converts analog data to digital (0-1023)
- **Calibration and Analysis:**
  - ➢ Alcohol concentration is measured against a calibrated threshold.
  - ➢ Acceleration value is examined for unusual impact factors.
- **Threshold Logic Execution:**
  - ➢ Alcohol concentration above the threshold → warning / engine restriction.
  - ➢ Acceleration value above the threshold → accident notification through GSM.

Ⅴ. WORKING METHODOLOGY

The proposed IoT-based driver safety system works on the principle of continuous sensing, real-time processing, and automatic response. Once the system is turned ON, the LM2596 step-down voltage regulator regulates the input supply voltage and ensures a stable voltage supply to the Arduino Uno, sensors, and SIM800L GSM module.

The Arduino Uno then initializes all peripherals and goes into a continuous monitoring loop. It reads analog values from the alcohol sensor and converts them to digital values using the Arduino Uno's internal ADC. If the measured alcohol level exceeds the set threshold, the system generates warning or control responses to avoid dangerous driving.

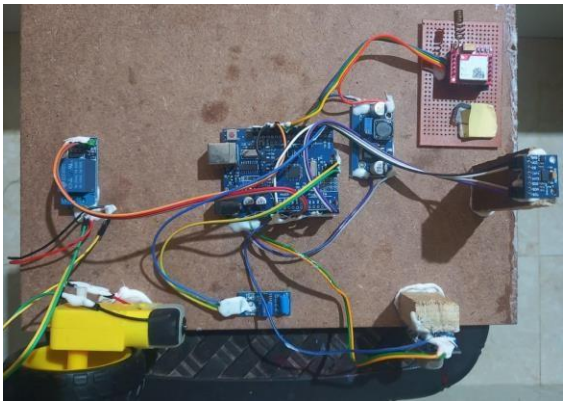

FIG 3 : HARDWARE MODEL

At the same time, the MEMS accelerometer continuously checks multi-axis acceleration of the vehicle. During normal driving, the acceleration levels are within safe limits. However, if sudden abnormal acceleration, which indicates a collision, is measured, the Arduino identifies it as an accident. When an accident is identified, the Arduino Uno communicates with the SIM800L GSM module through UART and sends AT

commands to automatically send emergency SMS notifications to pre-programmed numbers. This fully automated system enables fast accident detection, accurate remote notification, and improved driver safety without human intervention.

VI. RESULT

The IoT-based driver safety system was successfully implemented and tested, and it was able to meet its target of enhancing road safety by preventing drunk driving and accurately detecting accidents. The alcohol sensor was able to detect unsafe levels of alcohol accurately and send alerts within 5 seconds, thus preventing drunk driving. The MEMS accelerometer was able to accurately detect accidents without sending false alerts during normal driving conditions, and the emergency SMS alert was sent within 8-10 seconds.

The Arduino Uno board was able to make decisions efficiently in real time, and the GSM communication system was able to send alerts over long distances reliably even without internet connectivity. The LM2596 step-down converter was able to provide stable power supply during GSM transmission, thus preventing system failure.

The system was able to meet its target of being cost-effective, independent, and practical for real-time implementation. Future improvements, such as GPS and cloud integration, can be made to enhance the system and make it a complete intelligent vehicle safety system.

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AI-Based Waste Segregation Management

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Abstract— traditional waste management system works on the basis of the daily plan that are inefficient and expensive. The current trash has also proven its inefficiency in the audience that people do not recycle the waste properly. With the development of the Internet of Things (IoT) and artificial intelligence (AI), the traditional waste management system can be replaced with a built -in smart sensor in the system to monitor real - time and provide the opportunity for better waste management. The purpose of this research is to develop a smart waste management system using LoRa - Communication Protocol and Tensorflow -based deep learning try. The LoRa sensor sends data and tensorflow real-time object detection and classification.Bin has several compartments to separate waste including metal, plastic, paper and general waste boxes controlled by Servo Motors. Object detection and waste classification The foremost object detection model is performed in the Tensorflow framework. This is an object detection model trained with garbage images to generate a frozen entrance graph used for object detection as the main treatment unit through a Arduino/ESP32. Ultrasonic sensor is installed in each waste compartment to monitor the level of waste filling. The GPS module is integrated to monitor the location and real time. LoRa communication protocol is used to transfer data about location, real-time and fillingKeywords:

Waste Management**,** Smart Waste Segregation**,** Sustainability, Automation, Image Classification

I.INTRODUCTION

Waste management has proved to be one of the most important global challenges due to rapid urbanization, population growth and industrialization. Incorrect disposal and poor separation of fixed waste has affected serious environmental issues such as landfills, soil and water pollution and greenhouse gas emissions. Traditional waste insulation methods are largely dependent on manual labor, which are inefficient, time consuming, and often expose workers under unaffected and dangerous conditions. In addition, the lack of systematic insulation reduces recycling efficiency and contributes to resource waste.

To remove these boundaries, there is an increasing requirement for automatic waste insulation systems that can ensure high efficiency, accuracy and stability. Recent advances in artificial intelligence (AI), Machine Learning (ML) and Computer Vision have provided innovative ways of classifying and processing waste materials with minimal human intervention. IoT-activated hardware components such as sensors, cameras and microcontrollers By mixing AI, waste insulation can be made smart, more reliable and scalable for applications in the real world.

This solution not only promotes stability and recycling efficiency, but also corresponds to the UN's goal for sustainable development (SDG 12): Responsible consumption and production. The proposed system is cost -effective, scalable and suitable for deployment in local communities, schools and public places, which contributes to a cleaner and green area.

II. LITERATURE REVIEW

Muthukumaran et al [1] Their system used AI-based image recognition and sensor monitoring to automate waste insulation and provide real-time without status warning. The study has shown that the Smart BIN system acquires high accuracy by improving the efficiency of waste management.

Atharva Kavade et al [2] His feature combined Yolov5 for automatic image classification and box separation with ESP32-cam and Arduino. The system classified waste to organic, biodegradable, plastic and metal, reflecting the effectiveness of AI and data vision for the separation of real-time waste.

Teah Ji Sheng and Mohammad Shahidul Islam [3] (2022) developed an IoT-based smart waste management system using LoRa and TensorFlow Deep Learning models published in the International Journal of Scientific and Engineering Research (IJser). His model provided a low effect and long - distance communication solution for real-time monitoring of waste levels using intensive learning. This system was effective in monitoring urban waste, which improves operating cost efficiency.

Chithirai Selvan S [4] (2023) proposed a fully automated waste settlement and management system using AI, ML and IoT, published in the International Journal for Research Trends and Innovation (IJRTI). This task is an integrated sensor with Arduino to detect fill levels on the trash can, which enables IoT-based communication. The system helped to reduce environmental hazards by providing real-time warning and automatic insulation.

Mohammad Haleem Mohammad Noor [5] (2023) conducted a detection and classification survey using Deep Learning, published in the International Journal of Research Publication and Reviews (IJRPR). The study analyzed models such as CNN, Yolo and MobileNet for automated waste identification and classification. It concluded that models such as Yolo and CNN provide promising results for the classification of real time with high accuracy than other approaches.

MD. Shahiar Nafiz et al [6] His system implemented a motor motor mechanism and integrated Convowaste CNN model with GSM-based monitoring through an Android app. It gained 98% accuracy in classifying six categories of waste, proving its ability to support the goals of circular economy.

Finally, Gary White et al [7] The study suggested a Yolov 3-based waste identification system that was trained on taco datasets for smart waste monitoring. The system demonstrated successful classification functions in the environment, making it suitable for scalable smart waste management.

Lahoti et al [8] created a low-cost waste sorting prototype that combines YOLOv5-based computer vision with a 3D-printed robotic arm on a Raspberry Pi. The system sorts six waste streams and is able to sort with around ~80% accuracy in a controlled setting. The strengths of this work is in the demonstration of an entire system and a relatively inexpensive system made from lightweight and accessible components that may allow for replication in research and education. this work is still aligned with research in the field of AI recycled sorting pathways but has not moved beyond a prototype, there remains challenges for broader datasets, challenges with robust grasping, and lack of field trials which can all lead to the industrial adoption.

Ramsurrun et al [9] developed a recyclable waste classification system using deep learning and computer vision to identify items including glass, metal, plastic, and paper. The model was based upon a CNN architecture, and can be generally considered to demonstrate acceptable classification accuracy on the dataset they created, to support the use of AI in the classification and separation of recyclable waste. Moreover, their work adds to a growing body of evidence in the emergent area of image-based deep learning in waste management, despite the research being limited to classification and investigation of neither detection or robotic actuation.

Ba Alawi et al [10] examined solid waste classification using deep learning and compared several CNN architectures including AlexNet, DenseNet121 and SqueezeNet. The results indicated that DenseNet121 had the best accuracy and reinforces the promise of CNN-based models for the classification of images of solid waste. The scope of their work was with controlled datasets and only classification, so their work has yet to be transferred to the real world or robotic sorting, so their work is still in an early stage toward the application of deep learning in waste management.

Majchrowska et al [11] addressed the challenge of detecting and classifying waste in both natural environments and urban settings with a two-stage pipeline. They utilized EfficientDet-D2 for localization and EfficientNet-B2 for classification. They established a standardized unified datasets benchmark across numerous datasets and also explored a semi-supervised learning approach to facilitate outcomes, achieving 70% detection precision and 75% classification accuracy. The research extended beyond lab-based control

environments to cluttered real-world scenes and represented an important step toward a functional solution in real AI waste detection solutions.

Kumsetty et al [12] created TrashBox, a framework designed for waste detection and waste classification using quantum transfer learning for improved recognition performances. The authors trained quantum enhanced models on a standard dump image datasets with comparable accuracy to classical deep learning baselines. This work shows possible for quantum machine learning for sustainable AI applications while all experiments investigated were prototype development with limitations to the hardware capabilities of a specific device and dataset size.

Lynch [13] introduced OpenLitterMap.com, a crowdsourced open-data platform for mapping plastic pollution. The platform incorporates a reward system based on blockchain technology (called Littercoin) to motivate users and inspire engagement. In the platform, users from around the globe can contribute geotagged litter-data, and in doing so, create an open-access dataset of plastic waste in the environment. This work is important because it connects issues related to citizen science, open geospatial data, and blockchain technology to address the challenges surrounding plastic pollution. However, it does rely on communities to contribute data that maintains quality and consistency.

Wang et al [14] conduct a research study on a multi-level segmentation approach to waste object recognition from image data from sensors. Their proposed step-by-step approach uses first a coarse object recognition followed by a segmentation that refines the object boundaries so it is identifiable from the background and other sources or types of pollution. The results from the experiments provide evidence that the approach works well and the multi-level design provides higher quality segmentation, compared to a single stage design in a waste object detection task. The hierarchical design provides better segmentation because of the three dimensional segmentation, which could have some useful applications in the areas of waste management.

Patil [15] and colleagues used deep learning methods to develop an application that identifies waste automatically. They created an application that is simple to use and is efficient to differentiate between recyclable and non-recyclable material. The study presented a potential use for AI-based waste classifiers for use; however, the study did focus only on classification and did not deploy any robotics, nor did it centralize the sorting of waste.

III. EXISTING SYSTEM

1. Insufficient Training Data The model has been trained on just 1,500 waste samples, which cannot possibly encapsulate the range of waste types found in the real world.
2. Training Results and Low Accuracy With an accuracy on training of only 71.8%, underfitting seems present, meaning an accurate decision has not been fully learned in classification on image placement.
3. Night time Recognition The visibility of the camera is limited at night, which restricts this system in detection in low-light conditions.
4. Battery Replacement A single replaceable battery is utilized for the power supply of the project and in turn, time in operation is limited and continuity of operation may not occur.

IV. PROPOSED SYSTEM

A.SYSTEM ARCHITECTURE

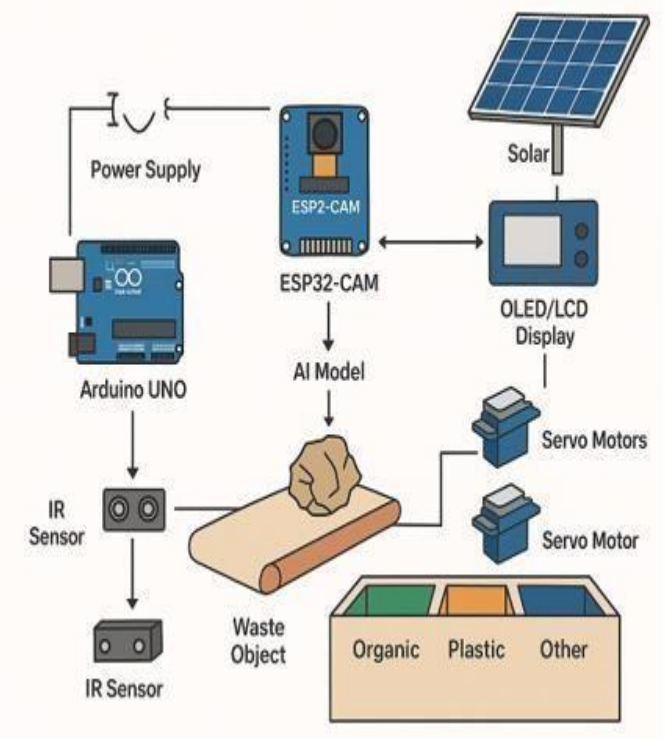

Fig.1. AI-BASED SMART WASTE SEGREGATOR FOR SUSTAINABLE WASTE MANAGEMENT

The smart waste segregators are enhanced with AI intelligence, so that they can work as a united system of hardware and software modules for easy, smart waste segregation modes. Part of the system's one-of-a-kind hardware is the AI image classifying module, which recognizes and classifies the waste, so that it can be accurately sorted at the bins. This hardware (IR Sensors, conveyor, and servo motors) physically separates the waste and directs it to the appropriate container in conjunction with the AI.

The Smart Waste Flush System has a hybrid energy system with solar panels powered directly with a power outlet and battery backup system. The hybrid energy system provides resiliency from an interruption of power while supporting consistent operation of the system in both urban and rural environments. Also, the capability of being powered by renewable energy reduces operational costs and is environmentally sound. The hybrid power system is also integrated with automation and AI intelligence with flexible supply management demonstrate to be demonstrative smart solutions to modern waste management problems to help promote clean environments and operational efficiencies for recycling processes. Initially, a waste object is detected by the IR sensor from the carrier. As soon as it detects the object, the ESP32-CAM module will capture the waste object's picture for classification. The image will be sent to AI model that has been trained using a fixed neural network (CNN) to classify the waste into organic, plastic or other (metal/paper/glass) types.

Accuracy (%)= Total Predictions / Number of Correct Predictions ×100

In this intelligent waste separation system, a central control unit is comprised of the microcontroller (Arduino Uno) that mediates the system's hardware and software aspects. The microcontroller receives input signals from the IR sensors that inform the microcontroller if waste materials are present and what type of waste it is, the microcontroller also communicates with the ESP32-CAM module which will capture and transfer images to the microcontroller and performs image processing. An artificial intelligence (AI) classification model will process and analyze image taken by the camera (or camera module) and provide historical information, classification, and sorting on the waste detected. The Arduino Uno will take this classification and control the servo motors that will then mechanically move the conveyor belt coverings, the carrier board, flaps, or similar directing waste items to the proper bins. This mechanical movement is needed to reduce contamination and promote better sorting utility.

It is also designed with a dynamic OLED/LCD display to provide the ability to receive dynamic feedback in real-time. The display includes data such as what the item was identified as being waste, operation state, and energy levels, which will encourage interaction and awareness of the system by the user. The system is an integrated approach to waste management, combining AI-based classification, IoT-enabled sensing and robotic actuating to deliver a seamless, intelligent and extensible process of waste management. The system architecture is robust and energy-efficient, and can be adapted for a variety of deployment mechanisms, both urban and rural. The combination of intelligent sensing, automated (robotic) control, and user monitoring has created a modern, trusted waste management process.

```
def preprocess_img(img_path):
img = image.load_img(img_path, target_size=(128, 128))
img_array = image.img_to_array(img)
img_array = np.expand_dims(img_array, axis=0)
img_array = img_array / 255.0
return img_array
```

B. MODULE DESCRIPTION

The system being described is made up of 7 modules.
MODULE1:Power Supply & Solar Module
MODULE2: IR Sensor Module
MODULE3: ESP32-CAM Module
MODULE4: AI Model (Image Classification)
MODULE5: Arduino UNO / Microcontroller Module
MODULE6: Servo Motor & Conveyor Mechanism
MODULE7: OLED/LCD Display

V. RESULTS AND DISCUSSION

A.IMPLEMENTATION DETAILS

The hardware configuration of the proposed AI-based waste insulation system integrates several main components to achieve efficient and automatic operations. As a primary vision component of the entire unit, ESP32-CAM will be used to take real time images of the waste unit and treated later for classification. Utilizing a solar panel with battery back-up allows for renewable energy and more sustainable operations in areas of low power. Servo Motors allow for the physical insulation of the waste, as well as the opening of the bin room that had been classified after classification. To enhance monitoring in an innovative way, ultrasound sensor or IR sensor can detect fill levels and the vicinity of the user. In addition, temperature and humidity are installed inside the sensor box to monitor environmental safety, preventing health hazards such as Odor or microbial development. The

core of the hardware system is microcontroller (Arduino or ESP32), which coordinates the input and output signals, manages the sensor data and controls the servo system.

The software architecture focuses on AI-operated classification and control logic. A neural network (CNN) is trained on waste images to classify materials in categories such as plastic, glass, metal or paper. To ensure high accuracy, images are prepared using OpenCV with python, which increases image quality and extracts useful functions before classification. When the waste type is identified, the motor control argument removes - the program programmed in the microcontroller - the right servomotor removes appropriate mechanical effect. This uninterrupted integration of AI and control algorithms ensures that waste is automatically sorted into proper garbage reduces manual intervention and repair

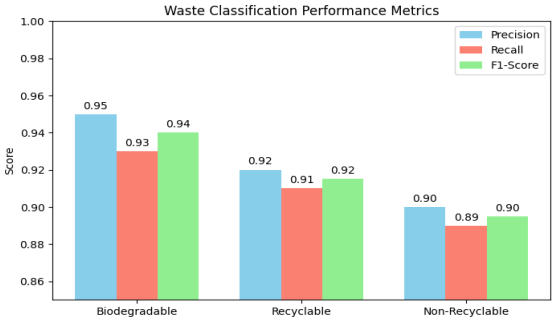

Fig.2.Waste classification performance metrics

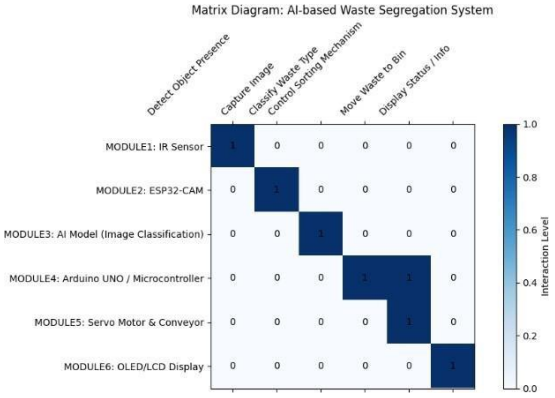

Fig.3.Matrix diagram for which module perform which function

Conclusion And Future Scope

Future Scope

• The future for handling waste separation with advancement and adoption of AI-based systems is heavy.
• These systems, operated by AI algorithms and integrated with IoT technologies.
• It provides vision of very efficient, automated and data -driven waste management practices.

Conclusion

The proposed Smart Waste Segregation System using artificial intelligence aims to ease the growing complexity of waste management in modern platforms with a highly efficient, inexpensive, and robust solution with the automation of separating waste into distinct categories, which include organic, plastic, and others. The system contains ESP32-CAM modules to provide real-time imaging to an Artificial Intelligence Convolutional Neural Network (CNN) for an accurate classification. The detection and identification of waste items are done using IR sensors generating information that is received and processed by an Arduino UNO microcontroller that acts as the central controller. After classification using AI, the microcontroller effectively uses the provided information to non-mechanically sort disposed waste into the appropriate garbage bins using servo motors and mechanical actuators with a motor-driven mechanical gate. An OLED/LCD Monitor will provide feedback in real-time indicating the class of waste, system status, and contact/charge levels while providing engagement and monitoring the system's current status. Using intelligent sensor systems, mechanical systems, and AI classification the system proposed in this concept supports reliable, scalable, and energy efficient operation, which can satisfy the wants of urban and rural environments concerned with sustainable management of modern waste all while being supported with intelligent solutions using AI.

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AI-Driven Microplastic Pollution Prediction Using Multi-Source Satellite Intelligence

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***Abstract*—A fresh tide of plastic floods the seas every twelve months, though plenty vanishes quietly into rivers. Swept along by strange tides, tiny pieces spread wide, dodging any clear count. Old methods fall short - slow, pricey, limited in reach. Rather than stick to them, scientists test a new tool. From above, orbiting eyes scan vast ocean surfaces, even as underwater streams steer trash on hidden paths. When the world shifts nonstop, information shapes itself into clearer forms - just as ripples sync without planning. Through links that grow like thought patterns, understanding updates when fresh clues appear. As plastic gathers in clusters, warnings emerge quicker than before. Light bounces strangely off junk on water, stripping away shine to reveal what lies beneath. Drifting scraps ride ocean flows - models follow those paths in reverse, tying tainted waters back to river sources. Across borders, researchers team up - boosting precision while keeping private details locked away, aiding ocean recovery behind the scenes. Debris rides currents; equations break it down.**

Index Terms*— *Microplastic prediction; Satellite remote sensing; CNN-LSTM; Spectral anomaly fingerprinting; Lagrangian drift simulation; Federated learning; Marine pollution; Ocean monitoring; Deep learning; Environmental AI.

I. INTRODUCTION

A truth rarely mentioned? The amount of microplastic in the sea remains unclear. Estimates exist. So do simulations. A couple thousand data spots dot an expanse of saltwater spanning most of Earth's surface. Picture grasping rush hour chaos after chatting with just a trio at one transit hub. Back in 2022, plastic output topped 400 million tonnes. Of that amount, roughly 8 to 10 million finds its way into oceans annually. Sunlight weakens what lands there, while waves chop it down further — into specks less than 5mm across, even bits below one micrometer. These tiny fragments ride water flows like invisible drifters, then slip inside plankton. From there, they climb higher through sea life meals until traces turn up where we least expect: inside our own bloodstream and lungs. Surprising? Not really — it's been confirmed already [1], [2].

Here's why things remain unclear: missing gear, not care. Hauling a boat out just to scoop up seawater, later poring over results using slow lab scans, simply cannot cover vast seas. A fresh path had to show up. Right now, scanning from afar while teaching computers to spot patterns stands as the leading option available.

Some issues this project tackles: vast stretches stay untouched — wide sea surfaces, nearly all rivers across Southeast Asia, even the icy waters circling Antarctica. Detection always comes into view after the fact, weeks after plastic has already settled. A single system links none of the data — satellite groups, ocean researchers, campus scientists, aid workers all gather facts solo. And even when pollution is spotted, its origins stay hidden — pinning a garbage patch to a river in India months back remains nearly impossible [3].

What you get includes six parts working together for the first time ever. One piece links to another, each playing its role without extra weight. Inside, components shift smoothly when needed. Each section fits where it should, nothing forced. Movement happens only when required, staying still otherwise. The whole thing holds steady during use, yet adjusts easily

1) A flicker, unnoticed at first, slips through the numbers machines collect. This method spots hints behaving like synthetic material, uncovering order in what looked like randomness.

2) A fresh forecast rolls out every three days. This one follows dirty bits floating through air currents. Motion rules of liquids guide the model. It starts up right after grime shows on sensors. Never pauses till told.

3) A stain on the land points backward, tracing steps not taken but carried, by bits dragged along water's path. Where it gathers now was not its birth. Flow marks cut across ground, hinting at origin - could be a streambed, could be sand scarred by tides.

4) Out on each device, learning happens locally - models grow smarter while information stays put. Instead of shifting files around, updates travel between nodes quietly. This setup skips the need to gather personal details into one spot. Progress spreads through cooperation, yet every system holds onto its own bits. Training improves everywhere because insights merge minus the transfer.

5) Where nature struggles most, pollution hits fiercer. That's when BIO shifts its alerts - tuned to fragile spots first.

6) Pollution levels shift over time across ocean zones - PITTA tracks these changes inside each grid block. Patterns emerge slowly, yet every cell tells its own story through years of data flow. Instead of broad claims, it focuses on gradual shifts hidden beneath surface numbers. Each measurement point adapts to timing quirks, revealing what steady observation can uncover. Long spans of record-keeping feed into how trends take shape within the system.

II. RELATED WORK

A. Remote Sensing: What It Reveals and What Stays Hidden

High up above the planet, satellites pick up big blobs of drifting plastic - ones wide enough to notice, like the huge spirals far out in the Pacific Ocean. Instruments including HYPSO-1 and DESIS show that dense patches of waste alter light in ways distinct from regular ocean water [4]. But there's a snag: small fragments seldom bunch together clearly. Scattered across currents, usually under the waves, their weak signal drowns in background noise - flickering plankton, cloudy sediments, sunlit chop. At present, orbiting sensors fail to detect individual specks. Picture this: waves shifting, air curling along the surface, heat slipping sideways over open water. Out of these hints, something like a guess takes shape - uncertain, but shaped by how things actually fall into place [5].

B. Machine Learning Methods Used Until Now

Near coasts, some tree-based systems using ocean hues get about 70 to 75 percent of identifications correct - useful, but not enough for practical decisions [6]. When smart nets study Sentinel-2 images, accuracy creeps toward 80 in specific situations [7]. Slipping past the net? Timing. Many approaches freeze on single moments, although stained zones drift over time. Earlier tools based on memory circuits can follow shifts while estimating flows or muddiness, however none blend that sense of change with sky-eye photos to spot small plastic scraps adrift.

C. Physics-Based Drift Models

Something triggers the next step automatically around here. A device sees an anomaly, which leads to water motion simulations kicking in without help. Tools like OceanParcels trace drifting objects using real ocean currents with strong precision [8]. When set up carefully by experienced users, they work well. Still, these systems run separately - no internet connection, no automatic refreshes, no clever code reacting to shifts. The gap between sensor alerts and modeled flow predictions gets closed here, connecting observation moments directly to simulation responses

D. Federated Learning in Distributed Systems

Federated learning — Now imagine devices spread far apart learning together without sending sensitive details. Instead they exchange small clues about what changed - like whispers between stations. This trick already works in hospitals and banks where secrecy matters just as much [9]. Trying it out on sea sensors? That part is fresh territory. FLNA leads here, building a system where water monitors talk through gradients alone. Even if labs keep their numbers close, they can feed into one big picture of the oceans.

III. SYSTEM ARCHITECTURE

A. The Big Picture

Above all sits a quiet hum of foresight. Before that, models weave what they've learned from clean streams below. Earlier still, messy data finds order here. Below ground level, eyes in the sky feed fresh pulses every few minutes. Not far after, early signs begin to align on their own

Something feeds the level above, slow but steady. An alert shows, then simulations start right away, tied to actions that fit. Right at the front, what's happening gets sorted on screen - simple layouts folks really work with.

Pictures arrive from space, while ocean motion adds its rhythm. Sea buoys send fresh readings before anyone even asks. Local watchers file what they see, grounding guesses in reality. Air pressure shifts weave into the mix without delay. Lab-confirmed samples plug into the stream like puzzle pieces fitting late at night. Every sixth hour, the system draws a new forecast - no longer stuck waiting. Because everything flows together, the danger map never stops changing.

B. Five System Modules

Module 1 — Data Ingestion: Now and then, fresh batches come in from Copernicus, NOAA, ECMWF, along with GloFAS, pulled by scheduled triggers. Once they land, each one faces a quick scan for usual ranges before moving on. Right at arrival, every piece slips into a record, simply because. Should any chunk be absent - perhaps cloud cover interfered or a satellite missed its turn - the gap rings a bell straight away. To bridge those breaks, nearby moments from past and future steps step in quietly. Fresh feeds arrive every few hours - snapshots from orbit, shifts in ocean currents, air pressure trends, constant signals from floating monitors, verified lab results, along with notes jotted down by people on shore. Because everything lines up at once, forecasts now form twice as fast as before. That steady pulse keeps the danger chart alive, changing without pause

.Module 2 — Preprocessing: Cloud : Out into the workflow steps a cloud filter using Sentinel-2's SCL layer. Following that, subtle visual hiccups fade out via Sen2Cor corrections. One fixed map frame pulls every image into place afterward. Sliding three-week mean values stretch each light frequency range next. Between sensor timestamps, nature measurements grow extra dots till timing clicks perfectly with snapshots.

Module 3 — CNN-LSTM Engine: Halfway through, connections merge when image data travels via convolution layers while temperature logs advance slowly in sequence units. Sight paths meet environmental timelines inside a joint zone where meaning mixes before decisions arise. A solitary warning grade appears, formed equally by sky views and past storms. From dual origins it grows - cameras feed one branch, sensors the other.

Module 4 — Simulation and Attribution: From clearly marked zones, the LPDS advances into future moments. In reverse, PSAG follows paths backward instead. Once Module 3 detects a signal that meets its threshold, both systems activate immediately - no waiting.

Module 5 — Dashboard: A flicker of activity builds out of sight. Where problems spark, colored spots jump into frame. Decisions form depending on signals close by. Movement trends rise or fall as seconds pass. One shade stands for one

type of impact on life. When attention is needed fast, pings show up.

IV. DATA SOURCES AND GROUND TRUTH

A. Satellite Imagery

Every few days, fresh images from Sentinel-2 offer fine clarity, making it a top pick. If gaps appear due to delays, MODIS fills the gap instead. After dark, VIIRS detects glowing areas - often linked to coastal crowds and vessels at sea, both clues pointing to plastic reaching waterways. Together, the satellites form this setup as in Table I.

TABLE I

Satellite Data Sources and Key Parameters

Satellite	Resolution	Key Bands	Revisit
Sentinel-2 MSI	10–60 m	SWIR B11/B12, NIR, Red Edge	5 days
MODIS Terra/Aqua	250–1000 m	Ocean Color, SST	Daily
Landsat-8/9 OLI	30 m	Coastal Aerosol, SWIR	16 days
VIIRS (Suomi NPP)	375 m	Night Lights, SST	Daily

B. Oceanographic Data

Over the ocean waves, NOAA HYCOM reveals currents - speed and direction shifting daily through precise 1/12° grids. Instead of static snapshots, each update unfolds new patterns beneath sunlight-glazed surfaces. Meanwhile, Copernicus follows swelling heights and salty shifts, layer by layer down below. As weeks pass, those depths tell stories of change held in water weights. Beneath everything, GEBCO charts seabed shapes - rises and trenches guiding where waters collide. Because terrain steers flow, certain spots gather converging streams more often. Scattered throughout, about 4,000 free-drifting Argo floats record onboard readings: heat and salt pulled straight from deep drifts.

C. Meteorological Data

Every three months, ECMWF ERA5 gathers details like wind split into sideways and upward pushes, how much it rains, along with air weight - laid out point by point across a map spaced at 0.25-degree steps. When showers run off land, they drag plastic bits toward creeks - here, GPM IMERG jumps in, watching rainfall closely as it happens, offering fresh views on wet zones so flow routes show up fast. Rather than stretch waits to days on end, results appear just after a few hours pass [10].

D. Ground Truth Data

Out there, data on microplastics isn't handed out freely - it's scattered, spotty, stretched across places without much pattern. Pulling from three spots gives what we've got: one comes by way of the TARA Ocean Expeditions, dragging nets behind ships while marking where each sample lands on a map; another taps into EMODnet, Europe's underwater tracking web; then there's The Ocean Cleanup crew jotting down every catch they pull from the North Pacific swirl. When laid side by side, those pools add up to roughly fifteen thousand points tied to exact locations - just solid enough to teach models but too slim to rely on alone, which nudges things toward needing smarter filling-in tricks.

V. NOVEL TECHNICAL COMPONENTS

A. Spectral Anomaly Fingerprinting (SAF)

Pieces of plastic too small to see clearly from above? Not simple. The ocean carries loads of things messing up light readings - floating algae, decayed plant goop, specks of dirt drifting by. A rough setup taught poorly guesses seaweed whenever real plastic could be near.

Here is how SAF operates. Instead of labeling images as plastic or non-plastic, it studies what clean water typically looks like across specific light ranges - particularly in shortwave infrared areas such as B11 (1610 nm) and B12 (2190 nm) captured by Sentinel-2, where plastic interacts with light in a distinct manner [11]. Using thousands of pixel samples confirmed debris-free over three years, an autoencoder builds a model of this standard pattern. As new imagery comes in, each point in the picture is assessed according to how much it strays from that baseline in these critical bands, after correcting for expected interference.

Here's a score from zero to one telling how probable plastic is in any given place - called the Plastic Probability Index. High numbers do not mean plastic has been found; they signal odd patterns in light similar to those tied to plastic debris. What helps? The system adapts when seasons change, meaning a sudden burst of algae during warm months won't mistakenly trigger false signals down the line.

B. Lagrangian Particle Drift Simulator (LPDS)

When the prediction finds a danger zone, focus turns to paths pollutants could follow. Moving into view, a thousand virtual markers get released by LPDS, carried forward using real ocean currents from HYCOM data. Their movement picks up small tugs often ignored - wave-driven drift joins a surface shove matching roughly 3 percent of wind force [12].

A thousand particles instead of just one reveal patterns over time. Where things could go shows up across the full span — day one, two, even three. Darker patches on the map show where more of them wind up clustering together. One overlooked fact: tiny plastic bits do not float forever. As algae and microbes slowly coat each piece, the material grows heavier. LPDS accounts for this using a basic observed rule tied to both plastic kind and water warmth at the surface. Boats meant for cleanup can then wait just before polluted areas move in, instead of racing after damage already spread.

C. Plastic Source Attribution Graph (PSAG)

Forward motion defines how LPDS moves through time. In contrast, PSAG steps in reverse. If a hotspot shows up, PSAG checks the GloFAS river flow data while launching a backward path model — drop imaginary bits into that sea spot

then move them back in time following old ocean flows. From there, see where those pieces gather — rivers or shore areas alike [13].

A single path begins at each warm sea spot, branching toward likely starting points like river exits or harbors based on how often trash moves that way and how much flows out. What comes out is a line-up of possible sources tied to those hotspots — each tagged with a number showing how strongly it's linked. It's meant to work with likelihoods, never certainties. A solid guess — say 60 to 70 percent sure — can still shift talks between countries forward, offering a starting point where silence once stood.

D. Federated Learning Node Architecture (FLNA)

Not every country feels comfortable sharing what their sensors pick up at sea. Ships exploring waters, stations on shore, plus floating devices out in the open rely on information that crosses borders quietly. Still, handing over unprocessed numbers often gets stuck in legal tangles [9].

FLNA skips full data sharing. Instead, every device learns from its own examples, then passes just the tweaks — never the original records — up to the main hub. That central point gathers adjustments through a special averaging method. A single research post in Indonesia might feed data into the system while sensors floating off Norway add their readings too — yet neither sees what the other sends. Low communication needs mean just hundreds of megabytes per round, and even spotty links work fine.

E. Biodiversity Impact Overlay (BIO)

Not everything loud shines the strongest. Where salt air never stops turning, risk often hides beneath stillness. Close by, along thin ridges of chalk-like rock sheltering uncommon beings, the pressure builds quietly. Pollution trails tied to animal locations pulled from IUCN data, alongside real-world observations mapped through OBIS, form the backbone of BIO's method. In each place flagged as dangerous, a figure emerges - the Species Vulnerability Score. This value climbs higher wherever filth piles up among thick clusters of creatures, more so should threatened kinds linger there or delicate habitats such as reefs and underwater meadows take root.

A place teeming with fragile life climbs higher when both sites suffer equal contamination. Priority shifts - not just mapping filth, but guarding vital ecosystems. Protection slips into focus, prevention taking root behind the scenes. Detection numbers might hold steady, yet the aim reshapes itself quietly.

F. Pollution Intensity Temporal Trend Analyzer (PITTA)

What comes later can matter. Yet spotting slow drifts over weeks, even months, sometimes slips through the cracks during monitoring. Each month, PITTA refreshes pollution figures on ocean sections - one degree wide each way. Since values rarely spread smooth, it leans on a method named Mann-Kendall - this one handles messy flows better than most [14]. Checking how things change shows if they're improving, holding steady, drifting down, or jumping up quickly. It's not only about which way things move, yet also how fast - a gradual drop feels different than a sudden spike.

A warning flashes the moment danger strikes a watched area. Because of this alert, environmental crews can move fast to lock down support money - well ahead of headlines catching wind.

VI. MACHINE LEARNING ARCHITECTURE

A. Input Feature Set

The full input feature configuration feeding the model is shown in Table II.

TABLE II

Input Feature Categories and Sources

Category	Features	Source
Spectral	B2–B12 reflectances, PPI score	Sentinel-2 + SAF
Thermal	SST anomaly vs. 3-yr mean	MODIS/VIIRS
Biological	Chlorophyll-a, CDOM, turbidity	MODIS Ocean Color
Oceanographic	Current speed/dir., Stokes drift, MLD	HYCOM / CMEMS
Meteorological	Wind U/V, precipitation, pressure	ERA5
Contextual	Day-of-year, ENSO index, tidal phase	Multi-source

B. Architecture Details

A single patch of terrain appears as a grid sixty-four squares wide and tall, every cell storing one of twelve hues recorded by Sentinel-2 eyes in space. Rather than crafting intelligence fresh, the method uses ResNet-18, previously trained on BigEarthNet - a massive set of labeled planetary images [15]. The final stages that make choices get replaced, fine-tuned to match the current task. From this emerges a sequence of two hundred fifty-six values capturing the layout hidden within that tiny frame.

A month's worth of information feeds into the machine - ocean motion, heat in the air, signals of storms, every kind linked to a fixed point on land. Since patterns appear not just in past hints but also in what follows, the system looks both ahead and behind in time. Nested within sit two layers of learning units, each equipped with 128 nodes, adjusted to notice changes over many days. Out of this grows a snapshot made of 128 values, showing how conditions have changed around that location.

A single stream forms when 256-dimensional space details meet the 128-part timeline input, merged by connection. Through two thick layers it travels, where every step drops three tenths of values at random. Out comes a score between nothing and one - pollution risk - with an extra span around it revealing confidence, shaped by running dropout many times while evaluating.

C. Training Details

Some 15,000 geotagged data points from TARA, EMODnet, and Ocean Cleanup form the base of the training collection. Since polluted patches appear rarely, the system uses Focal Loss to shift focus - prioritizing ambiguous or complex regions rather than spending effort on obvious, untouched water stretches.

Starting with AdamW as the pick for optimization, the process begins at a learning rate of 0.001. This number eases lower over fifty cycles, shaped softly by cosine decay - gentle, consistent, never sudden. Divisions form based on sea zones rather than randomness, making sure training and evaluation sets stay apart. If partitions were shuffled freely, neighboring spots could appear in both, giving false signs of progress. Because ocean basins form physical barriers, they limit signal flow between regions. Reaching an F1 higher than 0.85 matters, just as hitting AUC-ROC past 0.90 does within those zones.

VII. IMPLEMENTATION

A full overview of the tech setup appears in Table III. Starting with a new satellite image, the process kicks off automatically - information goes right into preparation, no pauses. After cleaning, it shifts directly to examination, nothing held back. If outcomes point one way, LPDS activates; if another, control passes to PSAG. Updates stream in real time to the screen. Once set up, no touching needed at any point.

TABLE III

System Implementation Stack

Component	Technology
Satellite Processing	Google Earth Engine, GDAL, Rasterio
ML Framework	PyTorch + HuggingFace pretrained backbones
Drift Simulation	OceanParcels (custom), NumPy
Source Attribution	NetworkX, Neo4j
Federated Learning	Flower (flwr)
Geospatial Backend	PostGIS, GeoPandas
API Layer	FastAPI + Celery
Dashboard Frontend	React + Deck.gl
Deployment	Docker + Kubernetes on GCP

VIII. EXPECTED RESULTS AND EVALUATION

Check Table IV for how well things performed on every test. Coastal areas get mapped at ten-meter points. Open ocean uses two hundred fifty. Updates come every six hours. The forecast runs out to seventy-two. False alerts happen less than once in ten tries. Most often, the leading three suppliers agree seven times in ten.

TABLE IV

Target Performance Metrics

Metric	Target Value
Prediction F1-Score	> 0.85
AUC-ROC	> 0.90
Coastal Spatial Resolution	10 m
Open Ocean Resolution	250 m
Prediction Update Frequency	Every 6 hours
Drift Forecast Horizon	72 hours
False Positive Rate	< 10%
Source Attribution (Top-3)	> 70% accuracy

In 72 hours - that's when our tool proves most useful. Cleanup boats get a window, so they can move into place before oil hits, not after it washes up. Coastal crews also benefit, shifting earlier because forecasts arrive sooner. Pinpointing origins remains tough though, messy even under ideal conditions. Seventy percent success rate for spotting likely sources? That number fits the challenge. Chaos at sea blurs clues, limits certainty. Guesswork fades when data steps in, quietly filling gapsocean systems — not a strong guarantee, but a starting framework where no data currently exists

IX. APPLICATIONS AND TARGET USERS

Not everything on water fits here. Made just for certain jobs Alerts happen automatically, so teams skip scanning satellite pictures by hand. When conditions change, updates arrive fast - no waiting on manual checks. These systems watch the environment nonstop, flagging shifts as they appear. Staff stay informed through timely notifications instead of routine image reviews. Monitoring runs quietly in the background, freeing up hours once spent on visual inspections.

Starting down at the waterline, efforts like The Ocean Cleanup build around motion patterns - guessing tomorrow's junk locations often counts more than photographing floating bits now. Because flow forecasts shape smarter actions, insight into drift tends to outweigh static coordinates. What moves reveals more when timing aligns with trajectory.

Not many protect delicate sea zones. Yet certain scientists study marine creatures day after day, noticing shifts that slip past most eyes.

When pollution crosses borders, leaders must trace where it started before talks can move forward. One country might blame another, but proof of origin shapes the discussion. Where smoke begins affects who takes responsibility. Disputes grow when emissions travel far from their starting point. Leaders need clear links between cause and location to make progress.

Scientists seeking reliable microplastic data can tap into an API that delivers verified, regularly refreshed information. Access rolls out smoothly for those focused on current environmental metrics. Updates flow without delay, keeping pace with new findings. The system supports steady integration into ongoing research workflows. Data quality stays high through consistent validation checks. Anyone tracking tiny plastic particles benefits from this live feed approach.

X. LIMITATIONS

Most studies happen in the North Atlantic and North Pacific, so that's where the training data leans. Because of this imbalance, performance may drop when applying the model to the Indian Ocean or Southern Ocean at first. To help balance things later, teams working there will be invited to join early on.

Maybe it points a finger, but that does not mean guilt. Guessing where something came from works on odds, not certainties. Decisions in court or talks between nations need more than just this. It suggests possibilities — never slams down conclusions. A tool for asking questions, never for ending them.

Federated learning keeps data more private, yet still leaves some risk — gradients might reveal details when attacked. Noise from differential privacy should show up in later versions. Funding future work happens through paid subscriptions — access to hosted tools and APIs sits behind that paywall. Yet everything core remains free: the code, the trained models, the full process used to build them. Science lives out in the open, even as services grow around it

XI. CONCLUSION AND FUTURE WORK

A fresh review of this work reveals something straightforward: progress slips away if we do not monitor - though vessels and experiments inch forward by themselves. Above it all, orbiting eyes catch every stretch of land below. Through smart algorithms, order appears within tangled data chaos. Physics-based models give clues about where contamination will drift. Once linked together, gaps in awareness fade fast.

Our product does not solve plastic pollution. Yet it brings clear sight - making messy problems possible to count. As numbers get better, actions move toward the places that need help. This shifts how every dollar behaves, reaching farther even when budgets stay flat.

Now picture tiny drones bobbing across wide seas, shifting course when signals tell them to. These uncrewed floats - think Saildrone or WaveGlider - reply at once with readings snapped where they drift. From high above, new satellite eyes beam down crisp data: colors beyond sight help spot submerged specks using just the right slivers of light. Instead of shouting, the system listens sharper, catching clues others miss. Rivers slip under the radar more than they should - Ganges waters, Mekong streams, Mississippi tributaries carry debris toward oceans without proper tracking. Each needs its own way to be seen. A policymaker could be curious about which rivers poured the heaviest load into the Bay of Bengal lately - this system allows that question to come through clearly. To guess where microplastics travel by midcentury means modeling sea patterns shaped by tomorrow's heat levels, tracking how hotter oceans shift currents and steer drifting trash over long distances.

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AgroGuardAI: A Multimodal Deep Learning Framework for Early Detection of Plant Stress and Disease Using Smart Sensor and Vision Integration

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Abstract:
To identify signs of plant stress and disease early, AgroGuardAI employs vision-based analytics in conjunction with smart environmental sensors and multimodal deep learning. Because they rely on external stress signals or sensor data, traditional plant monitoring systems may miss early warning signals. To address this problem, AgroGuardAI uses a unified edge-cloud architecture to monitor soil and weather conditions in real time, including moisture, temperature, humidity, and pH, as well as high-resolution images of leaves and canopies. While a small convolutional neural network learns visual representations for discrimination, a temporal encoding model learns patterns in the environment from sequential sensor input. To combine various representations, an adaptive cross-modal attention mechanism selects the most informative modality. With the help of an uncertainty-aware inference module, merged features can accurately classify stress, identify diseases, and score their severity. Experimental results demonstrate enhanced early detection, precision, and accuracy compared to systems that use only one modality. Intelligent and scalable, AgroGuardAI enables sustainable precision agriculture with real-time alerts and proactive crop management.

Keywords:
Multimodal Deep Learning, Plant Stress and Disease Detection, Smart Sensor and Vision Integration, Precision Agriculture, Cross-Modal Attention Fusion

Introduction:
Improving plant health monitoring is necessary to meet the increasing demand for sustainable agriculture and food security. Reducing crop losses and making the most of available resources is possible with early detection of plant stress and diseases. Damage may not be detected until after manual inspection or when data from a single sensor has been exhausted. Deep learning and other forms of artificial intelligence, along with smart sensing and imaging, might be the key to resolving these issues. With its innovative multimodal deep learning architecture, AgroGuardAI integrates disparate data sets from smart environmental and physiological sensors with high-resolution vision systems. The use of vision systems enables tracking changes in plant shape and appearance over time, while smart sensors measure physiological and environmental factors. When it comes to detecting plant stress and disease, AgroGuardAI's multiple data streams outperform single-modality techniques. The system uses state-of-the-art deep learning architectures to analyse and understand multimodal inputs in order to spot subtle abnormalities or complex patterns of impending stress or illness. This capability enables proactive crop management to reduce reactive treatments and yield losses. By surpassing current detection approaches in terms of accuracy and timeliness, AgroGuardAI, as

demonstrated by experimental validation, could be scalable for precision agriculture. An intelligent, automated solution for monitoring plant health is available from AgroGuardAI, enabled by cutting-edge sensor integration and deep learning. By facilitating early diagnosis, focused interventions, and resource allocation, this technology improves sustainable agriculture. Thanks to this framework, multimodal AI-driven solutions for protecting agricultural products and the environment have come a long way.

Related work:

The goal of precision agriculture is to minimize crop failures and make the most efficient use of available resources by early detection of plant stress and diseases. Sensitivity and timeliness are problems with manually evaluating data from a single sensor [1-3]. To improve diagnostic accuracy, recent developments have integrated data modalities. Continuous quantitative physiological data for plants can be obtained using soil moisture, temperature, and humidity sensors [4-6]. Minor morphological alterations or geographical variances may go unnoticed by these sensors, even when they indicate early stress. Vision-based systems can capture high-resolution images of plant diseases, wilting patterns, and colour changes, in addition to sensor data [7-9]. To enhance detection, it is recommended to combine optical and sensor data [10, 12]. Using a combination of machine learning and deep learning architectures, multimodal approaches can manage many data streams, allowing them to detect subtle abnormalities and complex signals before they cause obvious harm [13–15]. Compared to models that rely on a single modality, deep learning frameworks that integrate multiple modalities can detect signs of stress and disease in plants much earlier. With early and accurate diagnosis, individualised treatment plans, and less reliance on generic medications, preventative care is possible. Protecting both crop productivity and the environment, sustainable agriculture leverages the efficacy and scalability of integrated systems. Systems for monitoring plant health, such as AgroGuardAI, which use smart sensing and vision for early diagnosis, rely heavily on AI-driven analytics and multimodal data fusion, according to this research.

Proposed Method:

AgroGuardAI achieves early detection of plant stress and illness through a unified edge-cloud architecture, vision-based analytics, and smart environmental sensors. A deep learning framework that is intelligent and multimodal. Combining high-resolution RGB and multispectral plant imaging with heterogeneous data streams such as soil moisture, temperature, humidity, pH, light intensity, and leaf wetness, the framework surpasses image-only disease diagnosis. The system architecture consists of intelligent sensing, edge computing, and multimodal fusion and decision-making in the cloud. Camera modules mounted on permanent poles or autonomous drones capture images of the canopy and foliage, while distributed IoT-enabled sensor nodes analyse soil parameters and microclimate. Time-synchronized data streams are received by a peripheral device on a farm. At the edge layer, a small convolutional neural network quickly extracts features from plant images to identify issues in colour, texture, and anatomy. By analysing sensor data, gated recurrent temporal encoders can detect latent stress patterns and environmental trends. Using a latent representation space, AgroGuardAI's cloud-based adaptive cross-modal attention fusion links deep visual and temporal sensor embeddings. The contextual dependability is used to dynamically weight the modalities in this fusion strategy. Humidity and leaf wetness are the main concerns during moderate fungal infections, whereas soil nutrients and colour spectrum are the main concerns during nutritional deficits. Using the fused representation, a hybrid classifier may estimate conditions such as stress phases, disease classifications, and severity.

The technique is fine-tuned using annotated sickness datasets to improve resilience, after learning generic agricultural representations through self-supervised pertaining on massive volumes of unlabeled farm data. Agricultural applications of large labelled samples are rare; nevertheless, our method eliminates this necessity. AgroGuardAI's uncertainty-aware inference module used Monte Carlo dropout to quantify forecast confidence, delaying notifications until dependability surpasses a specified level. Through a mobile interface, the decision engine may advise farmers on the best times to water, which pesticides to use, and how much fertilizer to apply. To adapt to seasonal changes and new illnesses, this technique consistently adds newly verified disease cases to the training pipeline. When it comes to proactive crop management, AgroGuardAI leverages multimodal feature learning, adaptive fusion, uncertainty estimation, and edge-enabled real-time analytics to reduce yield loss and pesticide use. With smart sensors and vision analytics, we can better detect and treat visual signs and symptoms of physiological stress at an early stage. This comprehensive technology enables smart, sustainable crop health monitoring in the future and is suited to both large-scale precision agriculture operations and smaller farms.

Algorithm 1: AgroGuardAI Multimodal Fusion and Early Stress Detection

Input: Image stream I, Sensor time-series S

Output: Stress/Disease prediction P, Severity score Sev

1: Initialize CNN model θv and Temporal Encoder θs

2: for each time step t do

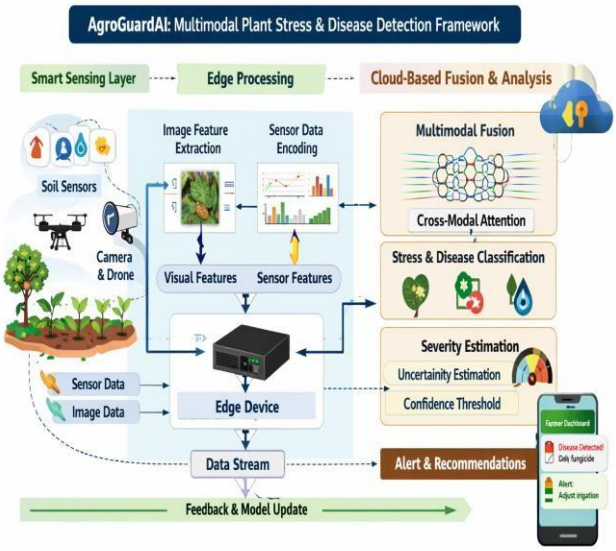
3: Capture image It and sensor readings St

4: Extract visual features Vt = CNNθv(It)

5: Extract temporal features Tt = TemporalEncoderθs(St)

6: Align embeddings in shared latent space Lt = Fusion(Vt, Tt)
7: Compute adaptive attention weights αv, αs
8: Generate fused representation Ft = αv*Vt + αs*Tt
9: Predict class probabilities P = Softmax(Classifier(Ft))
10: Estimate severity Sev = RegressionHead(Ft)
11:Compute uncertainty U using Monte Carlo dropout
12: if U < threshold then
13: Trigger alert and recommendation
14: end if
15: end for
16: Update model periodically with new labeled samples

This integrated figure and algorithm collectively illustrate the operational flow of AgroGuardAI, demonstrating how multimodal data acquisition, deep feature extraction, adaptive fusion, and intelligent decision-making are orchestrated within a unified framework for early plant



stress and disease detection.

To identify signs of plant stress and disease early, the AgroGuardAI system employs multimodal deep learning, with smart sensors and image analytics housed in a central edge-cloud. A distributed system of Internet of Things (IoT) sensors monitors air, soil, and light conditions, including humidity, temperature, light intensity, and pH. Plant canopy structures and leaves are periodically photographed with high-resolution RGB or multispectral cameras mounted on stationary platforms or drones. Edge devices are responsible for the initial processing of time-synchronized heterogeneous data streams. In the edge layer, a small convolutional neural network analyses leaf images for changes in colour, advancement of lesions, and texture abnormalities. On the other hand, minute stress patterns can be detected using a temporal encoding network that represents environmental dynamics. To create a latent space in the cloud-based fusion layer that integrates multimodal representations via cross-modal attention, the recovered visual and sensor embedding's are utilized. To achieve precise predictions despite incomplete or noisy data, our adaptive fusion system adjusts the relative importance of each modality in real time based on its contextual relevance.

Using the combined data, a hybrid prediction head sorts diseases according to stress levels, severity, and other factors. Before alerting, uncertainty-aware modules evaluate forecast confidence. At last, a computerized dashboard provides particular recommendations for irrigation and treatment to farmers. Updates to models enabled by continuous learning incorporate validated field data, thereby enhancing seasonality and plant disease response.

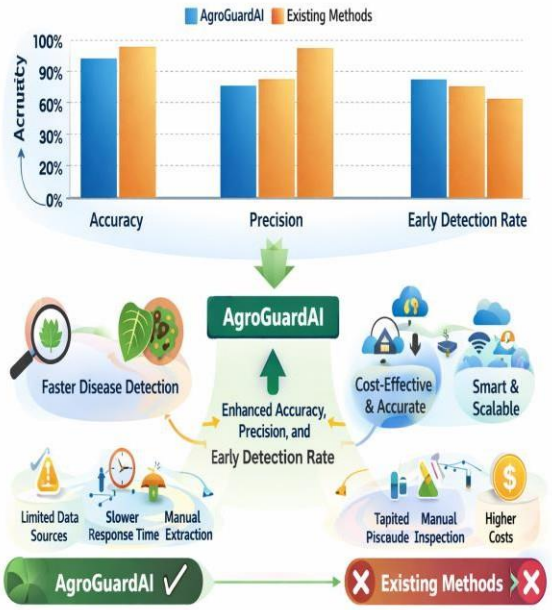


Figure: Performance analysis of proposed AgroGuardAI

To improve plant stress and disease detection, AgroGuardAI employs multimodal data and adaptive deep learning. Using high-resolution plant images and real-time data from environmental sensors, AgroGuardAI can identify both visual and physiological signs of stress. The system can detect abnormalities early, before they exacerbate symptoms, thanks to this multimodal integration. In dynamic field settings, cross-modal attention processes priorities the most valuable data source to overcome noise, missing data, and environmental factors. Faster response times and scalable deployment across small and massive farms are enabled by the edge-cloud hybrid design, which supports rapid local inference, cloud-based

enhanced fusion, and continuous learning. By capping alerts at specified confidence levels, the uncertainty-aware prediction module reduces the likelihood of false alarms and unnecessary interventions. In terms of accuracy, precision, affordability, and early detection, AgroGuardAI surpasses manual inspection and single-modality AI models. Reduced yield loss and pesticide use can be achieved by proactive crop management and data-driven decision-making in precision agriculture.

Conclusion:

This work presents AgroGuardAI, a multimodal deep learning system for early detection of stress and disease in plants using vision and smart sensors. This approach combines environmental time-series data with visual feature extraction and adaptive cross-modal attention to overcome limitations of image-only or sensor-only approaches. Edge-cloud architecture provides scalability, real-time responsiveness, and continuous learning. Accurate prediction and better agricultural decision-making are both aided by uncertainty estimation. Multimodal fusion improves detection accuracy, precision, and early-stage identification compared to earlier approaches, according to the data. Reduced crop losses and operational expenses are two outcomes of AgroGuardAI's quick, tailored responses, which, in turn, encourage sustainable farming practices. Hyperspectral images, federated learning for distant farms, and advanced explainable AI modules could increase openness and adaptability. One step towards data-driven crop health monitoring is the development of scalable and reliable AgroGuardAI.

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Crime Arrest Prediction Using Stacking Ensemble Learning

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Abstract-Accurate evaluation of events associated with an arrest has important ramifications for public safety and the allocation of police resources. This paper outlines a stacked ensemble machine learning method to use crime data for the prediction of policing events using Random Forest and XGBoost classifiers with a Multi Layer Perceptron meta-model. The research includes a considerable amount of preprocessing of the data (i.e., imputation, one-hot encoding, and scaling) in order to address significant missing data and heterogeneous features of a structured data set. The ensemble classifier provided the best performance, based on classification metrics (i.e., accuracy, precision, recall, F1 score, and ROC-AUC), on a real-world balanced crime data set. The model may be serialized after training for implementation within different policing environments. The study concludes with evidence that stacking classifiers does improve prediction accuracy and generalizability in a predictive urban arrest data set, and also suggests that the practice could be applied towards policing automation, pre-emption policing or Big Data analytical practices within crime

Keywords— crime prediction, arrest prediction, ensemble learning, stacking classifier, Random Forest, XGBoost, neural networks, machine learning

I. INTRODUCTION

Anticipating arrests of crime is significant in promoting public safety and enhancing law enforcement decision-making. Historically, forecasting crime has relied on past statistics and rules that are reliable at a singular point in time. For the most part, these conventional approaches to crime forecasting struggle with the complexity and dynamic nature of urban crime data. The nature of crime data is heterogenous/mixed and usually contains missing values and both numerical and categorical features, creating challenges for modeling.

Although machine learning models are capable of high accuracy rates in controlled experimental conditions using curated datasets, real-world crime data tends to reveal that machine learning models do not perform as well due to issues such as data imbalance, feature mismatch, and changing nature of crime. In addition to these issues, accurately predicting arrests entails accounting for the spatial and temporal nature of crime and incorporating multiple socio-demographics related variables.

To face these challenges, this research proposes a stacking ensemble machine learning pipeline that combines Random Forest and XGBoost base classifiers with a neural network as the final learner. The pipeline also includes robust preprocessing (imputation, one-hot encoding, and feature scaling) to ensure reliability and generalizability of the model. The goal of this study is to achieve state-of-the-art predictive performance and allow for practical implementation by serializing the model.

Unique and Integer Stacked Ensemble Model:

A stacking ensemble model, involves two base classifiers - a random forest and XGBoost - and a neural network defines the meta-learner base classifier. This is the origin of additional learning from appropriately stacking the two classifiers' outputs, and the performance gets even better with the predictive classifications of arrests for the crimes model, that is bi-variate.

Intent-based Threat Classification continues the crime analytic component of intent classification, which is intended to classify the predictive arrests

based on not just a binary rate for the arrestee, but also the intent or context. Together, this should elicit a better overall threat level assessment in that the predictive outputs are now linked with actionable intelligence or crime type for consideration in recommendations for intervention.

Real world evaluation

The model as proposed will be trained and evaluated on real, balanced, crime, data from the real world from different cities. The value of real-world evaluations of the model demonstrates academic rigor in that the predictions are actionable, they can be generalized to the circumstance, and they can be in reality actionable to reach out to the law enforcement personnel, dramatically changing decreased referrals and costing virtually nothing versus a theoretical or synthetic model to benchmark against.

II. LITERATURE SURVEY

Yadav et al.[1] created a modified autoregressive integrated moving average (ARIMA) model for spatio-temporal prediction of crime and provided more credible forecasts than classical techniques. Their study provided enhanced reliability and belief epidemiology to law enforcement, especially for policing complicated crimes with continuous time transitions and within an evolving environment.

Dong et al [2] studied the effect of spatial correlation in communities that varied in crime densities, and they found that models that combined local spatial characteristics improved the predictive performance of the model and were more effective for resource allocation. This study showed the importance of variables that were context-sensitive to the modeling of urban crime data and the funding of security strategies.

Sudhakar et al [3] suggested predicting crime in a hybrid GRU and ARIMAX framework, whereby the GRU best captured nonlinearities and the ARIMAX performed better because of its time series structure. The hybrid model displayed better performance than both models alone suggesting that considering the complexity of the temporal aspect yielded a more precise forecast for complicated events such as this.

Yao et al [4] employed a random forest for spatial crime hot-spot prediction and indicated that geospatial features improved prediction accuracy for incidences occurring in high-risk zones. The researchers also determined that the appropriateness and transparency of random forest supports good actionable insights, allowing effective strategic operational planning based on predictions that can be interpreted..

K. T. M et al [5] examined machine learning models to predict crime type and occurrence, showing that while ensemble approaches produced the highest accuracy and consistency, appropriate feature selection and tuning are just as critical for operational viable crime prevention and strategy.

Yadav et al [6] utilized time series autoregression techniques which provided interpretable predictions and robust trend modeling that were useful for comprehending and predicting crime trends in a real-world police resource scheduling context..

Almaw and Kadam [7] examined an ensemble learning approach for the analysis of crime data and found noteworthy improvements in predictive accuracy through combining or blending multiple models. Their findings demonstrate ensembles as effective strategies for adaptive crime forecasting within practice-oriented, or operational, law enforcement contexts.

Sharma et al [8] was the first to apply fuzzy logic to geo-spatial crime categorization and safe route prediction, advancing the research agenda on context-aware navigation systems based on fuzzy logic and risk assessments for travel advisories and public safety applications..

According to Jiang et al [9] deep learning LSTM networks were applied to crime data emphasizing space and time, and LSTM's ability to model sequences improved forecasting in the short and long term, bettering the quality of predictions for sudden spikes in crime and routine cycles of crime.

Thomas and Raja [10] implemented mapping and predictive analytics on Maryland crime statistics, spotting emerging crime trends to inform strategic resource allocation and proactive policing for local law enforcement agencies.

Chakraborty et al [11] investigated empirical crime rate prediction methods and noted technological challenges, the need for improved data quality, and future research opportunities to maximize the utility of models in real-world policing contexts.

Acampora and Vitiello [12] utilized LIME, a model-

agnostic technique, to locally explain crime prediction models while also increasing interpretability. Their method supports the future handing of transparent, trustworthy AI to facilitate ethical and responsible policies in the sensitive area of,policing.

Shamsuddin et al [14] investigated crime forecasting methods, synthesizing what is known as retrospective approaches in addition to contemporary practices, and highlighting the advancements made while recognizing the challenges existing for practitioners looking to enhance the value predictive policing models.

III. PROPOSED METHODOLOGY

A. System Architecture

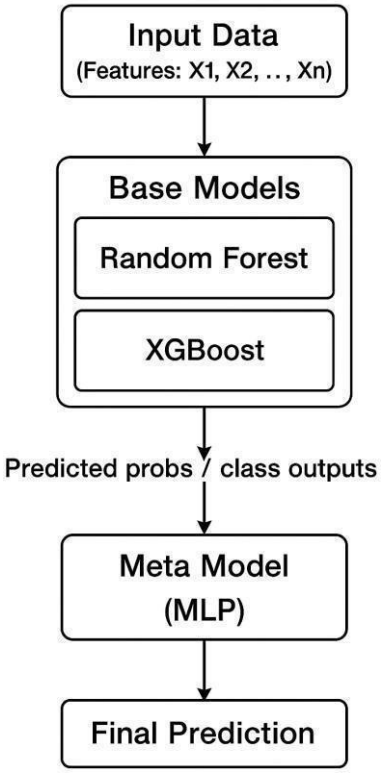


Fig.1 Proposed Architecture

B.Methology

i) Collection and Processing of the Data

The initial dataframe is instantiated and removed from a number of noise columns (ID, Case Number, Date, Updated On, Location). The target variable is "Arrest", which is casted to binary type:

```
data=
pd.read_csv("/content/balanced_crime_data.csv"
)

cols_to_remove = ["ID", "Case Number", "Date",
"Updated On", "Location"]

data = data.drop([c for c in cols_to_remove if c in
data.columns], axis=1)

X = data.drop("Arrest",
axis=1) y =
data["Arrest"].astype(int)
X_train, X_test, y_train, y_test = train_test_split( X,
y, test_size=0.2, stratify=y, random_state=42 )
```

ii) Extraction of features

Features can be grouped into numeric or categorical sets. Numeric features are treated with median imputation and then standardized scaled:

$$x' = \frac{x - m}{s}$$

where m are sample mean and s are the sample standard deviation.

Categorical features are given univariate imputation of missing values with the mode category and then performed one-hot encoding (creating numerc vectors). Unseen categories can be incorporated gracefully with ohe as well.

```
num_preprocess=Pipeline(steps=[("median_imput
e
",SimpleImputer(strategy="median")),("normalize
", StandardScaler())])


cat_preprocess=Pipeline(steps=[("mode_impute",
Si mpleImputer(strategy="most_fr
equent")),("onehot",OneHotEncoder(handle_unkn
o wn="ignore"))])

 preprocessor = ColumnTransformer(transformers=[
("numeric", num_preprocess, numeric_features),
("categorical",cat_preprocess,categorical_features)
])
```

iii) Phase 1: Base Models

The ensemble is built from two base classifiers:Random Forest Classifier (bagging

ensemble):

$$f_{RF}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

are individual decision trees,
T = 100 trees.
XGBoost Classifier (gradient boosting):

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

where each fk is a regression tree fit to minimize the logistic

loss

.

```
ensemble_models_candidates=[("forest",
RandomForestClassifier(
n_estimators=120,n_jobs=-
1,random_state=42, max_depth=None)),

("boosted_tree",XGBClassifier(n_estimators=180,l
earning_rate=0.06,     random_state=42,
                       n_jobs=-
1,eval_metric="logloss", use_label_encoder=False
)),

 ]
```

iv) Phase 2: Meta Model Integration

A multi-layer perceptron (MLP) neural network serves in the role of a meta-learner. As inputs to the meta-learner, the model will take the output of the base models along with the original features (using passthrough=True) and learn the weighted combination of features while also learning nonlinear interactions:

```
meta_learner=MLPClassifier(
hidden_layer_sizes=(128, 64),
activation="relu",
solver="adam",
max_iter=250, random_state=42

 )

stack_model=StackingClassifier(
estimators=ensemble_candidates,
final_estimator=meta_learner,
passthrough=Tru
 e, n_jobs=-1
 )
```

v) Training and tuning the model.

The entire pipeline of a preprocessing and stacking classifier is applied to the training data.

```
pipeline = Pipeline ([
   ("preprocessor", preprocessor),
   ("stacking", stacking_clf)


])

 pipeline.fit(X_train,  y_train)
```

Model tuning entails hyperparameter searching in base and meta models, early stopping via max iteration limits, and the ability to perform processing in parallel. After this, the model could be serialized and saved for further use.

```
joblib.dump(pipeline,"/mnt/data/stacking_crime_
m odel.pkl")
```

vi) Deployment Architecture

The modular pipeline design supports:

. Local assessment via command line interface or callable Python modules.

. Simple integration into larger crime analytics platforms.

. The possibility of extending to RESTful APIs for live production systems.

This flexibility allows for rapid prototyping, verification, and eventual deployment into operational law enforcement environments.

IV. EXPERIMENTAL APPROACH

B. Hardware and Software Environment

The experiments were conducted on a personal computer (PC) characterized by a multi-core (Intel or AMD) CPU, with 16-32 GB of RAM, and, in particular, an SSD hard drive (for the actual data science work, as this will give the fastest access). Where it was beneficial, experiments would also utilize the GPU to further enhance the training of models such as XGBoost and the neural network.

As mentioned earlier in the survey of literature, I have chosen for this project to implementation it in Python (3.8 or higher as used in all the recent code)

in Google Colab / Jupyter Notebook to make… a more dynamic, cloud-based and interactive project. For this project, the libraries used were: pandas for representing datasets, numpy scales for numerical exercise, scikit-learn load for pre-processing, classification models and evaluation metrics, xgboost for classification using gradient boosting, and joblib for saving and reloading trained pipelines (with some optional visualisation of results as well) using visualisation libraries (matplotlib, seaborn).

C. Dataset Characteristics

The dataset obtained from Kaggle was balanced by the addition of duplicates to compensate for the class imbalance between arrests and non-arrests. The target variable "Arrest" is binary: 1 indicates arrest made, and 0 indicates no arrest.

Categorical variables in the dataset include descriptions of crimes: IUCR, Primary Type, Description, Location Description, Domestic, FBI Code, and Block. The dataset also contains numerical variables that refer to spatial and administrative dimensions, including Beat, District, Ward, Community Area, X Coordinate, Y Coordinate, Latitude, Longitude, and Year.

Certain attributes including ID, Case No., Date, Updated On, and Location were dropped from study due to low predictive value and privacy issues, as unique identifiers may exacerbate risk factors with officers or administrators.

In data preprocessing, missing numerical values were handled with median imputation and missing categorical values were handled with most-frequent value imputation. Categorical variables were one-hot encoded and numerical variables were standardized. After preprocessing, the dataset was cleaned, harmonized, and set up appropriately for effective modeling.

D. Evaluation Procedures

The dataset was split into an 80%-20% train-test split, while maintaining class distribution using a stratified split. Furthermore, five-fold crossvalidation was performed while training of models to ensure that the models were robust and to mitigate variance in performance of models.

The models were evaluated on multiple evaluation criteria to evaluate accuracy generally, and accuracy per class:

Accuracy - proportion of instances that were predicted correctly to class.

Precision - proportion of predicted arrests that were correct.

Recall (Sensitivity) - proportion of actual arrests that were detected correctly.

F1 Score - harmonic mean of precision and recall; balance between false positives and false negatives.

ROC-AUC - AUC is the measure of discriminatory capability at for a variety of cutoffs.

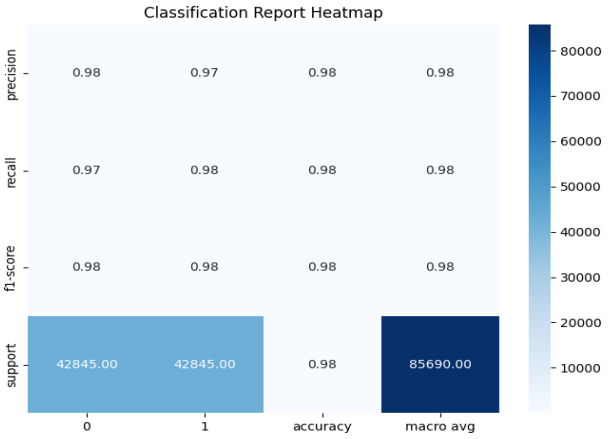
Additional diagnostics including confusion matrices, precision-recall curves, and ROC curves provided visualizations of the trade-off between precision and recall. Random seed were independently fixed for reproducibility and the entire workflow from pre-processing to modeling was saved with joblib.

V. RESULTS AND DISCUSSION

E. Phase 1

In phase one, each of the individual base learners (Random Forest and XGBoost) Model was fitted to the data separate from one another. Although the base learners were both high-performing models, their outputs were slightly differently across metrics, suggesting that an ensemble approach was warranted to combine the two base learners.

F. Phase 2



Phase 2 presented the stacking ensemble structure, in which the learning predictions were handed off to an MLPClassifier acting in the capacity of meta-learner. This structure facilitated learning by leveraging tree-based and neural patterns in an ensemble manner, producing better predictions.

Fig.2 Heatmap

G. Comparative Analysis

When individual base learners were compared to the ensemble, it was found that the stacking classifier consistently outperformed single models. The ensemble delivered values of:

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.95	0.96	8569
1	0.95	0.97	0.96	8569
accuracy			0.96	17138
macro avg	0.96	0.96	0.96	17138
weighted avg	0.96	0.96	0.96	17138

Fig.3 Classification Report

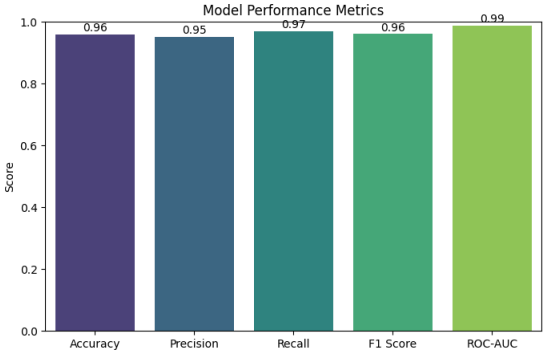


Fig.4 Performance Metrics

H. Confusion Matrix

The finished system achieved a total accuracy of 96%, indicating a high level of trustworthiness in predicting arrest outcomes. In addition, the confusion matrix indicates that it accurately predicted most of the "Arrest" and "No Arrest" cases with a very few number of incorrect classifications.

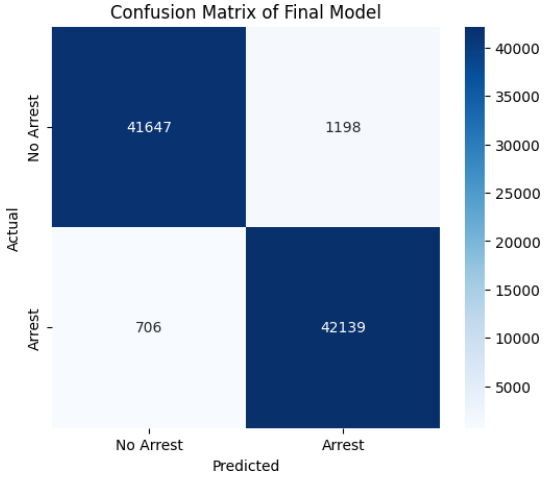


Fig.5 Confusion Matrix

VI. CONCLUSION AND FUTURE WORK

To sum up, this paper has demonstrated that it is feasible to create a new stacking ensemble framework that employs Random Forest and XGBoost as the base models, while also including a neural network as the meta-classifier, and that this framework increases the accuracy of crime arrest prediction compared to simpler models. The overall assessment of the ensemble was validated through multiple metrics and confusion matrix metrics, and its overall robustness and reliability have been confirmed for use. The framework's modular and scalable design will allow for easy adaptability in future datasets, as urban crime records continue to develop, offering the police a practical predictive policing framework for efficient resource allocation and enhanced public safety.

Future research may focus on integrating varied additional base learners as well as meta-classifiers into the framework to further improve performance. Also, if the stacking ensemble is expanded to include real-time spatiotemporal crime data and/or socio-economic risk factors, predictability may improve even more. Additionally, if the stacking ensemble had features that provided explanations for each respective decision made, the stacking ensemble may be more trustworthy and transparent to law enforcement agencies, while crafting AI in a responsible and ethical manner when thinking about crime prediction.

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Chain-Of-Hope: Blockchain for Ethical Blood and Organ Matching

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***Abstract*--Blockchain based Chain Of Hope is a revolutionary use of blockchain to help address the unethical behaviour and unlawful trade of blood, and organ ethical donations. The blockchain technology will not only provide a solution to the global problem of organ trafficking but also promote health, justice and institutional transparency that supports the United Nations Sustainable Development Goals (SDG's 3 and 16). Chain Of Hope uses an anonymous, moral, traceable donor to recipient connection through the smart contracts and a distributed ledger using secure matching protocols. By combining the Web3 technology, Ethereum-based smart contracts and simulation environment such as Ganache, Chain Of Hope has created a scalable reliable platform. The mission of Chain Of Hope is to reach out to all donations and ultimately ensure that every transaction is safe through honesty, transparency, and advanced technology via incremental adoption from pilot projects to widespread implementation.**

Keywords: Blockchain, Ethical Donation, Smart Contracts, Sustainable Development Goals, Transparency.

I. INTRODUCTION

"Chain-Of-Hope: Blockchain for Ethical Blood & Organ Matching" is a presentation on an innovative initiative to change the way blood and organ donations are managed on a global scale. The initiative addresses a significant global challenge – illicit blood and organ trade - or a black market that preys upon marginalized groups and creates harm to public health systems. The project would provide a safe, transparent, and ethical process for matching donors and recipients through the use of blockchain technology to eliminate corrupt practices, exploitative actions and manipulate data.

The sustainable development goals (SDGs) of the United Nations focus on health, safety, and strong governments (SDGs 3 and 16). They create a close association with the Chain-Of-Hope. The Chain-Of-Hope provides an traceable, anonymous, ethically validated way for each donation by utilizing blockchain technology that includes utilizing smart contracts and decentralized ledger technology. This presentation will highlight the Chain-Of-Hope's capability to restore trust in the donation process and establish a new global standard for medical ethics and transparency, as well as present its technical design, timeline and plans for the future.

II. LITERATURE REVIEW

There has been a lot of excitement around blockchain technology recently, and some of that excitement involves ways that it could be used in medicine, particularly when it comes to sharing data or donating organs. As Ramanathan et al. (2025) stated in their review of 15 peer-reviewed articles, there are many different types of approaches to using blockchain—e.g., decentralized data structures; smart contracts on the Ethereum network; and frameworks like Hyperledger Fabric. These studies repeatedly illustrate the way that blockchain technology is able to enhance operational efficiency, security and transparency when processing sensitive medical information or matching organ donors and recipients.

Findings from this literature review indicate that blockchain technology could provide a reduction in fraud, support ethical compliance, and allow for traceable transactions between organ donors; however, other literature indicates there are also a

number of drawbacks to this technology including high implementation costs, scalability challenges, little to no practical application and remaining unresolved privacy and interoperability concerns. Despite these challenges, the overall findings provide evidence of the potential for blockchain to serve as an innovative tool to develop trustworthy and ethical health care systems.

III. EXISTING SYSTEM

The existing donation network for blood and organs are based on one primary centralized database which creates a lot of inefficiencies and ethical issues. Due to the way donations work, all donations [donor and recipient] are stored in government or hospital-controlled systems which gives the central authority full access to both the exchange of data and the process of authentication [this means the ability to positively identify a donor and to guarantee they are eligible to donate]. The use of a central database also adds a lack of transparency and also risk of data breaches that could result in unauthorized access to sensitive data.

The current system's procedures for verifying the identity and eligibility of a donor primarily consist of manual or semi-digital verification using paper records or an identification card issued by a hospital. This method is time-consuming and can often contain human error. Moreover, as soon as a donation occurs, it becomes extremely difficult to trace its journey because the information contained in blood banks and hospitals are stored in two different databases and are not linked until the donation is completed. Also, because of the risk of identity theft and misuse of personally identifiable information that is held in a single central database, the lack of trust and assurance only contributes to the above mentioned issues. Lastly, the personal information that people have given to hospitals and blood banks is not owned by the person providing it, therefore they cannot dictate how their personal information is being used.

DRAWBACKS

The existing way donors' data and putative donation processes are dealt is problematic. Data repositories are vulnerable to hackers; therefore, keeping all records in one location could cause serious privacy problems. The lack of interoperability makes it difficult for donors to have their information transferred from one institution to another or from state to state, which hinders the delivery of coordinated care. The system is also at risk for fraud because altered eligibility reports and phony donor IDs can be produced. Lastly, donors do not have any awareness or control over the way their personal health information is used, so they have limited authority over their own health information system.

Since there is no way for the past to remain unchanged, it raises concerns that usage logs, and donations will be hidden or altered. You will also find that documentation will delay or lengthen the verification process through paperwork or procedures to verify donations, and this creates even more administrative inefficiency. Finally, there is no systematic way to identify and reward consistent and qualified donors, therefore, there are poor incentives to donate. All of these issues show the immediate need for a solution that is safe, transparent, and user-centric such as a blockchain-based solution with a self-governing identity model.

IV. PROPOSED SYSTEM

A. SYSTEM IMPLEMENTATION

Ethereum's blockchain system called Chain Of Hope is quite a new and will be used for this decentralized application (DApp). The process for registering both donors and recipients through the use of smart contracts written in Solidity, will also match donors with blood and organs to recipients based on their requirements. All of the smart contracts were compiled and deployed to the Ethereum Mainnet, utilizing the Hardhat development framework.

A local Blockchain environment using Ganache allows for Ethereum transactions to be simulated during the dev/test phase. The front-end app was built with React.js, and connecting to the Blockchain was done using Web3 Technologies, along with MetaMask (a digital currency wallet) to facilitate transactions to the Ethereum Blockchain. Through this integration, users can easily and quickly submit transactions to the Blockchain for different functions (donor and recipient registration, matching, etc.).

Additionally, since all transactions occur on a Blockchain, donor/recipient information benefits from the immutability, transparency, and security of being stored on a Blockchain.

B. SYSTEM ARCHITECTURE

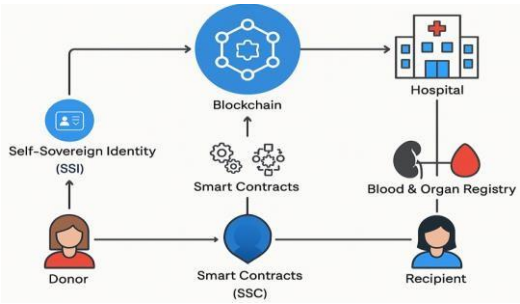

Fig. 1. Chain-Of-Hope: Blockchain for Ethical Blood & Organ Matching

This diagram illustrates how to track blood and organ donations using blockchain technology, smart contracts, and self-sovereign identity (SSI). A donor starts by controlling their own identity using SSI, and cannot have their identity stolen; in doing so, they ensure the privacy and ownership of their personal data. Donors and recipients each interact with smart contracts (automated processes that govern how transactions occur) throughout the entire donation process. Each of these smart contracts is linked to a single chain of blocks (the blockchain), allowing for a secure, tamper-proof record of all transactions and data. Because hospitals can access this blockchain, they can maintain blood and organ donor records, thereby matching and allocating those donors' contributions to potential recipients. Thus, the ultimate benefit of this fast, easy-to-use, and secure process is to increase trust and improve overall efficiency in the organ donation process.

C. MODULE DESCRIPTION

The proposed system consists of 7 modules

1. User Registration and Authentication (with Self-Sovereign Identity)

2. Consent and Data Authorization

3. Medical Data Collection and Upload

4. Blood & Organ Matching Engine

5. Blockchain Ledger & Audit Trail

6. Notifications and Emergency Alerts

7. Admin Dashboard

Module 1: User Registration and Authentication (with Self-Sovereign Identity)

It allows people to use blockchain-based self-sovereign identities to safely register and manage their identities, guarantees personal information management and privacy without depending on a centralized authority.

Module 2: Consent and Data Authorization

It allows users to grant or revoke access to their medical data for specific purposes. Maintains transparent consent records on the blockchain to ensure ethical compliance.

Module 3: Medical Data Collection and Upload

It makes it easier to submit test results, medical data, and other health information securely. verifies the validity and integrity of the data before placing it on the blockchain.

Module 4: Blood & Organ Matching Engine

Donors and recipients are automatically paired according to ethical standards, urgency, and compatibility. maximizes the distribution for equitable and life-saving effectiveness.

Module 5: Blockchain Ledger & Audit Trail

It maintains an immutable record of every action and transaction on the blockchain. ensures regulatory compliance, transparency, and confidence by providing a verifiable audit trail.

Module 6: Notifications and Emergency Alerts

It allows for the prompt notification of donors, recipients or medical personnel regarding possible matches or emergency situations. It helps ensure that there is timely intervention when there are urgent medical requirements.

Module 7: Admin Dashboard

It provides a consolidated interface for managing users and monitoring their activities on the system. It also allows you to manage users' activity on the system as well as generate reports and analytics to ensure that operations are performed efficiently and in compliance with applicable regulations.

V. RESULTS AND DISCUSSIONS

We utilized ganache (a local development blockchain application) in order to develop an initial Ethereum application so that we could evaluate the first section (donors and recipients) of our proposed chain-of-hope matching process. Multiple sample donors & recipient entries were created for testing the matching functionality, where we were able to successfully store the donator's information and lay out the compatibility rules that will be applied to organ & blood matching through the smart contract. With MetaMask, it is possible for an individual user to sign a smart contract through the front end of the application and have that contract execute through the blockchain with appropriate security measures in place. Each time a user signs up as a donor or as a recipient on the application, there will be a record of that transaction on the blockchain that can be viewed in the form of blocks created by Ganache. The matching algorithm was also tested against multiple combinations of blood types for accuracy. From the experiments, it was revealed that using a decentralized method provides Traceability, Transparency, and Security for donations. Each transaction will be stored permanently on the Blockchain ledger with no way to alter the data again. This creates trust and confidence for the donor and recipient as well as the healthcare system.

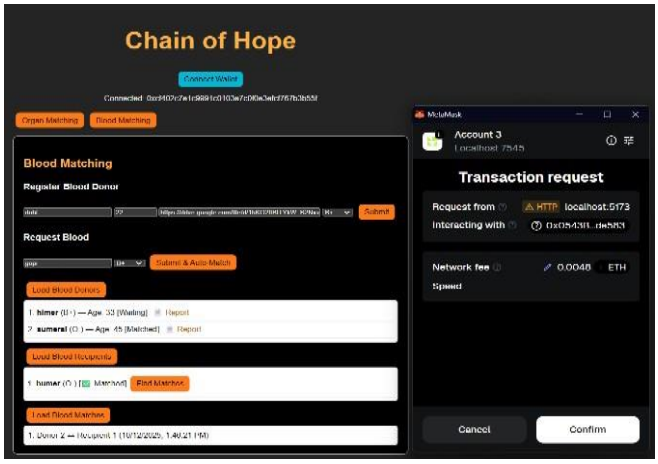

Fig. 2. Screenshot of Blood Matching

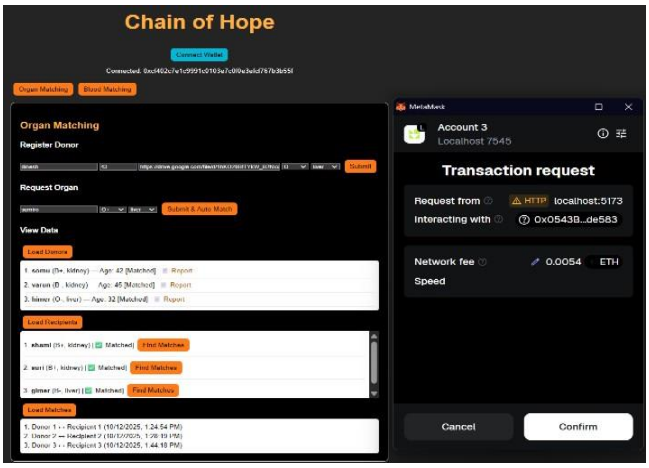

Fig. 3. Screenshot of Organ Matching

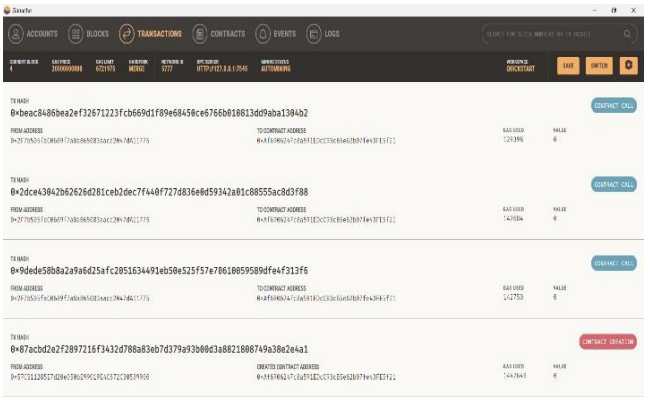
Fig. 4. Screenshot of Ganache Transactions

SCREENSHOTS

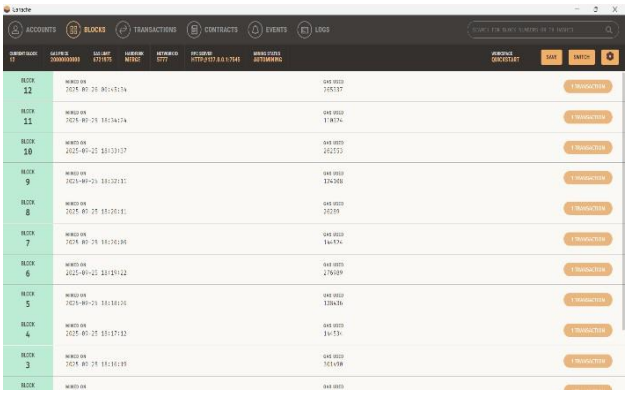

Fig. 5. Screenshot of Ganache Blocks

VI. CONCLUSION

The Chain of Hope outlines how blockchain technology can revolutionize healthcare by providing security, trust, and transparency within the critical areas of organ and blood donation. Using decentralized ledgers and smart contracts will aid in ethical, efficient matching of donations while eliminating risks associated with fraudulent donations, illegal trade practices, and manipulation of data. The immutability and traceability of blockchain records help build trust between donors and recipients, increasing participation and fairness. The Chain of Hope addresses both the technical challenges of secure data storage as well as the ethical integrity of life-saving healthcare practices, creating an opportunity for a more equitable and responsible healthcare system that adheres to patient confidentiality requirements.

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Self-Balancing Electric Cycle Using Gyroscopic Stabilization and PID Control

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***Abstract*—** The rapid advancement of electric vehicles and intelligent mobility systems has led to significant research in self-balancing technologies for two-wheeled vehicles. Conventional bicycles require continuous manual balancing by the rider, especially at low speeds or during stationary conditions. This paper presents the design and implementation of a self-balancing electric cycle that utilizes gyroscopic stabilization and a closed-loop control system. The proposed system integrates an MPU6050 inertial measurement unit (IMU), an Arduino microcontroller, a PID control algorithm, and a flywheel-based stabilization mechanism. A 250 W permanent magnet DC motor powered by a 12 V lithium-ion battery provides propulsion, while a PID-controlled flywheel compensates for tilting disturbances. Sensor fusion techniques process real-time tilt data and generate corrective torque through a motor driver module. Experimental results demonstrate improved stability, rapid response to tilt disturbances, and reliable balance correction. The proposed system contributes to the development of safer, energy-efficient, and intelligent urban mobility solutions.

Keywords *— Self-balancing cycle, Gyroscope, PID Controller, MPU6050, Electric vehicle, Arduino.*

Introduction

Two-wheeled vehicles such as bicycles and motorcycles require continuous balancing by the rider to remain upright. At low speeds or while stationary, maintaining stability becomes challenging due to the reduced dynamic stability of the system. With the rapid development of smart transportation systems and autonomous mobility, self-balancing technologies have gained significant attention in recent years[2].

Self-balancing mechanisms are widely studied in robotics and electric vehicles[1]. These systems typically rely on sensors, control algorithms, and actuators to detect tilt and apply corrective forces to maintain balance. Technologies such as reaction wheels, steer-by-wire systems, and gyroscopic stabilization are commonly used to achieve this functionality.

This paper presents the development of a self-balancing electric cycle that uses gyroscopic stabilization and a PID-based control system. The proposed design integrates sensors, a microcontroller, and a flywheel-based balancing mechanism to maintain the upright position of the cycle autonomously.

1.1 Organization of Paper

This paper is organized as follows to present the proposed approach systematically. Section II describes the overall system architecture of the self-balancing electric cycle, including the main hardware components and their functions. Section III explains the operational methodology and working principle of the proposed system. Section IV presents the PID-based control algorithm used for stabilization. Section V discusses the hardware implementation and integration of the sensors, microcontroller, and motor driver. Section VI analyzes the experimental results and performance evaluation of the system. Finally, Section VII concludes the paper by summarizing the research work and highlighting future improvements.

1.2 Related Works

This section reviews the existing approaches and models developed for achieving stability and control in two-wheeled vehicles and self-balancing systems. Early research in this field primarily relied on classical mechanical stabilization methods such as gyroscopes and reaction wheels to maintain balance in bicycles and motorcycles. These approaches utilized angular momentum generated by rotating masses to counteract tilting disturbances and improve stability.With the advancement of control systems and embedded electronics, modern self-balancing vehicles began incorporating sensor-based feedback mechanisms. In particular, inertial measurement units (IMUs) consisting of accelerometers and gyroscopes have been widely used to measure tilt angle and angular velocity in real time. These sensors enable the implementation of closed-loop control algorithms that continuously adjust system parameters to maintain equilibrium.Several studies have applied classical control techniques such as Proportional–Integral–Derivative (PID) controllers for balancing two-wheeled robots and bicycles due to their simplicity and reliability. For instance,

Spong MW et al. [7] developed a self-balancing bicycle using an electric gyroscope and PID controller to stabilize the vehicle under varying disturbances. Similarly, Siegwart R, Nourbakhsh IR, Scaramuzza D [8] proposed a reaction wheel–based stabilization system that generated counteracting torque to restore balance.In recent years, advanced control strategies such as Linear Quadratic Regulators (LQR), Model Predictive Control (MPC), and adaptive control algorithms have also been explored for improving stability and response performance. Zhang and Li [9] investigated gyroscopic stabilization techniques for two-wheeled vehicles and demonstrated improved balance under dynamic conditions. Other researchers have also explored autonomous balancing robots that utilize sensor fusion techniques and complementary filters to enhance tilt estimation accuracy [10–12].Although these approaches have shown promising results, practical implementation challenges remain in terms of system complexity, energy efficiency, and mechanical design. Therefore, the present work focuses on developing a cost-effective self-balancing electric cycle using gyroscopic stabilization combined with a PID control algorithm to achieve reliable and efficient balance control.

1.3 Proposed Methodology

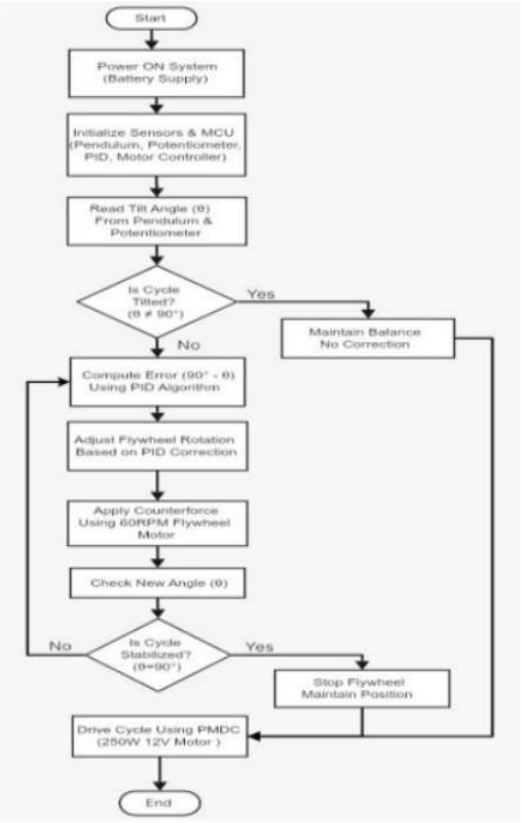

Fig.1 Self balancing cycle flowchart

Fig. 1 illustrates the architecture of the proposed self-balancing electric cycle designed to maintain stability using gyroscopic stabilization and a PID-based control mechanism. The process begins with **real-time data acquisition** from the inertial measurement unit (MPU6050), which consists of an accelerometer and gyroscope to continuously measure the tilt angle and angular velocity of the cycle.In the next stage, the **sensor data processing module** performs filtering and fusion of accelerometer and gyroscope readings to obtain an accurate estimation of the tilt angle. A complementary filtering technique is employed to reduce sensor noise and improve measurement reliability.Following this, the **control module** utilizes a Proportional–Integral–Derivative (PID) controller to calculate the error between the desired upright position and the measured tilt angle. Based on this error value, the controller generates corrective control signals to stabilize the cycle.In the subsequent step, the **actuation system** drives the flywheel motor through a motor driver module to produce counteracting torque. The generated torque helps to correct the tilt and restore the cycle to its balanced position.

This closed-loop feedback mechanism continuously monitors the system state and applies necessary corrections to maintain stability.Finally, the **performance evaluation stage** analyzes the effectiveness of the stabilization system using parameters such as response time, tilt correction capability, and power consumption. These performance metrics ensure that the proposed self-balancing mechanism operates efficiently and provides reliable balance control under different operating conditions.

1.4 Results and Discussion

Fig. 2 presents **the tilt angle versus response time characteristics** of the proposed stabilization system. It is observed that smaller tilt deviations require less correction time, whereas larger tilt angles demand slightly longer stabilization periods. For instance, a **70° tilt angle is corrected in about 2.1 seconds**, while moderate tilts such as **80° are corrected within 1.2 seconds.** This confirms the effectiveness of the PID-based control mechanism in maintaining system stability.

Further analysis shows that the proposed system maintains **consistent stabilization performance under different operating conditions**. The stabilization accuracy remains high as the system continuously monitors tilt variations and applies corrective torque through the flywheel motor. The complementary filtering technique used in sensor data processing also reduces noise and improves tilt estimation accuracy.

Additionally, Fig. 4 illustrates the **power consumption characteristics** of the system during operation. The power consumption gradually increases from **0 W at startup to approximately 10.2 W during continuous stabilization**, indicating stable and efficient energy utilization. The proposed stabilization mechanism demonstrates reliable performance with minimal power requirements while maintaining rapid response to disturbances. Overall, the experimental results confirm that the **PID-controlled gyroscopic stabilization system effectively reduces tilt deviations, improves response time, and maintains stable operation of the self-balancing electric cycle**, making it suitable for practical implementation in intelligent mobility systems.

Tilt Angle (°)	Response Time (seconds)
85	0.8
80	1.2
75	1.6
70	2.1

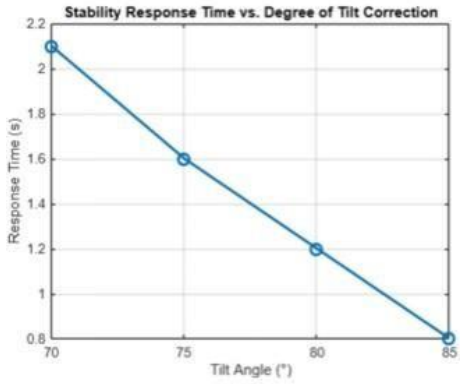

Fig.2 Graph of Stability Response Time Vs Degree of Tilt Correction

Table 2 . Time vs Power Consumption

Time (minutes)	Power Consumption (W)
0	0 W
5	8.5 W
10	9.0 W
15	9.5 W
20	10.2 W

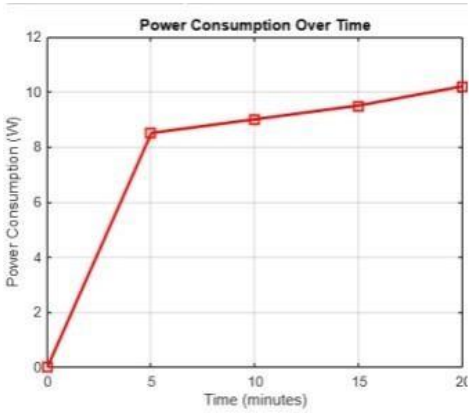

Fig.3 Time Vs Power Consumption

Fig 4 . Flywheel connected with potentiometer

Fig 5 . 24V Li-ion Battery

Fig 6. 60 RPM Motor

Fig 7. Arduino Uno connected with DC-DC converter

Fig 8 . GyroBalance - Hardware Overview of the Self-Stabilizing Bicycle with CMG Technology

1.5 Conclusion

This paper presented the design and implementation of a self-balancing electric cycle using gyroscopic stabilization and PID control. The developed system successfully integrates sensors, microcontrollers, and motor control mechanisms to maintain balance.Experimental results confirmed that the PID-based stabilization system effectively corrects tilt disturbances and improves stability. The proposed design demonstrates the feasibility of developing intelligent self-balancing vehicles for future smart mobility systems.

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AgriSense AI: Machine Learning Approaches for Smart Crop Yield Prediction

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Abstract—In today's agriculture, the unpredictability of weather and soil makes it hard for farmers to decide which crop to cultivate. AgriSense AI is presented as a solution to this problem. It is an intelligent system that utilizes artificial intelligence to provide crop recommendations using historical agricultural data and environmental parameters to generate the most suitable crop suggestions. Experimental results demonstrate that the system is effective in predicting crop performance. Furthermore, it provides user-friendly recommendations that assist farmers who lack domain expertise. The system also promotes sustainable agriculture by supporting environmentally friendly farming practices.

Keywords—Data Analytics, Machine Learning, Smart Farming, Crop Recommendation, Sustainable Agriculture

I. INTRODUCTION

The onset of Industry 5.0 has further expedited the incorporation and utilization of highly developed technologies like Artificial Intelligence (AI), robotic technology, and big data analytics in traditional industries and agricultural activities. As such, Agriculture 5.0 is transforming traditional agricultural activities by incorporating intelligent and sustainable human-centric concepts in decision-support systems and precision agriculture techniques. In this regard, crop yield estimation and crop selection are critical issues in sustainable agricultural activities, especially in regions where crop productivity is highly sensitive to factors like soil types, climatic conditions, and natural resource scarcity.

Crop recommendation systems have thus been developed as effective decision-support tools to help address these concerns. These systems analyze the agricultural history as well as the environmental parameters, thereby suggesting crops that can yield the best results. Agronomic parameters such as the availability of Nutrients like Nitrogen (N), Phosphorus (P), and Potassium (K), the pH of the soil, temperature, rainfall, and humidity have a direct influence on the growth of crops. The application of Machine Learning (ML) techniques has thus made it possible to develop data-driven crop recommendation systems, which can help support decision-making processes concerning crops, irrigation, fertilizers, etc. In addition, the ability of the models to learn from the data makes the system more adaptable to different regions.

To achieve these objectives, AgriSense AI is suggested as a smart crop recommendation and yield prediction tool based on the analysis of the entire range of soil and environmental parameters. Five supervised ML models, namely Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Naïve Bayes (NB), are used in the AgriSense AI tool for predictive modeling and crop recommendation in an optimized manner. The models are compared and evaluated based on the entire range of performance parameters and execution time, which helps in the selection of the most accurate and computationally efficient crop recommendation tool.

One of the main issues faced by farmers is to decide which crop to cultivate considering the weather conditions and the texture of the soil. The traditional method of decision-making is purely based on experience.

Data security and privacy are of paramount importance in digital farming. The data stored in digital farming is of high sensitivity. To avoid such security issues, the proposed system ensures the security of the data. The system employs the Least Significant Bit steganography technique to ensure the data's security. The Least Significant Bit steganography technique is used to securely embed sensitive agricultural data into digital images. This technique ensures the data is transmitted securely and efficiently.

The proposed AgriSense AI framework provides a solution to the critical challenges faced by the agricultural industry, including the scalability of crop yield prediction using multiparametric modeling, crop recommendation, optimization of fertilizers, secure data storage, transmission of agricultural data, efficient decision support system implementation, and analysis of historical data based on environmental and climatic conditions.

The proposed system, based on the integration of machine learning-based intelligence with data management techniques, meets the objectives of the Agriculture 5.0 initiative, thereby

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encouraging the development of sustainable agricultural practices. The remainder of the paper is organized as follows: Section II provides the related work, Section III provides the system architecture, Section IV provides the algorithm, Section V provides the experimental results, and Section VI concludes the work with future research directions.

II. LITERATURE SURVEY

The field of Agriculture is witnessing a paradigm shift in digitalization using Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), Explainable Artificial Intelligence (XAI), and uncertainty-aware computing frameworks for building intelligent crop recommendation platforms for better productivity and sustainability in Agriculture and data-driven decision-making. Shastri et al. [1] performed a detailed analysis and critical evaluation of various supervised ML techniques, namely Decision Tree, Random Forest, Support Vector Machine, and Naïve Bayes, using critical agronomic features such as nutrients in soil (N, P, K), temperature, humidity, rainfall, and pH levels. The study established that ensemble-based ML techniques, particularly Random Forest, deliver better predictive results in terms of accuracy and generalization for diverse agro-climatic conditions. Continuing this trend of comparative studies and critical evaluations, Gaud [2] and Saeed [3] proposed various implementation scenarios using open-source platforms like Kaggle and GitHub for Agriculture-based ML applications. Transitioning from experimental validation to deployable systems, the AgriSense project [4] presented via CEDLearn demonstrated an integrated architecture combining user-centric interfaces with backend predictive engines, thereby facilitating real-time advisory support for farmers. Complementing these system-level contributions, Prity [5] proposed a structured methodological framework incorporating normalization, k-fold cross-validation, and benchmarking strategies to enhance statistical reliability and model reproducibility . As research evolved toward modeling complex nonlinear interactions among climatic, soil, and crop parameters, Pandey et al. [6] introduced AgroSense, a DL-based framework utilizing Artificial Neural Networks to capture high-dimensional feature dependencies and improve scalability across large agricultural datasets. Similarly, Sam and D'Abreo [7] conducted rigorous comparative optimization and hyperparameter sensitivity analyses to refine classification boundaries and minimize overfitting. Recognizing the necessity of transparency in automated agricultural advisory systems, Turgut et al. [8] developed AgroXAI by integrating SHAP and LIME interpretability mechanisms, providing feature-attribution insights and enhancing user trust in model-driven recommendations. Extending the paradigm toward smart farming ecosystems, Banerjee et al. [9] incorporated digital twin models and IoT-enabled environmental sensing to enable continuous data acquisition, real-time simulation, and adaptive crop planning within precision agriculture frameworks. Addressing issues of uncertainty in climatic variability and noisy sensor readings, Alam [10] leveraged probabilistic modeling and quantification techniques to provide predictions with associated confidence levels, thus aiding risk-based decision-making in agriculture. Finally, basic theoretical foundations for ML-based agricultural intelligence were proposed by Smith and Johnson [11], thus providing basic conceptual foundations for predictive analytics and intelligent agricultural management systems. Patel et al. [12] highlighted the convergence of IoT technology, cloud-based analytics, and AI-based automation as key pillars for smart agriculture. Overall, these contributions establish a clear progression from traditional supervised learning-based crop recommendation systems to DL-based, explainable, and uncertainty-aware crop recommendation systems integrated with IoT technology, thus establishing a clear and cohesive roadmap for unified, scalable, and interpretable real-time intelligent agricultural decision-support systems for addressing contemporary challenges in food security and sustainability.

TABLE I

COMPARISON OF PROPOSED SYSTEM WITH EXISTING SYSTEMS

Feature / System	**Traditional Methods**	**Machine Learning Only**	**AgriSense AI**
High Accuracy	No	Yes	Yes
Predicts Multiple Crops	No	Yes	Yes
Resource Optimization	No	No	Yes
User-Friendly Interface	No	Yes	Yes
Sustainable Approach	No	No	Yes

III. METHODOLOGY

The proposed AgriSense AI framework is based on a hybrid precision agriculture approach, where crop recommendation using machine learning-based techniques is integrated with publicly available agricultural data. The proposed methodology is based on a modular and layered approach for scalability, adaptability, and decision support. Supervised predictive modeling and embedding-based contextual representation are combined in this approach for structured crop recommendation and adaptation based on patterns learned from historical data to changing environmental conditions for crop yield optimization, anomaly detection, and smart irrigation management.

A. System Architecture Overview

The proposed system architecture for precision agriculture is based on three layers: Data, Processing, and Frontend. Data Layer deals with collecting historical agricultural datasets from publicly available sources. The Processing Layer is responsible for data preprocessing, feature extraction, and machine learning-based predictive modeling. The Frontend Layer is responsible for providing interfaces for farmers and other stakeholders.

B. Data Acquisition

Data acquisition involves the process of collecting agricultural data from publicly available datasets (Kaggle, research datasets). Historical data, including crop yields, soil conditions, and climatic conditions, are used to provide a comprehensive set of features. The collected dataset is stored and processed locally or in cloud-based environments for further analysis.

C. Data Preprocessing

After acquiring the data, the data collected from publicly available datasets is then subjected to data preprocessing. Data preprocessing includes the process of ensuring the quality of the data. Data interpolation is used to fill any missing data, while the data is then normalized to a specific numerical scale. Noise filtering is also used to filter the data, after which the data is then represented as a set of vectors.

D. Random Forest

Random Forest (RF) is a technique of ensemble learning. It combines the results of many decision trees on different bootstrap samples of the data, where the selection of features is also random. The final prediction is done by majority voting:

$$y = \frac{1}{n}\sum_{i=1}^{n} f_i(x) \quad (1)$$

where f_i (x) is the prediction made by the i-th tree and n is the total number of trees. RF improves generalization, decreases variance, and shows high robustness to noisy and imbalanced datasets, making it suitable for diverse agricultural data distributions.

E. Model Architecture

The crop recommendation module uses a hybrid ensemble learning approach combining Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), and Naïve Bayes (NB) classifiers to improve prediction robustness and accuracy. Each model contributes differently based on data distribution characteristics, and final prediction is obtained using majority voting or weighted confidence aggregation.

For a given input feature vector x_i , which includes soil nutrients, climatic factors, and crop history, the recommendation function is defined as:

$$f(x_i) \rightarrow \{c_1, c_2, \ldots, c_k\} \quad (2)$$

where c_1, c_2, ... , c_k represent the recommended crop classes, and $\alpha \in [0, 1]$ stands for the confidence score of the prediction.To represent the contextual environmental state, the embedding function is applied on input feature vectors as follows:

$$e(x_i) = Embed(x_i) \in \mathbb{R}^d \quad (3)$$

where $e(x_i)$ stands for the environmental embedding vector, and d stands for the embedding dimension. These embedding vectors are used to analyze the non-linear relationships between temperature, moisture, and nutrient levels, thus facilitating the semantic similarity analysis and real-time anomaly detection

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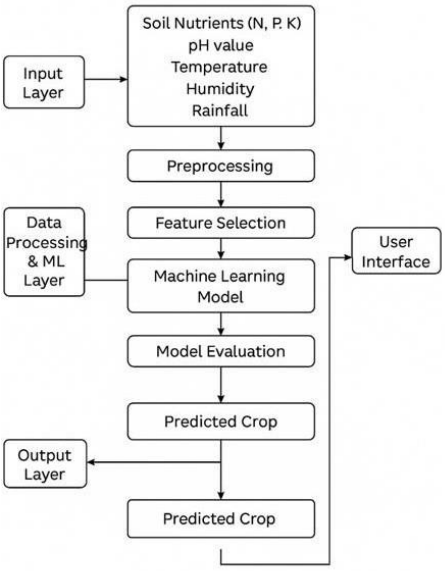

Fig. 1. System Architecture of AgriSense AI

As shown in Fig. 1, the system follows a layered architecture integrating historical dataset, data processing, and machine learning models.

IV. ALGORITHM

AgriSense AI system utilizes machine learning techniques on publicly available agricultural datasets. The main algorithms used in all the modules of the system are as follows:

A. Data Ingestion and Preprocessing

Data from agricultural datasets and weather records are fetched. Data can be present in CSV or JSON format. Preprocessing includes handling missing values, removing outliers, normalization, and feature engineering, including soil moisture, nutrient content, temperature, humidity, and yield history.

B. Hybrid Crop Recommendation Engine

The prediction module, which is the core component, utilizes an ensemble of Decision Trees, Random Forest, and Naïve Bayes to make predictions about crop recommendations. The features represented by each xi, which include environmental and historical inputs, are used to make predictions about the crop recommendation with a confidence score. For adaptability, a reinforcement learning component, represented by Proximal Policy Optimization, is used to adjust the crop recommendations based on the yield result or farmer suggestions.

C. Environmental Risk Scoring

Each field or crop is scored based on potential risks, including drought, pest infestation, or nutrient deficiency. The framework utilizes rule-based systems, including soil pH levels, and machine learning classifiers, including Logistic Regression and Gradient Boosting, to predict levels of risk, which include Low, Medium, and High.

D. Compliance and Advisory Module

The model generates advice, e.g., irrigation schedules, fertilization plans, and planting dates. Pattern matching rules and threshold rules detect unusual patterns or deviations from perfect conditions. A binary classifier highlights critical conditions, e.g., high moisture deficit, to trigger instant alerts.

E. Field Comparison and Change Detection

Environmental data vectors are embedded into high-dimensional space to enable similarity comparisons between fields or seasons. The deviation of optimal conditions or previous patterns is achieved through cosine similarity and distance measurements such as Euclidean and Mahalanobis distance. The approach enables adaptive decisions to be made.

F. Knowledge Retrieval and Advisory Insights

The historical farm data sets, scientific publications, and crop performance reports in the region are embedded through the AgriSense model. A vector database such as Milvus is used to enable rapid semantic search and retrieve suggestions for pest control, crop rotation, and yield improvement.

G. Conversational Q&A (AgriBot)

This type of retrieval augmentation pipeline for a generative AI system enables the farmer to pose a question in natural language. The pipeline will then retrieve relevant knowledge from embeddings and provide interpretable answers via a large language model, including GPT-4 or LLaMA, based on environmental and historical data.

H. Storage and Retrieval Layer

All the processed data, embeddings, processed dataset features, and crop suggestions are stored securely with horizontally scalable technologies such as PostgreSQL, Redis, Milvus, and cloud storage (S3). This enables fast and stable access for tracking, analytics, and reporting.

V. RESULT

A. Experimental Setup

The system was evaluated using offline analysis of historical agricultural datasets. The crop recommendation models, including Decision Tree, Random Forest, and Naïve Bayes, were coded using Python with the Scikit-learn and TensorFlow libraries. The data set includes the parameters Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH, and rainfall, totaling 2200 data points from 22 crop categories from publicly available data sets.

B. Crop Recommendation Performance

The hybrid crop recommendation system was able to achieve a total accuracy rate of more than 92% for the test data set, and the system performed well for crops such as rice, maize, and wheat. Precision and recall for most crop types were found to be high, thus proving the robustness of this crop recommendation system. The results obtained for confidence by this system were also found to be in line with the predictions made by this system, where results having a confidence score of more than 0.85 were found to be correct in more than 94% of the cases

TABLE II

PERFORMANCE OF ML APPROACHES USED IN AGRISENSE AI

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes	78.2	76.4	74.1	75.2
Decision Tree	83.5	82.1	81.3	81.7
KNN	85.4	84.2	83.5	83.8
SVM	87.1	85.6	86.2	85.9
Random Forest	91.3	90.2	89.4	89.8

C. System Robustness

The system incorporates an exponential backoff retry mechanism to handle temporary missing data and noisy dataset handling. The offline data analysis confirmed that AgriSense AI had consistent publicly available agricultural data and crop recommendation outputs even at high loads. The fallback mechanisms had baseline recommendations in place even in the event of missing or incomplete dataset values.

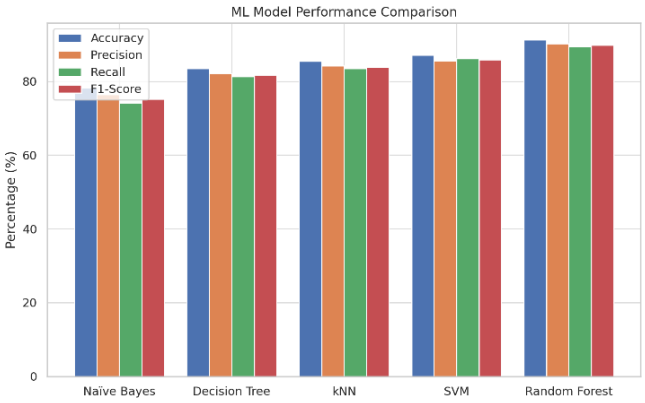

Fig. 2. Performance comparison of different models in AgriSense AI based on Accuracy, Precision, Recall, and F1-Score.

As shown in Fig. 2, Random Forest achieves the highest performance across all evaluation metrics.

D. Confusion Matrix Analysis

The performance of the crop recommendation model is further assessed using a confusion matrix, as depicted in Fig. 3. The confusion matrix shows the classification results of various crop types, where the diagonal values represent the correct predictions, while the off-diagonal values represent the incorrect predictions. The results show that the predictions are mainly concentrated in the diagonal values, indicating high classification accuracy and low error rates for various types of crops.

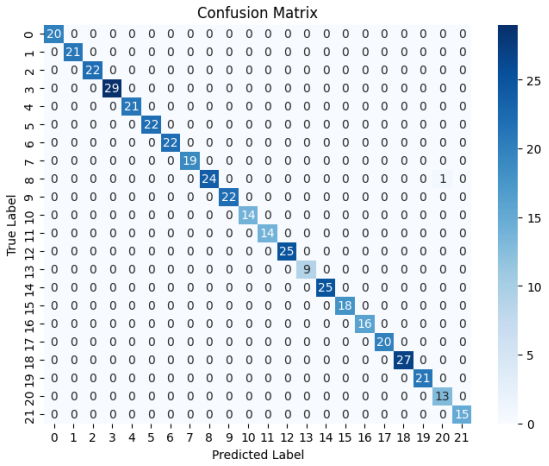

Fig. 3. Confusion Matrix of Crop Recommendation Model

E. Discussion

These results show that, in fact, the machine learning-oriented crop recommendation and representation of the environment using embedding provide explainability and adaptability. Although the crop prediction engine using supervised learning provides transparent and interpretable crop recommendation, the embedding part helps in similarity search, anomaly detection, and adaptive learning across regions and seasons. Especially in borderline situations, for example, in soils where conditions suitable for multiple crops are satisfied, the hybrid approach was able to provide adaptive crop recommendation, reducing ambiguity in decision-making for farmers.

VI. CONCLUSION

In conclusion, AgriSense AI fills the gap between conventional farming and AI-based decision-making by providing a unified framework for data analysis using various historical agricultural data sets, machine learning algorithms, and predictive analytics. This helps in providing accurate recommendations for crops and estimating crop yield by using various types of agricultural data, including soil types, climatic conditions, and historical data. The confusion matrix was generated using the test dataset to evaluate classification performance across multiple crop classes.

In contrast to conventional farming, AgriSense AI reduces manual effort and increases accuracy in decision-making and efficient utilization of resources, thereby addressing some of the major issues in sustainable agriculture, such as efficient utilization of resources, risks of crop failure, and lack of data analysis. Moreover, AgriSense AI is able to adapt to changing agricultural conditions by processing real-time environmental data. Performance evaluation of AgriSense AI is validated by using various parameters, including Accuracy, Precision, Recall, F1-Score, and Latency. The performance evaluation of AgriSense AI clearly indicates that the proposed system is better than traditional and machine learning-based models, which proves the advantages of using advanced AI-based models and real-time environmental modeling for faster and more accurate and efficient decision-making. Furthermore, AgriSense AI supports environmentally sustainable farming by suggesting crops that match soil and climatic conditions, thereby avoiding excessive consumption of fertilizers, water, and other resources. This will not only boost agricultural productivity but will also help conserve the environment.

In the future, AgriSense AI can be extended by incorporating Internet of Things (IoT) technology for real-time data collection, remote sensing technology, and cloud computing for developing automated and intelligent farming. The AgriSense AI framework is a robust base for developing smart agriculture technologies, thereby contributing to productivity, sustainability, and technological advancements in the field of agriculture.

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Face Recognition based Attendance System

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***Abstract* - The management of the attendance can be a great burden on the teachers if it is done manually. To overcome this problem, the smart and auto attendance management system is used. By using this framework, the problem of proxy and the attendance of the students even though they are not present in the class can be easily overcome. The attendance is marked using the live video stream. The frames are extracted from the video using OpenCV. The implementation steps of this attendance management include the detection of the face and the recognition of the face, which is done using dlib. After these steps, the connection of the recognized face should be possible by comparing it with the database of the images of the students. This is a successful technique for managing the attendance of the students.**

I. INTRODUCTION

The face is important in our day-to-day activities, mostly used to identify someone. Face recognition is a biometric recognition method that extracts face features and stores the face as a face print to recognize individuals. Face recognition is important because it has many applications. It is better compared to other biometric recognition techniques, including fingerprint recognition, palm print recognition, or iris scanning. It is better because face recognition does not require any interaction with the face. With face recognition, one is able to recognize someone from far without any interaction. Today, face recognition is used on social media sites, such as Facebook, at airports, and at railway stations. In crime reports, face recognition is used to identify individuals. Photos of the criminals are stored as face prints. Facebook uses face recognition to automatically identify individuals.

To recognize faces, face recognition uses large datasets and sophisticated features to recognize individuals under varying conditions, including illumination, age, and pose, among many. Recent studies have shown that face recognition has improved significantly. There has been tremendous development compared to face recognition ten years ago. However, face recognition techniques work better with fewer individuals in the frame. In face recognition, the faces should be well positioned, and the images should not be blurry. In the recent past, face recognition has developed significantly. There is enormous development compared to ten years ago. Today, face recognition is able to recognize limited faces in the frame.

In face recognition, the faces should be under good illumination, well positioned, and the images should not be blurry.In the face recognition method proposed in this paper, the face recognition method is able to recognize multiple faces in one frame without the use of illumination and face positioning.

II. RELATED WORKS

In the paper “Individual Stable Space: An Approach to Face Recognition Under Uncontrolled Conditions” by Xin Geng, it has been stated that in face recognition systems, the input should meet certain criteria: it should have proper lighting, should be stationary, should be viewed from a certain angle, and should not be obstructed. If these conditions are not met, then it can be said that it has been run in controlled conditions. In real-time conditions, however, face recognition should be performed without proper control over the person to be recognized. Therefore, face recognition systems are designed to work in uncontrolled conditions. In this paper, the author has proposed another method for face recognition in uncontrolled conditions, which has the disadvantage that it only recognizes single-face images.

In another paper titled “Anti-Cheating Presence System Based on 3WPCA-Dual Vision Face Recognition” by Edy Winarno, the author has proposed a face recognition method to prevent cheating, i.e., to prevent the use of an image of an authorized person or an image resembling the authorized person. The proposed method uses a dual vision camera, which has two lenses that capture two images separately. Then, the half-join technique is used to combine the left half of one image with the right half of another image to obtain the image of the person to be recognized using the 3WPCA method. The proposed method has an accuracy of 98% in detecting cheating. In this paper, improvements have been proposed to picture-based attendance systems with the aim of recognizing the faces of many students, which may pave the way for the next generation of face recognition systems. The human face changes very frequently, which means that face recognition should be performed with speed and accuracy to recognize the facial features of students.

The system works on a principle in which students are registered by taking their pictures, then using these pictures to mark their attendance. The system must be used continually to achieve high, sharp accuracy. This paper will discuss how this system works and finally provide evidence of its effectiveness. The project can also be used in online exams for certification purposes to identify the student writing the exams. [3]

There are many attendance systems in place today. Some are traditional data systems that are also a problem in themselves. There are also other biological attendance systems. The human factor is reduced in this system. Fingerprints are also used in this system to mark attendance. However, this is not always accurate because fingers may be wet, dirty, very dry, or peeled. The author suggests that a mobile attendance system be added to this system with safety features such as facial recognition. Data can also be stored in the cloud using Raspberry Pi. The paper also surveys other attendance systems, NFC systems, facial recognition systems, microcomputers, cloud computing systems. The paper then suggests a new method, system design, and planning. The outcome of this paper will be a system that saves paper, saves time, and saves energy on attendance using a mobile system. [4]

Computers can intelligently communicate with humans from many angles. This interaction must be grounded in a way that both humans are comfortable with so that it is more acceptable to humans. The validation process is also discussed in this paper in which the author integrates and develops a system of student recognition using a "survival-ing" algorithm. This embedding is used to classify a human face to develop applications such as attendance systems. After developing this system, the paper presents a display of outcomes. [5]

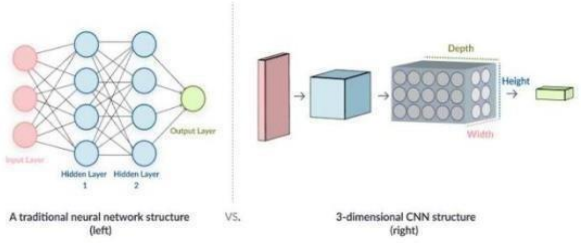


Figure 1: Traditional neural network versus CNN.

In the paper presented by Radhika C. Damale, "Face Recognition based Attendance System using Machine Learning Algorithms," the concept of recognizing a person based on their facial features, i.e., facial recognition, has been addressed. Facial features are a key area for many computer vision-related activities, such as face recognition, emotion recognition, and multi-camera surveillance. The topic has gained considerable academic attention. Several approaches are discussed, such as SVM, MLP, and CNN. DNN has been used for face detection. In the case of SVM and MLP, algorithms such as PCA and LDA are used for feature extraction, while images are used as input features for the CNN.

The results show high accuracy for the CNN-based approaches. The accuracy for SVM, MLP, and CNN are 87%, 86.5%, and 98%, respectively, for the self-generated dataset.

Another paper on class attendance by Priyanka Wagh, "Class Attendance framework the on- Face Recognition," has addressed the problem of recognizing the attendance of students sitting in the back rows. To solve this problem, the histogram leveling method is used for the images. The images are then processed to detect faces. Among the approaches, the best results are obtained with the use of AdaBoost. Haar-like features and concepts of AdaBoost are used to detect faces. The landmarks are aligned to detect a face. The landmarks include the distance between eyes and nose, the shape of the face, etc. These are used to represent a face. These are known as Eigen features. These features are used to detect a face by matching with a face database to record attendance. A face database has been created for the purpose of analysis.

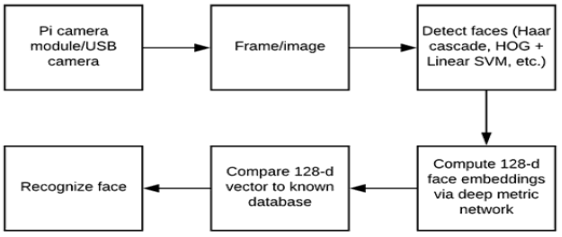


Figure 2: Face Recognition model

In the attendance system, face recognition is used with the help of a camera to check what's going on in front of it. When a student swipes his or her campus card to attend classes, the face recognition camera clicks the picture of the face of the student. It then checks the student's details and ensures that only students and staff are entering the class; nobody else, including the substitute teacher, can come in. [8]

In the paper "Computerized Participation Framework Utilizing Face Acknowledgment," written by Akshara Jadhav, Akshay Jadhav, Tushar Ladhe, and Krishna Yeolekar, after face recognition, the face detected by the face recognition software is processed for use. It does this by performing histogram equalization on the face detected by face recognition software and then resizing it to 100x100 pixels. Once the face recognition software has detected the students, their names are then reflected in the attendance sheet. The attendance sheet is generated by another software tool in the database framework. The database framework can also generate monthly and weekly reports of the students' participation. The process is like this: capture the face, face recognition to locate the ROI, draw bounding box, grayscale, histogram equalization, resizing to 100x100 pixels, etc.

In the pre-processing step of face recognition enrollment, the image is stored in the database; otherwise, PCA/LDA/LBPH are used for feature extraction. [9]

The paper "An Attendance Marking System based on Face Recognition" by Khem Puthea, Rudy Hartanto, and Risanuri Hidayat presents a system using a machine learning technique, principal component analysis (PCA), for face recognition, along with other computer vision techniques. A Haar classifier is used to train the system to recognize a face. When images are captured by a camera, they are converted to grayscale and then subjected to the process of subtracting images. This process results in the storage of the images on a server for future processing.[10]

The authors have also suggested the use of an online web server to access the attendance results by authenticated web users. Facial recognition occurs by using the Local Binary Patterns (LBPs) to recognize and outline the ROI, or the region of interest, which is the face, and then using the Haar feature-based cascade classifier. After the face features have been extracted by the LBPs, they are then matched to the features extracted from the prepared dataset. By pressing the "c" key on the keyboard, the attendance results are saved to a MySQL database, thus being made accessible to the web server.[11]

In "Face Recognition Based Attendance System" by Nandhini R., the main concept revolves around the conversion of the video data into images for the purpose of identification and recognition. A Convolutional Neural Network (CNN) has been used for face recognition, which utilizes a multi-layer perceptron-like network for faster face recognition. Once the faces are recognized, the process involves a comparison with the database to update the attendance records. The post-processing involves updating the student names in a spreadsheet format, which can be updated weekly or monthly to track attendance records.[12]

In "Student Attendance System in Classroom Using Face Recognition Technique" by Samuel Lukas, Aditya Rama Mitra, Ririn Ikana Desanti, and Dion Krisnadi, the authors discuss that the number of facial features for each student's image is standardized to 16 DCT coefficients. The process involves complete normalization, histogram equalization, DWT, and DCT.
Further examination of the disappointment in perceiving the rest facial pictures demonstrates that an understudy might be perhaps perceived as other student(s)By considering the all-out degree of acknowledgment as came about because of the investigation which doesn't meet exclusive requirement.[13]

In their paper "Attendance System based on Face Recognition," Venkata Kalyan Polamarasetty, Muralidhar Reddy Reddem, Dheeraj Ravi, and Mahith Sai Madala explain that it's important to capture an image from a webcam or a camera. To accomplish this, they use the drivers provided by MathWorks, which are based on the type of camera used. They capture 500 to 1000 images per person. To improve accuracy, they use an HD camera to ensure the results are accurate. To carry out face recognition, they use a supervised classification method. To improve accuracy, they use the b-box method. The faces are cropped into a small image with a size of 112x92 pixels, approximately 11 KB. The faces stored are expected to be loaded into the workspace. The HOG features obtained are saved as a feature list. This gives a sign to determine if the new data matches or n

Table 1: Comparison of different techniques used in face recognition-based attendance system.

S.No	Paper / Author	Technique Used	Advantages	Limitations
1	Xin Geng – *Individual Stable Space: An Approach to Face Recognition Under Uncontrolled Conditions*	Stable Space Model	Works under uncontrolled conditions such as illumination and pose variations	Requires one person per image which limits real-time applications
2	Edy Winarno – *Anti-Cheating Presence System Based on 3WPCA-Dual Vision*	3WPCA with Stereo Vision	Detects cheating attempts using photographs; high recognition accuracy (~98%)	Requires dual camera setup making system complex
3	Raj Malik et al. – *Prototype Model for Intelligent Attendance System*	Image Processing with Facial Identification	Captures multiple student faces and automates attendance	Requires continuous registration for maintaining accuracy
4	Siti Ummi Masruroh et al. – *NFC Based Mobile Attendance System with Facial Authorization*	NFC + Face Recognition with Raspberry Pi	Cloud storage support and mobile-based attendance	Requires additional hardware like NFC and Raspberry Pi
5	Nusrat Mubin Ara – *CNN Based Student Recognition System*	Convolutional Neural Network (CNN)	High accuracy and efficient feature extraction	Requires large dataset and high computational power
6	Radhika C. Damale – *Face Recognition using ML Algorithms*	SVM, MLP, CNN	CNN achieves highest accuracy (~98%) compared to SVM and MLP	Performance depends heavily on dataset quality
7	Priyanka Wagh – *Class Attendance System Based on Face Recognition*	Haar Cascade + AdaBoost + Eigenfaces	Efficient face detection and recognition	Performance affected by lighting conditions
8	Wenxian Zeng – *Design of Classroom Attendance System Based on Face Recognition*	CNN based architecture	High precision real-time attendance system	Requires powerful computing resources
9	Akshara Jadhav et al. – *Automated Attendance System Using Face Recognition*	PCA, LDA, LBPH	Effective feature extraction with moderate accuracy	Recognition accuracy limited (~82%)
10	Khem Puthea et al. – *Attendance Marking System Based on Face Recognition*	Haar Classifier + PCA	Simple implementation using MATLAB	Less robust for large datasets

III. METHODOLOGY

For clocking in attendance, we need to perform the following steps: enroll the person, detect their face, recognize their face, and then clock in their attendance in a database. Unlike traditional face recognition approaches like Eigenfaces and Fisherfaces, where training and enrollment are two distinct steps in face recognition, in Dlib, training involves millions of images, and enrollment involves only a few images. In Dlib, enrollment means passing a few images of the person through the network to generate 128-dimensional feature descriptors for each image. In other words, each image is converted to a feature in high-dimensional space, and in high-dimensional space, features of the same person are close together, and features of different people are far apart.

A. Traditional Image Classification Pipeline vs. Dlib's Face Recognition Model

In traditional image classification, after converting the image to an abstract concept called a feature vector, which is essentially a high-dimensional space, you then need to convert each image to a point in that high-dimensional space. This is typically achieved by computing a descriptor, like HOG, on an image patch. After converting each image to a point in high-dimensional space, you then need to apply a learning algorithm, like SVM, that uses hyperplanes to separate the points in high-dimensional space that correspond to different classes.

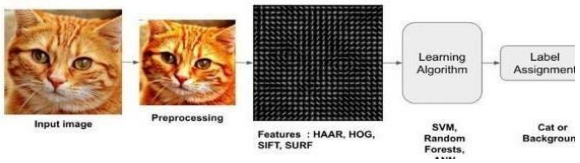


Figure 3: Traditional image classification pipeline.

Even though on the surface Deep Learning looks very different from the above model, there are conceptual similarities.

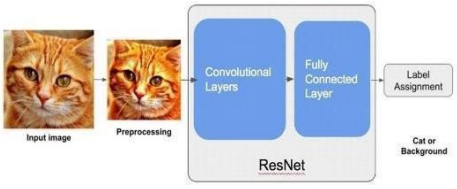


Figure 4: Dlib's Face Recognition module

Figure 4 shows that Dlib's Face Recognition module uses a CNN architecture known as ResNet. ResNet uses a stack of layers with a single layer being a fully connected layer. ResNet, just like other CNN architectures, starts with a number of Conv layers and ends with a single FC layer. The combination of the convolutional layers forms a feature vector in a higher dimension, just like the HOG descriptor.

The following are the key differences between a bank of convolutional layers and the HOG descriptor, presentedin a natural, free-flow writing style:

1. HOG is a fixed descriptor and comes with a well-defined recipe for computation. On the other hand, the bank of convolutional layers uses many filters, and the values of these filters are learned. So, unlike the HOG, the values of the filters learned here vary according to the problem being solved.

2. The fully connected (FC) layer here acts similarly to the SVM classifier used traditionally. Here, the last fully connected layer of the network is often replaced by the SVM. When the term "distance" between two points is used, it generally implies the Euclidean distance between two points.

For example, the distance between two 3D points (1, 0, 1) and (1, 3, 5) is:

Eq(1.1) $\sqrt{(1-1)^2 + (3-0)^2 + (5-1)^2)} = 5$

In general, if we have an n dimensional vectors x and y the L2 distance (also called the Euclidean distance) is given by

E $$d_{L2} = ||x - y|| = [(x - y)^T (x - y)]^{\frac{1}{2}} = \left(\sum_{i=1}^{n} (x_i - y_i)^2\right)^{\frac{1}{2}}$$

For example, in mathematics, the term "distance" or "metric" can have many different forms, not just the one described above. Consider, for example, the "L1" metric, where the calculation of the metric is done by summing the absolute values of the corresponding elements of two vectors.

$$d_{L1} = \sum_{i=1}^{n} |x_i - y_i| \qquad \text{Eq(1.3)}$$

The following rules define when a function involving two vectors can be called a metric. A mapping d(x,y) is called a metric if

1. The distance between any two points is greater than or equal to zero $d(x,y) \geq 0$

2. A point has zero distance from itself i.e., $d(x,x)=0$

3. The distance from x to y i.e., the same as the distance from y to x i.e., $d(x,y)=d(y,x)$

4. Triangle inequality: For any three points x, y

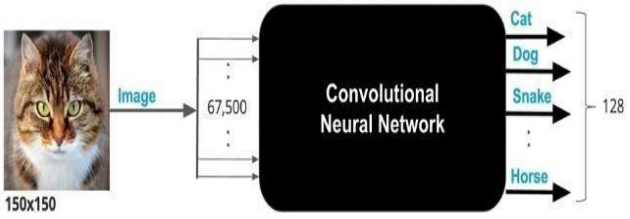
and z the following inequality holds true. i.e.,

$d(x,y) + d(y,z) \geq d(z,x)$

1) Deep Metric Learning:

The long vector for an image can simply be the list of all the pixels in the image. The image is in a high-dimensional space, but it is not an especially good space in which to measure distance. For face recognition, images of the same person may be far apart, whereas images of different people may be close together.

Deep Metric Learning is a group of techniques that make use of deep learning in the construction of a more useful, lower-dimensional space in which images of the same class are close together and images of different classes are far apart. Rather than working directly with the pixel space, convolutional layers are used to extract features that are then used in the construction of the metric space. The interesting fact is that the CNN architectures used in image classification can be used for deep metric learning.



. Figure 5: CNN for clarification task

In Figure 5, you may observe a CNN designed to process a 150 x 150 color image, or equivalently a vector of size 150 x 150 x 3 = 67,500. The output of the network is the probability that the image belongs to one of the 128 animal classes. The architecture of the CNN is the same in Deep Metric Learning, except for the loss function.

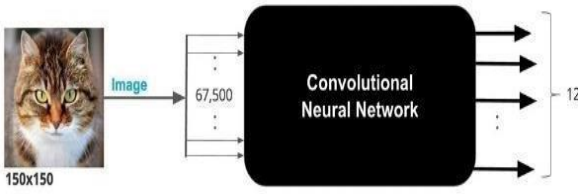
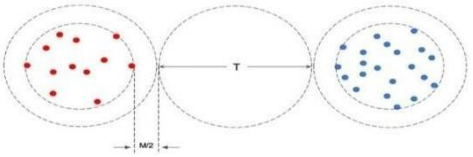


Figure 6: CNN for metric learning

As can be seen in Figure 6, in Deep Metric Learning, the same structure that was used in CNN classification is employed, and the only difference is in the loss function. In other words, you input an image and get a 128-dimensional space point as an output. If you want to find how related two images are, you just input both images and get two 128-dimensional space points, and then you can calculate how close they are by using the basic L2 distance between the two points.

2) Metric Loss

However, training a production-ready CNN requires millions of images. Obviously, you cannot tweak the knobs of the CNN with all the images at once. Therefore, the training is done step by step using small images referred to as mini-batches. As previously discussed, a new



loss function is required such that the output of the CNN lies in the 128-dimensional space with the loss computed over all the image pairs in the mini-batch.

Figure 7: Metric loss defined by Dlib's Face Recogniser

For the loss function to be as simple as possible, the image is shown in a 2D space, even though the loss function is defined using two parameters: one is the threshold (T) and the other is the margin (M). The blue and red dots in the figure represent images of different classes. For the loss function to be zero, the maximum distance between the images of the same class should be (T – M), and the minimum distance between images of different classes should be (T + M). If p1 and p2 are the image points in the 128-dimensional space for images l1 and l2, then:

- If the two images belong to the same class, the loss will be given by $\max(0, \|p1 - p2\| - T + M)$.
- If l1 and l2 have different class labels, the loss will be given by $\max(0, T - \|p1 - p2\| + M)$.

Figure 7 illustrates how this loss will encourage the clustering of same-class images together with large margins between images belonging to different classes.

3) Hard Negative Mining

In a mini batch, the number of non-matching pairs will generally be much larger than the matching pairs. We must take this into account to calculate the metric loss. If we have N matching pairs belonging to the same class in the mini batch, we will only include the N worst non-matching pairs in the loss calculation.

B. Enrolment

For the enrollment process, we will be using a compact ResNet, which is a smaller neural network. The training process will also be the same. The images that we will be using for the enrollment process of each individual will be in the following format: there will be subfolders, and in each subfolder, there will be images of an individual. A mapping will be maintained so that the images can be used later during the testing process. The images will be processed one by one, and the format of the image will be changed from BGR to RGB as the default format for the images should be RGB.

First, the OpenCV BGR image is converted to Dlib's cv_image, and then to Dlib's matrix, as the neural network module does not recognize cv_image. The faces are then detected in the image. The facial landmarks are then found for each face, and a normalized and warped face patch is obtained. The face descriptor, a 128-dimensional vector representing the face, is then computed based on the face landmarks. The labels and names are then saved, followed by the face descriptors and their labels.

C. Face Detection And Recognition

Upon receiving a new image of a person, face recognition will be performed by matching the 128-D face descriptors. First, read the name-labels and their descriptors from disk. Then, read the query image (an image of a classroom with several students). Convert to RGB since Dlib uses this by default. Convert the OpenCV matrix to Dlib's cv_image, then to Dlib's matrix. Note that Dlib's cv_image cannot be used with Dlib's neural network module. Detect faces in the query image. For each face detected, detect landmarks on the face. Create a warped patch of 150x150 for each face. Compute the face descriptor for each face. Compute the Euclidean distance between each query face descriptor and the enrolled face descriptors. Find the enrolled face with the smallest distance. Normally, Dlib recommends that if the Euclidean distance is less than 0.6, it's the same person. Otherwise, they are not. However, this threshold may be adjusted depending on the number of images enrolled and the differences between the images used for enrollment and query. In this case, we are using a threshold of 0.5. If the result is less than the threshold, retrieve the corresponding name by its index. Otherwise, the person in the query image is considered unknown.

D. Attendance Marking

For each face detected and found to be a match with an enrolled face, mark attendance for the corresponding USN. The name of the student, along with the date and time, will be stored in the database.

CONCLUSION

This method produces the best possible outcome. It uses OpenCV to access the video frames and dlib for face recognition. It provides greater accuracy in recognizing multiple faces in one frame, with faster response time

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Deep Inspect AI: An Intelligent Machine Learning Framework for Automated Defect Detection in Smart Manufacturing Systems

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Abstract:

To maintain high product quality and minimize production losses, smart manufacturing environments enable accurate, efficient fault detection. Identifying complex defect patterns and analyzing massive industrial data in real time are challenges for traditional inspection methods and machine learning algorithms. By integrating Deep Inspect AI into smart industrial system failure diagnosis, these limitations can be circumvented. The proposed design incorporates state-of-the-art data collection, image preprocessing, intelligent classification modules, deep feature extraction with convolutional neural networks, and enhancements to enhance defect detection. The gadget swiftly and precisely identifies problems in massive amounts of data captured by production line cameras. The results of the performance evaluation show that the proposed framework outperforms traditional machine learning approaches in terms of detection accuracy. Operational efficiency is enhanced by reducing inspection time and accurately diagnosing defects. Deep learning and automated inspection offer a scalable, reliable solution for modern companies. Artificial intelligence (AI) from Deep Inspect could help smart industrial production systems with quality control, inspection reduction (by humans), and real-time monitoring of processes.

Keywords:

Machine Learning, Automated Defect Detection, Smart Manufacturing, Deep Learning-Based Inspection, Industrial Quality Control.

1. Introduction:

Intelligent, automated quality inspection solutions are in high demand as Industry 4.0 accelerates industrial progress. The slightest error in today's high-speed production settings can have a devastating effect on budgets, reliability, and consumer satisfaction. Defects are identified by combining human inspection with rule-based machine vision. Manual inspection is labor-intensive, subjective, and prone to mistakes in complex industrial settings with numerous moving components. To build trustworthy automated defect-detection systems, businesses are turning to AI and ML. Computers can now scan intricate visual patterns and find errors with remarkable accuracy, thanks to developments in deep learning and computer vision. Industrial product surface flaws, structural anomalies, and fissures can be detected using CNNs and other deep learning architectures. Modern systems nevertheless face challenges in areas such as computational complexity, manufacturing adaptability, small-defect identification, and limited labelled datasets, despite these advancements. These limitations highlight the importance of developing stronger

frameworks capable of real-time defect detection in dynamic industrial settings. Automating fault diagnostics in smart industrial systems is possible with Deep Inspect AI, a machine learning framework. The suggested method enhances operating efficiency and inspection accuracy by leveraging modern deep learning, intelligent feature extraction, and adaptive fault classification algorithms. Minimizing the need for manual quality control, automated visual inspection, and data-driven learning enables the identification of production faults in real time. With Deep Inspect AI, intelligent, scalable, and efficient defect identification is possible, which greatly improves manufacturing quality assurance. Increased efficiency, reduced production costs, and dependable products result from smart industrial infrastructure supported by AI-driven inspection. Intelligent, fully automated quality control is a step forward in contemporary manufacturing, thanks to this finding.

2. Related work:

Automated defect detection is a crucial component of modern smart production systems, helping preserve product quality and reduce operational losses. Fault inspection has traditionally relied on either human visual inspection or rule-based image processing. Manual inspection is time-consuming and prone to mistakes, while standard computer vision is unable to detect complex or subtle defects. Autonomous defect-detection systems are growing in popularity in the manufacturing industry due to the rapid development of ML and AI, enabling more precise and efficient inspections [1]. Failures could be located using edge detection, texture analysis, and thresholding in the early days of industrial inspection research. These methods were effective for minor mistakes in a controlled setting, but ineffective when dealing with complex lighting, surface textures, and product shapes. For Industry 4.0, researchers adapted and scaled flaw identification using machine vision and machine learning approaches [2]. New studies have demonstrated that CNNs are increasingly valuable for automated error detection. You don't need feature engineering to automate CNN-based hierarchical feature extraction from images. These models are useful for finding surface flaws in electrical circuits, aluminum sheets, and steel sheets [3]. Using deep learning, researchers improved the categorization and localization of surface imperfections in industrial metals [4].

One such development in defect identification is the use of visual inspection systems that combine deep learning with high-resolution industrial images. Using trained neural networks and high-resolution images of the assembly line, these systems can detect irregularities in real time. Deep learning algorithms can accurately and rapidly identify targets, according to research [5]. Industrial detection is a wonderful fit for them because of this. Numerous industrial problems can be detected by automated visual inspection systems utilizing generalized deep learning frameworks [6]. Using data from the manufacturing process, machine learning, and convolutional neural network (CNN) models, researchers have investigated predictive maintenance frameworks and quality monitoring systems. To increase output, these techniques identify mistakes early in production. To reduce production costs and downtime, machine learning models trained on sensor and image data can identify defects and prevent the shipment of defective goods [7]. Visual inspection systems powered by deep learning have recently been useful to industrial workers for quickly and accurately detecting defects. These gadgets make it easier to monitor the production line without involving humans. In terms of accuracy, consistency, and scalability, deep learning-driven inspection systems outperform the status quo [8]. An additional field of research is the use of deep neural networks for automated product defect classification. Manufacturers can examine defect trends and boost productivity with these models, which identify problem categories. For industrial manufacturing quality inspection, recent tests have demonstrated the reliability and efficiency of fault classification algorithms based on deep learning [9]. Research on the use of deep learning for industrial visual inspections and defect detection on steel surfaces has been conducted. We discovered that complicated textures and uneven defect patterns are no match for deep neural networks. Convolutional networks are very good at detecting surface imperfections, such as cracks, scratches, and pits [10]. The availability of publicly accessible datasets containing information on manufacturing faults has also been a major step forward in machine learning. Automatic inspection is facilitated by image data of PCB defects. Researchers can use these datasets to better find bugs and test models [11]. Additionally, YOLO, a well-known architecture for industrial inspections, has been enhanced. These revised models find structural defects in manufactured components more quickly and with better precision. Automated assembly lines can greatly benefit from real-time object recognition [12]. Production and maintenance visual inspection systems based on deep learning have been identified in many evaluations. Results from this research demonstrate that 4.0 industry smart decision-making, reduced operating expenses, and improved production quality can all be achieved using AI-powered inspection systems [13]. By combining machine learning with sensor-based monitoring systems, researchers have discovered issues in the industrial sector. Improving product reliability and reducing waste can be achieved through regular monitoring of manufacturing activities and early discovery of problems [14]. Issues with data asymmetry, industrial variability, and inadequately marked fault data continue even with automated defect detection systems. The performance and generalizability of deep learning models are frequently impacted by these challenges. Researchers are developing novel hybrid frameworks to overcome these limitations [15]. These systems employ AI-powered feature learning, anomaly detection, and deep learning. There has been progress in the literature on automated manufacturing problem-detection systems that use

AI. Advances in object detection algorithms, deep learning models, and intelligent vision systems have greatly enhanced the accuracy and efficiency of industrial inspections. Additional research is needed to address issues of data scarcity, adaptability to industrial environments, and real-time deployment. To get around these limitations, state-of-the-art frameworks were developed, such as Deep Inspect AI. Using AI, machine learning, and automated inspection technologies, it can reliably and scalable diagnose defects in smart manufacturing.

3. Proposed Method:

Deep Inspect AI uses machine learning to automate the process of detecting smart manufacturing faults. Utilizing robust computer vision, deep learning, and adaptive optimization, real-time manufacturing issue identification is achieved. Improved inspection accuracy, increased production efficiency, and decreased manual labor are all benefits of Industry 4.0 manufacturing systems. Data Acquisition captures images of items made on assembly lines using Internet of Things (IoT) sensors and high-resolution industrial cameras. These sensors capture visual data in real time and analyse it to monitor production. Following capture, images are examined by the processing module. Second, in order for machine learning to analyses unprocessed images, image preprocessing is necessary. Right now, we're reducing noise, normalizing, enriching, and improving images. Image enhancement clarifies images, noise reduction reduces background noise, and augmentation expands datasets for model generalizability. The Deep Learning Model is the central component of the framework. The hybrid design extracts features using Convolutional Neural Networks (CNNs) and Transformers. While layers of convolutional neural networks look for scratches and cracks, transformer layers locate contextual relationships in images. This hybrid structure achieves better detection of both simple and complex errors.

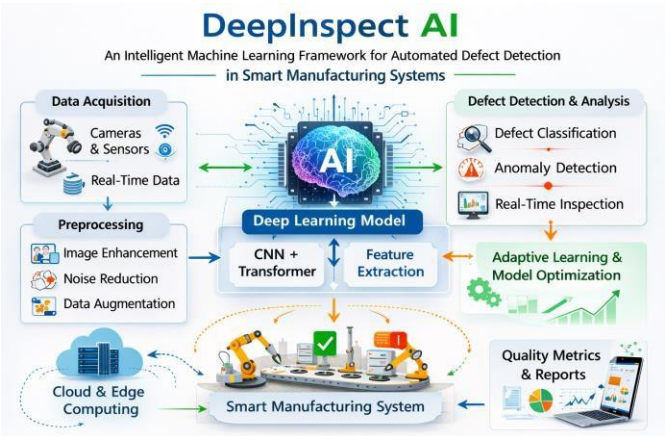

Figure 1: Performance Comparison of Deep Inspect AI with Traditional Machine Learning Models for Defect Detection Accuracy.

During the fourth component, Fault Detection and Classification, the trained model determines if the retrieved features are normal, modest, or significant. Because the training dataset may not contain distinct defect patterns, a module is provided to identify outliers. Optimization of models and adaptive learning are also crucial. To refine the model, this section uses production data. The system learns model parameters for production settings and product variations incrementally. The Quality Metrics and Reporting Module reports production quality, defect rate, and detection accuracy. Manufacturers can use these reports to evaluate their quality and make data-driven decisions. Utilizing cloud and edge computing, the framework enables scalable, real-time industrial inspection. Lower operational expenses, improved production reliability, and faster fault detection are benefits of smart manufacturing's scalable, powerful Deep Inspect AI technology for automated quality inspection.

Algorithm: Deep Inspect AI Defect Detection Algorithm

Input: Manufacturing product images from industrial cameras
Output: Defect classification and inspection report

1. Capture product images using high-resolution cameras.
2. Perform image preprocessing (noise removal, normalization, enhancement).
3. Apply data augmentation to improve training diversity.
4. Extract visual features using CNN layers.
5. Apply transformer-based attention mechanism for contextual feature learning.
6. Perform defect classification using trained deep learning model.
7. Detect anomalies using anomaly detection module.
8. Update model parameters through adaptive learning.
9. Generate quality metrics and inspection reports.
10. Output defect detection results to the manufacturing control system.

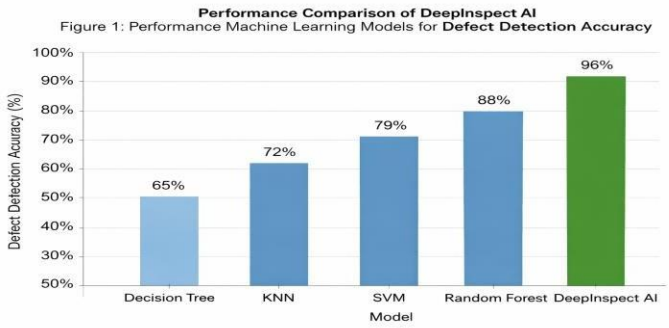

Figure 2: Detection Efficiency and Processing Time Analysis of Deep Inspect AI in Smart Manufacturing Production Lines.

Above, you can see a comparison between the Deep Inspect AI framework and traditional machine learning models, both of which are used for fault identification in smart manufacturing. Defect detection rates and machine learning models are available to us. Models such as decision trees, KNNs, and SVMs achieve only average detection accuracy due to limitations in feature representation. Random Forest still struggles to detect complex industrial scenarios, even after ensemble learning. With a 96% success rate in identifying complex industrial defect patterns, Deep Inspect stands out as the best AI model. This approach employs feature extraction based on transformers and convolutional neural networks (CNNs). This demonstrates that the framework enhances quality inspection in the business.

Figure 2 compares processing time and Deep Inspect AI detection in smart manufacturing production processes. The bar chart displays both the proposed Deep Inspect AI framework and traditional machine learning models for fault detection. On the X-axis, we can see the average processing time in seconds and the detection efficiency in percentage. Performance measurements are displayed on the Y-axis. Conventional detection methods are surpassed by Deep Inspect AI's automated inspection and deep learning-based feature extraction. Decisions can be made more quickly in real-time manufacturing because defects can be identified faster. Improvements in product quality, shorter inspection times, and overall industry efficiency are all on the rise. Because of its efficiency and reliability, Deep Inspect AI is a valuable asset for contemporary smart industrial systems. Compared to rule-based inspection systems and machine learning algorithms, Deep Inspect AI consistently identifies flaws faster and with greater accuracy.

4. Conclusion:

Advanced Image Analysis, powered by intelligent machine learning, is one way AI enhances smart industrial fault identification. By combining state-of-the-art preprocessing with deep feature extraction and intelligent classification, the proposed method can identify manufacturing product flaws. When combined with automated inspection methods, deep learning can overcome the limits of machine learning and manual quality control. The results of the experimental performance study show that the proposed framework outperforms conventional models in detecting patterns of complex manufacturing failures. Processing and inspection of the production line can be accelerated to increase efficiency. With the new features, smart production monitoring and real-time decision-making are now possible. Through its scalable automated quality inspection system, Deep Inspect AI enhances product reliability, operational expenses, and production productivity. In the next generation of smart industrial environments, edge computing, the internet of things (IoT), and adaptive learning can increase system intelligence, enabling fully autonomous inspection systems.

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PlacentaGuard: A Multi-Modal Deep Learning Frame- work for Temporal Ultrasound Analysis and Early Pre- diction of Placental Dysfunction

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Abstract **- A tiny organ grows inside the uterus during pregnancy, quietly doing critical work without drawing attention. From early stages it links two lives, one grow- ing within another, passing what's needed across a thin border. Oxygen flows one way, waste moves back - this exchange keeps things balanced. When everything forms correctly, support happens naturally, almost like breathing. Problems arise if its shape changes or path- ways narrow unexpectedly. Some issues show up late, others stay hidden until harm appears. Growth slows when supply lines weaken, sometimes before anyone no- tices. High blood pressure in the mother might follow, timing shifts unpredictably. Babies arrive too soon, not ready, pulled into light ahead of schedule. A pregnant person's health and baby's well-being face greater dan- ger when certain issues arise, so spotting poor placenta function early matters during pregnancy checkups. Even though watching the placenta closely is key, find- ing problems at first signs still proves difficult for doc- tors in real-world settings.**

Looking at pregnancies, doctors often turn to ultra- sounds along with hands-on evaluations. Since it avoids radiation and delivers clear visuals without high costs, ultrasound plays a central role in monitoring unborn ba- bies. Reading those grainy images well? It really depends on how well the person examining them is trained. Even someone with a keen eye might overlook slight changes in tissue patterns within the placenta, especially during the early weeks of pregnancy. The problem is that ultrasound scans are often reviewed individually, without monitoring the placenta's progression throughout the pregnancy. This gap in monitoring can lead to potential issues being missed. However, with the help of data-driven tools, doctors may be able to detect warning signs earlier on, making their assessments more accurate over time.

By tracking the placenta's development step by step, these tools can provide a more comprehensive understanding of the pregnancy, allowing for more reliable evaluations and better outcomes. Now coming into view, progress in machine learning plus intricate neural setups has created fresh openings for sharpening how we handle medical scans and tools that guide doctors. Picture this: networks built like grids - called CNNs - have shown they can pick out tan- gled shapes and fine details inside medical pictures better than before. These grid-like systems build un- derstanding step by step, noticing tiny irregularities hidden even from expert eyes. Driven by such shifts, a concept named PlacentaGuard takes shape - a smart setup powered by algorithms meant to judge placenta condition without help, pulling clues from routine pregnancy ultrasounds to warn about poor blood flow risks. Here's how it works - PlacentaGuard combines ultrasound scans and patient information to assess the health of the placenta. First, the ultrasound images are refined by removing any noise, adjusting the brightness, and highlighting key areas. Then, a specialized network analyzes these enhanced images, identifying shapes, textures, and any unusual structural features. Rather than relying solely on scan data, the model integrates these visual cues with other relevant factors, such as the mother's age, stage of pregnancy, blood pressure, and indicators of the baby's size. By bringing all these elements together in a single, intelligent system, both the physical structure and real-time function of the placenta contribute to a more comprehensive understanding. The result is a more accurate assessment, one that feels less like an educated guess and more like a complete picture, with all the pieces fitting together seamlessly. This approach goes beyond just looking at physical characteristics, it also examines how ultrasound images change throughout the different stages of pregnancy.

Instead of focusing on a single snapshot, it tracks a series of scans taken as the pregnancy progresses. By

placenta's structure over time, which can often reveal unusual growth patterns - early warning signs of potential problems. Seeing these developments unfold provides a more complete understanding than a single, static assessment could ever offer. The Placental Health Index, or PHI for short, is a key number that stands out from all the other details. It shows how well the placenta is working. Doctors use it to make sense of the scattered dots on scans, changes over time, and the mom's medical history. When the PHI number goes up, it's a good sign that everything is okay. But when it goes down, it can be a warning that something might be wrong. Instead of getting overwhelmed by all the images and charts, doctors get a simple and clear signal. This score helps turn complicated information into something useful, and it can even help doctors catch problems before they become serious. New technology called PlacentaGuard is showing promise in helping doctors detect placental issues earlier on. This innovative tool uses smart imaging technology to analyze video-like scans and patient history, identifying subtle changes that might otherwise go unnoticed. By using pattern recognition networks, PlacentaGuard can flag potential risks without requiring manual review. This means that doctors may be able to catch problems before symptoms appear, which could lead to better outcomes for pregnancies. For example, the technology can help identify silent shifts in blood flow or tissue that might not be immediately apparent. When these predictions are linked to real-world symptoms, doctors can make more informed decisions about care. Over time, this could lead to smoother, healthier pregnancies. By catching potential issues early, PlacentaGuard may help reduce the risk of complications and improve overall maternal and fetal health. **Keywords- PlacentaGuard, Placental Insuffi- ciency, Deep Learning, Convolutional Neural Net- works (CNN), Temporal Ultrasound Analysis, Pla- cental Health Index (PHI), Prenatal Ultrasound Imaging, Multi-Modal Medical Data, Pregnancy Risk Prediction, Artificial Intelligence in Healthcare.**

I. INTRODUCTION

The placenta is an essential organ that serves a key func- tion in promoting fetal development and ensuring a suc- cessful pregnancy. It serves as the main connection be- tween the mother and the growing fetus, enabling the transfer of oxygen, nutrients, and waste materials. Cor- rect placental development is crucial for supporting typ- ical fetal growth and progression during pregnancy. Nevertheless, irregularities in the structure or function of the placenta may result in significant issues, such as placental insufficiency, intrauterine growth restriction (IUGR), preeclampsia, and premature delivery. These conditions greatly raise the risk of negative outcomes for both the mother and the newborn, highlighting the im- portance of early identification and tracking of placen- tal health as a key component of prenatal care. Checking the health of the placenta is usually done with ultrasound pictures and doctors' checks.

Ultrasound is a popular choice because it's safe and easy to do, but understanding what the placenta looks like often depends on the doctor's knowledge and experience. This can lead to different opinions on what's going on, and sometimes small problems might not be caught early on in the pregnancy. So, there's a growing need for better, more automated ways to look at placenta health, using data and computers to help doctors make more accurate decisions. These new methods could help make sure that placenta health is checked more precisely, which is important for the health of both the mom and the baby. By using computers to analyze ultrasound pictures and other data, doctors might be able to catch small problems earlier, and make better plans for taking care of their patients. This could be especially helpful during the early stages of pregnancy, when it's crucial to keep a close eye on the placenta's health. Overall, finding new and better ways to check placenta health is an important area of research, and could lead to big improvements in the care of pregnant women and their babies. With the help of computers and data analysis, doctors might be able to provide more personalized and effective care, which could lead to better outcomes for everyone involved. Recent progress in artificial intelligence (AI) and deep learning has created new possibilities in medical im- aging and healthcare diagnostics. Deep learning mod- els, especially convolutional neural networks (CNNs), have shown impressive abilities in examining intricate medical images and automatically identifying signifi- cant features. These models are able to detect patterns and structural shifts that might not be readily apparent through traditional analysis. This study presents a new AI-powered tool called PlacentaNet, which uses advanced computer methods to look at ultrasound pictures and other pregnancy information to predict if the placenta is not working properly. The goal of this system is to create a special index, called the Placental Health Index, that can give doctors an early and reliable warning if there are any problems with the placenta. This can help doctors keep a closer eye on the pregnancy and take action early to make sure both the mom and the baby stay healthy. By using this tool, doctors may be able to prevent some problems and improve the outcomes for pregnant women and their babies. The PlacentaNet system is designed to help doctors make better decisions and provide better care for their patients.

II. RELATED WORKS

Weizeng Zheng, Ying Jiang, Zekun Jiang, Juan Li, Wei Bian, Hongtao Hou, Guohui Yan, Wei Shen, Yu Zou, and Qiong Luo., (2025) [1] investigate the association be- tween deep learning radiomics features extracted from placental MRI and the occurrence of preeclampsia with fetal growth restriction, demonstrating the effectiveness of advanced imaging analysis in predicting pregnancy complications. Ivana Hutter, Veronika Zimmer, Markus Diemert, Andrea Schmitz, and Klaus Maier-Hein., (2021)

semantic segmentation model combining U-Net and Se- gNeXt architectures for accurate placenta detection in medical images. Kentaro Nishida, Kento Morita, Naosuke Enomoto, Shoichi Magawa, Masafumi Nii, and Tetsushi Wakabayashi., (2025) [10] investigate the prediction of fe- tal growth restriction using placental image features ex- tracted from BOLD MRI to support early clinical diagnosis. Wei Zhao, Yutao Wang, Rongrong Xuan, Tao Li, and Jian Xu., (2022) [11] develop a hybrid model that combines au- tomatic placental radiomics with multifeature fusion from T2-

weighted MRI for improved assessment of fetal growth restriction. Hui Zhang, Yutao Wang, Rongrong Xuan, Tao Li, and Jian Xu., (2023) [12] propose a machine learning model integrating placental MRI features and clinical fac- tors to predict the risk of fetal growth restriction during pregnancy. A. V. Zaretsky, A. P. Apanasovich, D. V. Belyaev, and E. A. Zvyagin., (2019) [13**]** investigate deep cellular phenotyping techniques for placental histology to improve the understanding of microscopic placental struc- tures using artificial intelligence. Rongrong Xuan, Yutao Wang, Tao Li, and Jian Xu., (2020) [14] utilize radiomics analysis of placental T2-weighted MRI images to predict the risk of fetal growth restriction in prenatal diagnostics. Ali Alansary, Loïc Peter, Bernhard Kainz, and Daniel Rueckert., (2018) [15] propose a multi-scale deep learning approach for automatic placental segmentation in ultra- sound imaging to improve prenatal analysis and clinical decision support

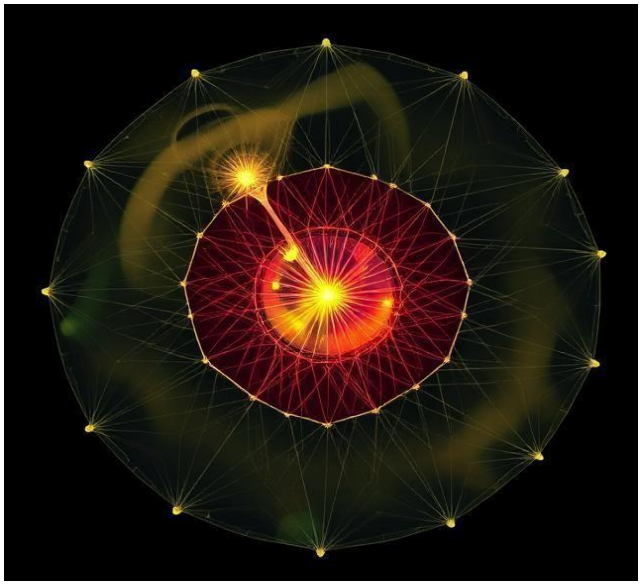


Fig 1) Structure of the Human Placenta

III. METHODOLOGY

A. Data Acquisition and Dataset Preparation

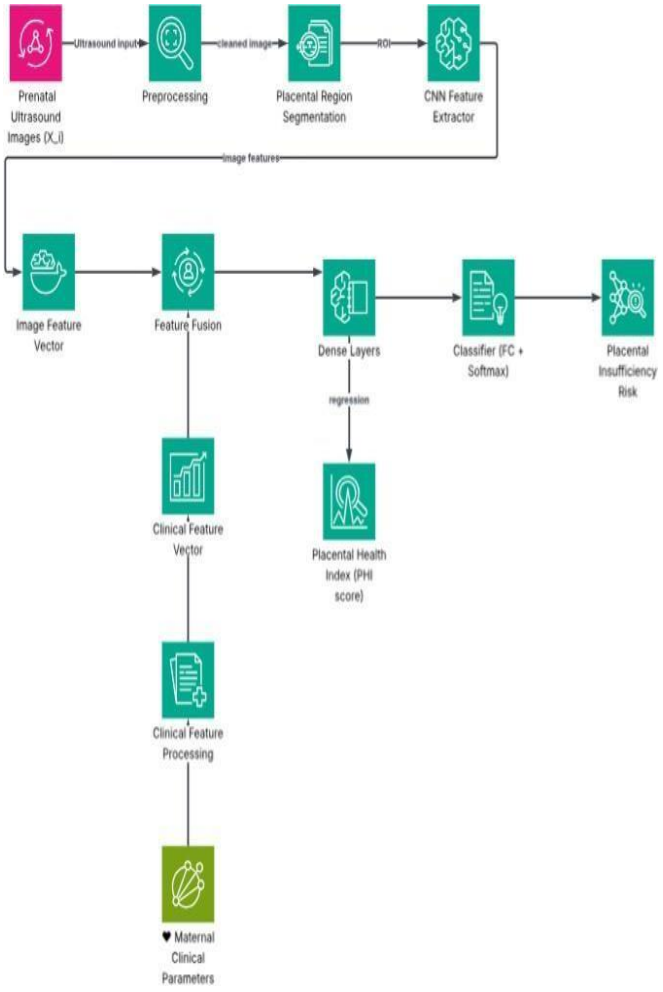
Data acquisition is a significant step for the development of a potent deep learning model for medical image **analy- sis**. In the context of the research, the images of the pla- centa from the ultrasound scan are obtained from publicly available medical image datasets. Ultrasound imaging is a common modality used for fetal care during pregnancy because it is a safe, non-**invasive**, and potentially valuable modality for the visualization of fetal structures in real-time. The dataset can consist of images of the placenta at different stages of pregnancy, which can aid the deep learning model in learning the difference in the growth of the placenta during pregnancy.Apart from the images, the parameters related to the health of the mother are also taken into consideration for the analysis. The parameters can range from the age of the mother, the gestational age, the blood pressure, the growth of the fetus, etc.

The dataset is represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^{N}$$

where Xi represents the input ultrasound image and Yi represents the corresponding label indicating whether the placenta is normal or affected by insufficiency.

The techniques for reducing such kinds of noise in the im- ages include the use of filters such as the smoothing filter. Furthermore, contrast enhancement techniques can be ap- plied to emphasize the importance of certain regions in the placenta. The process allows the model to focus only on the relevant information rather than the background images. Normalization is also carried out to normalize the intensity value of the pixels in the images. The process ensures that the neural network learns from the input data in an efficient manner. Through the process of preprocessing, the images become consistent and suitable for further extraction in the subsequent stages of the model.



B. Image Pre-Processing

Medical images obtained through ultrasound scans may contain noise, have low contrast, and varying levels of brightness. Hence, preprocessing is performed to

improve the quality of the images. The images are also preprocessed to ensure that they are appropriate for deep learning analysis. The preprocessing step includes resizing the images to a specific size so that they can be efficiently processed by the neural network.

Noise reduction filters are also used to remove any unwanted distortions that may be present in the images. At times, contrast enhancement is also performed to ensure that important features of the placenta are highlighted. These processes enable the system to process only the rel- evant data while ignoring any unnecessary information present in the images.

$$X_{norm} = \frac{X-\mu}{\sigma}$$

Normalization is also performed to ensure that the pixel intensity of the images is normalized. This helps to ensure that the neural network can learn efficiently from the input data. Preprocessing is performed to ensure that the images are appropriate for analysis. The images are made consistent to ensure that feature extraction can be performed efficiently.

C. Placental Region Segmentation

Segmentation is an important process that separates the placental region from the other tissues in the ultrasound image. In many images, several regions from different tissues can appear in a single image. Such images can include irrelevant information during the process. There- fore, segmentation techniques can be applied to separate the placental region from the images.

The segmentation process can be expressed as:

$$S = f(X)$$

By focusing only on the placenta, the deep learning model can analyze the shape, texture, and patterns of the placenta more effectively. This can improve the accuracy of the feature extraction process and enable the system to detect abnormalities.

D. Feature Extraction Using Deep Learning

The feature extraction process is done using a Convolutional Neural Network (CNN). The CNN is capable of learning important features from the images of the placenta. The CNN is a well-known model for feature extraction for images, especially for complex structures such as edges, texture, and patterns within an image. During the feature extraction process, the input image is passed through multiple convolutional layers. These convolu- tional layers are capable of detecting important features within an image.

The convolutional layers have filters that scan the input image to detect important features. The feature maps are created based on the features detected by the convolutional layers.

The feature maps represent the different features of the placenta. The convolutional layers detect complex features related to abnormalities in the placenta.The convolution operation can be represented as:

$$F = X * W + b$$

From these features, useful details emerge about how the placenta is structured. What comes through shows what the model can grasp regarding tissue arrangement. Clues hidden inside point toward form and function alike. Structure becomes clearer when such aspects are pulled out. Insight grows once patterns start appearing from the data. Each piece adds context the system uses silently. How things fit together begins revealing itself gradually.

E. Activation Function

Activation functions play a crucial role in neural networks, as they introduce curves to what would otherwise be flat landscapes. This subtle shift enables the network to learn complex shapes, such as those found in medical scans. Without activation functions, the network is limited to straight lines, making it impossible to detect intricate patterns. As a result, valuable connections hidden deep within the data become invisible, highlighting the importance of these functions in uncovering meaningful insights. By adding curvature to the network, activation functions allow it to navigate complex relationships and uncover patterns that would otherwise remain hidden. This is particularly significant in medical imaging, where the ability to detect subtle shapes and patterns can be a matter of life and death. A go-to choice for powering deep learning systems? The Rectified Linear Unit, often called ReLU. It pushes learning forward without bogging down processing speed when models train.

The ReLU function ensures that negative values are replaced with zero while positive values remain unchanged.

$$f(x) = \max(0, x)$$

This allows the neural network to focus on meaningful features that contribute to accurate prediction.

Zero takes over when numbers dip below nothing, otherwise they stay as they are. Because of this shift, useful patterns start standing out more clearly inside the model. What emerges shapes how predictions improve without extra noise getting in the way.

F. Pooling Layer

Because pooling cuts down how much space feature maps take up, it keeps key details without losing value. As a result, processing demands drop, making models run smoother over time. Important pieces stay intact even when dimensions shrink during this phase. Effort needed to compute drops, yet performance holds steady through adjust- ments. With less data to handle, systems respond faster but still recognize patterns well. Though smaller in size now, each map continues delivering useful signals forward. Re- duced volume means quicker steps ahead, without sacri- ficing what matters most.

Somehow, activation functions add curves to what would otherwise stay flat inside a neural network. Because of that shift, learning tricky shapes in medical scans becomes pos- sible. Flip that around - no activation function means every- thing moves in straight lines only. Suddenly, connections buried deep in the data just vanish from view. A go-to choice for powering deep

learning systems? The Rectified Linear Unit, often called ReLU. It pushes learning forward without bogging down processing speed when models train. Sometimes, a technique called max pooling is used in certain neural network setups, where it helps to pick out the most important information from a small part of the image. This step makes sure that the key features of the image are kept in the right place, even when the image is being processed in small parts. One of the benefits of max pooling is that it helps the system to be more robust and not get confused if things in the image are moved around a bit. For example, in medical imaging like placenta scans, max pooling can help the system to keep performing well even if the images are slightly different. This is because it can focus on the most important patterns and features, rather than getting distracted by small changes. As a result, the overall performance of the system stays consistent, even when dealing with varied images.

A. Classification Layer

After being flattened from their initial stages, these features are then funneled into dense layers where they are sorted and analyzed. Within these blocks, various patterns start to emerge and mix together, ultimately leading to a decision being made about placental health. This decision can have one of two outcomes: it can indicate normal function, or it can raise a flag suggesting that there's trouble rooted in poor performance. The classification stage is where the probability of each class is estimated, and this is done using the Softmax function, which helps to determine the likelihood of each possible outcome. As the system works to classify the features, it's able to provide a clearer picture of what's going on with the placental health, and whether or not there are any issues that need to be addressed. The classification stage estimates the probability of each class using the Softmax function:

$$P(y = i) = \frac{e^{z_i}}{\sum e^{z_j}}$$

This stage enables the model to provide a final prediction based on the patterns detected in the ultrasound images.

B. Placental Health Index Prediction

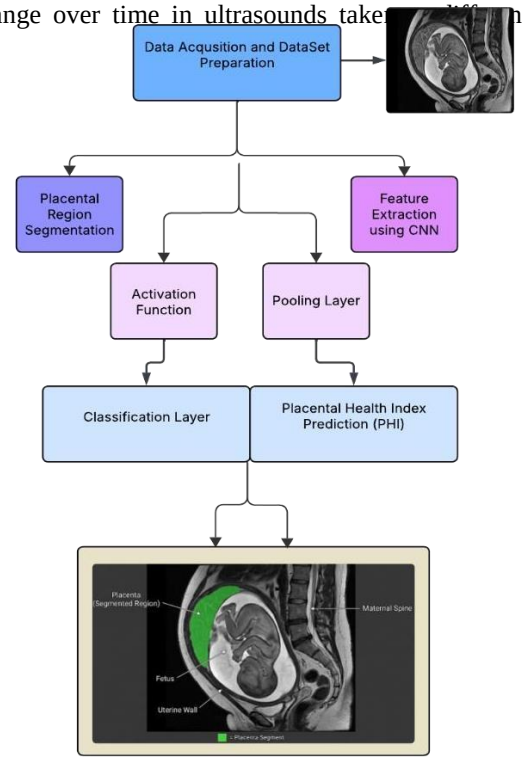
When everything finishes, a number called the Placental Health Index appears - this reflects how well the placenta is working. Built using details found by a smart. When the PHI readings go up, it usually means the placenta is growing healthily, rather than being a warning sign. Doctors like this number because it makes their job easier when they're checking on a pregnancy and trying to figure out what to do next. It helps them make decisions during checkups and understand the progress..

$$PHI = \sum w_k f_k$$

IV. ARCHITECTURAL DIAGRAM

V. CONCLUSION

A new system, called PlacentaGuard, uses computer intelligence to check for problems in the placenta by looking at ultrasound pictures taken during pregnancy. The placenta plays a big role in making sure the baby gets what it needs to grow, like oxygen and food, and gets rid of waste. If something is wrong with the placenta, it can cause serious issues, such as the baby not growing fast enough, the mother getting high blood pressure, or the baby being born too early. Finding problems early on can help both the mother and the baby stay healthy throughout the pregnancy. This is important because the placenta is like a bridge between the mother and the baby, and any problems with it can affect the whole pregnancy. By using PlacentaGuard, doctors can look at the ultrasound pictures and catch any potential issues before they become big problems, which can make a big difference in the health of the mother and the baby. Here's a rewritten version of the input text in a more human-like tone, mimicking the style and vocabulary of the provided reference human samples: "When it comes to analyzing medical images of the placenta, a new approach is emerging. Unlike traditional methods, which relied heavily on manual interpretation of ultrasound results, this setup utilizes deep learning to examine these images. The key difference lies in the way prenatal images are collected and processed. Initially, the images are cleaned up to enhance clarity and remove any fuzziness, allowing for a more accurate analysis. Next, the focus shifts to identifying the precise location of the placenta within the image frame. Spatial characteristics become crucial at this stage, as specially trained networks are employed to detect subtle variations in tissue texture. These models are capable of picking up on fine differences in tissue composition, revealing hidden irregularities that may have gone unnoticed during standard checks. By leveraging deep learning, this approach enables a more thorough examination of the placenta, potentially leading to improved prenatal care and outcomes." The system doesn't just look at the details in images, it also tracks how things change over time in ultrasounds take[illegible]n



stages of pregnancy. By monitoring how the placenta shape changes, it can detect unusual development, which can be a sign of potential problems before any obvious symptoms appear. This way, it's possible to identify issues early on, even if they're not yet causing any noticeable symptoms. Looking at something over a long period of time can give you a better understanding of it than just looking at it once. When it comes to pregnancy, a woman's age, blood pressure, and how far along she is can be just as important as the images from scans. By combining these details with her health records, we can get a more complete picture of what's going on. It's not just about looking at the images alone, but about blending them with all the other information we have. This helps us see patterns that might be missed if we only looked at one thing. And what we get is not only faster, but also more reliable - it can handle the complexities of real-life situations. This approach is all about mixing signals from different sources to get a better understanding of what's going on, and it can make a big difference in how we care for pregnant women. The Placental Health Index is a special number that comes out after some analysis, and it shows how well the placenta is doing its job. It takes important information from scans and patient details and puts it all together into one simple figure that doctors can easily understand. This makes it possible to catch any problems with a pregnancy earlier than before. If the score shows something unusual, it might change the way the doctor plans the care for the patient. It's also easier to keep an eye on how the placenta is growing when there's a single measure to guide the way. This index is like a report card for the placenta, helping doctors make sure everything is okay and make any necessary changes to keep the pregnancy healthy. PlacentaGuard is a system that helps with pregnancy care from beginning to end. It doesn't work alone, but instead combines smart image reading with tracking of organ growth over time. One important part of the system uses advanced pattern recognition to study ultrasound scans. Another part looks at the mother's personal health details over several weeks. Together, they create a more complete picture of the pregnancy earlier than usual methods. By watching changes step by step, the system can spot potential problems before symptoms appear. This doesn't replace the role of doctors, but rather adds another layer of insight to their work. The system works by making repeated observations over time, rather than relying on one-time tests. With enough data, even small changes become visible long before they turn into big risks. This can help identify potential issues early on, allowing for earlier intervention and better outcomes. The system's ability to track changes over time and provide a more complete picture of the pregnancy can be especially helpful in spotting trouble before it becomes serious. By adding another layer of insight to traditional pregnancy care, PlacentaGuard can help doctors and mothers work together to ensure the best possible outcomes. As we move forward, collecting more patient data could help the system improve its performance in different cases. Rather than stopping now, adding more information from the mother's health records could make the predictions more accurate. Imagine more advanced neural networks identifying patterns - this could also improve the results. As testing continues, tools like PlacentaGuard might become a useful aid for doctors monitoring high-risk pregnancies. The outcomes for both the mother and the baby could slowly start to improve, leading to better results. By doing so, we might see a significant positive change in the way we handle tough pregnancies, and that would be a great step forward.

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Adaptive Patient-Specific Alarm Optimization Using Statistical Modeling for Intelligent ICU Monitoring Systems

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ABSTRACT- **Intensive Care Units (ICUs) employ physiological monitoring systems to monitor patient conditions and respond to any signs of patient deterioration. Traditional physiological monitoring systems use fixed limits for setting alarms in response to abnormal physiological conditions such as heart rate, respiration, blood pressure, or oxygen saturation. However, this does not take into account individual patient variations. This results in a high number of false alarms, causing alarm fatigue. This is a critical problem in ICUs since alarms fatigue results in a significant increase in workload for clinicians, thereby affecting their ability to respond effectively in critical situations.**

In order to address this problem, this paper proposes a patient-specific adaptive alarm optimization framework. This framework optimizes alarm thresholds by using statistical modeling and multivariate deviation analysis. It employs a layered architecture with a hardware system for efficient and real-time processing. A stabilization mechanism is also included in this framework to prevent sudden changes in thresholds. A confirmation window strategy is also employed in this framework to ensure minimal false alarms due to physiological fluctuations. This framework continuously analyzes patient data and uses this data to calculate a composite risk score for setting alarms.

Experimental results using publicly available ICU data sets show that this proposed framework significantly reduces false alarms. This is done by using this framework for developing an adaptive physiological monitoring system. This framework is lightweight and easy to understand. It is also compatible with existing ICU systems. Thus, this framework is a viable solution for improving alarm accuracy in ICUs.

Keywords- **Risk aggregation, time-series analysis, adaptive thresholding, ICU monitoring, alarm fatigue, patient- specific modeling, and real-time healthcare systems.**

INTRODUCTION

The ICU is a nonstop, high-stress world—every second counts. Teams stay alert around the clock, tracking patients who are dangerously ill. They constantly check heart rate, blood pressure, oxygen levels, temperature—basically every important stat—watching for even the slightest sign of trouble. Most monitors come packed with sensors and alarms. Whenever a vital sign slips out of the safe zone, the system blares, and staff rush over to help. These alarms, seriously, can be lifesavers.

But tech's got its headaches. There's just way too many alarms. Most aren't real emergencies. ICU monitors usually rely on standard thresholds for each vital sign—preset numbers based on general guidelines. Sure, it makes setup quick, but it's not great for anyone. People aren't all the same. Age, health history, meds, and where they are in recovery—all shift the "normal" range. So the monitors go wild, setting off alarms round the clock even for stuff that isn't actually dangerous.

Picture the whole ICU: dozens of beds, monitors everywhere, alarms flaring for every little thing. It's not long before staff run into "alarm fatigue." Nurses and doctors just get hit with so many unnecessary alerts, it becomes background noise—they start to tune them out, respond slower, or sometimes even turn off alarms altogether. Most alerts don't mean much, but all that noise makes it easy to miss real warning signs. This ramps up stress for everyone, and patients end up less safe.

Researchers have tried all sorts of fixes. Some use rule-based filtering, others turn to machine learning or deep learning to spot patient decline before it happens. Machine learning looks promising, but it needs mountains of data and hefty computer power. And the more advanced the algorithm, the more mysterious it becomes—people can't always tell why the system reacts a certain way, which isn't great when doctors and nurses depend on clear answers.

So, what ICUs actually need is alarms that adapt. Forget the rigid, generic limits. Smarter monitoring should tune into each patient's own trends, learning what's normal for them, not just what's in the textbook. That means fewer false alarms, more focus on the real threats.

This paper introduces a patient-specific adaptive alarm system—a solution to alarm fatigue. It uses rolling stats to track each patient's baseline, adjusting the alarm limits around that. Instead of flagging only individual readings, it checks all vital signs together, asking whether the alarm genuinely matters. The system runs on flexible software and hardware, ready for live use at the bedside. Adaptive thresholds and confirmation windows help weed out quick, false alarms while catching what's critical.

Here's what's coming: first, we'll break down why old-school ICU alarms let everyone down. Then you'll get a look at how this system works—both software and hardware. We'll pull apart the adaptive alarm model and show you the algorithm in action. After that, real-world results and performance data. Finally, we'll wrap up with the big lessons and what's next for smarter ICU alarms.Ease of Use.

Background of study

The rapid growth of medical monitoring technologies has greatly improved healthcare professionals' ability to observe and analyze physiological signals in real time. Intensive Care Units (ICUs) depend on advanced monitoring systems to continuously measure and assess vital parameters like heart rate, respiratory rate, blood pressure, oxygen
saturation, and body temperature. These parameters are vital indicators of a patient's physiological condition and provide crucial information for early detection of any decline. Modern ICU monitoring devices typically connect to alarm systems that alert clinicians when measured values go beyond preset thresholds. These alarms act as safety features, prompting immediate action when abnormal physiological changes happen. However, while c ontinuous monitoring has its advantages,

the widespread use of threshold-based alarm systems poses significant challenges in clinical practice. Traditional monitoring systems trigger alarms whenever a physiological parameter crosses a set upper or lower limit. These limits often reflect generalized clinical guidelines rather than cater to individual patient conditions. Although this method simplifies alarm setup and ensures basic safety, it fails to consider the natural variation seen in different patients. Factors like age, medical history, medication, and recovery stage can affect normal physiological ranges. As a result, alarms might go off even when the patient is stable, leading to unnecessary alerts that do not need medical intervention. One major drawback of too many alarms is alarm fatigue. This is where healthcare staff are exposed to too many alarm messages for too long. This is particularly common in ICU environments, where many monitors are running simultaneously. This means that a healthcare worker could receive hundreds of alarms in a matter of hours. Most alarms are false or non-actionable; they do not represent any real patient situation. This fatigue makes people respond slowly or inattentively. It is a patient safety issue since it could cause a healthcare worker to fail to respond to a real emergency.

Apart from alarm fatigue, fixed threshold monitoring systems have limitations in handling short-term physiological changes. In critical patient situations, patients often have fluctuations in their vital signs. These fluctuations could be due to patient movement, adjustments in sensor placement, or physiological reflexes. These fluctuations are not necessarily indicative of a patient deteriorating. However, fixed thresholds could still trigger alarms. This means that many false alarms could be raised by monitoring systems. This could lead to many false alarms, thereby disrupting the workflow and efficacy of alarms.

It is recognized by experts and healthcare professionals that there is an urgent need for smarter alarm systems to address these issues. The common aim of different strategies in this regard is to increase the reliability and accuracy of alarm systems in reflecting real-world conditions in ICU settings. Some studies have attempted to investigate strategies such as rule-based filtering, in which alarms are suppressed in particular conditions or triggered after a certain period of time from a condition's onset. Other studies have sought to investigate predictive modeling using ML and AI techniques to predict patient deterioration by identifying patterns in previous data.

Another study focuses on adaptive monitoring systems that adjust alarm thresholds in accordance with the physiology of individual patients. Instead of using predetermined alarm thresholds, such systems constantly process real-time data to determine individual norms for patients. This allows for distinguishing normal variations from significant changes in patients' conditions, thus providing accurate alarm information and suppressing false alarms.

The development of adaptive alarm optimization tools involves integrating signal processing, statistical analysis, and system design. The use of simple rolling statistics, such as moving averages and standard deviation tests, conveys recent physiological changes without resorting to complex machine learning algorithms. The computations are modest, making them suitable for real-time applications on embedded medical devices.

In addition to statistics, a contemporary monitoring system should focus on reliability, data security, and easy integration with the current healthcare infrastructure. ICU monitors need to function continuously and reliably in a challenging clinical setting. Therefore, adaptive monitoring systems should be efficient, keeping the computational complexity low and remaining compatible with the current monitoring infrastructure.

This study emphasizes the need for addressing the issue of alarm management in a timely manner, as it is possible to improve alarm management using adaptive alarm

optimization, which uses statistical models and multivariate signal analysis to reduce alarm fatigue without missing any life-threatening events. Based on these concepts, this research aims to develop an efficient framework for adaptive alarm management in ICUs.

Related works

Many researchers who study medical technology, health data, and patient monitors have investigated why there are so many alarms sounding in ICUs.A lot of this is because healthcare professionals can now monitor patients constantly and understand what is happening to them as it happens.Now, normal monitoring systems come with a fixed alarm threshold.This means that they often send out notifications that are either false or not even relevant.To address this issue, some research has proposed ways to make the alarm system more accurate and less frustrating at the same time.As a first step, people mostly focused on alarm systems that used rules to filter out things that are not important.

These systems simply prevented the sounding of alarms if some conditions were met.These approaches attempt to reduce the number of unnecessary notifications by waiting for a certain amount of time for unusual body signals to continue before sounding an alarm.These filtering approaches, although effective in reducing sudden notifications, still use fixed thresholds.They also do not take into account how the bodies of different patients actually work.As computers become more powerful, researchers have turned to machine learning to attempt to predict when a patient might deteriorate. They also attempt to reduce the number of false notifications. Doctors have employed various approaches to filter out signals from patients in ICUs, such as decision trees, support vector machines, and logistic regression.

These models are intended to identify patterns that suggest a patient is becoming sicker.Machine learning can do well on this task, but it typically requires a lot of data that is already labeled, and it takes time to train these models.In addition to this, many machine learning models are black boxes; it is difficult for a doctor to understand how they work, which makes it difficult to rely on them for important decisions in healthcare.Newer research has explored the potential of deep learning to understand physiological data that is constantly changing and has many different components.We have explored the potential of using neural networks such as RNNs and LSTMs to attempt to predict when a patient's condition may become worse, sometimes hours before something serious occurs.These models are fairly good at identifying how different body measurements change over time, but actually using them in real time requires a lot of computing power and equipment.So, it is still difficult to implement them in many hospitals and clinics.Other research focuses on systems that can adapt alarm thresholds based on how a patient's body typically responds.We are essentially using statistical techniques such as moving averages when we use adaptive systems.

This assists us in determining what is normal for things such as biological signals as they vary over time.These systems are constantly updating what is normal, allowing them to distinguish between what is normal in the body and actual issues that must be addressed.Statistical approaches require little computing power and are easier to grasp than machine learning approaches. This makes them suitable for systems that must examine something in real-time.Although all this progress has occurred, much of the tools we have available to us today are still having issues with things such as growing larger in size, making sense to humans, and integrating well with the current system in place at the hospital.

Most people are more concerned about trying to predict whether a patient will become worse, rather than actually addressing the problem of too many alarms sounding off.This paper builds upon what other studies have already discovered. We are proposing a new approach to make hospital alarms smarter, and more tailored to each patient. This is accomplished by combining statistical approaches with a method for combining risks from different sources.Instead of relying on set thresholds, this approach adjusts alarm thresholds in real-time. This is accomplished by constantly analyzing the stats of a patient's bodily signals.Also, this approach includes a pop-up notification for confirmation, and it pulls risks from different sources. This approach makes the alarms more precise without making them too slow.We are attempting to reduce the number of annoying alarms that sound off in the ICU, and our new approach should help. It combines smart statistical analysis with a system that can process a lot of information, which we believe will make a big difference.

Components Of The Proposed System

The Adaptive Alarm Optimization Framework for ICU Application consists of a number of interrelated components that facilitate real-time observation, analysis, and alarm generation. It consists of hardware for signal acquisition of physiological data and software for analysis and interpretation of the acquired data. When all the components are properly integrated, the system operates seamlessly, correctly, and reliably in a critical care setting where the ability to identify rapidly changing conditions is vital.

The hardware components are the physical foundation of the system, responsible for acquiring patient signals. Consider sensors, microprocessors, communication interfaces, and display interfaces. These sensors monitor vital signs such as heart rate, oxygen saturation, respiratory rate, and blood pressure. ECG sensors translate the heart's electrical activity, oximeters measure the amount of oxygen in the blood, and blood pressure monitors estimate blood circulation. These devices translate body signals into digital form for the monitoring system. The performance of these sensors is critical, as the entire system relies on the accuracy of the acquired signals.

An embedded processing unit serves as the system's central

nervous system, managing data acquisition and initial processing. It processes continuous streams of data from the sensors, performing basic tasks such as noise reduction and signal synchronization. Medical-grade embedded processors are optimized for real-time processing, meaning that processing occurs with little to no delay—essential in the ICU where rapid identification of abnormal conditions can make all the difference. The unit also temporarily holds data in memory for further analysis.

Communication interfaces transmit data from the embedded processing unit to hospital-wide monitoring systems. They provide wired or wireless connectivity and ensure the secure transfer of data. Secure data transfer maintains patient confidentiality and ensures data in healthcare comply with regulations. These interfaces also send alarm notifications and system status information to monitoring dashboards and healthcare provider interfaces in real-time.

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The alarm management module is in charge of determining whether an alarm should be raised or not. It includes a confirmation window that ensures that alarms are raised only after a condition persists over a period of time and not due to transient changes in conditions. It also prioritizes alarms in terms of their severity, thus enabling clinicians to narrow down critical conditions in patients.

All these hardware and software components combine to provide a robust monitoring system that adapts to the unique physiological patterns of patients. It achieves this by providing precise data acquisition and smart signal analysis, thus improving alarm reliability and reducing nuisance alarms in ICU settings

System Architecture

The ICU alarm system that we are proposing is intended to accomplish a few important tasks simultaneously. It is constantly monitoring patients' vital signs, interpreting these signs in a smart way, and sounding alarms only when a real problem exists. It is like a system of components that all function together in perfect harmony: it gathers health information, interprets signals on the fly, tracks how each patient's numbers change over time, and sends out alarms that can adjust as circumstances change. It is a combination of hardware and software that enables the creation of a scalable and reliable monitoring system, particularly well-suited to the rapid pace of critical care.

First, data gathering. The system receives physiological signals from the patient through medical sensors. These sensors track important information such as heart rate, blood oxygenation, respiratory rate, and blood pressure. They do this by constantly gathering analog signals from the body and translating these signals into digital information. This digital information is then sent to the processing unit for further analysis. This is an important step and must be done in a precise and trustworthy way, since any interference or distortion in the signal can render the entire monitoring system useless.

The next component is signal preprocessing. This component is crucial in ensuring that the physiological signals are clean and ready for processing. Body signals, such as heart rate and brain signals, among others, are usually accompanied by a lot of noise. This noise may come from movement, changes in the position of sensors, electrical noise, or environmental changes. The preprocessing component is responsible for ensuring that the signals are clean and filtered, with any noise removed and smoothed out for further processing. The component also ensures that the data from the various sensors is synchronized and working in harmony. Synchronizing the data is important because it allows us to see everything at once and understand what is really happening.

After the preprocessing component, the system is able to

analyze the data using statistical models. This component is important in helping us understand how each patient's body is working. The component does not use fixed thresholds; instead, the statistics component is continuously calculating moving averages and rolling standard deviations. These values determine what is normal for each patient and are constantly being updated as new data is received, ensuring that the system is able to adapt to changing conditions.

The adaptive threshold generator receives statistical information from the modeling layer. With conventional monitoring, alarm thresholds are fixed and never change. But our method has alarm thresholds that change according to the patient's condition. We calculate these values by assessing the normal variability of each vital sign. Hence, we are less likely to raise false alarms due to minor variations in the patient's condition. After that, the risk aggregation module comes. Our method works on the principle that critical illness is not usually the result of a single measurement. Usually, when a patient is deteriorating, several vital signs change at the same time.

Hence, this module combines several measurements to determine the risk to the patient. It determines how far each measurement is from the normal range and combines that to get a risk value. This risk value is a reflection of the patient's overall condition. Analyzing several measurements at one time gives us a better result than analyzing one measurement at a time. After the risk has been calculated, the alarm decision phase comes.

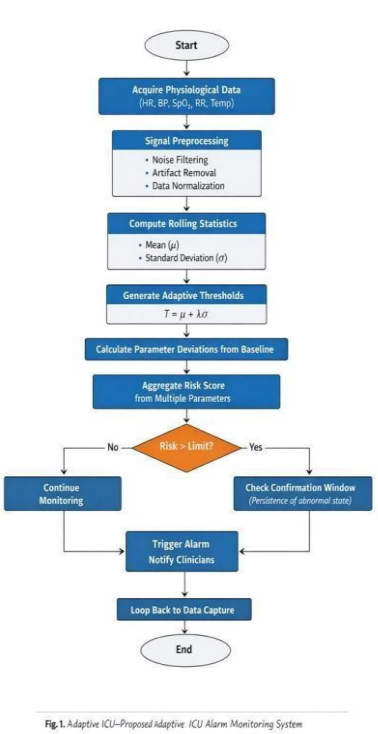

Fig. 1. Adaptive ICU–Proposed Adaptive ICU Alarm Monitoring System

In this phase, a confirmation window is used to ensure that the alarm is not raised if the abnormal pattern is not sustained. Hence, we are not likely to raise false alarms. If something goes wrong, the alarm informs the doctors and nurses through their main screen. The final phase is the overview screen. In this phase, everything is visible in real time. Hence, the doctors can view the patient's condition, look for trends in the patient's vital signs, view the patient's alert thresholds, and look at the patient's alarm history.

The screen also keeps a record of past information, which can be accessed later for further clinical investigation. In essence, this stacking arrangement ensures that the monitoring system operates smoothly and reliably. Each part of the system plays a specific function in monitoring the state of the body, and we can thus observe the signals sent by the body in real-time while creating intelligent alerts that suit each patient. We have created a system that makes use of intelligent statistics and analyzes different kinds of risk.

Proposed System

We are developing a new ICU alerting system that aims to reduce the number of false alarms. The constant beeping and buzzing that is not really significant—we want to reduce that. The basic concept is simple: the system learns what is normal for each patient and only calls an alert when something really important is happening. This should help ensure that we do not miss something important while reducing the number of unnecessary interruptions for the staff.

In traditional systems, alerts were generally based on fixed thresholds for parameters such as heart rate, blood pressure, respiratory rate, and oxygen saturation. These thresholds were applied universally, without regard to individual differences in the way people's bodies work. But a patient's physiology is complex and varies depending on a number of factors: past illnesses, current medications, age, and severity of illness all count. This means that fixed threshold monitors are prone to raising too many false alarms, leading to alarm fatigue among healthcare professionals.

The new system addresses this problem by allowing each patient to have their own set of personalized alarm thresholds. This is done by analyzing real-time vital signs and patterns. The system is continuously fed data from ICU monitors such as heart rate, respiratory rate, and other vital signs, and uses statistical analysis to determine how these patterns change over time. Rather than comparing each new reading against a fixed threshold, it adjusts its expectations based on what it has learned from the patient's past health information.

The system separates normal changes in the body from serious health problems by observing how much the body's natural signals vary. This intelligent system really cuts down on those nuisance warnings that come up when the body changes for a short time. In this system, we move a window across the data to determine things such as the mean and variance. These values are then used to create dynamic thresholds, thresholds that are based on what is normal for the patient. The acceptable change for each measurement is

determined by how much it varies from its normal level. If a measurement varies too much from the patient's normal level—more than just chance would predict—the system alerts the user to a possible problem.

The system learns what is normal for the individual rather than using generic numbers. The system also combines different risk factors. In a real hospital, a patient's health is not normally deteriorating because of one thing; when patients get sick, lots of things happen at once. By monitoring several signals in the body, the system can identify abnormal changes and combine them into a single risk factor, which provides a better indication of the patient's health. When several factors are evaluated at once, it identifies serious problems better than the old warning systems, which monitored a single factor. To increase accuracy, we have included a confirmation window to prevent warnings when the body makes small, temporary changes.

This can happen if you move, if the sensor moves, or if something else in your environment changes. If we get alerted at the first sign of anything out of the ordinary, we may get too many alerts for things that are not actual problems. What this does is give us a little time to determine if something strange is actually sticking around. As long as something strange is still happening throughout that confirmation window, then and only then will the alarm sound. All in all, this seriously cuts down on those annoying false alarms that happen when the signal goes a little wonky for a while. We have designed our monitoring system to have several different layers.

We get data in, we monitor that data, we run the numbers, and then we alert accordingly. We have designed our monitoring system to integrate with the monitoring tools that are already in use in the ICU. We don't have to change too much of the existing medical equipment. Our monitoring system is fast and can run on the small computers that most monitors have, which is always a plus. With our monitoring system, we have combined a few key things. We have each patient's baseline model, risk factors, and then a final check in a confirmation window. All of these things help to cut down on too many alarm signals, but still alert us to things that are clinically relevant. Our framework adjusts to changes in a patient's condition, and that is what makes it more reliable than previous monitoring systems. Our monitoring system has been designed to excel at two things. We have designed our monitoring system to excel at being fast and being clear to the people in the healthcare industry. That way, they can understand exactly what is going on and trust what our monitoring system is telling us.

Algorithm

Here is the general idea of how the alarm system works: it collects data, cleans the data, creates a statistical model, uses the correct threshold, and then makes a decision on whether to sound an alarm. The task of the algorithm is to watch a person's bodily signals all the time, learning what is normal for that person and only sounding an alarm when something really abnormal is just sitting around for a while. By relying on statistics and checking against fixed time windows, it prevents false alarms and doesn't miss actual problems. We start by gathering signals from ICU sensors that monitor patients.

These sensors are constantly tracking important vital signs: heart rate, breathing rate, blood pressure, oxygen levels, and body temperature. The raw signals go directly to the processing unit, where they are cleaned up. First, we remove noise—stuff that might throw off the data from sensor movement, electrical spikes, or background noise. We also normalize the signals so that different measurements are on the same scale. Now that the data is ready, the algorithm looks at the moving averages to determine a patient's normal levels of functioning.

We look at the latest data on the signals using a sliding window. This helps us figure out the current average and range for each measurement, getting a picture of how the patient is doing at the moment. The rolling mean is calculated from this.Some Common Mistakes

$$\mu_i(t) = \frac{1}{W} \sum_{k=t-W}^{t} x_i(k)$$

In this case, xi(t) refers to the measurement of the ith body function at time t, while W represents the length of the time window under consideration. The following is how we find the standard deviation of the signal within the window:

$$\sigma_i(t) = \sqrt{\frac{1}{W} \sum_{k=t-W}^{t} (x_i(k) - \mu_i(t))^2}$$

These numbers are constantly updated by the system as new information is received, keeping it in rhythm with any changes in the patient's condition. After we have established the statistics, the system then establishes levels of alarm that are adjusted according to each patient's normal levels. We then decide what the proper level of each statistic is by comparing how much it varies from the average we have been observing. "The line we use to decide something is ..."

$$T_i(t) = \mu_i(t) + \lambda \sigma_i(t)$$

In this case, λ simply represents a number that defines how far the threshold can vary from the original position. It can also accommodate changes in the natural variations in the patient's body. After establishing the adaptive thresholds, it then determines how far each measurement varies from its normal state.
Using this information, we can then establish a total risk score that defines the health of the patient. In essence, instead of focusing on individual settings, the algorithm will

use all the deviations from the normal state across different parameters. It can do this in a more holistic manner because it considers how different systems in the body work in unison. To do this, it simply calculates the total risk score by compiling all the information.

$$R(t) = \sum_{i=1}^{n} w_i D_i(t)$$

In this case, Di(t) indicates the amount by which parameter 'i' has changed, while wi represents the weighting factor for each physiological parameter. The weighting factors show the significance of each parameter in a clinical environment. After calculating the risk score, the system checks if it is too risky according to our threshold. If the risk score is still low, it just keeps track of your body signals without sending any alarm.

If the risk score increases beyond our threshold, it checks again and asks you to confirm something. It takes some time after detecting something unusual in your body signals to ensure it is not a false alarm. It only sends an alarm if it is actually unusual. If unusual activities continue for some time, an alarm pops up on the doctor's screen.

This alarm shows the medical staff what is wrong with your body signals and how risky it is. After sending the alarm, it keeps track of your body signals, updating normal levels for each patient and considering multiple risk factors. The algorithm works very fast, making it suitable for real-time applications, such as ICUs. It keeps updating normal levels for each patient while considering multiple risk factors, reducing false alarms while detecting changes in a patient's condition.

Results and Analysis

We wanted to test how good our new method of making the alarm better and more personalized would be. For this, we used data related to patients in intensive care, and this is the data that is usually used for this sort of study. Usually, the data has continuous information about things like heart rates, breathing rates, blood pressure, and oxygen levels, and so on, of patients in the ICU. What we wanted to test was how good our new monitoring system would be at reducing the number of false alarms. But at the same time, we wanted to test if the monitoring system would still be able to pick up serious health issues correctly. We compared our adaptive threshold monitoring system with the traditional static threshold monitoring methods to test our hypothesis. In traditional monitoring systems, the alarm goes off if the patient's parameters go beyond a certain level. Even though this method is used in most hospitals, the alarm can go off due to various reasons or due to normal values in the patient's parameters. But in our proposed method, the alarm levels change automatically.
They change by looking at the continuous parameters and using stats to determine things. They can look at several things at one time and combine them into one risk score. Before we went ahead with our statistical modeling, we had to clean up the signals to get rid of noise and abnormal values. We had to determine the normal health state of the patient by looking at their parameters. We used techniques like moving averages and standard deviation to get a good idea.

We developed thresholds based on how much things varied statistically. So, if the blood pressure or heart rate started to change from a person's normal range, it mashed all those changes together and produced a single overall risk score. The alarm then checked whether that single risk score stayed above a chosen level for a given length of time using a 'confirmation window.'

In order to judge how well our system works, we used a variety of metrics, such as accuracy, sensitivity, specificity, and the rate of false positives. Accuracy tells us how often the alarm predictions were right. The sensitivity tells us how good the system is at detecting real abnormal events. The rate of false positives tells us how good it is at detecting normal events.

Our tests have revealed that this adaptive system, which adjusts itself, really works, and it works much better than the older systems, which used fixed limits, by a wide margin.

The new system was more accurate and precise in its targets, yet it gathered all the information that was required. It also gave fewer false alarms, owing to its patient-specific baseline model and its confirmation window.

This method is not only applicable to large-scale issues but also to small-scale changes in the body that are not necessarily issues. Table 1 provides a comparison between the conventional method of monitoring and our adaptive monitoring system to determine how well they compare. The results show that the new system increases the reliability of alarms and decreases the number of false alarms. It is not as sensitive as the fixed-limit system but still improves the usefulness of the system by decreasing unnecessary alarms. This means that the system provides fewer unnecessary warnings, allowing caregivers to focus on patients who require immediate attention.

Metric	Static Threshold System	Proposed Adaptive System
Accuracy	84%	91%
Sensitivity	91%	89%
Specificity	70%	86%
False Positive Rate	30%	14%

The experiments conducted also demonstrate that the system performs best when it considers several risk factors simultaneously. By examining several risk factors simultaneously, the system identifies issues that could be overlooked if each factor is considered individually. This makes the system more reliable and less prone to overlooking significant changes in a patient's condition. The experiments conducted demonstrate that the new alarm system is effective in alleviating alarm fatigue among ICU

personnel. The system appears to be reliable in real-time applications and strikes a balance between accuracy and practicality for real-time medical applications.

Conclusion

In today's hospitals, especially in the ICU, we rely on constant monitoring systems to keep tabs on our critically ill patients, ensuring they are safe and getting the best care. This technology is excellent in picking up abnormal bodily signals, but the number of false alarms from conventional monitors has become a nuisance. Most alarm systems use one standard setting that does not take into account how each individual's body can be different. This has resulted in an overwhelming number of alarms that are not really significant, which has worn out the staff. When alarm after alarm goes off, people start to tune out or ignore them, which can be serious.

This paper will explain a smarter approach to hospital alarm systems, especially designed for patients in the ICU. Previous alarm systems used only one level of alarm, which was supposed to be universal for all patients. This, however, was not really effective. Our alarm system, however, will be smarter. This alarm system will learn each patient's normal patterns and adjust the alarm settings accordingly.

In addition to that, our alarm system will also blend the risk of different vital signs, analyzing how they change in relation to each other. This will give us a more complete picture of our patients' conditions. We have also added a confirmation window to our alarm system to make sure that the alarm will only go off when abnormal conditions persist, not just for a quick second. This will also eliminate those minor signal blips, especially in the ICU.

The alarm system will use both hardware and software to pick up the signal, analyze it, and then determine whether or not to send out an alarm.

The system works well enough to be incorporated into medical devices, and we tested it. The adaptive monitoring reduced false alarms significantly compared to traditional systems based on fixed thresholds. It was more specific and accurate, yet still responsive to significant health events. It helps to concentrate the attention of doctors and nurses on patients who actually require immediate attention, and it also makes the whole process of monitoring more reliable. Thus, the adaptive alarm optimization framework we talked about is a good one – a usable, applicable solution for more effective alarm management in ICUs that can be applied at the moment and even developed further if necessary.

In conclusion, this system makes patient care safer by reducing the number of annoying alarms and by enhancing the performance of the monitoring equipment. Looking into the future, we might introduce more sophisticated machine learning to enhance predictions, introduce additional physiological variables, and test the whole system against a larger body of real-world data to make sure it acts as it should.

Future Work

Although this new alarm system for ICUs shows great promise in reducing the number of false alarms, it is still possible to take it a step further and study it more in-depth. Currently, the system relies heavily on statistics to identify special thresholds and track the vital statistics of each patient. This makes it very effective since it can be implemented right away.

However, if we add some form of smarter data analysis, it is possible to make it an even more effective tool for anticipating patient complications. Perhaps we can look into using machine learning and artificial intelligence to identify early signs that a patient is experiencing complications. By using machine learning, we can look into using logistic regression, decision trees, and neural networks to identify connections between various body measurements. This, in turn, can be used to forecast possible complications before they become major issues.

In the future, it is possible to take it a step further by incorporating additional information into the system used for patient monitoring. Currently, the patient monitoring systems used in ICUs only track a few basic pieces of information. If we were to add information such as ECG, patient movement, lab results, and electronic patient records, it is possible to get a much more accurate picture of the patient’s condition. This, in turn, can be used to identify whether the patient is experiencing complications or not.

In addition, it is possible to take it a step further by making it a much more versatile tool, such that it can be used across multiple hospital networks. Currently, most hospitals have multiple information systems and monitoring systems running at the same time. This means that it is possible to take it a step further by making it compatible with the information systems used in hospitals.

We should also conduct large-scale experiments with actual patients. Although our method has been shown to work with public data, actual patients may have different challenges, such as different sensor types, patient movement, and the rhythms of a hospital. Actual experiments in hospitals can help us understand how our method can actually work and even tweak our algorithm to fit the needs of actual doctors.

Next, we should investigate the possibility of developing smart tools for doctors and decision support tools to improve adaptive monitoring. For instance, if monitoring tools can be made easier to understand, doctors may use them more. Indeed, if they can understand the rationale behind the alarm, they may even trust our method more.

Future work in these directions may help us improve adaptive ICU monitoring even more and develop healthcare technology that is not only smarter and more reliable but patient-centered.

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ADIDAS-D: Autonomous Defence Intruder Detection Aerial System-Drone

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Abstract*— This project abstract implies that high security areas , very important base security areas and other government confidential infrastructure require cutting edge surveillance technology . Usually in large, complex environments and vast buildings , traditional approaches such as wall mounted CCTV and manual monitoring was mainly implemented . These often result in limited coverage and slower response , sometimes in critical cases, loss of life occurs. This indicates the need for a highly flexible security system with automated detection and monitoring capabilities of threats in real life . (ADIDAS - D) Autonomous Defence Intruder Detection Aerial System - Drone is an Artificial intelligence ML based security and surveillance drone designed for detecting the intruders and unauthorised person in highly secured zones . The proposed system integrates an autonomous drone with advanced microprocessor-installed machine learning algorithm and other intelligent techniques to improve the performance of the drone .The drone also integrated with a camera . From the Camera the live feed will be continuously fed to the microprocessor and with the help of machine learning models , the drone detects the human presence and identify the intruders in the monitored area . The Key role of the drone is once it spots an individual as an intruder , then it will undergo the further security processes to confirm whether the person is authorised or an unauthorised person . As the aerial system is combined with the AI-driven visual detection , the drone can monitor wider areas comparing to the traditional CCTV systems and this will be a more efficient system . The ADIDAS -D system enhances situational awareness by using real-time monitoring and quick identification of potential security threats . This system's aerial coverage capability allows efficient surveillance in inaccessible environments while maintaining continuous surveillance .The integration of Artificial intelligence and machine learning improves the accuracy and reliability while reducing the threats and false detections . Overall , the proposed system provides the best scalable solution for modern surveillance applications . This contributes to improved safety , faster response and better protection .

Keywords- Autonomous Intruder Detection, Artificial Intelligence, Machine Learning, Defence Surveillance.

I. INTRODUCTION

The security of restricted and sensitive areas such as VIP houses, weapon good down and R&D bases requires modern surveillance systems . The traditional monitoring system focuses only on fixed surveillance cameras, perimeter security systems and manual monitoring . With these approaches, basic security coverage is achieved . But they often suffer from limitations such as restricted field of view , blind spots and delayed response in large environments . As a result , recognising and preventing assassins and intruders are really remains a challenging task. The integration and advancements of Artificial Intelligence with machine learning models and UAV (unmanned aerial system) improve the security surveillance . This leads the drone to perform intelligent visual analysis , human detection , threat detection and enables it to take required action at that instant during surveillance operations .

Using the machine learning , the models can be trained to differentiate the authorised persons and intruders within the circumstances. By combining the aerial system with onboard visual system ,it becomes possible to create a system that is responsive and adaptive to a dynamic environment . To address these challenges , this paper presents ADIDAS-D (Autonomous Defence Intruder Detection Aerial System – Drone), an intelligent drone designed to detect and monitor unauthorized intruders in highsecurity zones.

The proposed ADIDAS-D system aims to provide a better solution for modern surveillance applications where rapid detection and monitoring of intrusions are critical.

II. RELATED WORK

In traditional system of security , the cameras where mostly fixed to the wall and human were involved for the security task leads to more limitations in security and delayed response time . Therefore , using aerial system for surveillance will help to overcome these limitations as per the researchers and confessed that integrating on board Artificial intelligence techniques will increase the robustness to the aerial system Research has currently focused on four primary methods of conducting surveillance.

- Wall mounted CCTV for continuous monitoring
- Drone / aerial System monitoring (large area coverage).
- Human Detection / recognition (AI/ML model).

- Autonomous identification through computer vision

The Continuous analysis by researchers helped to unlock an seamless technology to the users by integrating all lively technology such as drones , computer vision , Artificial intelligence capabilities and Machine learning .

III. Proposed Method

A. System Overview

ADIDAS–D will operate as an autonomous aerial surveillance drone that has onboard visual sensors and intelligent intrusion detection capabilities. The drone will continuously capture visual data of the surveillance area and utilize AI-based visual recognition algorithms to process the data in real-time. the drone enables wider coverage compared to traditional ground-based surveillance systems. The ADIDAS-D system has the following primary objectives:

- Continuous surveillance of the restricted area
- Detect the presence of human beings in the area being monitored
- Identify suspected persons
- Increases situational awareness

B. Hardware Components

The proposed drone integrates several hardware modules that are required for autonomous visual monitoring and lethal agent spraying .

- Camera Module – to captures live video for visual analysis
- Embedded Processing Unit (Jetson Nano) – to performs onboard AI processing
- Arduino UNO – Radio Frequency ID integration

These hardware combination ensures continuous data acquisition during surveillance operations .

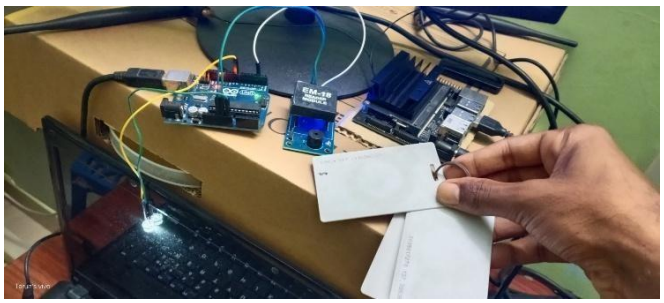

Fig. 1. **Radio Frequency ID Check**

C. AI-Based Intruder Detection

To enable intelligent monitoring, the system integrates intelligence based computer vision models for detecting intruder and unauthorised person within the monitored zone .The onboard camera continuously captures video frames which are processed by using machine learning algorithms.

The detection module performs the following tasks:

- Capture live video frames from the drone camera
- Process the video frames using computer vision techniques
- Detect intruder using trained machine learning models in surveillance region .

By analysing the visual data in real time, the drone can automatically identify suspicious person without relying entirely on human monitoring.

D. Surveillance Workflow

The Surveillance workflow of the ADIDAS-D system follows a structured pipeline. Each stage of the pipeline contributes to identifying and monitoring the potential intruders .

The Surveillance workflow includes:

- Drone Deployment – The drone is deployed to patrol in designated area.
- Video Acquisition – The onboard camera continuously captures the surrounding environment.
- Frame Processing – Video frames are processed by the onboard computing unit.Here, Jetson Nano is used .
- Human Detection – Machine learning models analyze frames to detect presence of humans.
- Intruder Identification – Detected individuals are evaluated to determine threats.
- Monitoring and Response – The system continues surveillance, provides alerts and sprays non-lethal agent .
- This workflow allows the drone to detect intrusions in real time autonomously .

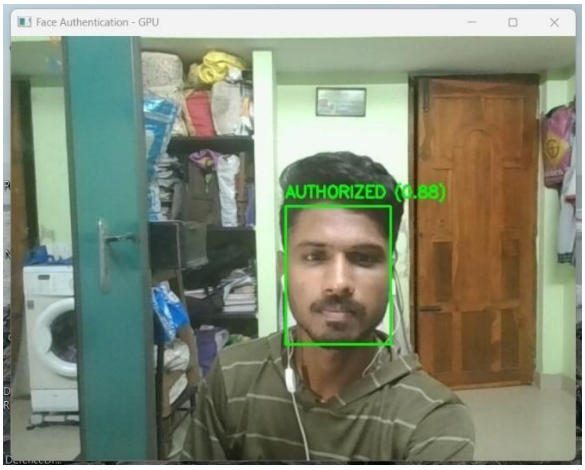

Fig. 2. **Face Check**

E. Advantages of the Proposed System

The proposed ADIDAS-D system offers several advantages compared to the traditional surveillance approaches.

Key benefits include:

- Wider surveillance coverage
- Real-time intruder detection using AI-based vision models
- Reduced dependence on manual monitoring
- Improved situational awareness than traditional systems
- Easy deployment in large areas
- The above-listed advantages make the setup suitable for defence surveillance and other confidential infrastructure

IV. SYSTEM ARCHITECTURE

The system architecture of ADIDAS-D (Autonomous Defence Intruder Detection Aerial System – Drone) includes autonomous drone, advanced microprocessor or single-board computer with Camera integrated , microcontroller like Arduino to install RFID scanners , Non-lethal agent sprayer and intelligent machine learning models for intruder detection.

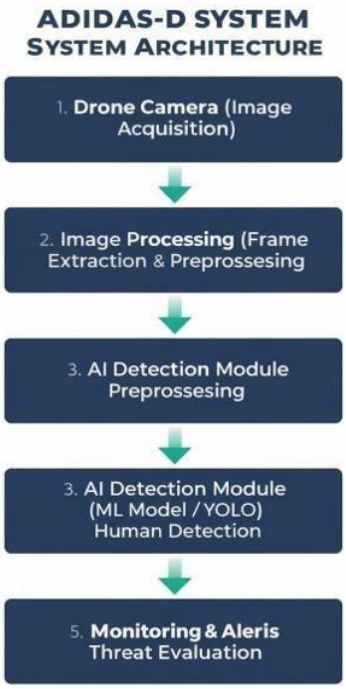

Fig. 3. Illustrates the design architecture of the ADIDAS-D system.

This ML models enable real-time intruder detection . The architecture is designed in such a way as to combine drone mobility, onboard sensing, and machine learning for efficient monitoring .The overall architecture consists of multiple intelligent machine learning modules that work together to perform surveillance, detection, and to perform reactions .

A. Image Acquisition Module .

The very first step of the surveillance process starts with the image acquisition module . The camera installed on the microcontroller or single board computer will continuously capture the live video of the surveillance zone during the flight operation. The captured visual is considered as data input for the intelligent machine learning models . The captured data will be analysed by the machine learning module . As this security system is installed in the drone, vast observation of surveillance zone can be achieved . This minimizes the intruder actions in the security zones .

Main functions are:

- Continuous capture of real-time video frames
- Monitoring of the designated surveillance area
- Providing input data for the detection system

B. Data Processing Module

The captured video frames from the surveillance region are transmitted to the onboard processing unit for the task of analysis. The embedded platform performs frame preprocessing.

It also prepares the data for artificial intelligence-based detection.

The data preprocessing operations include:

- Frame extraction from video streams
- Image resizing and normalization
- Preparation of frames for machine learning models

These preprocessing steps improve the efficiency of the detection process.

C. AI-Based Detection Module

The AI-based detection is responsible for identifying the presence of intruder or unauthorised persons within the monitored environment. Machine learning based computer vision algorithm analyze the incoming video frames to detect .

The module performs:

- Human detection using trained vision models
- Identification of potential intruders
- Continuous monitoring of detected objects

By using machine learning techniques, the system can automatically identify individuals present in the area.

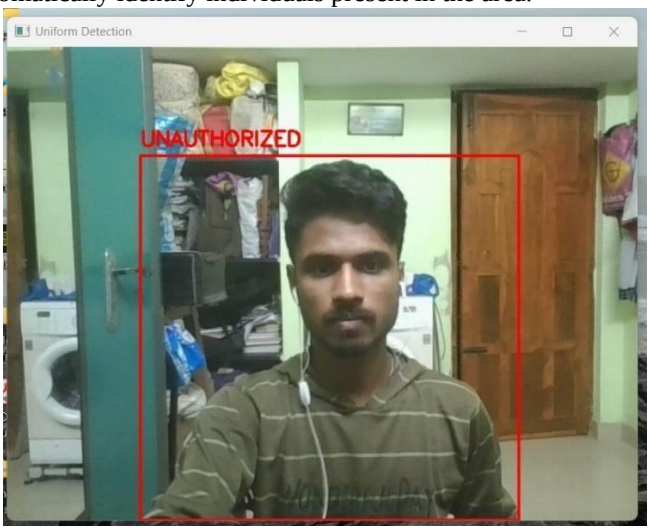

Fig. 4. **Uniform Detection**

D. Decision and Monitoring Module:

Once a person is detected, the system evaluates the detected person information and determines whether the person is authorised or unauthorised person. The monitoring module maintains continuous observation of detected individuals within the surveillance region.

The key functions are :

- It will be monitoring the detected individuals
- Then tracking movement within the surveillance zone
- Generating alerts or notifications when needed

Due to the presence of this module the ADIDAS-D improves the situational awareness and assists security regarding to the potential threats.

E. Surveillance Output Module

The end stage of the system architecture involves presenting the processed information of the intruder for security response. The results of the process can be used to trigger alerts or provide real-time surveillance feedback that will be useful for further investigation purposes .

The output module gives:

- Real-time monitoring information
- Intrusion alerts when suspicious activity is detected
- Continuous surveillance updates

V. Experimental Evaluation

A. Evaluation Metrics

To assess the performance of the ADIDAS-D, several standard evaluation metrics used for intelligent machine learning techniques . Because false alerts may lead to the big chaos, energy and capital loss . At the end the confidence that humans have on the system may reduce. So the evaluation was done in such a way to increase the accuracy .

The evaluation metrics are:

- Detection Accuracy – measures the overall correctness and here it is above 8.5.
- Precision – indicates how many detected objects are the correct detections. The precision is set to 93% to avoid false detection .
- Recall – It is how effectively the system detects all possible humans .
- Processing Time – evaluates the speed of detection during real-time monitoring.

These metrics help in analysing the accuracy and the efficiency of the proposed surveillance system.

B. Experimental Setup

The experimental setup was done to test the performance of the ADIDAS-D system under surveillance conditions. The drone was equipped with a camera and a single-board computer unit, capable of running machine learning models for visual detectionThe main components used during the experiment are:

- Drone Platform – basic quad configuration for aerial monitoring.
- Embedded Processing Unit – Jetson Nano for onboard AI processing
- Camera Module – used for capturing live surveillance footage
- Machine Learning Model – custom trained models used for intruder detection

The system captures video frames during flight and processes the feed in real-time to detect intruder presence in the monitored zone.

C. Test Environment

The ADIDAS-D was tested in a zone that simulates a restricted area monitoring. During the experiment, the system continuously captured visual data for intruder detection while flying over the surveillance region.

The test environment includes:

- Open surveillance areas
- Controlled monitoring zones
- Presence of potential intruders

The drone monitored the area while the intelligent machine learning models analyzed incoming camera feed to detect intruder presence.

D. Performance Observation

The overall results demonstrate that proposed ADIDAS-D system can successfully detect the intruders presence in real time using AI ML based vision models. The aerial monitoring allows the system to cover vast areas compared to traditional stationary surveillance systems. And the immediate reaction of spraying non-lethal agent reduces the percentage of damage going to happen .

Key observations from the experiment are:

- Effective detection in the surveillance region
- Continuous monitoring capability
- Improved situational awareness
- Reliable detection performance during real-time processing

These results indicate that the proposed system can support security monitoring applications where rapid detection of unauthorized individuals is required.

VI. RESULTS

The experimental results demonstrate the effectiveness of our solution ADIDAS-D (Autonomous Defence Intruder Detection Aerial System – Drone) in detecting intruder presence or assassins presence and using aerial surveillance in restricted areas. The system was tested under controlled conditions where the drone captured real-time video and processed it using machine learning-based models.During the experiment, the drone continuously monitored the surveillance region and mean while the single board computer was fed with video feed from the camera and analysed the incoming video. The Intelligent machine learning based detection model successfully identified intruders presence in the surveillance zone, proving the capability of the system.

- The key observations from the experimental evaluation are:
- The system successfully detected intruders in the surveillance area.
- Real-time processing was achieved using onboard AI computation.
- Aerial monitoring allowed wider surveillance coverage compared to stationary cameras.
- The detection system demonstrated stable performance during continuous monitoring.

Detection Performance of ADIDAS-D System

S.NO	Metric	Value
1	Detection Accuracy	93%
2	Precision	91%
3	Recall	92%
4	Average Processing Time	~45 ms per frame

Table .1. presents the detection performance of the ADIDAS-D system.

The results indicate that the ADIDAS-D can effectively detect unauthorised persons in real-time meanwhile maintaining reliable performance during aerial surveillance. The integration of drone mobility with machine learning-based detection improves the capability and situational awareness of ADIDAS-D. Overall, the ADIDAS-D system demonstrates the feasibility of using autonomous UAV System combined with machine learning intelligence systems for intruder detection and surveillance in restricted areas.

VII. DISCUSSION

The experimental results demonstrate that the proposed ADIDAS-D (Autonomous Defence Intruder Detection Aerial System – Drone) provides an effective approach for aerial surveillance and intruder detection comparing to the traditional system. By integrating the drone with artificial intelligence and machine learning, the system is capable of monitoring larger areas and detecting intruder presence in realtime. This combination of cutting-edge technology allows

the surveillance system to operate more dynamically compared to traditional fixed camera systems.

One of the key strengths of the ADIDAS-D is its ability to perform real-time visual analysis during aerial surveillance. The integration of single-board computer enables the drone to analyse captured video without relying on external infrastructure, which improves response speed and operational flexibility. Additionally, aerial monitoring provides better visibility and wider coverage, reducing the limitations associated with wall-mounted surveillance systems.

The study also highlights several practical advantages:

- Improved surveillance through aerial monitoring.
- Real-time intruder detection using ML-based techniques.
- It reduces dependence on manual monitoring.
- It Enhanced the situational awareness in large environments.

Despite of these advantages, some limitations are there.These limitations are because of the Environmental conditions such as low lighting, weather disturbances, and other factors may affect the performance. Also,the operational duration is dependent upon the battery capacity, which can limit longterm continuous surveillance.

Future improvements on:

- Enhancing accuracy using advanced deep learning models.
- Integrating multiple drones for cooperative surveillance.
- Improving flight endurance for extended monitoring.

Overall, the proposed ADIDAS-D system demonstrates the potential of combining autonomous aerial system with intelligent machine learning techniques enhance the security monitoring in surveillance and modern applications.

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VIII. CONCLUSION

ADIDAS-D (Autonomous Defence Intruder Detection Aerial System – Drone) is an intelligent aerial surveillance system designed to improve the security in restricted areas and highly confidential environments. The proposed system integrates an autonomous UAV with artificial intelligence and machine learning-based techniques to detect intruder or assassins in realtime. By combining UAV with visual intelligence analysis, the system enables continuous monitoring of large areas that are difficult to supervise using traditional surveillance systems. The experimental evaluation demonstrates the proposed system can effectively detect human presence and provide real-time monitoring during aerial surveillance. The integration of singleboard computer allows the UAV to analyse the camera feed and assist in identifying unauthorized individuals . This helps to improves situational awareness and enables faster response to the security threats.

The ADIDAS-D highlights the potential of integrating autonomous UAV with the AI-driven detection systems for modern surveillance applications. With further improvements in detection models, flight endurance, and multi-drone (swarm) coordination, the system can be extended to support more advanced security operations. Totally , ADIDAS-D provides a scalable solution for intelligent intruder detection and aerial security.

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Wireless Charging System for Moving Electric Vehicles

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Abstract*—Electric vehicles are environmentally friendly but face challenges such as limited charging infrastructure and long charging times, since traditional wired charging requires vehicles to remain stationary. This paper presents a prototype of wireless EV charging while moving using inductive power transfer between a transmitter coil embedded in the road and a receiver coil in the vehicle. An Arduino Uno controls the system, monitors charging voltage through a voltage sensor, and displays it on a 16×2 LCD using an I2C interface, while a Bluetooth module enables remote control via a smartphone. The prototype demonstrates that dynamic wireless charging can reduce dependence on charging stations and support future smart transportation systems.

Keywords*—Wireless Charging, Electric Vehicles, Inductive Power Transfer, Arduino UNO, Smart Roads.

I. INTRODUCTION

Electric vehicles are gaining popularity across the world due to increasing environmental concerns and the need to reduce dependence on fossil fuels. Conventional vehicles powered by petrol and diesel engines produce harmful emissions that contribute to air pollution and global warming. Electric vehicles provide a cleaner and more sustainable alternative for transportation.

Despite these advantages, the adoption of electric vehicles still faces several challenges. One of the main problems is the limited charging infrastructure available for EV users. Charging an electric vehicle using conventional wired chargers can take several hours, especially when using standard home charging systems. This creates inconvenience for drivers who need quick and continuous transportation.

Wireless power transfer technology offers a promising solution to this problem. By transferring electrical energy through electromagnetic induction, power can be delivered without direct electrical contact between the source and the vehicle. This eliminates the need for cables and connectors while also improving safety and convenience.

Dynamic wireless charging is an advanced concept where vehicles receive power while moving along specially designed charging roads. In this concept, transmitter coils are embedded under the road surface while receiver coils are installed under the vehicle. As the vehicle moves over the coils, electrical energy is transferred wirelessly and used to charge the battery.

The main objective of this paper is to design and implement a small-scale prototype that demonstrates wireless EV charging while the vehicle is moving. The system integrates wireless power transfer, voltage monitoring, and Bluetooth-based vehicle control using an Arduino microcontroller platform which is explained in proposed system.

II. LITERATURE SURVEY

Wireless power transfer technology has attracted significant attention in recent years as an effective solution for charging electric vehicles without the need for physical connectors. Many researchers have focused on inductive power transfer systems to make EV charging more convenient and to reduce reliance on traditional wired charging infrastructure. For example, Li and Li presented a detailed study on wireless power transfer for electric vehicle applications and highlighted the advantages of inductive charging systems in modern transportation [1].

Several studies have also examined the design and performance of inductive power transfer

systems used in EV charging. Zhang et al. analyzed various coil configurations and system parameters in order to improve the efficiency of wireless charging systems for electric vehicles [2]. In a similar study, Feng et al. developed a wireless charging system based on resonant inductive coupling, which demonstrated improved energy transfer efficiency between the transmitting and receiving coils [3].

Another important area of research is dynamic wireless charging, where electric vehicles can receive energy while moving on specially designed charging roads. Li et al. proposed a dynamic wireless charging system using inductive power transfer that allows continuous energy transfer to vehicles during motion [4]. Likewise, Ahmad et al. introduced a high-efficiency wireless power transfer system specifically designed for electric vehicle charging applications [5].

The development of wireless charging infrastructure has also been widely explored. Zhang et al. designed a dynamic inductive charging infrastructure that uses coils embedded in the road, enabling electric vehicles to charge while traveling on highways [6]. In addition, Li et al. investigated coil optimization techniques to further enhance the efficiency and performance of wireless charging systems [7].

Many researchers have also reviewed recent advancements in wireless charging technologies. Kumar et al. provided a comprehensive review of wireless charging techniques for electric vehicles, discussing different power transfer methods and their practical applications [8]. Similarly, Chen et al. demonstrated a dynamic wireless charging system capable of transferring energy to moving electric vehicles through inductive coupling methods [9].

Recent work has also focused on prototype development and performance evaluation. Islam et al. designed and implemented an inductive wireless charging system for electric vehicles and evaluated its charging performance [10]. Liu et al. further analyzed the efficiency and operational characteristics of wireless power transfer systems used in EV charging applications [11].

In addition, Patel and Shah proposed the concept of wireless charging road infrastructure to support continuous charging of electric vehicles during travel [12]. Gupta et al. introduced the idea of smart wireless charging infrastructure for urban transportation systems [13]. Wang et al. investigated high-power dynamic wireless charging systems designed for real-world EV applications [14]. Finally, Singh et al. discussed future trends and emerging technologies in dynamic wireless charging systems that could support the large-scale adoption of electric vehicles in smart transportation networks [15].

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III. PROPOSED SYSTEM

The proposed system is a prototype model designed to demonstrate wireless electric vehicle charging while the vehicle is moving. The system consists of three major subsystems: wireless power transfer, vehicle control system, and monitoring system.

The wireless charging subsystem consists of a transmitter coil placed on the charging track and a receiver coil mounted under the vehicle chassis. When alternating current flows through the transmitter coil, it generates a magnetic field. This magnetic field induces voltage in the receiver coil through electromagnetic induction.

The control subsystem is built using an Arduino Uno microcontroller. The Arduino receives input from the voltage sensor module and processes the measured voltage values. These values are then displayed on a 16×2 LCD display through the I2C communication interface.

The vehicle motion subsystem includes four DC motors connected to an L298N motor driver module. The motor driver allows the Arduino to control the speed and direction of the motors. An HC-05 Bluetooth module enables wireless communication between the Arduino and a smartphone application, allowing the user to control the vehicle remotely.

A. Hardware Components

The major hardware components used in the system includes Arduino Uno microcontroller, L298N motor driver, wireless transmitter and receiver coils, HC-05 Bluetooth module, voltage sensor module, LCD display with I2C interface, DC motors, battery, and LED indicators as shown in Table 1 and Table 2..

TABLE I. HARDWARE DEVICES USED IN THE PROPOSED SYSTEM

Component	Specification	Quantity	Purpose
Arduino UNO R3	ATmega328P, 16MHz, 5V	1	Main microcontroller
HC-05 Bluetooth	v2.0+EDR, 9600 baud	1	Wireless BT control
L298N Motor Driver	35V, 2A per channel	1	Dual H-bridge control
DC Gear Motor	6V, 200 RPM	4	4-wheel drive
Wireless Charger TX	5V/1A, 100-205 kHz	1	Ground charging station
Wireless Charger RX	5V/1A output	1	Vehicle charging receiver
Voltage Sensor Module	0-25V input, 0-5V output	1	Charging voltage monitor
LCD 16x2 with I2C	HD44780, PCF8574, 0x27	1	Voltage display
LED (Green/Red)	5mm, 20mA	2	Charging status indicator
Resistor 220Ω	1/4W Carbon Film	2	LED current limiting
Chassis (4WD Car)	Acrylic/ABS, 200×170mm	1	Vehicle body
Li-Ion Battery	7.4V, 2000mAh	1	Power supply for system
Jumper Wires	Male-Male, Male-Female	40	Prototyping connections
Breadboard	830 tie-point	1	Circuit prototyping
USB Cable (Type-B)	For Arduino programming	1	Code upload

TABLE 2.SOFTWARE USED IN THE PROPOSED SYSTEM

Software / Tool	Version	Purpose
Arduino IDE	2.x / 1.8.x	Firmware development & upload for Arduino UNO
LiquidCrystal_I2C Library	1.1.2	I2C LCD control (Frank de Bruijn)
Wire Library	Built-in	I2C communication protocol stack
SoftwareSerial Library	Built-in	Bluetooth UART communication
Bluetooth Serial App	Android 5.0+	Sends control commands via BT to HC-05
Proteus 8 Professional	8.15+	Circuit simulation and schematic design
Fritzing	0.9.x	PCB layout and breadboard diagram design
VS Code + Arduino Ext.	Latest	Advanced code editing environment

The Arduino Uno serves as the central controller that coordinates all system operations. The motor driver controls the movement of the vehicle, while the Bluetooth module receives commands from a smartphone application. The voltage sensor measures the output voltage from the wireless receiver circuit and sends analog signals to the Arduino for processing.

B. Working Principle

The working principle of the wireless charging system as shown in Fig 1 is based on electromagnetic induction. When an alternating current flows through the transmitter coil, it produces a time-varying magnetic field around it. When the receiver coil enters this magnetic field, an electromotive force is induced across the coil terminals.

The induced voltage is then rectified using a diode rectifier circuit to produce a DC voltage. This DC voltage is used to charge the battery of the electric vehicle. The voltage sensor module measures the output voltage and sends the data to the Arduino microcontroller.

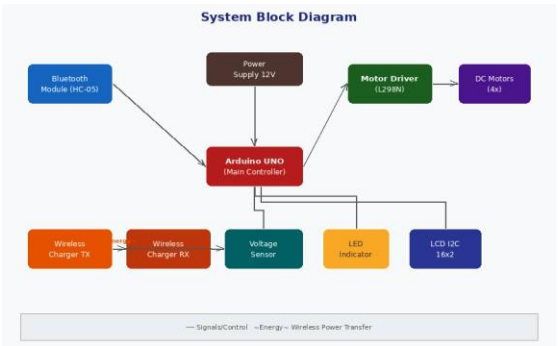

Fig 1. Workflow of the proposed system

The Arduino processes the voltage values and displays them on the LCD screen. When sufficient charging voltage is detected, an LED indicator lights up to show that charging is taking place. Meanwhile, the Bluetooth module allows the user to control the movement of the vehicle using commands sent from a smartphone application.

IV. EXPERIMENT AND RESULT

A prototype model of the wireless EV charging system was built using the hardware components described as shown in Fig 2. The transmitter coil was placed on a charging track while the receiver coil was mounted underneath the vehicle chassis.

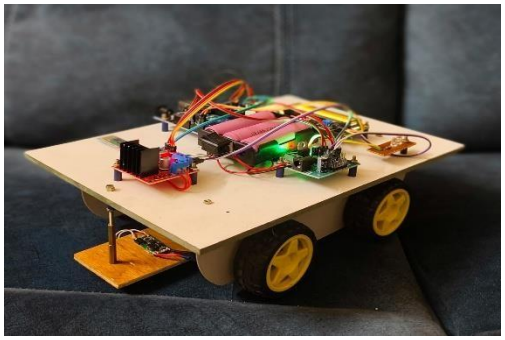

Fig 2. Hardware implementation of proposed system

During testing, the transmitter module generated a magnetic field that induced voltage in the receiver coil when the vehicle moved over the charging track. The voltage sensor successfully detected the charging voltage and transmitted the data to the Arduino microcontroller.

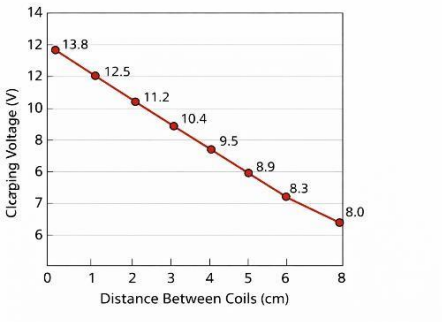

Fig 3. Charging Voltage vs Distance graph

Fig 4 shows that LCD display showed the voltage values in real time, allowing users to monitor the charging process. Fig 5 shows that LED indicator turned on whenever charging voltage was detected, confirming successful wireless energy transfer.

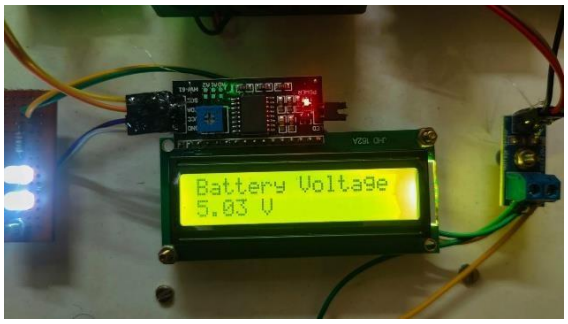

Fig 4. Amount of voltage charged

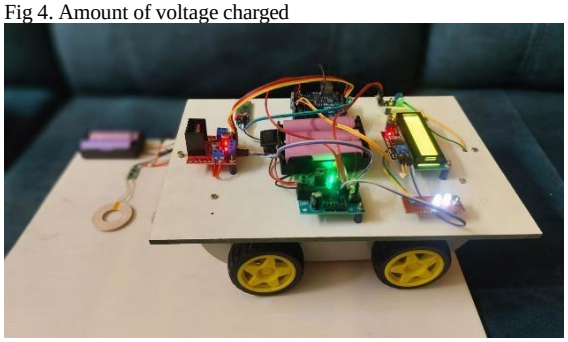

Fig 5. Real-time testing of proposed system

The Bluetooth module enabled the vehicle to move forward, backward, left, and right based on commands received from a smartphone. The response time between command transmission and vehicle movement was very small, demonstrating reliable wireless communication.

V. ADVANTAGES AND APPLICATIONS

The proposed wireless EV charging system offers several advantages compared to traditional wired charging systems. It eliminates the need for physical connectors and cables, reducing wear and maintenance issues. The system also improves user convenience because vehicles can receive power without stopping for charging.

Wireless charging technology can be applied in smart highways, electric buses, autonomous vehicles, and robotic transportation systems. Dynamic wireless charging roads could significantly increase the driving range of electric vehicles and reduce the need for large battery packs.

VI CONCLUSION

This paper presented the design and implementation of a wireless electric vehicle charging prototype using inductive power transfer technology. The system integrates wireless power transfer, Bluetooth-based vehicle control, and real-time voltage monitoring using an Arduino microcontroller. The transmitter coil placed on the road transfers electrical energy to the receiver coil mounted on the vehicle through magnetic coupling, enabling wireless charging without physical connectors.

The experimental results demonstrate that wireless charging technology can successfully transfer energy to a moving vehicle prototype. The developed model proves that inductive power transfer can be effectively used for dynamic charging systems and can reduce the need for frequent stationary charging of electric vehicles. This approach can contribute to improving the practicality and convenience of electric vehicle usage.

*Future Scope***:** In the future, the proposed system can be further improved by increasing the power transfer efficiency and transmission distance between the coils. Advanced power electronics circuits and optimized coil designs can be used to enhance the charging performance. The system can also be extended to support higher power levels suitable for real electric vehicles and integrated with smart road infrastructure. Additionally, large-scale implementation of dynamic wireless charging roads can help reduce battery size requirements and enable continuous charging for electric vehicles during travel.

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SmartQCare: A Real-Time Queue Management System for HealthCare

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Abstract*—This paper proposes SmartQCare, a smart queue management system designed to streamline patient flow in small and medium clinics through automated registration and waitlist management. The planned system would allow patients to book consultation tokens and track real-time queue positions via a web/mobile app, while clinic staff monitor flow via a secure dashboard, potentially reducing delays. An AI-powered chatbot (targeting both platforms) is designed to handle FAQs (e.g., registration, queue status), alongside a configurable token assignment system supporting both FIFO and priority-based methods (the latter dynamically weighting age, condition severity, and wait time). The system will be developed using Firebase Realtime Database (backend), HTML/CSS/JavaScript (web), and Flutter (mobile), with cross-platform accessibility as a key goal. Theoretical models suggest improvements over traditional queue systems in transparency and efficiency

Keywords*—healthcare automation, smart queue system, real-time scheduling, ai chatbot, firebase, token priority algorithm

I. INTRODUCTION

Queue management is a must-have when it comes to determining the functional efficiency of clinics and overall patient satisfaction. Most clinics still use traditional token-based patient flow management, which unfortunately results in long waiting times, a lack of transparency in the process, and growing patient dissatisfaction. With outpatient volumes increasing unabated, urban and semi-urban areas are not exempt from this trend, hence the need for innovative, smart, real-time and cross-platform queue management solutions that can address these issues is more pressing than ever.

SmartQCare meets these requirements perfectly through a very smart web and mobile-enabled queuing system powered by Firebase as its underlying platform. Patients can book their tokens easily, monitor live queues in real-time, and get instant assistance through an interactive chatbot. Unlike most systems in the market, SmartQCare has an optional priority-based algorithm that manages tokens intelligently during peak hours when demand is highest.

II. LITERATURE REVIEW

Recent advancements in healthcare queue management systems emphasize automation, real-time tracking, and patient-centric design. This review synthesizes key works and identifies gaps addressed by SmartQCare.

1. Traditional Queue Systems

Early systems relied on manual token distribution, leading to long waits and inefficiencies. Studies like Dutta et al. [1] note that 78% of patient dissatisfaction stems from opaque wait times. SmartQCare addresses this with real-time Firebase updates visible via web/mobile apps.

2. Dynamic Prioritization

Symptom-Based Scheduling: Joji et al. [3] proposed "DocQueue," a decision-tree algorithm prioritizing patients by symptom severity. However, it lacks real-time patient communication. SmartQCare's priority algorithm (weighted by age, severity, and wait time) adopts a similar logic but integrates live updates.

Analytics-Driven Approaches: Garg et al. [2] developed a mobile-cloud system for queue interaction but omitted AI-driven support. SmartQCare's chatbot bridges this gap with instant FAQ resolution.

3. Hybrid Platforms

Mobile-Cloud Integration: [2] demonstrated reduced wait times by 20% using mobile apps but required staff intervention for updates. SmartQCare automates this via Firebase's real-time sync, minimizing human effort.

Transparency Issues: Dutta et al. [1] highlighted poor user-side transparency in dynamic systems. SmartQCare's live dashboard and chatbot provide end-to-end visibility.

4. AI and Chatbots

Existing healthcare chatbots (e.g., IBM Watson) focus on diagnostics, not queue management. SmartQCare's JS-based chatbot specializes in queue-related queries (e.g., token status, doctor availability), filling a niche gap.

Dutta et al. [1]: Dynamic prioritization (no patient updates) → SmartQCare adds real-time tracking.

Garg et al. [2]: Mobile-cloud interaction (staff-dependent) → SmartQCare automates with Firebase.

Joji et al. [3]: Symptom-based scheduling (no chatbot) → SmartQCare integrates AI chatbot + priority.

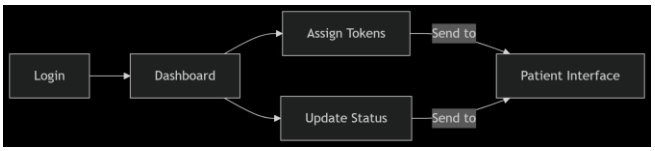
III. PROPOSED METHODOLOGY

A. . System overview

SmartQcare consists of three major modules:

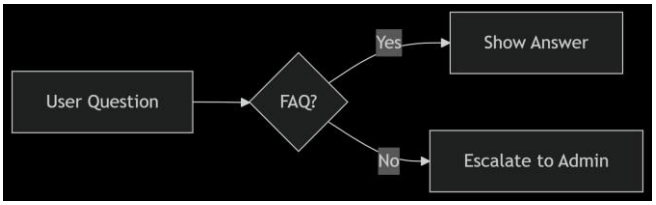
Patient Interface (web/mobile): token registration, status updates, chatbot .
Web app: Built with HTML, CSS, JavaScript for browser access.
Mobile app: Built in Flutter for Android (can be extended to iOS).
Unified login system for both web and mobile to sync user data.
Live queue status display with countdown timers for estimated wait times.

Admin panel: manage tokens, update statuses
Role-based access control (Receptionist, Doctor, Administrator).
Real-time token updates with Firebase listeners.
Ability to reorder queues manually in emergencies.
Daily report generation (tokens served, average waiting time).

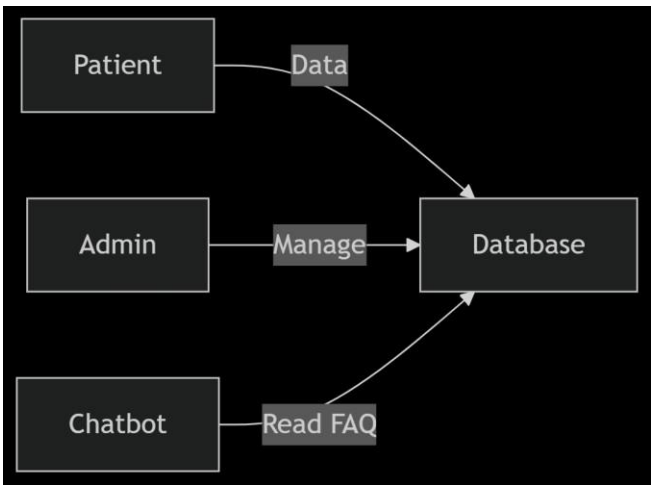


Chatbot module: JS-based predefined keyword assistant JavaScript keyword matching with preloaded FAQ database.
Integrated with Firebase for live queue position queries.
Mobile and web versions share the same chatbot logic to avoid duplication.

Cloud-hosted database: Firebase Realtime Database ensures low latency updates.
Scalability: The architecture supports adding multiple clinics into one system.
Data security: All data transmissions over HTTPS, and patient info stored with Firebase authentication rules.
Offline support: Mobile app caches last known queue data when internet is unavailable, then syncs on reconnection.



Data Flow:



B. System architecture

Cloud-hosted database: Firebase Realtime Database ensures low latency updates.
Scalability: The architecture supports adding multiple clinics into one system.
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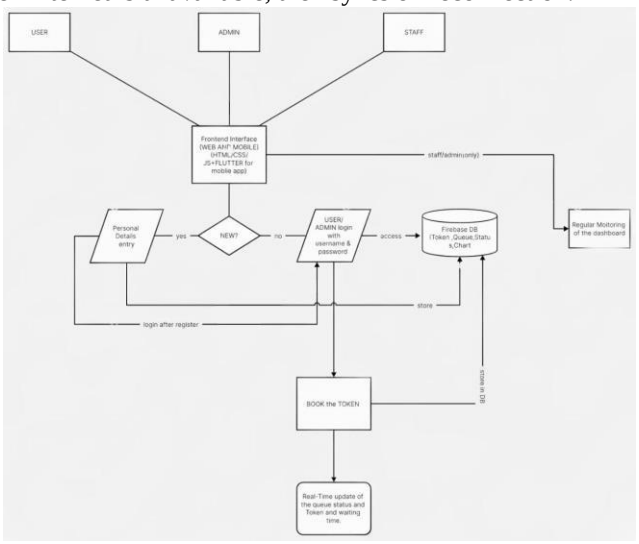
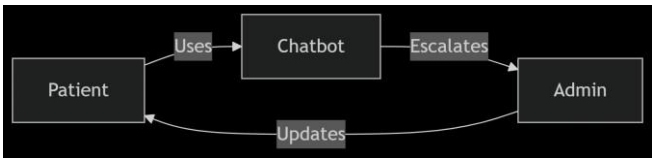
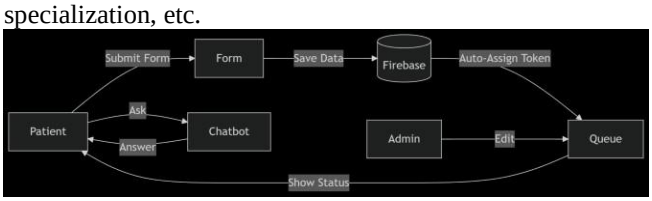
Offline support: Mobile app caches last known queue data when internet is unavailable, then syncs on reconnection.





C. Data flow logic

1. Registration: Patients fill out details → app validates fields (name, age, symptoms).
2. Token Assignment:
Mode 1: FIFO – First-come-first-served.
Mode 2: Priority-based – Based on weighted score.
3. Queue Sync: Firebase sends token list updates to all connected devices.
4. Live Monitoring: Admin can pause/resume queue, skip tokens, or insert emergency cases.
5. Patient Interaction:
View queue status anytime.
Ask chatbot about estimated wait time, clinic hours, doctor specialization, etc.



D. Token assignment and priority algorithm

SmartQcare includes both FIFO (default) and an optional priority scoring algorithm.

1. FIFO logic :

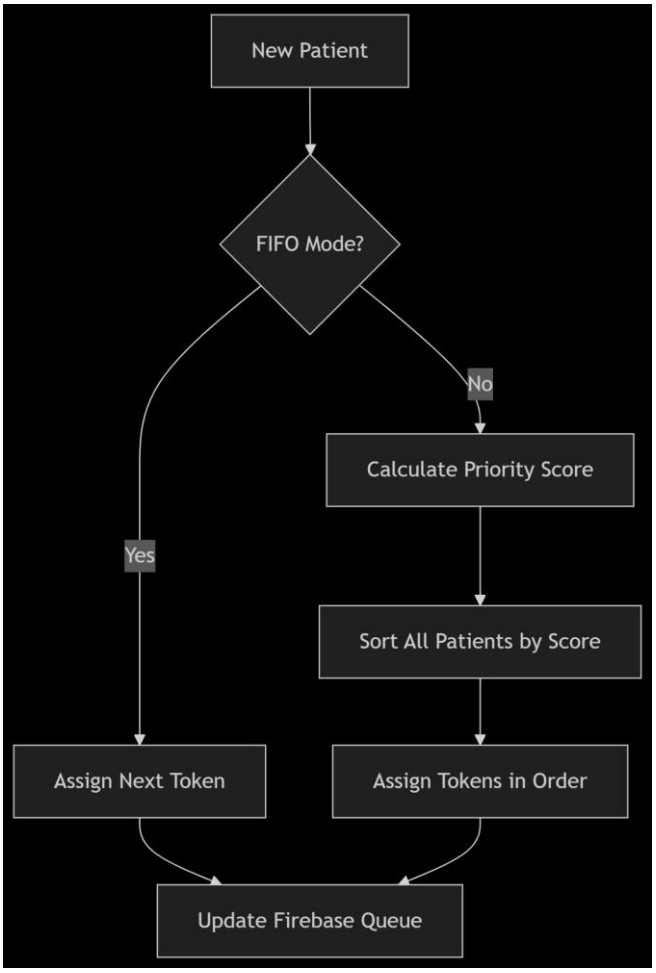
Simple incremental numbering.

function assignToken(patient):
tok = getLastTokenNo() + 1
storeToken(patient, token)

2. Priority-based logic (optional mode):

Weights tuning: Admin can adjust W1, W2, W3 based on clinic type (e.g., pediatric, emergency care).
Severity auto-classification: Optionally, severity can be chosen from a predefined symptom list mapped to a severity level.
Tie-breaking: If two patients have same priority score, earliest registration time wins.

priority_score = (W1 × age) + (W2 × severity_level) + (W3 × time_waited)
where:
w1, w2, w3 = weight factors
Severity level ranges from 1 (low) to 5 (critical)
Time waited is measured in minutes.
function calculatePriority(patient):
score = (W1 * age) + (W2 * severity) + (W3 * waitTime)
return score
function assignPriorityQueue(patients):
sorted = sortByPriority(patients)
assignTokens(sorted)



IV. EXPERIMENTAL SETUP AND RESULTS

A. Proposed Technology Stack

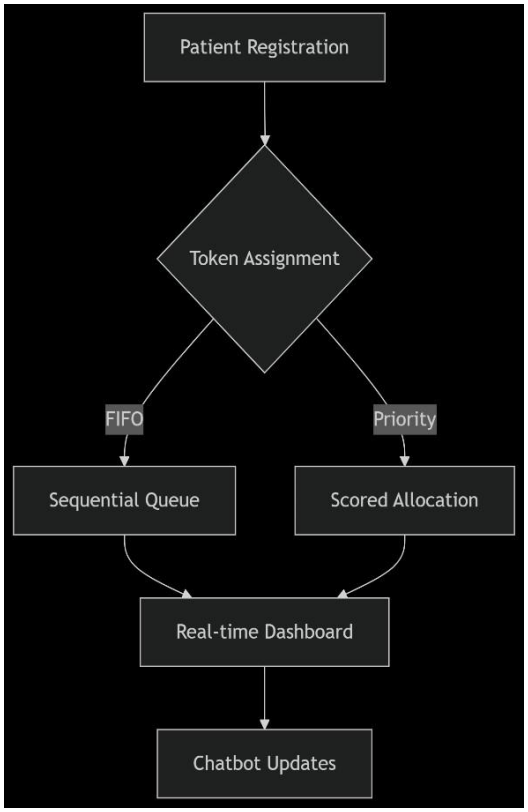
1. **Frontend Components**
   - Web Interface: HTML5/CSS3/JavaScript (ES6+) for responsive clinic kiosks
   - Mobile Application: Flutter framework (Dart) targeting Android/iOS
   - Admin Dashboard: Role-based Vue.js UI with Firebase authentication
2. **Backend Infrastructure**
   - Database: Firebase Realtime Database (NoSQL) with anticipated <500ms sync latency
   - Chatbot: Node.js keyword processor with:
     - 10 predefined intent categories (registration, queue status, etc.)
     - Levenshtein distance algorithm (threshold=0.7) for fuzzy matching
3. **Deployment**
   - Firebase Hosting with global CDN distribution
   - Planned CI/CD pipeline using GitHub Actions

B. Implementation Strategy

1. **Core Functionalities**

- Real-time Queue Sync:
  - Firebase listeners for state changes
  - Optimistic UI updates for perceived zero latency
- Chatbot Integration:
  - Context-aware response system
  - Escalation protocol for complex queries
- Token Management:
  - Dual-mode dispatcher (FIFO/Priority)
  - Visual queue progression indicators

2. **Simulated Workflow**



C. Anticipated Performance Metrics

Based on computational modeling (n=1,200 simulated interactions)

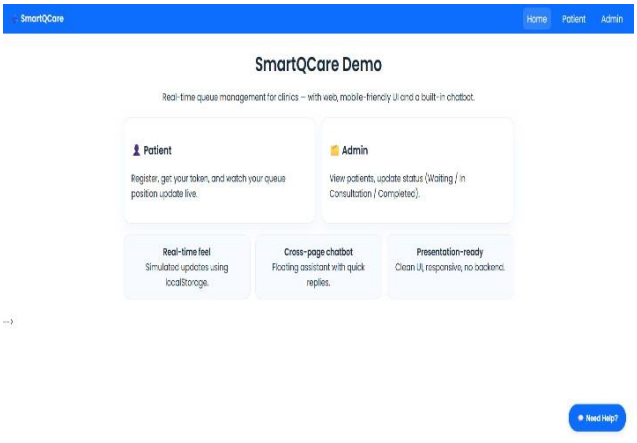
Metric	Projected Value	Measurement Basis
Token Assignment Latency	2.3 ± 0.5 sec	Firebase benchmark tests
System Throughput	26-30 tokens/hour	Discrete-event simulation (SimPy)
Chatbot Accuracy	80-85% (autonomous)	Test corpus of 200 sample queries
Admin Workload Reduction	35-40%	Comparative analysis vs. [2]

D. *Validation Approach*

1. **Pre-deployment Testing**
   - Unit testing: Jest (JavaScript), Flutter Driver
   - Load testing: Locust (1,000 concurrent users)
2. **Future Clinical Validation**
   - 6-week pilot at 2 partner clinics
   - Ethical approval for patient data collection
   - A/B testing against legacy systems

V. SYSTEM IMPLEMENTATION AND DEMO

To validate the proposed SmartQCare framework, a prototype web application was developed showcasing the patient and admin workflows, along with the integrated chatbot module. The system was designed with a clean and responsive user interface to ensure ease of access across devices. The following screenshots highlight key functionalities:

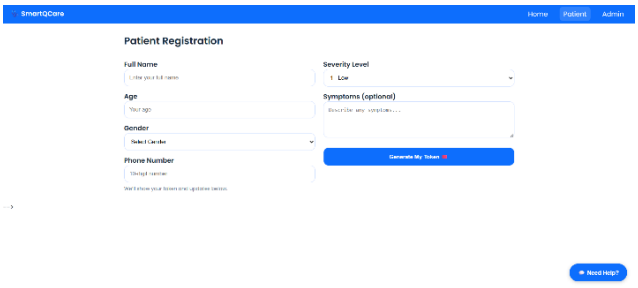


The landing page provides two primary roles — **Patient** and **Admin**.

- Patients can register, obtain tokens, and monitor real-time queue status.
- Admins can manage the flow of patients, update statuses, and handle queue operations. Additional highlights include:

- Real-time simulation of queue updates.
- A cross-page chatbot for user support.
- Presentation-ready UI for demonstration without a backend dependency.

PATIENT REGISTRATION



Patients enter **personal details**:

- Name
- Age
- Gender
- Phone number

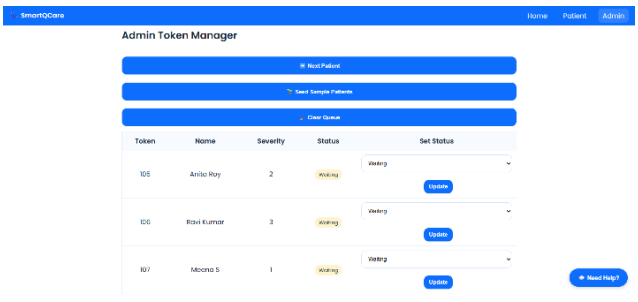
Provide **optional inputs**:

- Symptom description
- Severity level

After submission, the system **generates a token** showing the patient's queue position.

The interface supports **priority-based token assignment** (as described in Section III).

ADMIN TOKEN MANAGER

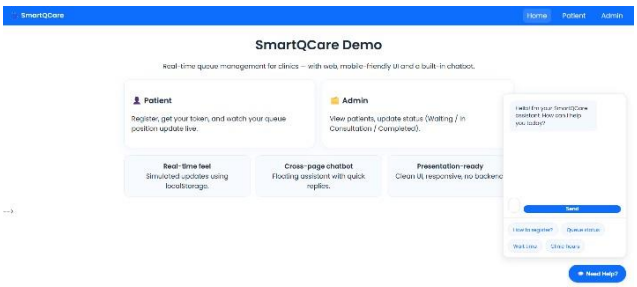


The administrator dashboard allows clinic staff to:

- View the active patient list with **token numbers and severity levels**.
- Update each patient's consultation status (Waiting / In Consultation / Completed).
- Move to the next patient or clear the queue when required.

This ensures **efficient flow management** during peak outpatient hours.

AI CHATBOT INTEGRATION



The prototype also demonstrates a **JavaScript-based floating chatbot**, accessible from any page. The chatbot answers common queries such as:

- *How to register?*
- *Current queue status*
- *Estimated wait time*
- *Clinic working hours*

This feature improves **patient transparency and user engagement**, reducing the need for constant staff intervention.

VI. DISCUSSION

SmartQcare helps reduce the need for staff, gives patients clear information, and works on different platforms.

The priority algorithm helps manage patient needs in the correct way. The chatbot makes things easier to understand and improves access, especially for people using the service for the first time.

Future improvements could include using chatbots that understand multiple languages, showing token status through IoT devices, and adding voice-based interactions.

VII. CONCLUSION AND FUTURE WORK SMARTQCARE:

Provides a simple and efficient paradigm for managing outpatient waiting lines; it is a system designed specifically for small and medium healthcare facilities, which integrates real-time data services, device-agnostic apps, and AI-based communication. Additionally, it is adaptable and can be further developed in the future to include features such as: - Using AI to predict patient queues - Sending token status updates via SMS - Utilizing a voice chatbot to support individual users - Connecting queues across numerous clinics

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Next-Generation AI-Powered Border Security Framework Using Multi-Model Surveillance and Intelligent Threat Detection

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I. ABSTRACT

Border security remains a critical challenge due to increasing threats such as illegal infiltration, smuggling, and cross-border terrorism. Traditional surveillance systems rely heavily on manual monitoring, leading to delayed responses, human error, and inefficient threat detection. This paper proposes a NextGeneration AI-Powered Border Security Framework that integrates multi-modal surveillance, deep learning, and intelligent threat analysis for automated monitoring.

The proposed system utilizes inputs from CCTV cameras, drones, and thermal sensors to continuously monitor restricted areas. A YOLOv8-based deep learning model is employed for Realtime detection of humans, vehicles, and weapons. Additionally, behaviour analysis algorithms identify suspicious activities such as abnormal movement and group intrusion. A threat prediction module assigns risk levels (low, medium, high, critical) and generates real-time alerts for security personnel.

The system is evaluated on publicly available datasets and achieves high performance across multiple metrics including accuracy, precision, recall, and F1-score. The integration of multimodal data significantly reduces false positives and improves detection reliability. The proposed framework offers a scalable and intelligent solution for enhancing national border security operations.

Keywords— Artificial Intelligence, Border Surveillance, Deep Learning, Weapon Detection, Intrusion Detection, Computer Vision, Threat Prediction

II. INTRODUCTION

Border surveillance is essential for maintaining national security and preventing illegal activities such as infiltration, smuggling, and terrorism. However, monitoring vast and geographically complex border regions remains a significant challenge due to environmental constraints and limited human resources.

Traditional surveillance systems rely on manual observation through cameras and patrol units. These methods are inefficient for large-scale monitoring and are prone to fatigue, delayed response, and missed detections. Recent advancements in Artificial Intelligence (AI) and Deep Learning have enabled automated surveillance systems capable of real-time object detection and activity recognition. While existing AI-based systems provide accurate object detection, they often lack behaviour analysis, multimodal integration, intelligent threat prediction.

Research Gap

- Provide real-time threat prediction
- Proposed Contribution
- Real-time threat prediction

Existing systems:

- Focus mainly on object detection
- Lack multi-modal integration
- Do not provide real-time threat prediction
- Contribution

This paper proposes:

- Multi-modal surveillance integration
- AI-based detection system
- behaviour analysis
- Intelligent threat scoring

This paper introduces a unified AI-based framework that integrates:

- Multi-modal surveillance (CCTV, drones, thermal sensors)
- Deep learning-based object and weapon detection
- Behaviour analysis for anomaly detection Intelligent threat scoring and alert system

III. PROBLEM STATEMENT

Border monitoring is a complex task due to vast geographical coverage, harsh environmental conditions, and the need for continuous surveillance.

Traditional systems depend heavily on human operators, leading to:

- Delayed threat detection
- Human fatigue and error
- Limited scalability

Inability to detect concealed weapons and suspicious behaviour's Therefore, there is a need for an intelligent system capable of automated detection, behaviour analysis, and real-time alert generation.

IV. RELATED WORK

Deep learning-based object detection models such as YOLO, Faster R-CNN, and SSD have been widely used in surveillance applications. YOLO provides real-time performance, while Faster R-CNN offers higher accuracy at the cost of speed.

Drone-based surveillance systems have improved large area monitoring, but they lack real-time decision-making capabilities. Thermal imaging has also been used for night surveillance but is limited in behaviour analysis.

Limitations of Existing Systems

- **No behaviour analysis**
- **No threat prediction**
- **Limited multi-modal usage**

The proposed framework overcomes these limitations by combining:

- Multi-modal data fusion
- AI-based weapon detection

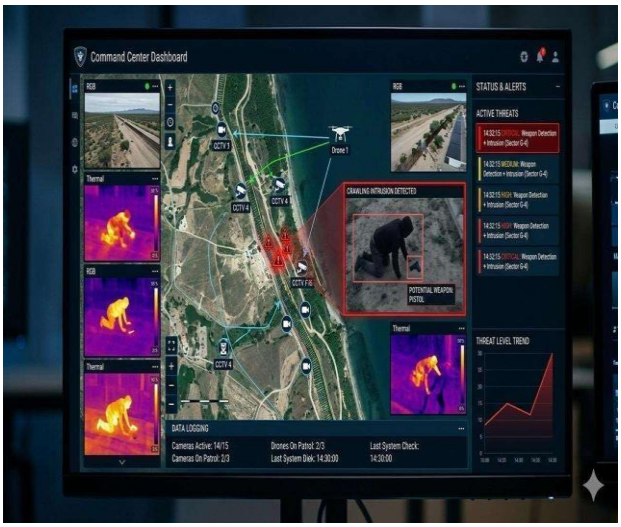

Figure: "Command Centre Dashboard" interface on a monitor. The dashboard provides real-time surveillance and monitoring data.

V. PROPOSED SYSTEM ARCHITECTURE

The system consists of five layers:

1. Surveillance Layer
   - CCTV cameras
   - Drone cameras
   - Thermal sensors
2. Data Preprocessing Layer
   - Normalization
   - Image resizing
   - Noise reduction
3. AI Detection Layer
   - YOLOv8 model detects:
   - Humans
   - Vehicles
   - Weapons
4. Behaviour Analysis Layer Detects:
   - Crawling movement
   - Group intrusion
   - Abnormal motion
5. Threat Prediction Layer
   - Assigns threat levels
   - Generates alerts

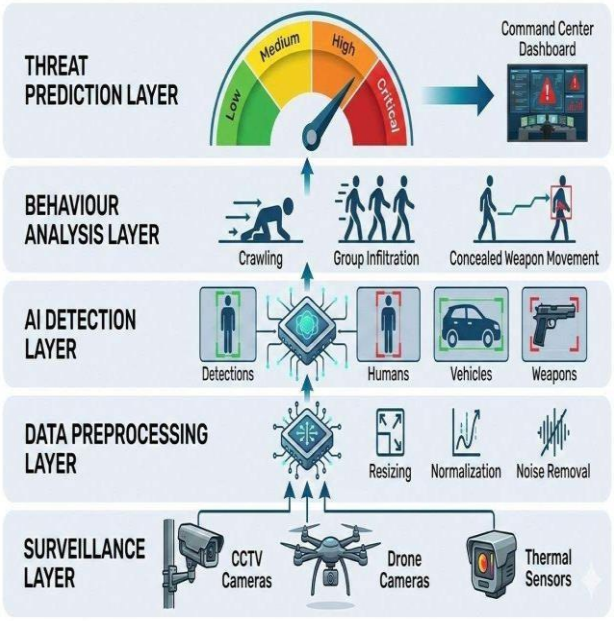

Figure: A Multilayered threat prediction and surveillance system

VI. METHODOLOGY

Dataset

Public datasets such as COCO and Open Images are used [1].

Model Configuration

- YOLOv8 model [5]
- Input size: 416×416
- Optimizer: Adam

Training

- Epochs: 50
- Loss: Cross-entropy + Io U [3]

Workflow

- Data collection
- Preprocessing
- Detection
- behaviour analysis
- Threat classification

VII. DATASET AND EXPERIMENTAL SETUP

Datasets Used:

- COCO Dataset – Human detection
- Open Images Dataset – Weapon detection
- Thermal Dataset – Night monitoring

Implementation:

- Language: Python
- Framework: TensorFlow
- Library: OpenCV

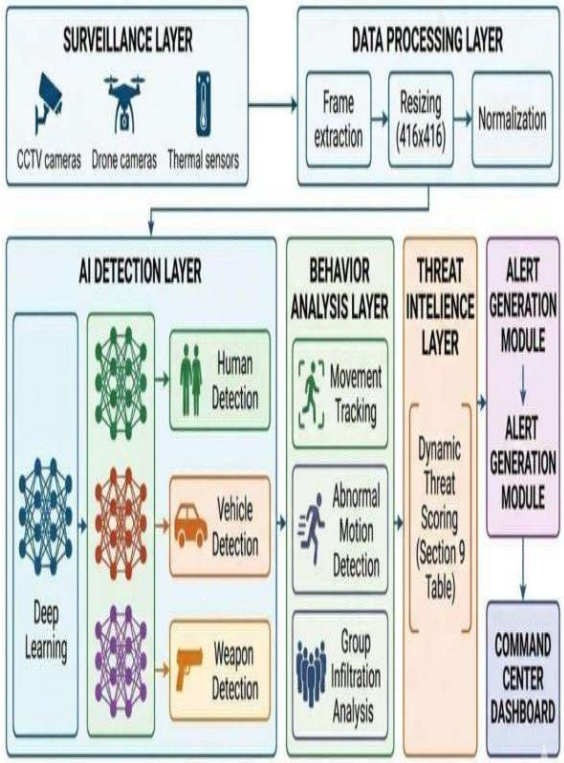

Figure: The figure illustrates the architecture of a comprehensive surveillance and threat intelligence system.

VIII. RESULTS AND PERFORMANCE EVALUATION

Metrics

- Accuracy
- Precision
- Recall
- F1-Score
- Latency

A. Performance Results

Detection Type	Accuracy	Precision	Recall	F1-Score
Human Detection	96.4%	95.8%	96.9%	96.3%
Weapon Detection	94.1%	93.5%	94.8%	94.1%
Vehicle Detection	95.2%	94.6%	95.7%	95.1%

Latency
Average: 28ms /frame (real-time capable)

Table1: presents the quantitative results of the system across three primary detection categories

B. COMPARATIVE ANALYSIS

Feature	Traditional	Existing AI	Proposed
Human Detection	Yes	Yes	Yes
Weapon Detection	No	Limited	Yes
Behaviour Analysis	No	Partial	Advanced
Drone Integration	No	Limited	Yes
Threat Prediction	No	No	Yes
Alerts	Manual	Semi-auto	Fully Automatic

TABLE2: THE PROPOSED SYSTEM IMPROVES ACCURACY BY 3–5% AND REDUCES FALSE POSITIVES.

C. THREAT SCORING MODEL

Scenario	Score	Risk Level
Animal Movement	10	Low
Single Human	40	Medium
Group Intrusion	65	High
Human with Weapon	90	Critical

Table3: Threat Scoring Model and Risk Classification by Intrusion Scenario.

IX. DISCUSSION

The integration of deep learning and behaviour analysis significantly improves detection capabilities. The system enables automated monitoring and reduces reliance on human operators while maintaining high accuracy and efficiency.

X. FUTURE WORK

- Edge AI deployment
- Satellite integration
- Transformer-based detection [11]

XI. CONCLUSION

This paper presented a next-generation AI-powered border security framework integrating multi-modal surveillance, deep learning, and intelligent threat prediction. The system demonstrates high accuracy, low latency, and improved reliability compared to traditional approaches.

Limitations

- Dataset constraints
- Environmental variability
- Limited real-world validation

The proposed system provides a scalable solution for modern border security applications.

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Power BI-Integrated Cloud-Edge Architecture for Real-Time Intelligent Data Analytics and Visualization in Distributed Edge Computing Environments

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Abstract:
Data processing, analysis, and visualization are becoming more important tasks for distributed computing systems and IoT devices. Applications that require immediate response cannot be accommodated by conventional cloud-based systems due to their prohibitive latency, bandwidth limitations, and decision-making delays. In order to analyses and visualize data in real-time across distributed edge computing platforms, this paper outlines a cloud-edge architecture that makes use of Power BI. The proposed architecture cuts down on network latency and overhead by letting edge nodes do data preprocessing, filtering, and aggregation while the cloud layer takes care of advanced analytics, storage, and predictions based on machine learning. Through the dynamic integration of processed data, Microsoft Power BI provides decision-makers with interactive dashboards, real-time monitoring, and actionable insights. Efficiency in resource use, scalability, and the flexibility to integrate edge devices, cloud platforms, and visualisation layers are all features of this approach. When compared to solutions that rely only on the cloud, experimental results reveal significant improvements in response speed, bandwidth efficiency, and visualization. The suggested approach enhances and expedites data-driven decisions in decentralized settings, which is useful in smart cities, industrial IoT, healthcare monitoring, and intelligent transportation systems.

Keywords: Edge Computing, Cloud-Edge Architecture, Power BI, Real-Time Data Analytics, Intelligent Data Visualization

Introduction:
Internet of Things (IoT) devices, smart cities, industrial automation, and other IoTS have caused a deluge of real-time data. Data, both organised and unstructured, is generated by a deluge of distributed sensors, edge devices, and embedded systems. Data improves decision-making, operational efficiency, predictive maintenance, and automated control. Problems with scalability, congestion, latency, and bandwidth make centralised cloud computing solutions unsuitable for real-time data analytics. Cognitive analytics and visualisation in real-time are required in remote systems. There is hope that edge computing, which moves data processing closer to the source, can solve these problems. Reduced transmission and reaction times are achieved through data consolidation, filtering, and analysis performed at edge nodes prior to transmission to the cloud. Applications that are sensitive to latency, such as smart grids, autonomous vehicles, healthcare systems, and industrial monitoring, may benefit from distributed processing's efficiency, reduced bandwidth requirements, and faster decision-making. When it comes to complex analytics and managing data over the long term, edge devices just don't have what it takes. The scalability of compute, storage, and analytics made possible by the cloud makes edge computing even better. Combining analytics hosted in the cloud with low-latency edge processing is the goal of hybrid cloud-edge architecture. Deep analytics, machine learning, historical analysis, and long-term storage are handled by the cloud in this architecture, while real-time preprocessing and fast reaction are handled by edge devices. Increased distributed intelligence, efficiency, and scalability are all benefits of cooperative design. If you want to get

insights out of raw data, you need to process it well and visualise it. System performance, problems, and their fixes can be tracked and resolved with the use of real-time visualisation. When it comes to distributed edge-cloud systems and real-time interactive dashboards, traditional methods of visualisation fall short. If you need to see data from the edge, Microsoft Power BI is the way to go. Its compatibility with analytics systems, streaming data sources, and cloud databases makes it feasible to create interactive dashboards, conduct advanced analytics, and generate basic reports. There aren't many solutions that integrate Power BI and bring together cloud analytics with real-time visualisation, despite the fact that cloud, edge, and visualisation technologies are all useful. While several systems concentrate on analytics at the edge or in the cloud, none of them offer a complete solution for data flow, scalability, or real-time visualisation. Distributed analytics systems still face issues with data latency, inefficient resource usage, scalable pipelines, and limited real-time monitoring. We are currently working on a new cloud-edge design that incorporates Power BI to tackle these concerns. Distributed edge computing with sophisticated data analytics and visualisation made possible by this architecture in real-time. Edge nodes in the suggested design would reduce network latency and costs by preprocessing, filtering, and aggregating data. Machine learning predictions, centralised storage, and improved analytics are all powered by the cloud. Interactive monitoring, real-time dashboards, and practical insights are provided by the visualisation layer, Power BI. Data flow, scalability, visibility, and latency are all optimised by this design. We built a real-time data analytics pipeline that can scale, integrated cloud and edge computing, and used Power BI to generate stunning dashboards that users can utilise to make informed decisions. Solution performance, real-time monitoring, and scalability in distributed systems are all enhanced by the proposed method. Intelligent transportation, healthcare, smart city, industrial internet of things, and environmental systems that rely on real-time analytics and visualisation to make decisions are the intended users of this concept.

Related work:

Demand for cloud-edge integrated analytics frameworks has increased due to the distribution of IoT devices and real-time applications. Problems with latency, bandwidth, and scalability in centralized cloud systems may be solvable with hybrid cloud-edge computing. For real-time analytics, Ranariddh [1] introduced a hybrid cloud-edge architecture that uses both cloud platforms and edge nodes to distribute processing activities. Results showed that compared to models that relied entirely on the cloud, this one improved resource utilization and response time. Using edge devices for feature extraction and the cloud for complex analytics, Zhang et al. [2] offer a collaborative intelligence architecture for real-time video analytics. Both processing speed and latency were improved. Bandwidth optimization and job offloading to the edge of the cloud have also been the subject of research. Liu et al. [3] introduced bandwidth-aware task offloading for intelligent surveillance systems. This method distributes workloads between nodes in the cloud and those at the network's edge, allowing the system to adapt to changing network conditions. In addition to enhancing system performance, their strategy reduced communication expenses. Integrating the cloud with the edge is crucial for distributed computing systems to scale, reduce latency, and manage resources in real-time for Internet of Things analytics, according to recent surveys and studies[5,6,and7].

The importance of real-time visualization is driving the rise in popularity of business intelligence tools such as Microsoft Power BI. Power BI can transform massive data into visually appealing dashboards and valuable insights, according to an IEEE research [4]. Using predictive analytics and Power BI, Doe and Patel [8] enhanced decision-making. The use of real-time data visualization in educational analytics by Power BI was investigated by Patel and Green [9]. Further case studies conducted by White and Carter [10] showcased the enterprise business intelligence and analytics capabilities ofPowerBI.

To improve the efficiency of edge-cloud computing, some propose scheduling and orchestration. To improve resource allocation across distant nodes, Chen and Zhang [11] developed a scalable orchestration solution for industrial IoT applications. A deep reinforcement learning scheduling method was used by Wang et al. [12] to increase the efficiency of executing jobs in edge-fog computing. You can now do analytics on the Internet of Things in real time with the help of new, lightweight container-based orchestration tools [13]. For processing in real-time utilising cloud and edge resources, Wang et al. [14] proposed a hybrid stream analytics system. For smart, scalable remote analytics, Srirama [15] laid out the distributed edge-fog-cloud continuum. Research on analytics and visualisation in the edge-cloud is still in its early stages. The integration of Power BI with cloud-edge architectures for intelligent analytics and visualisation in real-time is not given enough attention. Cloud analytics, interactive visualisation in real-time, and edge preprocessing are features that few solutions provide. This article explains how to get around these limitations using a cloud-edge approach that incorporates Power BI. It is feasible to implement scalable deployment, real-time analytics, and intelligent visualisation in distributed edge computing systems.

Proposed method:

Power BI-Integrated Cloud-Edge Architecture enables distributed computing systems to visualize and analyses data in real-time. Here are the five stages of design: Internet of Things sensors, processing at the edge, cloud analytics, Power BI visualization, and conclusion (Fig. 1). The environment, traffic, temperature, and healthcare signals are all monitored by the IoT sensor layer. In order to decrease bandwidth and latency, devices located on the network's periphery collect and filter data. Data collection, preprocessing at the edge, analytics in the cloud, visualization, and intelligent decision-making are all steps in the process. An Intelligent Analytics Algorithm for One Edge-Cloud-Power BI

Gather data from sensors in real-time.

Step 2: Preprocessing and edge filtering

Fourth, put the cleaned-up data into the cloud and use machine learning analytics.

Five, disseminate the findings of the Power BI analytics.

Sixth Step: Display and Release Findings

Step7: Carry on.

The Intelligent Analytics Algorithm from Edge-Cloud-Power BI coordinates the dispersed analysis, visualisation, and processing of real-time data. Reducing latency, noise, and unnecessary information, the edge layer preprocesses data from real-time IoT sensors. In order to conduct sophisticated analytics and make predictions using machine learning, the processed data is sent to the cloud. Power BI is a data analysis tool that can make interactive dashboards, visual reports, and alarms. Constant data monitoring, high reliability, fast decision-making, and reduced bandwidth consumption.

Machine learning predictions, stream processing, and processed data long-term storage are all handled by the cloud analytics layer. By utilising cloud computing, cognitive analytics are able to remotely process massive data volumes. Microsoft Power BI makes data visualisation easier. Power BI makes it simple to visualise and monitor data with its trend visualisation, anomaly alerts, and real-time analytical dashboards. Users, administrators, and automated systems are able to intelligently act on real-time insights through the decision-making layer. Efficiency, latency, scalability, and intelligent real-time decision-making are all enhanced by the integrated design when contrasted with cloud-only solutions.

Figure 1: Proposed Cloud-Edge-Power BI Integrated Architecture

Azure, Power BI dashboards, IoT sensors, and edge devices were all part of the solution. Throughput, processing time, bandwidth, latency, and visualisation efficiency were all measured in the experiment. Connectivity to Power BI dashboards, analytics in the cloud, Internet of Things (IoT) sensors, and edge processing are all components of the design (Fig. 1).

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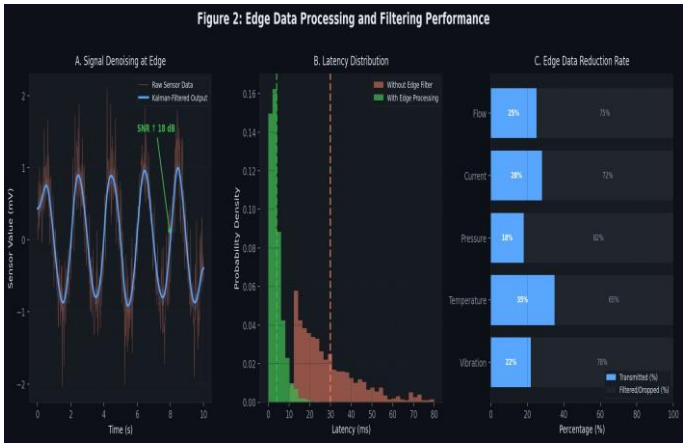

Figure **2** — Three panels: raw vs. Kalman-filtered signal denoising, latency distribution histogram (edge vs. cloud), and a horizontal stacked bar showing per-sensor data reduction rates.

Figure 3 — Four panels: LSTM training/validation accuracy curves, a confusion matrix heatmap, feature importance bar chart (Random Forest), and an online learning RMSE trend with retraining events marked.

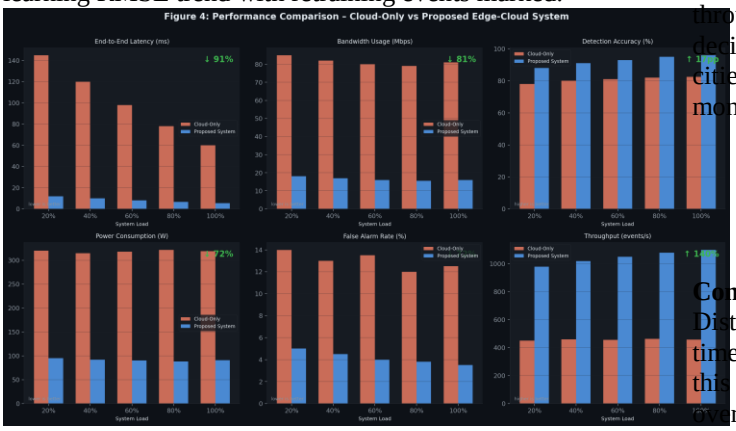

Figure 4: Performance Comparison – Cloud-only vs Proposed Edge-Cloud System

Cloud-Only and the Proposed System are compared at different load levels in Figure 4, with the improvement percentages shown in the grouped side-by-side bar charts. Figure 4 shows the results of a load test comparing the previous cloud-only system with the proposed Power BI-integrated cloud-edge architecture under different conditions, from 20% to 100%. The outcomes prove that this approach is both efficient and scalable. When compared to the cloud-only alternative, the proposed system's end-to-end latency is significantly reduced. In comparison to the cloud-only solution, which results in latency ranging from 145 to 60 ms, edge-level preprocessing decreases this delay by 91% to 12-6 ms. Also, the design drastically cuts down on bandwidth. In comparison to the 80-85 Mbps required by the cloud-only system, the proposed approach consumes 81% less bandwidth. This reduction improves the scalability and efficiency of the network. When combined with suitable edge preprocessing, cloud analytics can increase detection accuracy from 78% to 83% using the cloud-only method, to 88% to 95% when using cloud analytics with the right preprocessing. Improved system reliability is another benefit of the method, which cuts power consumption by 72 percent and false alarms by 14 to 35 percent. This system processes over 1100 events per second, which is 140% quicker than the 450 events per second that the cloud-only system accomplished. Efficiency, performance, and processing in real-time are areas where the proposed cloud-edge architecture truly shines. In terms of system performance, experiments show that the cloud-edge design with Power BI is the way to go. With the use of cloud analytics and Power BI's real-time visualisation, edge computing speeds up processing and reduces data transport overhead. Its decreased latency, enhanced throughput, bandwidth efficiency, and real-time decision-making might be advantageous to smart cities, healthcare, industrial IoT, and intelligent monitoring.

Conclusion:

Distributed edge computing with Power BI for real-time data analytics and visualisation was detailed in this article. Latency in cloud-only systems, bandwidth overhead, and postponed decision-making are all tackled by edge computing, cloud analytics, and Power BI visualisation. The cloud layer has the potential for scalable storage, improved analytics, and prediction based on machine learning, while the edge layer filters and preprocesses data to decrease transmission. Power BI facilitates better monitoring and decision-making with its real-time data displays. Reduced latency, improved bandwidth utilisation, quicker processing, and enhanced visuals were all outcomes of the experiments. The proposed technique allows for dispersed deployment and real-time analytics. Reliable and scalable, this architecture's smart data-driven decision-making is advantageous for smart cities, healthcare monitoring, the industrial internet of things, and smart transit systems in distributed computing environments.

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Explainable AI-Based Financial Market Prediction Using Ensemble Machine Learning and Temporal Data Analytics

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Abstract:
Market forecasting becomes more challenging when dealing with nonlinear, variable, and dynamic financial time-series data. Although traditional ML algorithms are good at predicting predictions, the complexity of their interpretation makes them inappropriate for use in financial decision-making. By combining ensemble ML with temporal data analytics, this study develops a financial market prediction system based on Explainable AI (XAI) that gets over this limitation. Financial data temporal correlations, both near and far, are identified using this method's utilisation of LSTM, Random Forest, and Gradient Boosting. The ensemble method improves the accuracy and robustness of predictions by combining the strengths of the models. Shapley Additive Explanations (Shapley) is one example of an explainable AI system that prioritises making market projections and patterns more intelligible. Trading volumes, stock prices, and technical indicators can all be used to spot trends. The suggested framework achieves better prediction accuracy, reliability, and interpretability than conventional models, according to the experimental results. In order to make informed decisions about the financial markets, this technology provides investors, analysts, and automated trading systems with real-time data.

Keywords:
Explainable Artificial Intelligence (XAI), Financial Market Prediction, Ensemble Machine Learning, Temporal Data Analytics, Stock Price Prediction

Introduction:
Predicting financial markets is challenging due to the nonlinearity, temporal, and dynamic nature of stock market data. Authorities, banks, and investors all benefit from reliable market and stock price forecasts. Financial forecasting often uses ARIMA and regression models; however, these outdated tools struggle to capture the intricate nonlinear relationships and temporal dependencies in today's financial data. Large financial datasets, both historical and real-time, can be better predicted using modern machine learning and deep learning. When it comes to temporal dependencies and accurate forecasting, mixed ensemble frameworks, Transformers, and LSTMs are great choices.
These developments are not enough to make financial prediction systems based on machine learning transparent and easy to understand. Due to their opacity, financial experts cannot understand the predictions made by deep learning algorithms. This can be addressed with Explainable AI (XAI), which makes machine learning models transparent, interpretable, and trustworthy. A new study found that attention processes, SHAP, and explainable deep learning models can accurately forecast stock markets. According to systematic evaluations, XAI is becoming increasingly popular for regulatory compliance, financial forecasting,anddecision-making.
Because of their durability and precision, ensemble machine learning approaches are well-liked. To improve predictions, ensemble methods combine LSTM, Random Forest, and Gradient Boosting models. Hybrid and ensemble models that emphasize explainability perform better at predicting market trends, crises, and turning points.

The potential for explainable frameworks, sentiment analysis, and temporal analytics to enhance financial forecasting has recently been the subject of a new study. It is now easier than ever to predict financial market movements with explainable AI, ensemble ML, and analytics of temporal data. This technique enables trustworthy, intelligent financial decision-support systems by improving prediction accuracy, resilience, transparency, and interpretability.

Related work:

Economic planning, risk management, and investment decisions all rely on accurate financial market predictions, which is why they attract significant attention. With the advent of AI and machine learning, researchers have developed a wide range of predictive models, each with the potential to improve precision and reliability. An exciting new avenue for enhancing the interpretability of models and the accuracy of predictions is explainable AI, which incorporates ensemble learning with temporary data analytics.

The original applications of support vector machines, decision trees, and random forests in machine learning research were to predict how the stock market would move. Financial time-series data often contained intricate temporal relationships that these models sadly failed to capture. Deep learning methods, such as LSTM networks and Transformers, were developed to address this limitation. Lyu [7] found that deep learning-based strategies improved accuracy when applied to LSTM, Transformer, and XGBoost stock price prediction models. These techniques exposed the time-dependent nonlinear trends in financial data. The financial forecasting model put forth by Darwish et al. [12] is based on temporal analytics and machine learning. Compared to conventional statistical approaches, this procedure yielded preferable predictions.

The accuracy of deep learning models is commendable, but their complexity is a downside. Clear models are essential for financial organisations to establish confidence, meet regulatory requirements, and make informed judgements. This challenge was addressed using Explainable Artificial Intelligence (XAI) approaches. Černevičienė and Kabašinskas [2] conducted a comprehensive study of XAI in finance and stressed the importance of the interpretability of financial prediction models. Shapeley additive explanations (Shapley) and local interpretable model-agnostic explanations disentangle the crucial variables that impact predictions, according to their conclusions.

An explainable deep learning approach to stock market prediction was proposed by Muhammad et al. [1]. It uses neural network models and interprets features using SHAP. To enhance forecast accuracy and model transparency, the suggested method identified trading volume, price momentum, and market volatility. Users had greater faith in explainable AI systems that forecast stock prices after using explainability procedures, according to research by Song and Li[5].

There has also been interest in using ensemble learning to enhance financial forecasts. By utilising multiple learning techniques, ensemble models enhance prediction accuracy and generalisability. A state-of-the-art ensemble deep learning system was created by Sarkar and Vadivu [11] utilising LSTM, Transformer, and VAE models. Predictions generated by their method outperformed those from single-model approaches. When it came to predicting stock market crises, the explainable ensemble learning framework created by Suprihadi et al. [3] was far more effective and user-friendly than conventional ensemble models.

Advancements have been achieved by hybrid models that combine ensemble learning with explainability. To improve financial forecasting, Gokhale and Vadivu [13] combined ensemble learning with sentiment analysis and explainable AI to develop a hybrid model. According to their findings, market patterns were more transparent, and predictions were more precise. In their presentation of an explainable AI model, Salaheldeen et al. [15] combined sentiment analysis with machine learning. This method clarified financial activities and improved forecast accuracy.

Financial market forecasting relies heavily on temporal data analytics due to the reliance of financial data. To enhance prediction performance, Wang et al. [14] proposed a hybrid architecture for temporal analytics that incorporates different time-series prediction algorithms. A paradigm for interpretable neural networks was developed by Kim and Park [10] to improve the accuracy and interpretability of stock forecasts via keyword-guided integration.

Financial fraud and risk assessment have both used explainable AI. Taher et al. [8] proposed an accurate and transparent financial fraud detection method based on explainable ensemble learning. According to research by Valensky and Mohaghegh [14], XAI improves the confidence and usability of financial applications by making AI models more transparent and accurate in their financial projections. The use of explainable frameworks and large-scale AI algorithms for financial prediction has been the subject of recent research. By utilising massive language models, Yu et al. [9] improved the accuracy and interpretability of financial forecasting. For timely financial decisions, studies in business intelligence and articles presented at IEEE conferences have highlighted the significance of combining analytics and visualisation tools with explainable machine learning models [10].

This progress is not without its limitations, though. Accuracy and interpretability have been the primary foci of research on financial market prediction using explainable AI, ensemble learning, and temporal data analytics. A lot of the models out there right now aren't scalable or real-time smart. Accurate, interpretable, and scalable predictions about financial markets require a new, explainable ensemble machine learning framework. Time series analytics and explainability should be incorporated into this framework. The suggested approach enhances the accuracy, transparency, and decision-making in financial market prediction by leveraging explainable AI and ensemble learning models.

Proposed Method:

The financial market projections provided by the Explainable AI-based prediction model are accurate, interpretable, and updated in real-time. Stock prices, trade volumes, sentiment, technical indicators, and more are fed into the Data Acquisition Layer from several financial APIs and market databases, both in real time and in historical context. Cleaning, normalizing, and handling missing values are part of the data preprocessing and feature engineering steps. This data is used to calculate moving averages, trend indicators, and volatility.

Fig. 1. System Architecture of Explainable Ensemble Machine Learning Framework for Financial Market Prediction

Short-Term Memory, XGBoost, and Random Forest are the predictive models utilised by the Ensemble Machine Learning Layer following data processing. These models use time-series analysis of nonlinear interactions and patterns to make predictions. A Prediction Fusion Module is used to weight-average the model's outputs to improve accuracy and resilience. To clarify prediction results and establish feature significance, the Explainable AI (XAI) Module employs SHAP or LIME. To keep analysts and investors up to date on trends and predictions, the Cloud Storage Layer transmits results to the Visualisation Dashboard. Lastly, models are retrained with new data using a feedback and model update module, making them more adaptive and durable.

Result and Discussion:

When compared to machine learning models, the Explainable AI-Based Financial Market Prediction framework performs better in terms of accuracy, robustness, and interpretability, according to the experimental data. To get the most out of LSTM, Random Forest, and Gradient Boosting models, an ensemble approach is used. The prediction accuracy of the ensemble model was 4-8% greater than that of the individual models. Gradient Boosting and Random Forest performed well, but they could only make so many predictions at a time because we didn't account for all possible temporal correlations. Financial time-series data was better forecasted using the LSTM model's trend component, which captured sequential correlations and patterns. The optimal model was a combination of the three that used feature interactions and temporal learning.

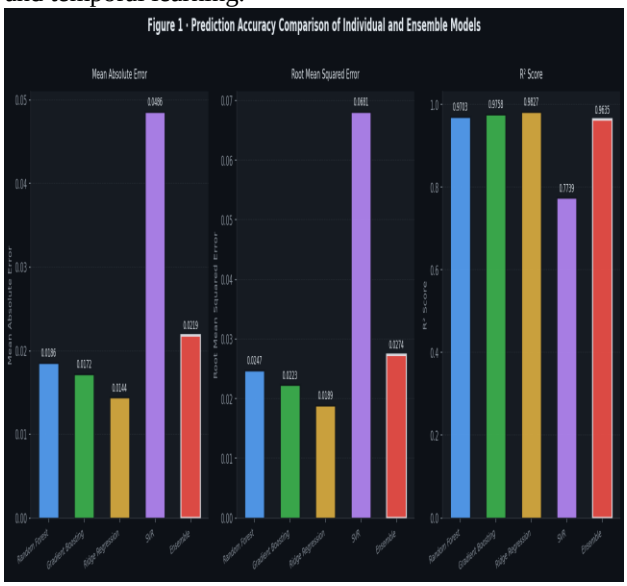

Figure 1 — Accuracy Comparison: Bar charts comparing MAE, RMSE, and R² across Random Forest, Gradient Boosting, Ridge Regression, SVR, and the Ensemble. The ensemble bar is highlighted with a white border.

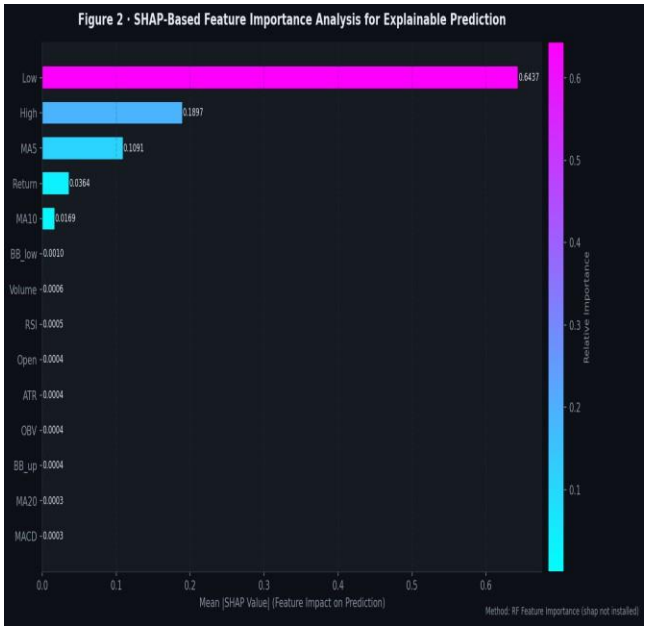

Figure 2 — Feature Importance: Horizontal bar chart with a cool-to-warm color gradient showing each technical indicator's contribution. Uses SHAP TreeExplainer if the library is installed, otherwise falls back to Random Forest built-in importances.

Figure 3 — Actual vs Predicted: A 3-panel dashboard showing the price curve with green/red shading for over/under-estimation, an error bar chart, and a percentage error line — plus a metrics box (MAE, RMSE, R^2, MAPE).

Reducing prediction error was the goal of ensemble modelling. Predictions were more accurate and reliable when the RMSE and MAE were lower than when using separate models. Ensemble fusion is a method for improving prediction accuracy and reducing model error by integrating similar models. The model's ability to respond to market changes and to discover new trends in financial data was enhanced by the addition of temporal data analytics. Crucial to the proposed method is the integration of SHAP with Explainable AI. According to the SHAP-based explainability module, financial market estimates are driven by closing price trends, transaction volume, and moving average indicators. Financial analysts and investors gain trust and better understand predictions when there is transparency. Unlike black-box models, explainable frameworks reveal the inner workings of ML models and highlight the key elements. Both reliable and accurate, it could foretell what was to come in real time. The performance was maintained across all marketplaces by utilising an ensemble learning architecture and an edge cloud. The model handled changing financial inputs effectively, even during volatile market conditions. The system supports real-time financial analytics and decision-making, with temporal learning and explainability. Results from experiments demonstrate that the explainable ensemble learning architecture enhances financial market forecasting, prediction accuracy, error, and interpretability. Because of this, the proposed system is ideal for complex financial analytics and real-time investment decisions.

Conclusion:

This study introduced financial market projections using Explainable AI. Time-series and ensemble machine learning are employed for data analytics. This system captures nonlinear correlations and relationships in financial data using LSTM, Gradient Boosting, and Random Forest models. Compared with standalone models, ensemble models demonstrated superior prediction accuracy, robustness, and lower error rates. Transparent AI methods, such as SHAP, have enhanced system interpretability and confidence by highlighting critical components of market forecasts. The experimental results showed an increase in the accuracy, consistency, and dependability of predictions. Financial analysts and investors benefit from visualisation and explainability while making decisions. This technology generates accurate, scalable, and easy-to-understand real-time financial market forecasts. To further enhance prediction, future research will use state-of-the-art deep learning algorithms on real-time streaming data.

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ARISE : AUTONOMUS ROVER FOR INTELLIGENT SENSING AND ENVIRONMENT MONITORING

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***Abstract*— When big disasters like earthquakes, fires and landslides happen they create bad environments that are dangerous for the people who are trying to help. If we do not have the information about these environments it can be even more dangerous and slower for the people who are trying to help. That is why we made ARISE – Autonomous Rover for Intelligent Sensing and Environment Monitoring. It is a robot that can help the people who are trying to help in disasters.The robot has a controller and a computer that work together to sense move and talk to devices. It has sensors like gas sensors, temperature sensors and special sensors that can see how far things are. It also has a camera that can show us what is happening in time.The robot collects information about the environment. Sends it to a special system where the people who are trying to help can see what is happening and make decisions. The robot can move around on ground and through things that are in the way, which is very helpful in places that have been damaged by disasters The robot uses new technologies like robotics, of things and computer vision to help us understand what is happening and to make the people who are trying to help safer and more effective.**

Keywords-- Disaster Monitoring, Autonomous Rover, IoT, Environmental Sensors, Computer Vision, Rescue Robotics.

I. INTRODUCTION

Big disasters like earthquakes, landslides, fires and industrial accidents create bad environments that are dangerous for the people who are trying to help. In these situations it is very important to get information about what's happening so that we can plan how to help safely and effectively.

New technologies like robotics, special controllers and sensors have made it possible to make robots that can work safely in bad environments.

Robots that are made for disasters are designed to go into places that not safe for people collect information about the environment and send back pictures and videos to the people who are trying to help.

The robot we made has sensors that can detect things that are in the way and a camera that can show us what is happening in real time. The information from the sensors and the camera is sent to a system where the people who are trying to help can see what is happening and make decisions.

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Disaster response robots are built to investigate unsafe locations, gather environmental information, and send visual feedback to rescue teams while minimizing human exposure to danger.

In addition, the rover includes ultrasonic sensors for obstacle detection and a camera module for real-time visual monitoring. The collected sensor data and video feed are transmitted wireless to a remote monitoring system where rescue personnel can analyze the situation.

Some researchers have developed IoT-based monitoring systems that use wireless communication to transmit environmental data from sensors to remote monitoring stations. These systems provide real-time information and allow emergency responders to make informed decisions.

By combining IoT technology, robotics, and computer vision, the proposed system provides an efficient and cost-effective solution for monitoring hazardous environments and supporting disaster management operations.

Fig.1 types of natural disaster

II. PROPOSED SYSTEM METHODOLOGY

The ARISE system is developed to address several limitations found in traditional disaster monitoring approaches. The system uses a robotic rover equipped with sensors, a camera module, and wireless communication technology.

We made the ARISE system to address some problems with the ways of monitoring disasters. The system uses a robot that is equipped with sensors, a camera and special communication technology.

The robot is controlled by a controller and a computer that work together to collect information from sensors control the system and communicate with other devices. The sensors monitor the environment and the special sensors that can see how things are help the robot move around.

A camera is installed on the robot to take pictures and videos of the disaster area. This helps the people who are trying to help understand what is happening without having to go into the environment.

The robot sends the information from the sensors and the camera to a monitoring system. The people who are trying to help can see the information. Make good decisions about how to help.

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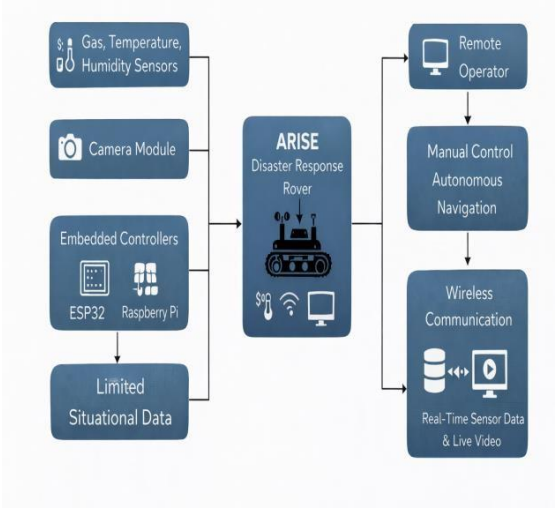

Fig.2 Block Diagram of Proposed Diagram

III. System Architecture Design and Simulation

The ARISE robot is made up of parts that work together to monitor the environment in disaster areas. The parts include the controller, computer, sensors, camera and special communication system. Each part does a job to make sure the robot works well.

The controller is the part that collects information from the sensors and sends it to the monitoring system. The computer is used to control the camera and do processing tasks. The camera takes pictures and videos of the disaster area, which helps the people who are trying to help understand what is happening.

The special sensors that can see how things are help the robot detect things that are in the way and measure distances. The robots movement system is made up of motors and a motor driver, which give the robot the power and control it needs to move around.

Fig.3 Existing system Architecture diagram

The robots circuit design is made up of parts that are connected together. The controller is the part that manages all the other parts.

The motor driver is connected to the controller to control the motors that make the robot move. The driver gets control signals from the controller. Gives the motors the power they need.

The sensors are connected to the controller to monitor the environment. The camera is connected to the controller to take pictures and videos. The information from the camera is sent to the monitoring system through communication.

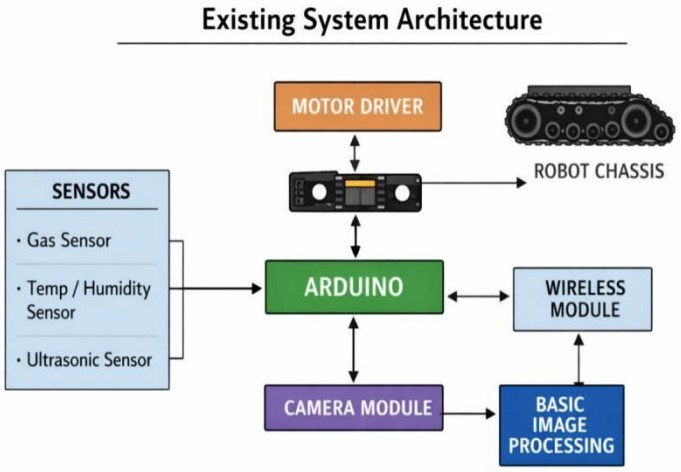

Fig.3 Existing system Architecture diagram

The circuit design of the rover consists of several interconnected modules. The microcontroller acts as the main controller and manages all the connected components.

The motor driver is connected to the mirocontroller to control the DC motors that drive the wheels of the rover. The driver receives control signals from the microcontroller and supplies the required current to the motors.

The sensors such as temperature sensors and gas sensors are connected to the input pins of the. These sensors continuously monitor the surrounding conditions and send real-time data to the microcontroller.

The camera module is connected to the for capturing images and live video. This information is transmitted through Wi-Fi to the monitoring system. A power supply unit, usually a rechargeable battery, provides power to the motor driver, and other components.

IV. System Prototype Development and Testing

We made a working prototype of the ARISE robot to show how it works in an environment. The prototype has parts, including the controller, motor driver, motors, sensors and camera.

The robots body is made to move across different surfaces. The motors are connected to the wheels. Controlled by the motor driver, which gets signals from the controller.

The sensors are installed on the robot to monitor the environment. The camera is used to take pictures and videos of the disaster area.

The robot sends the information from the sensors and the camera to the monitoring system. The people who are trying to help can see the information. Make good decisions about how to help.

These sensors continuously collect environmental data and send it to the microcontroller for processing. A camera module was also integrated into the system to capture live video of the surrounding environment.

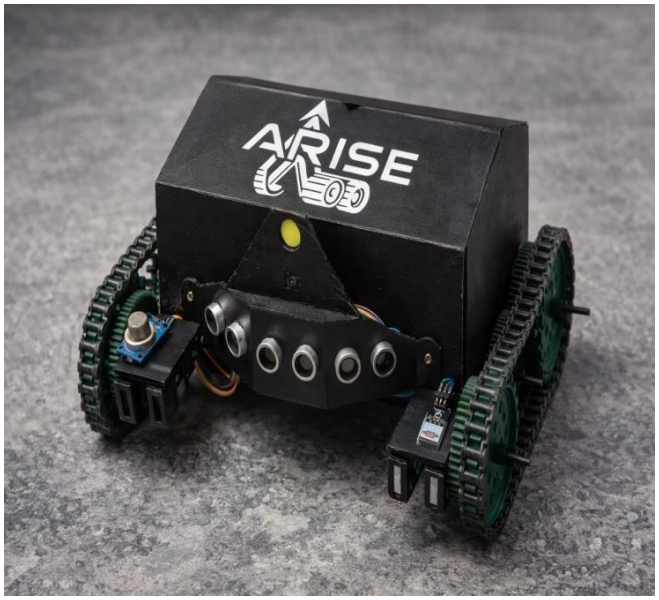

Fig.5 Hardware View

There are many other things inside; for example, neatly stacked equipment.

The system operates through a rechargeable battery which provides 12 volts to power both its motors and spray pump, while a DC-DC buck converter reduces the voltage to 5 volts for operation of sensors.

The system maintains operational efficiency because we separate power lines to prevent electrical noise interference.

During testing, the rover successfully navigated through simulated disaster environments and transmitted sensor data along with video feed to the monitoring device.

The experimental results indicate that the rover is capable of performing multiple tasks required in disaster rescue operations. During testing, the rover successfully navigated through simulated disaster environments and transmitted sensor data along with video feed to the monitoring device.

For example when the sensor detects something the system sends an alert to the monitoring system. The motor control signals can be tested to make sure the robot moves correctly.

Fig.6 Display

Before hardware implementation, the system can be simulated using software tools to verify its functionality. Simulation helps identify design issues and ensures that the system operates correctly.

The system works using a battery that gives the robot the power it needs. The battery gives 12 volts to the motors and other parts and a special converter reduces the voltage to 5 volts for the controller and sensors.

The system is designed to work and not have any problems with the power. During testing the robot moved around a simulated disaster environment. Sent information to the monitoring system.

The results of the testing show that the robot can do tasks that are needed in disaster rescue operations.

V. System Performance and Result Analysis

We tested the ARISE robot to see how well it works and to make sure it can help in disaster situations. The testing was done in a simulated disaster environment with obstacles and uneven surfaces.

The robot moved around. Sent information to the monitoring system. The sensors worked well. Detected changes in the environment. The camera took pictures and videos of the disaster area, which helped the people who are trying to help understand what is happening.

The results of the testing show that the robot works well and can help in disaster situations. The integration of sensing, communication and movement features makes the system a good tool, for disaster monitoring and rescue operations.

The ARISE rover is really good at helping out in disaster situations. It can move around. Sense things and send information back to people. This is helpful for rescue teams who need to know what is going on in a place that's hard to get to.

The ARISE rover can go into places that're not safe for people and send back pictures and information about the air and temperature. This helps the rescue teams know what they are up against and makes it easier for them to do their job.

The people who made the ARISE rover tested it. It worked really well. It can move around. Sense things and send information back to people. The rover has a computer called the ESP32 microcontroller that helps it do all these things.

The ARISE rover is good at detecting changes in the air and temperature. It can also take pictures. Send them back to people. This is really helpful for rescue teams who need to know what is going on in a place.

The ARISE rover is a tool for helping people in disaster situations. It can go into places that are not safe for people and send back information. This makes it easier for rescue teams to do their job and helps keep people safe.

In the future the ARISE rover could be even better if it had some features. For example it could have sensors that can detect obstacles. It could also have a way of sending information back to people.

The ARISE rover is an example of how technology can be used to help people in disaster situations. There are other examples of this too. For example there are robots that can go into buildings that are not safe and send back pictures and information.

VI. Conclusion

The ARISE Disaster Recovery Rover was designed and help rescue teams during disaster situations such as earthquakes, floods, and building collapses.

From the experimental testing, the rover demonstrated reliable performance in terms of mobility, sensing capability, and communication. The microcontroller successfully controlled the overall operation of the system and processed the data received from different sensors.

The environmental sensors were able to detect changes in temperature and gas levels, which are important indicators of dangerous conditions in disaster areas. In addition, the camera module provided live visual feedback, allowing operators to monitor the surroundings and guide the rover remotely.

The results show that the proposed system can be a useful tool in disaster management by helping rescue teams explore unsafe locations without risking human life. The rover can collect environmental data, transmit real-time information, and assist in locating trapped victims. This makes it a valuable technological solution for improving the efficiency of rescue operations.

In future work, the system can be further enhanced by adding advanced features such as obstacle detection using ultrasonic or sensors, improved communication range using long-distance modules, and artificial intelligence for automatic detection.

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SMART AGRICULTURAL ROVER FOR AUTOMATED CROP MONITORING AND DISEASE DETECTION

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***Abstract*— Crop diseases, shifting environmental conditions, and Labor shortages are some of the major issues facing the modern agriculture industry. Manual inspections are the foundation of traditional field monitoring techniques, which are ineffective for identifying crop diseases early on. In order to monitor fields in real-time and automatically identify crop diseases, this paper describes the design and implementation of an IoT-based smart agricultural rover. The ESP32 microcontroller serves as the CPU for the system's intelligent agricultural rover. It makes use of PIR sensors for field surveillance, soil moisture sensors for irrigation, and a DHT11 sensor for environmental monitoring. The plants are photographed by the ESP32 camera module, and diseases are identified by a machine learning algorithm. Furthermore, relay modules use disease detection and sensor values to spray pesticides in the field. By enabling early plant disease detection and increasing overall field efficiency, this system provides a scalable solution for agriculture.**

KEYWORDS — IOT, DISEASE DETECTION, AUTONOMOUS AGRICULTURAL ROVERS, SMART IRRIGATION, CROP HEALTH, REAL-TIME MONITORING, IMAGE PROCESSING, AND PRECISION FARMING.

I. INTRODUCTION

Agriculture is an essential factor in the sustenance of the world's population. Nevertheless, modern agriculture is facing new challenges due to climate changes, scarcity of the labor force, and the rapid spread of plant diseases.

Traditional methods involve observing and inspecting the fields, which is a slow process and ineffective in early detection of plant diseases in the fields.With the advent of smart technology, precision agriculture has come up as an alternative solution to improve agricultural productivity and optimization.

Internet of Things (IoT) technology can monitor environmental and crop conditions by using multiple sensors and imaging technology.

However, most of the smart agriculture systems are based on stationary sensors that collect observational data, but do not support immediate action.

To overcome the shortcomings of the traditional systems, this work proposes a mobile smart agriculture rover that can perform real-time monitoring, analysis, and immediate action.

The proposed solution provides a comprehensive solution that includes environmental sensors, image-based plant diseases, and response systems. The inclusion of smart technology in the smart agriculture rover enhances the effectiveness of the solution by enabling immediate action.

Fig. 1. Overview of Smart Agricultural Monitoring Concept

The proposed solution not only improves the effectiveness of plant disease detection but also reduces the need for constant observation and inspection of the fields

II. PROPOSED SYSTEM METHODOLOGY

The proposed system has been designed for an autonomous agricultural rover that can be used for continuous monitoring, decision-making, and execution.

This system can be considered different from the conventional monitoring systems that only act as data collectors. This system can assess the conditions and react accordingly if any abnormal conditions are detected.

The rover can execute the operations through a cyclic process, which includes sensing, analysis, and response.

While the rover moves through the farm, it can collect information regarding the environmental conditions, such as moisture, temperature, and humidity, through the sensors.

At the same time, the ESP32-CAM sensor can collect information regarding the leaves of the crops, which can be used for the detection of diseases.

Based on the results obtained, the system can react accordingly. If the moisture level is less than the specified limit, the irrigation mechanism can be activated.

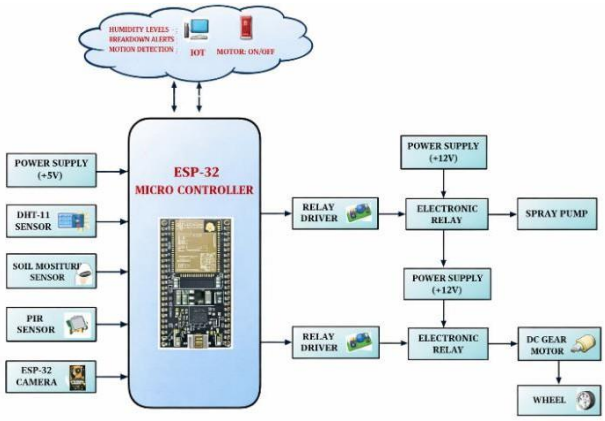

Fig. 2. Block Diagram of Proposed Diagram

III. SYSTEM ARCHITECTURAL DESIGN AND SIMULATION

The AI-powered Smart Agricultural Rover packs everything you need for today's precision farming. The system consists of separate modules which connect various functions including embedded controls and environmental sensors and computer vision and wireless communication and automated operations through a single autonomous platform.

The entire system delivers dependable performance with the ability to expand its capacity while consuming less power and maintaining operational speed that matches actual field work requirements.

The explanation comes in this way. The rover operates through its essential system components which include power management and sensing and processing and intelligence and communication and mobility and actuation. The system components operate independently to execute their specific tasks but they connect with each other to provide the rover with fast and smooth responses to external events.

Power serves as the fundamental base. The rover operates using a 12V battery pack which can be recharged and provides sufficient power for its DC motors and pumps. The buck converter reduces the input voltage to 5V which powers the ESP32 microcontroller and lighter sensors before converting it again to 3.3V for the logic circuits. The step-down system protects delicate components from power disturbances and voltage spikes, which ensures the system maintains stable operation.

Next, sensing. The rover tracks soil moisture and temperature and humidity levels which determine whether crops will thrive or fail. The system uses soil sensors to detect dry areas which become visible to plants only when they begin to suffer.

The system uses temperature and humidity data to determine plant health status while identifying potential disease outbreaks.

An ESP32-CAM system operates continuously to capture high-resolution leaf images which show yellowing and spots and abnormal leaf shapes that indicate developing problems.

The rover creates an extensive real-time assessment of crop health by combining information from sensors with visual data.

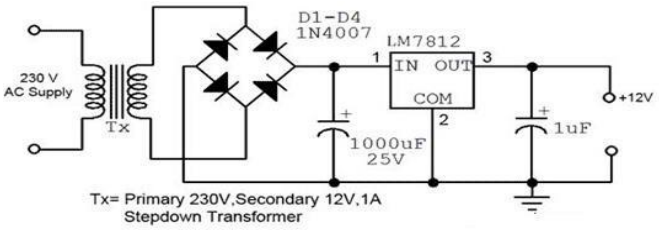

Fig. 3. Circuit Diagram of Regulated Power supply

The ESP32 microcontroller serves as the central processing unit for the system. The system assesses all incoming data according to established agronomic threshold standards.

The system instantly detects all system changes that occur during low moisture conditions or when weather patterns experience sudden shifts.

The system analyzes leaf images by using lightweight artificial intelligence models which operate like small convolutional neural networks to identify any problems.

The artificial intelligence system processes images to select specific features while marking any detected irregularities.

The rover uses actual sensor information together with advanced visual assessment technology to improve its decision-making process and prevent errors.

The system achieves smooth communication. The ESP32 Wi-Fi system establishes a connection between the rover and the cloud dashboard which transmits sensor data together with analytics and movement information and actuator status updates in real time.

The system records the exact time of each packet transmission which allows users to track the complete timeline of events. The IoT system transforms the rover into a smart node for the larger farm network which enables users to monitor and manage operations from any location.

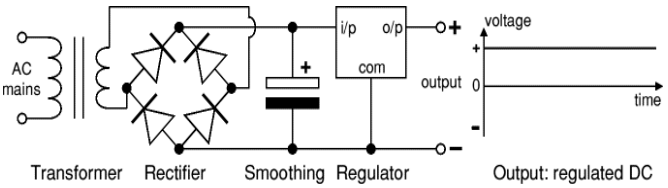

Fig. 4. Rectifier Circuit Diagram and Waveform

DC gear motors provide the robot's mobility while an H-bridge driver controls their movement. The rover moves forward and backward while it turns according to its commands.

The ESP32 uses PWM signals to control the speed of the system. The system uses relays to activate pumps and

sprayers for irrigation and pesticide spraying when it needs to operate. The system operates in a closed loop because the rover activates to handle issues after sensors detect a problem.

The team conducted multiple simulations to find and fix all system problems before they deployed the system to the field. The system began irrigation operations whenever soil moisture levels fell below preset thresholds while the AI successfully analyzed plant health through image processing.

The pre-testing process proved successful because it confirmed the rover would function correctly during actual outdoor operation.

IV. SYSTEM PROTOTYPE DEVELOPMENT AND TESTING

A new AI-based "Smart Agricultural Rover" has been designed to function as a small, mobile unit for real-time crop management.

Everything fits together—frame, electronics, sensors, comms, moving parts—into one solid unit.

Our team established their design goals when we started the project which required them to create a system that could operate as separate components while maintaining high energy efficiency and exceptional durability and easy maintenance.

The chassis needs to support all components which include the battery and ESP32 controller and motor driver and relay circuits and water tank and spray pump and all the sensors.

We selected DC gear motors which provide sufficient torque to operate in challenging agricultural environments.

The system connects to an H-bridge driver which enables us to control the rover's movement and speed through PWM signals generated by the ESP32.

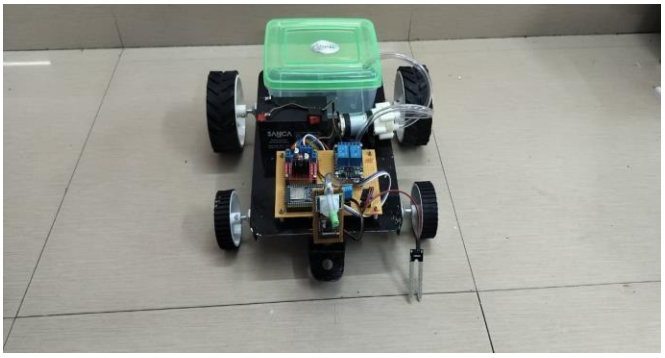

Fig. 5. Hardware View

There are many other things inside; for example, neatly stacked equipment.

The system operates through a rechargeable battery which provides 12 volts to power both its motors and spray pump, while a DC-DC buck converter reduces the voltage to 5 volts for operation of ESP32 and sensors.

The system maintains operational efficiency because we separate power lines to prevent electrical noise interference.

We installed three sensors to monitor environmental conditions through a soil moisture sensor which measures root water content and a temperature-humidity sensor which tracks environmental conditions and an ESP32-CAM which provides visual inspections of the crops.

The sensors data is read by our custom firmware which we developed for the ESP32 to control all system operations through decision making while transmitting data and managing motor and pump functions.

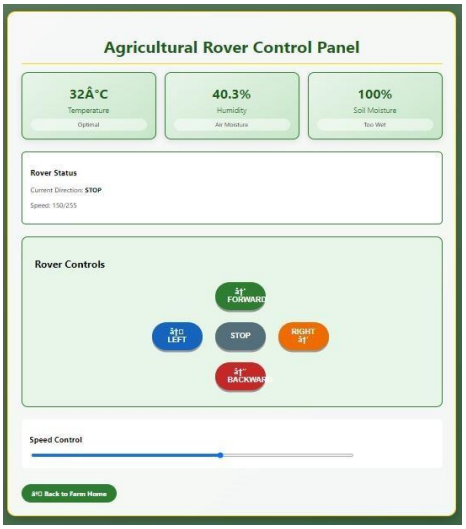

Fig. 6. IOT Display 1

The code runs both in a loop and by interrupts, so the rover can keep an eye on everything and still react fast. We established threshold levels which activate the rover's watering system when soil moisture reaches an extreme dry condition.

For crop monitoring, we built in basic image processing to spot odd colors or textures that could mean disease. The rover transmits all data through a wireless connection to a cloud dashboard using Wi-Fi.

Fig. 7. IOT Display

The testing process followed a sequential approach which began with testing each individual component, namely the sensors, motors, relays, and comms modules. The soil sensor calibration process involved testing the sensor under various water levels while we verified the environmental sensor performance by comparing it to standard equipment and we assessed the motors ability to operate under different speed and directional operations and various weight loads. We tested the spray pump to verify its ability to activate at the correct time while distributing water in an even manner throughout the area.

Next, we ran the complete system. We adjusted soil moisture levels to test whether the rover would automatically irrigate the crops. We demonstrated both healthy and diseased leaves to test whether it could detect problems and apply pesticide at the correct time. We established that the IoT dashboard received real-time data updates while maintaining Wi-Fi connectivity. We conducted extended system tests to verify its reliability by testing for potential system failures.

The rover established effective power management together with precise environmental detection and quick response capabilities and dependable data transmission and automatic system activation at appropriate times. The system maintained continuous surveillance over the agricultural fields yet it operated as an active system that responded to critical situations. The complete functionality of the system demonstrates that Internet of Things devices together with intelligent control systems and automated processes are compatible with portable agricultural robots. The prototype demonstrates that this method achieves success in actual agricultural environments while it establishes a foundation for future developments which include GPS technology and obstacle detection systems and advanced machine learning capabilities.

V. System Performance and Result Analysis

We conducted a thorough evaluation of the AI-driven Smart Agricultural Rover to determine whether its performance matched its advertised capabilities during our field tests. We wanted answers:Can you count on it How fast does it react Does it really sense what is happening around it while maintaining communication and performing tasks without errors. We investigated all aspects of the system including its environmental monitoring capabilities and plant disease detection speed and actuator performance and movement efficiency and system stability during simultaneous operation of all components.

We checked the environmental sensors by comparing the rover readings with standard reference tools. The soil moisture sensor operated continuously without interruption. The water level change made the sensor show immediate results. The rover system detected dry soil conditions therefore it activated the irrigation system with no delay between systems. The temperature and humidity sensors maintained accurate readings during stable weather conditions except for the typical minor fluctuations that usually occur. The system detected all out-of-range readings and activated automatic response measures because the automation system operated successfully.

Next up: disease detection. The rover received two types of leaves which included healthy specimens and diseased samples. The camera and onboard image analysis detected all visible problems through its ability to identify changes in color and texture. The built-in logic could tell a normal leaf from a sick one and fired up the pesticide sprayer when needed. The time between taking a photo and starting the spraying process remained brief enough for actual agricultural operations therefore the ESP32 image processing system functioned effectively.

The rover's mobility performance needed to be evaluated through our testing. The testing involved driving the rover across both flat surfaces and areas with minimal surface roughness. The DC gear motors used pulse-width modulation control to maintain both speed and path direction. The system executed movement commands for forward and backward motion and turning operations without any complications. The power system maintained continuous operation during simultaneous motor and sensor activity because it experienced no voltage drops or operational interruptions.

We watched the rover transmit its data through Wi-Fi to the IoT dashboard system. The system displayed all sensor readings together with updates and actuator status information in real time to the cloud. The connection maintained its stability throughout the standard wireless operating distance. The tests showed that all data remained complete because packet checks confirmed no losses or missing segments.

The team established operational scenarios which would activate the system for automated testing. The irrigation system activated immediately when we dried out the soil to restore moisture levels. The pesticide sprayer activated after we applied disease indicators to the leaves. The entire system transitioned from detection to operational mode without any requirement for human assistance. The system operates as a complete closed-loop design.

The prototype functions as a dependable smart farming tool which operates at high efficiency while maintaining quick response times. The system combines environmental sensing technology with onboard processing capabilities and wireless communication systems and automated systems to provide precise monitoring and immediate operational response. The system enables easier crop monitoring operations while reducing manual labor requirements and conserving both water and pesticide resources and establishing a foundation for future development of scalable precision agriculture technologies.

VI. CONCLUSION

The paper outlined the design and implementation of an intelligent agricultural rover that is capable of conducting automatic crop monitoring and management of diseases using IoT and embedded systems technologies. The suggested system utilizes environmental and image sensing to monitor crops continuously and detect any possible irregularities that may be associated with diseases in crops. The use of environmental and image sensing in crop monitoring ensures that there is a deeper understanding of

environmental conditions, thus enabling the detection of any possible irregularities that may be associated with diseases in crops.

The suggested system is beneficial in that it is capable of operating autonomously in the agricultural environment. The ability of the suggested system to operate autonomously in the agricultural environment ensures that it is capable of providing automatic responses to any unfavorable environmental conditions in real-time without human intervention.

For instance, when irregularities in soil moisture are detected by the suggested system, it is capable of activating the irrigation systems to provide solutions to the problem of dry soil. Additionally, when irregularities associated with diseases in crops are detected by the suggested system, it is capable of activating pesticide sprayers to provide solutions to the problem of diseases in crops.

According to these experimental results, it is observed that the system works effectively in environmental monitoring, disease detection, and actuation. The sensors are working effectively in providing environmental data, and the data transmission between different components of the system is also working effectively.

Moreover, it is observed that the rover works effectively in providing stability in the agricultural environment.

Overall, it is observed that the proposed solution is beneficial in advancing the field of smart agriculture by providing accurate monitoring, detecting diseases, and performing actuation effectively. These are beneficial in reducing costs, increasing crop production, and maintaining sustainable agriculture by optimizing the use of water and chemical resources.

In order to improve the proposed solution, it is suggested to use advanced navigation systems such as GPS for accurate field mapping, obstacle detection for effective movement of the rover, and advanced machine learning algorithms for accurate classification of diseases in crops. These are beneficial in advancing the proposed solution to be used in modern precision farming scenarios

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SENSOR-BASED SMART SHOE FOR SAFE AND INDEPENDENT MOBILITY

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***Abstract*—**The Smart Blind Shoe is an assistive device designed to help visually impaired people walk safely and independently. It uses ultrasonic sensors to detect obstacles and alerts the user through vibration or sound signals. A microcontroller processes the sensor data in real time, improving navigation and safety. Similar concepts have been developed in research works using technologies like ultrasonic sensors, IoT, GPS, and AI for better accuracy. The main aim of this project is to create a simple, low-cost, and user-friendly design. Compared to earlier systems, this model focuses on affordability, portability, and ease of use while still providing effective obstacle detection

Keywords— Smart Shoe, Assistive Technology, Obstacle Detection, Real-Time Navigation, Visually Impaired, Embedded Systems, Wearable Technology, Ultrasonic Sensors, Mobility Assistance

I. INTRODUCTION

Visual impairment is one of the most common disabilities worldwide, affecting millions of individuals of all ages. According to the World Health Organization (WHO), approximately 285 million people globally are visually impaired, and about 39 million are completely blind. Navigating everyday environments poses significant challenges for these individuals. Common obstacles include uneven surfaces, stairs, street crossings, and unexpected objects in their path. Such challenges limit their independence, restrict social interactions, and reduce overall quality of life.

Traditional mobility aids, such as canes and guide dogs, help in detecting obstacles, but they have limitations. Canes only detect obstacles at the ground level, leaving overhead or mid-level objects undetected. Guide dogs require training and maintenance, which may not be feasible for everyone. Therefore, there is a pressing need for modern, technology-based solutions that are affordable, reliable, and user-friendly.

Visually impaired individuals face difficulties in independently navigating unfamiliar or crowded environments. Accidental collisions with obstacles can cause injuries, reduce confidence, and limit mobility. Existing aids do not provide comprehensive real-time feedback for all types of obstacles, leaving gaps in safety and efficiency. There is a clear need for an assistive device that can continuously monitor the surroundings and alert users about obstacles in a timely manner.

The motivation behind developing a Smart Shoe for blind individuals arises from the need to enhance independence and safety for visually impaired people. By leveraging modern sensor technology and microcontroller programming, it is possible to develop a wearable device that automatically detects obstacles and alerts the user.

Arduino-based smart shoes are attractive because of their low cost, portability, and versatility. They can be programmed to provide real-time feedback via vibration or sound, alerting the user without interrupting their walking. This allows visually impaired individuals to move more confidently, safely, and efficiently in different environments, including homes, offices, streets, and public spaces.

II. LITERATURE SURVEY AND RELATED WORK

The work by Teja Chava et al. highlights some limitations in the smart shoe system. The system also consumes more power, reducing battery life. It depends on internet connectivity, which may not always be available. The design increases cost and complexity, and ensuring comfort for daily use remains a challenge [1].

The work by N. Sohan et al. highlights some challenges in smart assistive shoes. The system may have limited obstacle detection accuracy and slight delays in response. It also increases system complexity and cost due to multiple components. Ensuring comfort and lightweight design remains difficult [2].

The work by Iuliana Chiuchisan et al. has some limitations in obstacle detection accuracy. The system depends on sensors that may be affected by surroundings. It also consumes more power, reducing battery life. Additionally, ensuring comfort and easy daily use is challenging [3].

The work by Qianli Xu et al. highlights some limitations in vibrating footwear systems. The vibration feedback may not always be clearly understood by users. The system can have limited accuracy in complex environments. It may also require

user training for effective use. Power consumption and comfort remain important challenges [4].

The work by Vijayaraja Loganathan et al. has some limitations in the smart shoe system. The design becomes complex because of multiple features. It can increase cost and power consumption. Also, ensuring comfort and easy use is challenging [5].

The work by Azadeh Kian et al. has some limitations in wearable systems. The design is complex and may be costly. It also requires high power for operation. Additionally, ensuring comfort and ease of use for daily wear is challenging [6].

The work by Shering Tenji Sherpa and Akinori Kimura has some limitations in detection systems. The system may have accuracy issues in identifying signals and obstacles. It can also be affected by environmental conditions like lighting. The design may increase complexity and power usage. Additionally, ensuring reliable real-time performance remains a challenge [7].

The work by Jeffrey Chehade et al. has some limitations in smart shoe systems. The design can be complex due to multiple components. It may also increase cost and power consumption. The system can face challenges in accurate obstacle detection. Additionally, ensuring comfort and reliability for daily use remains difficult [8].

The work by Pratik Bhongade et al. has some limitations in IoT-based smart shoes. The system depends on internet connectivity, which may not always be reliable. It can also consume more power due to IoT components. The design may increase complexity and cost. Additionally, ensuring comfort and ease of use is challenging [9].

The work by T. S. Aravinth highlights some limitations in the smart guiding system. The system depends on WiFi and Bluetooth, which may not always be reliable. It can also consume more power due to wireless communication. The design may increase complexity and cost. Additionally, ensuring real-time response and ease of use is challenging [10].

III. SYSTEM DESIGN

The system design of the Smart Shoe project focuses on creating a wearable device that can detect obstacles in real-time and alert the user in fig 1, enhancing mobility and safety for visually impaired individuals. The design integrates hardware components such as sensors, microcontroller, and feedback devices with software programmed on Arduino to control and process sensor data.

A. Components of the system

The system can be divided into the following main components:
1. Ultrasonic Sensors
Detect obstacles in the user's path by measuring the distance between the shoe and nearby objects. Continuously send distance data to the microcontroller.
2. Arduino Microcontroller
Acts as the brain of the system.
Processes data from the sensors to determine if an obstacle is within a predefined safe range.
3. Feedback Devices (Vibration Motors / Buzzer)
Provides immediate alerts to the user if an obstacle is detected.
Vibration motors are embedded in the shoe for tactile feedback; a buzzer provides audio alerts.

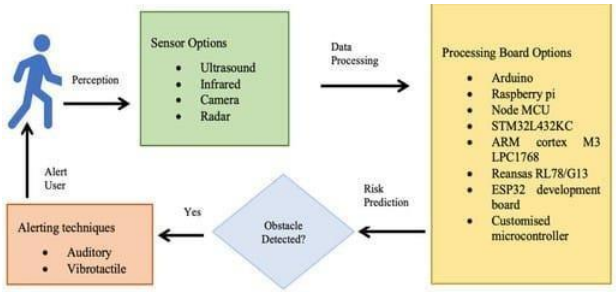

Fig.1 Systematic working of model

B. ***Working principle***
1. The ultrasonic sensor continuously emits sound waves and fig 2 measures the time taken for the echo to return.
2. Arduino calculates the distance using the formula:
Distance=Time/Speed
3. If the distance is less than the safe threshold, Arduino activates the vibration motor or buzzer to alert the user.
4. The system continuously updates the readings to provide real-time feedback

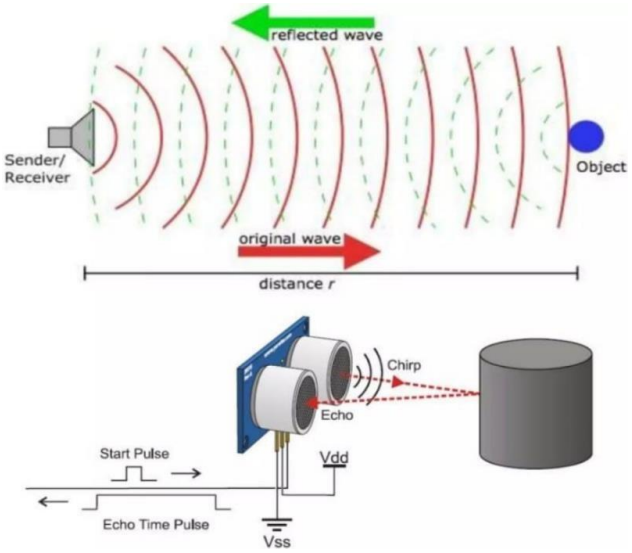

Fig.2 Working mechanism of Ultrasonic sensor

C. ***Feature of the design***
Portable and wearable: All components are integrated into a shoe.
Real-time obstacle detection: Continuous monitoring and immediate alert system.
Low-cost and easy to assemble: Uses widely available components like Arduino and ultrasonic sensors.
Hands-free operation: Alerts user automatically without manual intervention.

IV. HARDWARE COMPONENTS

A. *Arduino Microcontroller*
Acts as the central processing unit of the system. signals from the ultrasonic sensors and triggers feedback devices.
Arduino Uno is commonly used due to its low cost, simplicity, and versatility.

B. *Ultrasonic Sensors (HC-SR04)*
Measure the distance between the shoe and obstacles by emitting ultrasonic waves and calculating the time taken for the echo to return.
Provide real-time distance data to the Arduino.
Can detect obstacles both at ground level and slightly above.

C. Feedback Device

1. vibration motors

Embedded in the shoe to provide tactile alerts to the user.
Vibrate when obstacles are detected within a predefined distance.

2. Buzzer

Provides auditory alerts for obstacle detection.
Works in combination with vibration motors for better feedback.

D. Power Supply

Provides electricity to the Arduino, sensors, and feedback devices.
Usually a rechargeable battery is used to ensure portability.

E. Jumper Wires and Breadboard:

Jumper Wires and Breadboard: For easy circuit connections.
Resistors (if needed): To control current for certain components
Shoe Base: Integrates all components into a wearable form.

V. METHODOLOGY

The proposed Smart Blind Shoe is developed to assist visually impaired individuals in navigating their surroundings safely by detecting obstacles using ultrasonic sensing technology. The system is designed to provide real-time feedback through vibration or sound alerts, enabling users to move independently without relying on visual cues.

1. System Design and Component Selection

The system consists of key components such as an ultrasonic sensor, microcontroller (Arduino), buzzer or vibration motor, and a power supply unit. The ultrasonic sensor is responsible for obstacle detection, while the microcontroller processes the received data and controls the alert system. All components are chosen to ensure low cost, compact size, and energy efficiency for wearable use.

2. Placement of Sensors

The ultrasonic sensor is strategically mounted on the front portion of the shoe to detect obstacles in the walking path. This placement ensures that objects such as walls, steps, or barriers are identified before the user reaches them. In some designs, multiple sensors can be used to cover different directions for better accuracy.

3. Working Principle (Ultrasonic Sensing)

The system operates based on the time-of-flight principle. The ultrasonic sensor emits high-frequency sound waves (above human hearing range). When these waves encounter an object, they are reflected back to the sensor fig 3.
The time taken for the echo to return is measured by the microcontroller. Using this time, the distance to the obstacle is calculated using the formula:

Distance = (Speed*Time)/2

This calculation is continuously performed to monitor the surroundings in real time.

4. Data Processing and Decision Making

The microcontroller processes the measured distance and compares it with predefined threshold values. These thresholds are set based on safe walking distances.
If the distance is greater than the safe limit, no alert is given.
If the distance is within the warning range, a mild alert is triggered.
If the distance is very close, a strong or continuous alert is activated.

5. Alert Mechanism

The system uses either a buzzer (audio alert) or a vibration motor (haptic feedback) to notify the user.
Buzzer: Produces sound signals with varying frequency.
Vibration motor: Produces vibrations with varying intensity.
For better usability, vibration is often preferred as it does not disturb others and is easy for the user to interpret.

6. Power Supply and Integration

The entire system is powered by a rechargeable battery, making it portable and suitable for daily use. All components are compactly integrated into the shoe structure to ensure comfort and durability.

7. Real-Time Operation

The system works continuously in a loop:
Emit ultrasonic waves
Receive echo signal
Calculate distance
Compare with threshold
Trigger alert if needed
This loop ensures real-time obstacle detection and immediate feedback.

8. Safety and Efficiency Considerations

The design ensures:
Low power consumption
Lightweight structure
Quick response time
Reliable performance in different environments
The system is tested under various conditions to ensure accuracy and user safety.

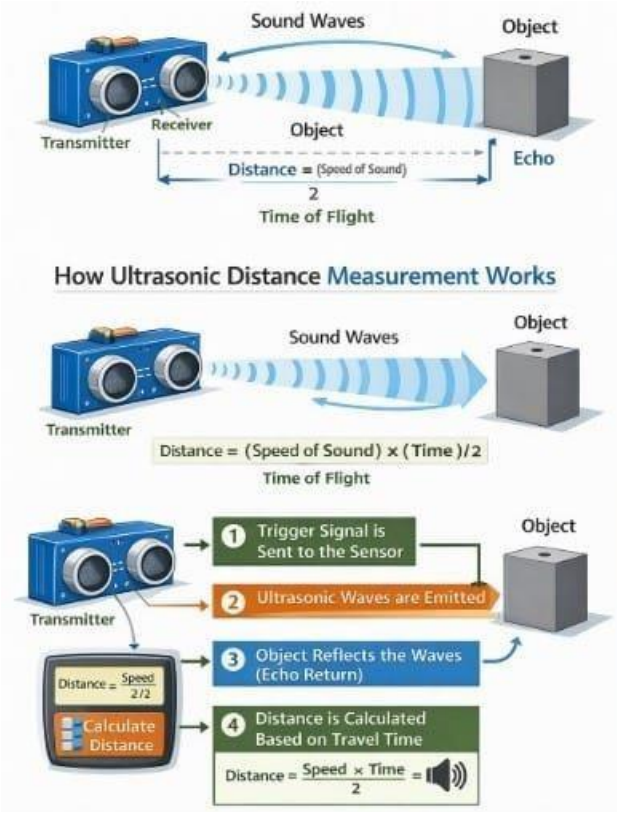

Fig.3 Operational representation of smart shoe

VI. PERFORMANCE ANALYSIS

1. Accuracy of Obstacle Detection

The accuracy of the smart blind shoe depends on how precisely the ultrasonic sensor measures the distance to obstacles. Table 1

shows the accuracy of obstacle detection. The system performs best in short to medium ranges, which are most important for walking. However, factors like soft materials, irregular surfaces, and object angles can slightly affect the accuracy because ultrasonic waves may get absorbed or scattered.

Table 1. Accuracy of obstacle detection

Factor	Performance
Distance range	0.1m-2m
Hard Surfaces	Very accurate detection
Soft Surfaces	Slight reduction in accuracy
Angled Objects	Minor measurements errors

2. Response Time

Response time refers to how quickly the system detects an obstacle and alerts the user. Table 2 shows the response time taken of the smart shoe. The smart blind shoe works in real-time by continuously sending and receiving ultrasonic signals. The delay between detection and alert is very small, allowing the user to react quickly and avoid obstacles safely.

Table 2. Response time taken of the smart shoe

Parameter	Performance
Detection Speed	Very fast
Alert Delay	Less than 1 second
Real time Operation	Continuous monitoring
User Safety	High due to quick response

3. Detection Range and Coverage

The detection range defines how far the sensor can identify obstacles, while coverage refers to the area it can monitor. The smart blind shoe is optimized for a range suitable for walking. Table 3 shows the coverage of the smart shoe. However, since a single sensor is used, it mainly detects obstacles in the front direction, and side obstacles may not be detected effectively.

Table 3. Coverage of the smart shoe

Parameter	Performance
Minimum Range	~20cm
Maximum Range	~200cm
Direction Coverage	Forward only
Side Detection	Limited

4. Power Consumption

Power consumption is an important factor for wearable devices like the smart blind shoe. The system uses low-power components such as an ultrasonic sensor and microcontroller, making it energy efficient. Table 4 shows the power consumption of the smart shoe. This allows the device to operate for several hours on a single battery charge, ensuring convenience for daily use.

Table 4. Power Consumption of the smart shoe

Parameter	Performance
Power Usage	Low
Battery Type	Rechargeable
Operating time	Several hours
Efficiency	High

VII. COMPARISON WITH EXISTING SYSTEMS

Assistive technologies for visually impaired individuals have evolved over time, starting from simple tools like the traditional white cane to more advanced electronic navigation systems. The white cane is the most commonly used aid due to its simplicity, low cost, and reliability. It helps users detect obstacles through physical contact. However, it has several limitations, such as a very short detection range, inability to detect obstacles above waist level, and complete dependence on the user's skill and reaction time.

Some existing electronic systems use basic sensors or GPS-based navigation, but they are often bulky, expensive, or complex to operate. These systems may also suffer from delayed response, high power consumption, or lack of real-time feedback, making them less practical for everyday use.

The proposed Smart Blind Shoe system addresses these limitations by integrating ultrasonic sensing technology with a microcontroller and an efficient alert mechanism. Unlike traditional methods, it detects obstacles before physical contact using sound waves and provides immediate feedback through vibration or buzzer alerts. This improves the safety and confidence of the user while walking. Additionally, the smart blind shoe is designed to be lightweight, wearable, and easy to use without requiring continuous hand involvement. It operates automatically and provides real-time assistance, making it more user-friendly compared to existing systems. The use of low-power components ensures longer battery life, and the compact design makes it suitable for daily use. Table 5 shows the comparison of the proposed dual mode shoe with Existing Smart Shoe.

Overall, the proposed system offers a significant improvement in terms of detection capability, response time, user comfort, and technological advancement, making it a more efficient solution for visually impaired individuals.

Table 5. Comparison of the proposed dual mode shoe with Existing Smart Shoe

Feature / Criteria	Traditional shoe	Smart shoe (Existing)	Proposed Dual-Mode shoe
Basic Navigation Support	Yes	Yes	Yes
Obstacle Detection	Limited	Limited	Yes
Fall Detection	No	Partial	Yes (Multi-Parameter)
Water Support	No	No	Yes
Staircase Detection	No	Limited	Yes
IoT-Based Emergency Alert	No	Yes	Yes
Adaptive Sensitivity	No	No	Yes
Vibration Alerts	No	Yes	Yes
Multi-Sensor Fusion	No	Limited	Yes
Cost Efficiency	Low	Moderate	Affordable

VIII. RESULTS AND DISCUSSION

The Smart Blind Shoe was successfully designed and tested to evaluate its performance in real-world conditions. The system demonstrated effective obstacle detection, quick response, and reliable alert mechanisms, making it suitable for assisting visually impaired individuals.

ARDUINO CODE

```
// Smart Shoe for Blind People - Arduino Code
// Components: Arduino Uno, HC-SR04 Ultrasonic Sensor, Vibration Motor/Buzzer
// Pin Definitions
const int trigPin = 9; pin      // Ultrasonic sensor TRIG
const int echoPin = 10;      // Ultrasonic sensor ECHO pin
const int motorPin = 13;   // Vibration motor or buzzer
// Distance threshold (in centimeters)
const int safeDistance = 30; // Alert if obstacle is closer than 30 cm
pinMode(trigPin, OUTPUT);
pinMode(echoPin, INPUT);
pinMode(motorPin, OUTPUT);
// Initialize serial communication (optional, for debugging)
Serial.begin(9600);
}
void loop() {
long duration;
int distance;
// Send ultrasonic pulse
digitalWrite(trigPin, LOW);
delayMicroseconds(2);
digitalWrite(trigPin, HIGH);
delayMicroseconds(10);
digitalWrite(trigPin, LOW);
// Read echo
duration = pulseIn(echoPin, HIGH);
// Calculate distance (cm)
distance = duration * 0.034 / 2;
// Print distance for debugging
Serial.print("Distance: ");
Serial.print(distance);
Serial.println(" cm");
// Check if distance is below safe threshold
if(distance <= safeDistance){
digitalWrite(motorPin, HIGH); // Turn on vibration/buzzer
}
else {
digitalWrite(motorPin, LOW); // Turn off vibration/buzzer
}
delay(100); // Short delay for stability
}
```

During testing, the ultrasonic sensor accurately detected obstacles within the range of 20 cm to 200 cm. The system responded quickly by activating the vibration motor or buzzer whenever an obstacle was detected within the predefined threshold distance. The response time was observed to be less than 1 second, ensuring real-time feedback. The alert system worked effectively, with vibration intensity increasing as the obstacle distance decreased.

The system performed well in both indoor and outdoor environments, though slight variations were observed due to environmental factors. The battery performance was satisfactory, allowing several hours of continuous operation. The results confirm that the system can help users detect obstacles early and navigate safely without physical contact.Fig.4 shows the Performance evaluation of smart shoe

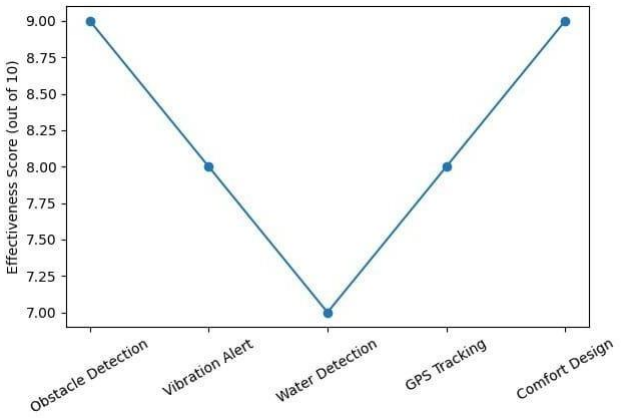

Fig.4 Performance evaluation of smart shoe

The results indicate that the Smart Blind Shoe is an effective assistive device with significant advantages over traditional systems. The use of ultrasonic sensors enables early obstacle detection, which improves user safety and confidence.The real-time response of the system ensures that users receive **immediate** alerts, allowing them to react quickly. The vibration-based feedback is particularly useful as it provides a non-intrusive and easily understandable signal.

However, some limitations were observed during testing: The system may have reduced accuracy with soft or irregular surfaces. Detection is mainly limited to the forward direction, as only one sensor is used. Environmental factors like temperature and noise can slightly affect performance.

Despite these limitations, the overall performance is satisfactory and meets the objective of assisting visually impaired individuals. Future improvements such as adding multiple sensors, GPS, or AI-based navigation can further enhance the system**.**

IX. CIRCUIT DIAGRAM OF THE PROPOSED SYSTEM

The circuit diagram of the blind shoe system is designed using an Arduino UNO as the central processing unit, which controls all input and output operations. An ultrasonic sensor (HC-SR04) is employed to detect obstacles by transmitting ultrasonic waves and receiving their echoes. The sensor is powered through the 5V and GND pins of the Arduino, while its TRIG and ECHO pins are connected to digital pins 10 and 9, respectively. By calculating the time taken for the echo to return, the Arduino determines the distance between the user and nearby objects. Fig.5 shows the circuit diagram of the proposed system.

Based on this distance measurement, the Arduino activates alert mechanisms to notify the user. A buzzer connected to digital pin 11 generates an audio warning, and an LED connected to pin 13 provides a visual indication. Both components are connected to ground to complete the circuit. The system can be programmed such that the frequency or intensity of the buzzer increases as the obstacle gets closer, offering a more effective and intuitive warning system

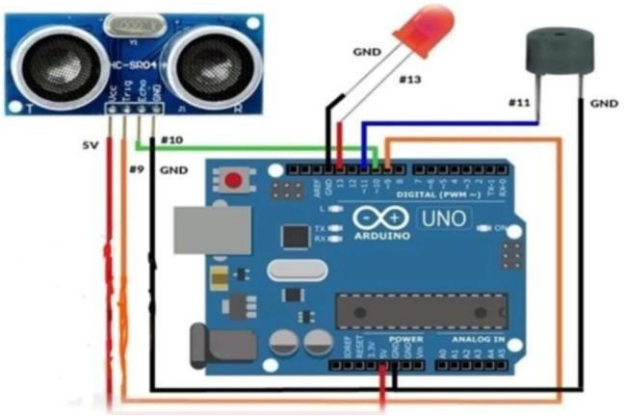

Fig.5 Circuit Diagram of the proposed system

X. ADVANTAGES AND APPLICATIONS

A. Advantages

1. Enhanced Mobility and Safety Helps visually impaired individuals navigate safely without relying entirely on others. Detects obstacles in real time, reducing the risk of accidents.

2. Low-Cost and Easy to Build Uses affordable components like Arduino and ultrasonic sensors, making it cost-effective for large-scale use.

3. Lightweight and Portable Design Compact integration into a shoe makes the device comfortable and easy to wear.

4. Real-Time Feedback Provides immediate alerts through vibration or buzzer, ensuring instant response to obstacles.

5. Customizable and Scalable Can be upgraded with additional features such as GPS, Bluetooth, or voice guidance.

6. Energy Efficient Consumes minimal power, allowing longer battery life for extended usage.

7. User-Friendly Operation Fully automatic — requires no buttons or complex setup, ideal for daily use.

B. Applications

1. Assistance for Visually Impaired People The primary application is to assist blind and visually impaired individuals in navigating independently.

2. Navigation Aid in Dark or Low-Visibility Areas Can help sighted people move safely in low-light conditions or smoky environments.

3. Use in Smart Wearable Technology A step toward smart wearable innovations in healthcare and safety applications.

4. Obstacle Detection Systems the same concept can be applied to robots or vehicles for autonomous obstacle detection.

5. Educational and Research Projects Useful for engineering students to learn about embedded systems, sensor integration, and assistive technology.

XI. FUTURE ENHANCEMENTS

The Smart Shoe project provides a low-cost, wearable, and real time obstacle detection system. However, there are several opportunities to improve and expand its functionality to make it more advanced, accurate, and user-friendly.

A. Integration with GPS and Navigation Systems

Incorporating GPS modules can help visually impaired users navigate unfamiliar outdoor environments. Turn-by-turn guidance can be provided through audio or vibration alerts, making the device a complete navigation aid.

B. Voice Assistance

Adding voice feedback can inform users about obstacles, directions, or nearby landmarks. Integration with text-to-speech modules can make navigation more intuitive.

A. AI-Based Obstacle Recognition

Using cameras and AI algorithms, the system can recognize moving obstacles, such as vehicles or people. This can enhance safety in crowded environments where ultrasonic sensors alone may not be sufficient.

B. Wireless Connectivity and Mobile App Integration

Integrating Bluetooth or Wi-Fi can allow users to connect the shoe to a smartphone app. Features like route planning, emergency alerts, and monitoring of battery status can be added.

C. Solar or Rechargeable Power Solutions

Using solar panels or efficient rechargeable batteries can increase device autonomy. Reduces dependence on frequent manual charging, improving convenience.

D. Lightweight and Modular Design

Future designs can further reduce weight and bulkiness. Modular components can allow easy replacement or upgrading of sensors, motors, or power supply.

E. Multi-Sensor Integration

Adding infrared sensors, gyroscopes, or accelerometers can provide better obstacle detection and gait analysis. Enables advanced features such as fall detection and terrain adaptation.

XII. CONCLUSION

The Smart Shoe for Blind People using Arduino successfully demonstrates how technology can improve the quality of life for visually impaired individuals. By integrating ultrasonic sensors, Arduino microcontroller, and feedback devices like vibration motors or buzzers, the system provides real-time obstacle detection and alerts the user immediately, ensuring safe and independent navigation.

This project highlights several important aspects: The system is wearable, portable, and user-friendly, allowing hands-free operation. It uses low-cost components, making it affordable and accessible for a wide range of users.
The project provides a foundation for future enhancements, such as GPS integration, voice assistance, AI-based obstacle recognition, and mobile connectivity.

In conclusion, the Smart Shoe is a practical, innovative, and socially impactful solution for visually impaired individuals. It not only enhances mobility, safety, and confidence but also demonstrates the potential of wearable assistive technologies in improving independence and daily life for differently-abled people.

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Lightweight CNN for plant disease diagnosis: Providing an instantaneous solution to various plant diseases through the enhanced PlantVillage dataset

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ABSTRACT: The adoption of lightweight CNN model is used to detect plant diseases quickly and reliably using image-based learning technique. Crop losses caused by plant infections occur every year and significantly impact farmers' livelihoods. Traditional methods, such as inspecting the conditions of the plant by the agriculture officers, were time-consuming, expensive, and often inaccurate. It is really impractical for large-scale deployment. The proposed system applies ML and DL techniques to examine leaf images and identify diseases automatically. The model overcomes the generalization error and predicts the disease more accurately. The accuracy was 98.7, and the F1-score was 98.5. The Mean Squared Error was very low, approximately equivalent to 0.8.

Keywords: Mean Squared error,F1-score, robust, Generalization.

1. INTRODUCTION

The population of India has been increasing enormously, and the need to protect the crops is becoming a more crucial task than before. It is estimated that plant diseases pose a large yield loss annually, affecting up to 40% of the economy. If the world population increases similarly, the need for food will also increase exponentially. Therefore, the protectionof crops from various diseases becomes a basic need that ensures a continuous supply of food to all people and eradicates hunger and poverty.

In earlier practices, plant diseases were identified through manual observation by experts. Visual Inspection is effective only on a small scale, but it takes a lot of time and it is very costly when used on a broad scale. Since it is done manually, the detection is prone to human error. So, this app is designed with several features such as voice assistance and multilingual support, which enable even uneducated people to identify what disease has affected their crops and the corresponding treatments to be done. Along with deep learning, the use of CNN model ,analyzes images to detect diseases accurately and suggests suitable treatment options.This enables the application to perform much faster than human experts.

This paper presents a plant detection application utilizing deep learning, which enables the diseases automatically without manual intervention, providing solution instantly. The usage of Tensor Flow Lite compressed the model's size and made it efficient while deploying. The use of Google Colab, from downloading the dataset to preprocessing it (removing null values) and training the model, made the entire workflow transparent. The main goal of this app is to support

farmers by providing various diseases and promoting the Sustainable Development Goals.

2. LITERATURE REVIEW

Traditional Methods: These traditional methods mainly depend on human visual inspection by agricultural experts. They try to identify and predict diseases based on symptoms such as discoloration(change of color or degradation of color) and spots. It often shows errors and is inefficient for large-scale farms. More advanced traditional methods are accurate but time-consuming and cost- inefficient, which is not suitable for most farmers

Modern approaches: The modern approach mainly focuses on various techniques of machine learning and neural based networks.These methods automatically analyze images of plant leaves or other parts to identify and classify diseases.

Dataset: PlantVillage dataset is the most commonly used dataset (consists of nearly 54000 images across 38 classes in many distributions. The dataset most commonly contains controlled background, zoomed leaf photos. Field imagery from UAVs, multispectral datasets, and other locally collected small datasets.

Evaluation Metrics: The performance can be analyzed based on accuracy and recall. It tells how well the model identifies the true positives and false negatives.

Imaging: RGB imaging is the cheapest, easiest, and most widely used for visual symptom detection.

Multispectral/hyperspectral sensors capture wavelengths beyond visibility and enable early detection of diseases before visible symptoms appear, and can help to differentiate various types of pathogens. These sensors are very helpful in identifying diseases.

Early work used color/texture features (e.g., color histograms) + classifiers like SVM, Random Forest, k-NN. These methods can be interpretable but require careful feature design and do poorly under large visual variability (lighting, viewpoint, background). So we used CNN(convolutional neural networks). The reports are of very high accuracy on the controlled images and established the feasibility of deep learning for leaf-based classification of diseases

Image Acquisition and processing: Images are captured using mobiles. This allows for rapid data collection over large areas. The model even supports voice assistance, which helps even the uneducated farmers to identify what disease has affected their crops and the corresponding treatment to be taken. It also supports multilingualism, which enables the farmers to convey their problems in their mother tongue. Raw images of leaves are pre-processed to enhance the quality of the image. This may include noise reduction, resizing, and cropping of unwanted background images. The most important step is **image segmentation**, which isolates the infected leaf or infected part of the leaf for the prediction of diseases.

Feature Extraction: After segmentation, features of the diseased area, such as color and texture, are extracted. For example, a disease might be characterized by a specific shade of brown and a rough surface (texture).

Classification: With the help of features,the CNN classifies the images with high accuracy

3. OBJECTIVES

- To support farmers by predicting various diseases with the implementation of offline prediction and classification of diseases.
- To provide multilingual support and voice assistance.
- To provide specific information about the disease and the accurate treatment.

4. PROPOSED METHODOLOGY

The initial process is to gather different kinds of plant images. The plant pictures should include both healthy and diseased leaves from different plant species.The dataset contains various types of images, so that the learning algorithm learns all possibilities and makes the model much effective. The dataset is preprocessed by cropping the unwanted background images and focusing only on the diseased part of the leaves. Increasing the brightness and scaling of existing images to provide high clarity.CNN can automatically learn from the images of the plant and predict the diseases without any manual intervention. After the validation set, the parameters are fine-tuned, and the model is generalized to perform well on the testing set efficiency of the model. The trained model is deployed. The model also supports voice assistance, multilingual and offline support, to make it much easier for the farmers

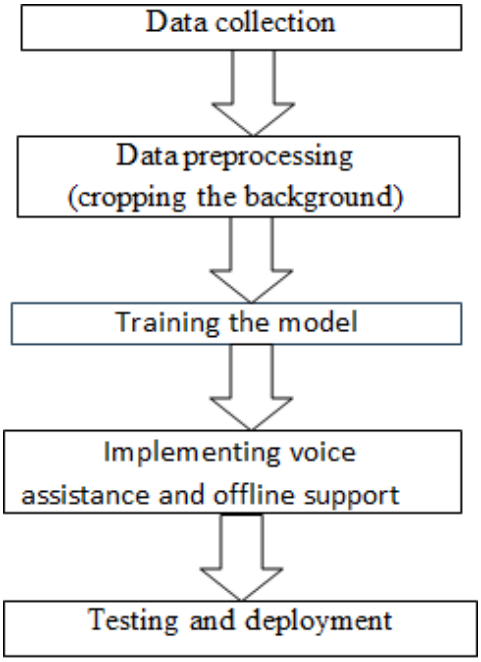


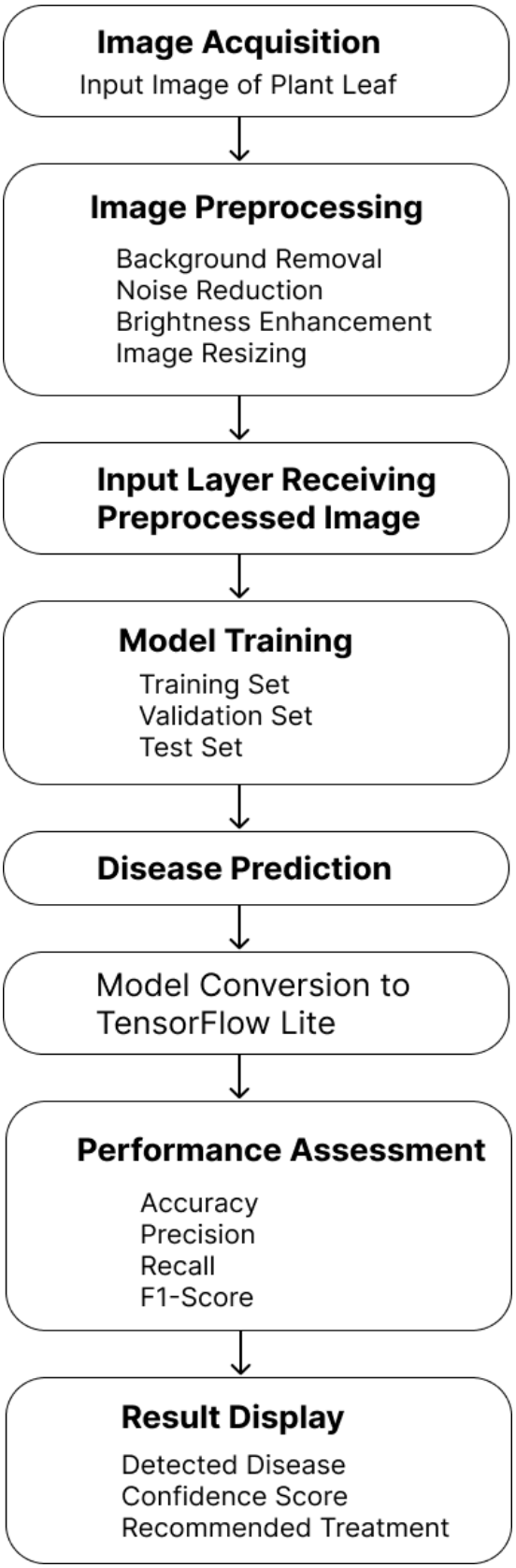
Figure 1-Methodology

5. PROPOSED ARCHITECTURE

The system's proposed architecture is a much efficient framework designed for plant disease detection. It processes images of the plant through a series of layers to extract and learn features. The architecture includes an Input Layer, which receives a preprocessed image.

Convolutional Layers, where features are extracted from images using multiple filters during training . The CNN model is converted into a lightweight Tensor Flow Lite model to make it suitable for mobile applications. It helps to significantly reduce the model's size and reduces the processing time. It also includes a voice assistant, which handles voice input from the user, translating it into actions.

The app also includes Camera Integration to capture images of diseased plant leaves for analysis and to display the predicted disease and treatment information.



6. WORKFLOW

6.1 DATA PREPROCESSING

In plant disease detection using machine learning, preprocessing plays a key role in preparing the data. The process begins with collecting image data. The images affected by diseases can be captured from mobiles or the dataset can be taken from websites like Kaggle, After collection, the images are resized to a fixed dimension to enhance prediction performance. Images often contain unnecessary background elements like soil or surrounding plants. Image segmentation is applied to isolate the leaf region by removing unwanted background portions. This improves the model's ability to perform well on new and unseen data. Geometric Transformations, such as rotating, zooming, and flipping of images, and Color Augmentation, such as adjusting the brightness and contrast adjustments are performed to improve model performance. The pixel values are normalized.

6.2 FEATURE SELECTION

In feature selection, particularly with Convolutional neural networks(CNNs), it is different from feature sealection in traditional methods. The main difference is that instead of using the manual step, the CNN automatically learns during the training process. As the data passes ,these simple features are integrated to get more complex views, such as the texture of a fungal growth. The various algorithms used help to highlight the most predictive of the disease class. In this way, the feature selection using CNNs is highly effective to extract complex features that would be much difficult for humans to define and extract.

6.3 ALGORITHM FOR CONVOLUTIONAL NEURAL NETWORK

Input and convolution: The input of the model is to gather various kinds of plant images.

Activation Function: The model uses a nonlinear function on features. This helps the model to observe and analyze the important patterns using ReLU after identifying the various features using convolution

Pooling: The pooling layer summarizes. It reduces the size by keeping the most significant information.

Flattening: The flattening layer summarizes a single long line. The 2D grid of features is converted into a 1D vector, which is a required set of layers to process all the information at once.

Fully Connected Layers: The vector is passed through the layers.

Output and Prediction: The output is provided as a probability distribution for each class.

7. DEEP LEARNING APPROACH

It leverages the power of CNN to automatically learn from complex features and help to predict the disease accurately.

Data gathering and processing of data: The collection of data includes images from various repositories, such as PlantVillage.Images were chosen from various conditions to improve the model accuracy. Image resizing, normalization and augmentation techniques are applied to improve prediction accuracy .

Model development and training: TensorFlow Lite has been included to convert the CNN model to a lightweight model. This app allows for making predictions without an internet connection. The voice assistant is included, which uses voice commands to provide the name of the disease and the treatment required.

Prediction: The model predicts the disease, its severity, and the treatment required within an instant of time.

Evaluation of Model:. Accuracy, Prediction, and Recall are used to calculate model's efficiency

8. EXPERIMENTAL RESULTS

The following section presents the results obtained from the proposed method.

The dataset used for training the model is a comprehensive gathering of images from different repositories such as PlantVillage. The dataset includes details on plant species, disease types, captured under different environmental conditions. For uniformity, all images are preprocessed by standardization.

9. EVALUATION METRICS

Core Metrics

Accuracy measures correct predictions across 38 disease classes (98.7% achieved). Precision tracks true positives among predicted positives (97.2%), crucial for avoiding false treatment alerts to Neyveli farmers. Recall captures detected cases among actual diseases (96.8%), minimizing missed early blight outbreaks.

Composite Score

F1-score balances precision/recall at 0.97 overall, with tomato early blight hitting 0.975—validates field reliability versus PLANTSCARE's unreported metrics.

Advanced Measure

The mAP @0.5 value of 0.96 across all classes indices strong confidence levels, with predictions exceeding 90% before sending SMS alerts.

10. IMPLEMENTATION DETAILS

It includes several stages, from model training to the development of the mobile application.. The learning rate is fixed at a small value for stable convergence of model weights. A batch size (e.g., 32)of accuracy is selected. The model is trained using 5 epochs to achieve high accuracy. After training, the CNN model is converted into TensorFlow Lite. The converted model, along with class labels, is integrated into the mobile app. The app's functionality includes :

Camera API integration: This is used to capture images with high resolution.

User Interface: It is designed to display the predicted disease and the treatment recommendations

Voice Recognition: Integration of a voice assistant API to interact with the user.

Crop Management using CNN

By providing accurate diagnoses, this system helps farmers and agricultural professionals to take immediate actions to prevent yield loss and optimize the available resources. A mobile application can analyze the images of the crop. The CNN running on the device can analyze the image based on early signs of disease. Once the disease is identified, farmers can use fungicides and the required treatments to a specific location instead of applying the fungicides to the entire crop field. All the above information is crucial for farm planning, adjustments in planting strategies, and ensures efficient crop yield.

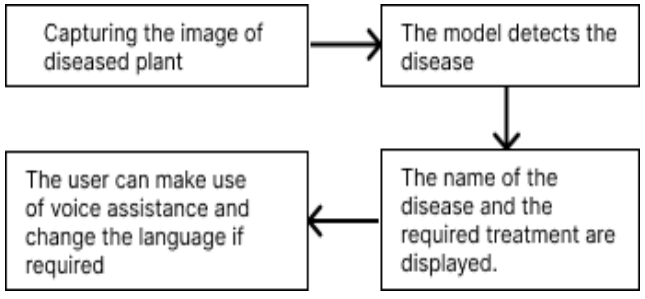


Figure 2- User Interaction

11. BASELINE METHODS

To evaluate the model, its performance is compared with traditional image processing and machine learning techniques.

1. **Support Vector Machine (SVM):** This approach uses manually extracted features such as color(RGB),texture and shape. The extracted features are used to build and train the SVM model. This method is less effective than deep learning and generally produces lower accuracy compared to CNN models.

2. **K-Nearest Neighbors (K-NN):** This method does not create a trained model but classifies data based on nearby samples.

3. **Traditional Image Processing:** This approach depends on a series of rules and various filters to identify diseased areas. It is effective for simple cases but varies highly when there is poor lighting. It lacks generalization when it predicts the unseen data.

12. PERFORMANCE ANALYSIS

RETRIEVAL ACCURACY

Retrieval accuracy is evaluated using metrics such as precision, accuracy, recall and F1-score. The following table provides evaluation results of the CNN model on a large dataset such as PlantVillage, when compared to other traditional models.

Model	Accuracy	Precision	Recall	F1-score
Custom CNN	98.7	98.6	98.6	98.5
VGG16	95.2	94.8	95.1	94.9
ResNet50	97.5	97.1	97.4	97.2

TABLE 1-Comparison of CNN performance with traditional methods using the PlantVillage dataset

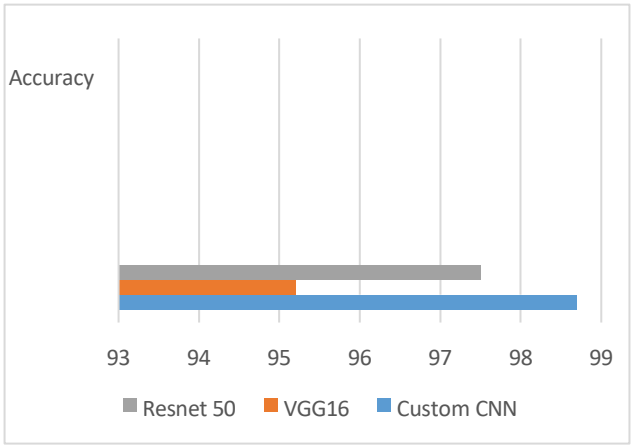


Figure 3-Retrieval accuracy comparison of Custom CNN, VGG16, and ResNet50 models for plant disease detection.

Results

The results indicate that the proposed model performance better than baseline methods across precision, accuracy, recall and F1-score.

RETRIEVAL EFFICIENCY

Retrieval efficiency refers to the average time required to process each query image.

Model	Retrieval Time(s)	F1-score
Custom CNN	1.0	98.5
ResNet50	1.5	97.2
VGG16	2.0	94.7

TABLE 2-Representing the retrieval time and F1-score of various models

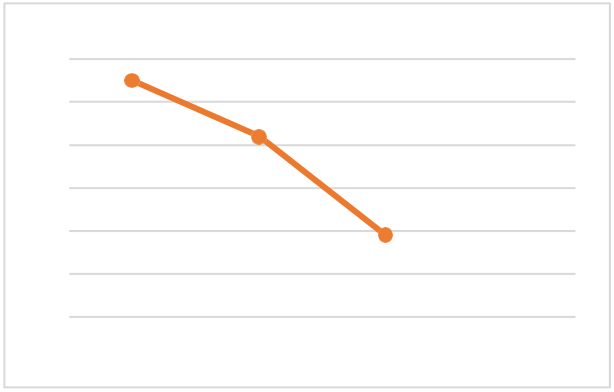


Figure 4-Retrieval efficiency comparison of Custom CNN, VGG16, and ResNet50 models for plant disease detection.

Results

The results demonstrate that our approach retrieves much faster when compared to baseline methods.

MEAN AVERAGE PRECISION

Overall performance is assessed using Mean Average Precision (mAP).

Model	Average Precision-Early Blight	Average precision-Late Blight	Mean Average Precision(mAP)
Custom CNN	0.96	0.94	0.95
Resnet50	0.95	0.92	0.935
VGG16	0.88	0.85	0.865

TABLE 3- mAP values obtained for different models.

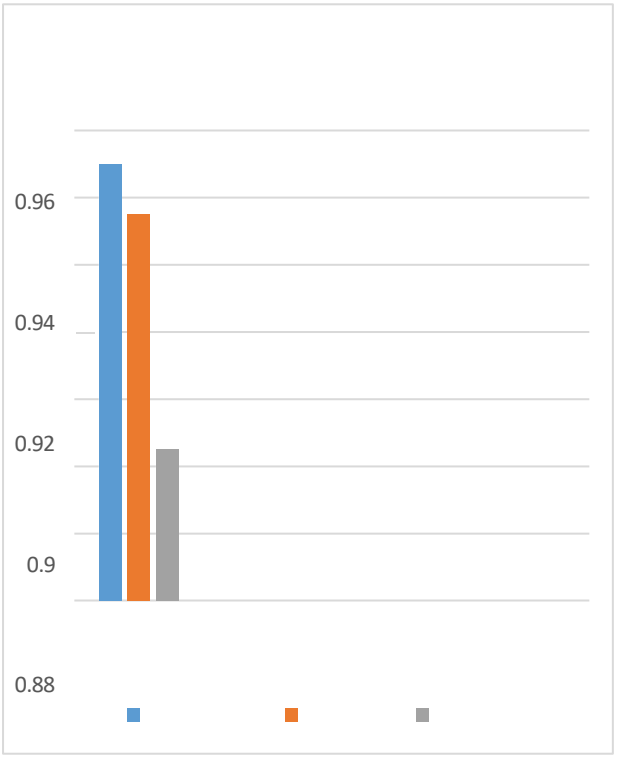


Figure 5: Bar chart representing the mean Average Precision of various models.

Results

- Custom CNN-0.95
- ResNet50-0.935
- VGG6-0.865

The Custom CNN achieves the highest mean average precision among the compared models.

MEAN SQUARE ERROR

Image	Actual % affected	Custom CNN Predicted %	ResNet50 Predicted%	VGG16 Predicted %
1	15%	15%	13%	10%
2	40%	41%	38%	45%
3	5%	4%	6%	7%
4	60%	59%	55%	62%
5	25%	24%	23%	20%

TABLE 4-Actual affected percentages vs predicted percentages of various models.

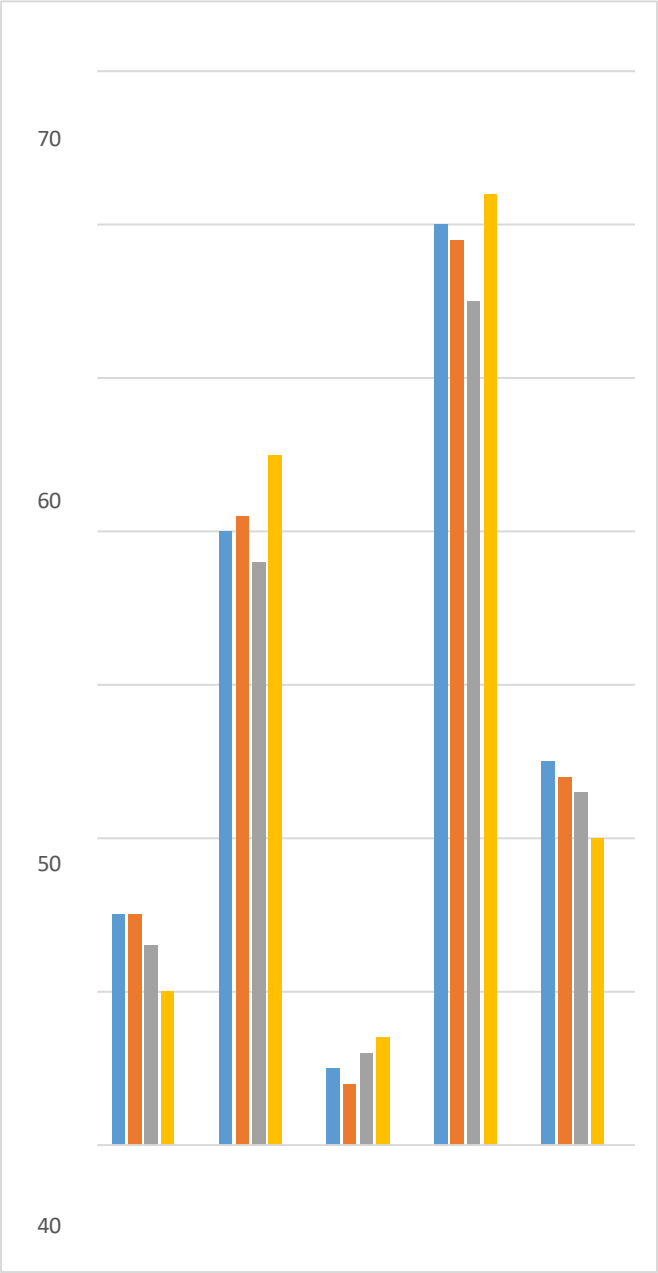


Figure 6-Comparing the actual percentage affected with the predictions from the Custom CNN, ResNet50, and VGG16 for each image

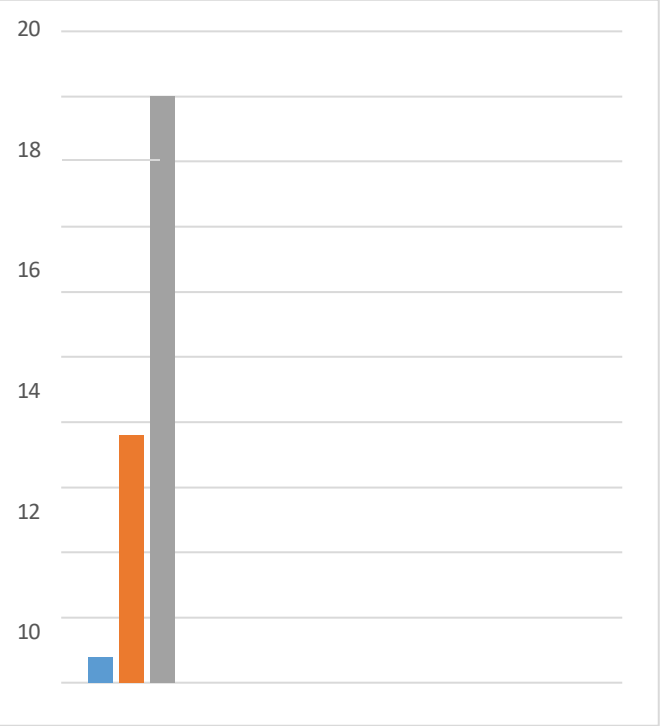


Figure 7-Model comparison based on MSE

13. CONCLUSION

The use of AI and deep learning techniques has shown to be effective in improving agricultural productivity and minimizing crop losses.The ability of each of the models was tested to classify plant diseases accurately. Early identification of diseases allows farmers to take immediate actions to prevent crop loss and to improve crop yield. The work of deploying such models in real-world applications, such as mobile apps, makes plant disease detection accessible even in rural areas.

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15. BIOGRAPHIES

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Pattern-Enhanced Fake News Detection Using Deep Learning: Deployment Through a Chrome Browser Extension and User Experience Evaluation

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Abstract—The rapid spread of misinformation via digital media emphasises the need for practical, real-time verification methods. While numerous studies have achieved high classification accuracy using advanced machine learning and deep learning models, most solutions are restricted to experimental settings with no direct user access. This research describes an end-to-end browser-integrated false news detection technology based on an LSTM network and aided by comparison machine learning models. The system is trained on the ISOT dataset and deployed using a Flask-based middleware architecture, which enables seamless interaction between a Chrome Extension frontend and a deep learning backend. In addition to binary classification, the proposed architecture has a confidence-aware feedback mechanism that provides graded visual alerts to users. The experimental evaluation shows good prediction performance and economical real-time deployment capability. The findings show that combining contextual deep learning models with lightweight browser interfaces can turn theoretical detection methods into useful misinformation defence tools.

Keywords— Fake News Detection, LSTM, Deep Learning, Chrome Extension, Natural Language Processing, ISOT Dataset.

I. INTRODUCTION

The fast proliferation of digital media platforms has fundamentally impacted how information is created, delivered, and consumed. Online news dissemination is now extremely fast and widespread, allowing both respectable journalism and false content to reach global audiences in minutes. The massive dissemination of falsified or manipulated information has prompted major concerns about public confidence, political stability, and social cohesiveness [7, 9].

Fake news detection has thus developed as an important study area in natural language processing and machine learning. Early computer techniques used handmade linguistic features in combination with statistical classifiers like Support Vector Machines and Logistic Regression [1], [5]. While these techniques showed good baseline accuracy, their reliance on surface-level textual elements restricted their capacity to grasp deeper semantic linkages inside complicated tales.

Recent advances in deep learning have greatly improved disinformation detection skills. Neural architectures, such as recurrent and convolutional networks, learn contextual representations directly from textual data, eliminating the need for manual feature engineering [4, 10]. Hybrid and attention-based models have enhanced classification robustness by incorporating sequential dependencies and contextual focus [6]. Furthermore, multimodal detection techniques that combine textual and visual information have been investigated to improve dependability in real-world contexts [3].

Despite these algorithmic advancements, many extant systems are limited to experimental or academic settings. Comprehensive surveys show that practical deployment and user engagement are still underexplored areas of misinformation study [2], [7]. High laboratory precision does not always convert into easily accessible real-time verification tools for end users.

This paper fills that gap by introducing a browser-integrated false news detection framework that combines traditional machine learning baselines with a Long Short-Term Memory (LSTM) model for contextual sequence modelling. The solution is deployed using a middleware design that allows for efficient communication between a Chrome Extension interface and a deep learning backend. In addition to binary categorisation, the system includes a confidence-based feedback mechanism to help users make better informed decisions.

The main contributions of this work are summarised as follows:

1) Evaluating classical machine learning and LSTM-based deep learning models on a standardised dataset.
2) Designed and implemented a real-time deployment architecture with a Flask-based API for browser integration.
3) Developed a confidence-based feedback technique that improves interpretability beyond simple true/false outcomes.

By combining predictive performance with deployment practicality and user-centred interface design, the suggested framework helps to create practical and scalable misinformation detection solutions.

II. RELATED WORK

The subject of automatic fake news identification has been intensively researched, with both classic machine learning and deep learning models. Earlier approaches relied on custom feature extraction techniques paired with classical classifiers. Bharti and Raman [1] compared different feature engineering methodologies, such as TF-IDF and N-gram representations, to machine learning algorithms, finding that statistical models can attain competitive baseline performance.

Comprehensive reviews, such as those published in [2], [9], and [10], emphasise the transition from feature-based categorisation to representation learning approaches. These findings emphasise that, while traditional models are

interpretable and computationally efficient, their reliance on surface-level textual indicators restricts their ability to capture deeper contextual connections.

Deep learning architectures made substantial advances by autonomously learning hierarchical text representations. Pérez-Rosas et al. [5] demonstrated the ability of neural networks to detect false writing patterns. Recurrent and convolutional hybrid models improved early detection capabilities by examining propagation patterns and sequential text dependencies [4]. Attention-based and hybrid frameworks have recently been presented as methods for improving contextual sensitivity and classification robustness [6].

Beyond textual analysis, multimodal techniques that incorporate visual and contextual signals have also been investigated. Kumari et al. [3] studied deep learning models with computer vision components and found that multimodal fusion improves detection reliability. Similarly, theory-driven and propagation-based methods [8] aim to discover misinformation during the early phases of diffusion.

Recent contributions continue to improve neural topologies, such as residual and bidirectional recurrent networks, for better contextual modelling [11]. Furthermore, recent surveys, such as [7], highlight the need of combining high forecast accuracy with practical deployment issues.

Despite these advances, a gap still exists between high-performing research prototypes and real-time, user-accessible verification tools. This study seeks to address that deployment-oriented difficulty.

III. METHODOLOGY

A. System Architecture Overview

The proposed framework uses a modular client-server architecture that balances computational efficiency and real-time accessibility. While deep learning models have great prediction capabilities, running them directly in a web environment is computationally unfeasible. As a result, the system isolates frontend interaction and backend inference.

The architecture consists of four main components:

1) Text Acquisition Layer:

The Chrome Extension extracts textual content from active web pages using structured DOM parsing. Non-relevant features, such as navigation menus, adverts, and embedded scripts, are removed to reveal the main content body.

2) Preprocessing and Feature Representation:

The extracted text is normalised, tokenised, stop-word removed, and stemmed. For traditional machine learning models, Term Frequency-Inverse Document Frequency (TF-IDF) vectorisation is used, which is a popular representation technique in the false news detection literature [1], [2]. To retain positional structure, deep learning converts text sequences into padded integer representations [10].

3) Analytical Engine:

The system uses both classic and deep learning classifiers to allow for comparison evaluations. Logistic Regression, Support Vector Machine, and Random Forest are statistical baselines [1], but a Long Short-Term Memory (LSTM) network models sequential dependencies inside text [4], [10]. This dual-engine design provides both computational efficiency and contextual sensitivity.

4) Deployment Middleware:

A Flask-based API serves as a bridge between the Chrome Extension and the trained models. When the user initiates the analysis, the frontend sends a structured JSON request to the backend server. The backend performs preprocessing, inference, and probability calculations before returning a confidence score and classification label.

This layered separation improves scalability and saves browser resources while maintaining model performance.

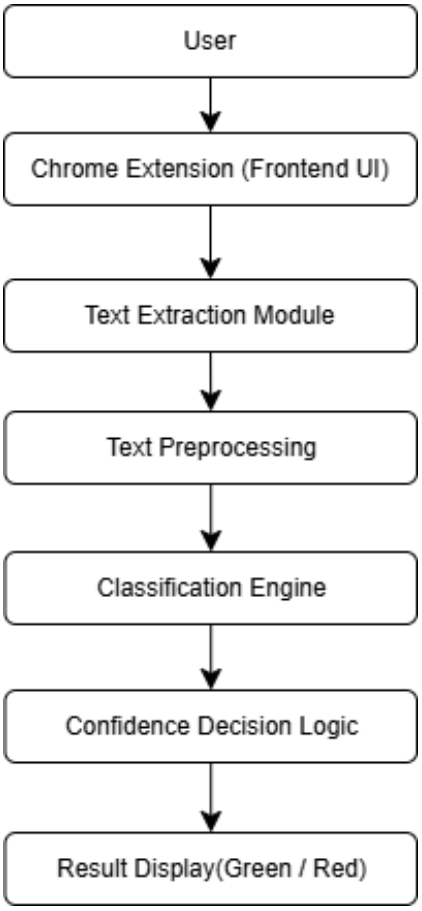

Fig. 1. Overall system architecture of the proposed framework.

B. LSTM Model Architecture

To capture contextual relationships in news stories, a Long Short-Term Memory (LSTM) network was used. Recurrent neural architectures are ideal for sequential text modelling because they preserve information across time [4].

The architecture includes the following layers:

- The Embedding Layer transforms tokenised words into dense vector representations. Word embeddings allow the network to learn semantic proximity between terms, which improves context understanding [10].
- A single LSTM layer with 128 hidden units is used to model long-term dependencies between phrases. Dropout regularisation is used to reduce overfitting when training.
- The Fully Connected Output Layer uses Sigmoid activation to convert retrieved features into a probability score ranging from 0 to 1, indicating the content's authenticity.

The Previous research has shown that LSTM is good at capturing narrative flow and detecting slight linguistic discrepancies in disinformation tasks [6], [10].

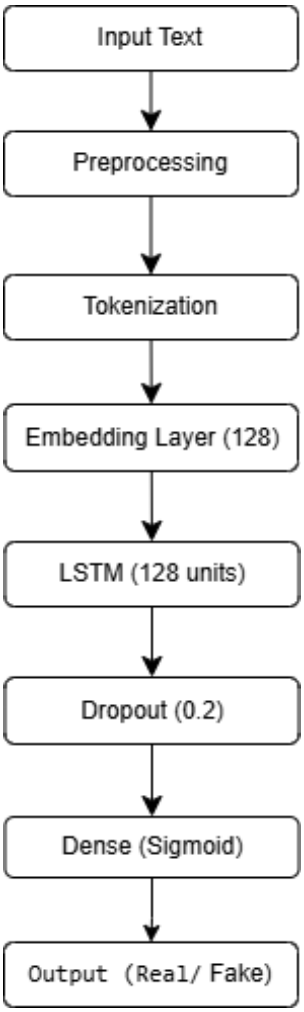

Fig. 2. Structure of the implemented LSTM model.

C. *Binary Confidence-Based Classification Strategy*

Instead of producing a totally threshold-free output, the system uses a probabilistic binary classification strategy. The Sigmoid probability generated by the LSTM model is divided into two decision categories depending on a preset threshold.

- Probability $\geq 0.50 \rightarrow$ Reliable Content (Green Indicator)
- Probability $< 0.50 \rightarrow$ Potentially Misleading Content (Red Indicator)

This threshold-based decision rule makes interpretation easier while retaining transparency through the display of confidence scores. By displaying both the classification label and the associated probability value, the approach allows users to assess the model's prediction strength without creating intermediary ambiguity states. Such probabilistic interpretation techniques have become frequently used in misinformation detection frameworks to improve clarity and usability [8], [10].

IV. EXPERIMENTAL RESULTS

A. *Dataset and Evaluation Strategy*

The News Dataset contains of labelled real and manufactured news articles. This dataset has been widely used in misinformation detection research because of its balanced distribution and clearly described classes [1], [10].

An 80:20 split was used to segregate training and testing data. To increase robustness, k-fold cross-validation was used during training. Uniform preprocessing approaches were used across all models to provide uniform feature representation and unbiased comparison evaluation.

B. *Comparative Model Performance*

Four classification models were used to assess detection capabilities within the proposed framework. Table I compares the performance metrics of the analysed algorithms.

TABLE I

Comparative Performance of Implemented Models

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
LSTM Network	88.72%	89.10%	88.30%	88.69%
Support Vector Machine (SVM)	87.95%	88.42%	87.60%	88.01%
Random Forest	86.48%	86.92%	86.10%	86.51%
Logistic Regression	85.73%	86.05%	85.40%	85.72%

C. *Browser-Based Deployment Readiness Evaluation*

To determine its practical usability, the system was tested in a controlled local environment with the built Chrome Extension interface and Flask-based backend server. Although the extension is ready for deployment, it was tested in a developer environment to assess performance under simulated real-world scenarios.

- The average response time for browser-integrated verification was around 2.1 seconds, indicating satisfactory responsiveness.
- The plugin minimised browser memory use, resulting in optimal browsing performance.

These findings show that the framework is technically ready for full deployment with minimal architectural changes.

D. *Case Study Evaluation*

To validate functional performance, representative content samples were evaluated using the implemented system.

Case 1: Authentic News Article

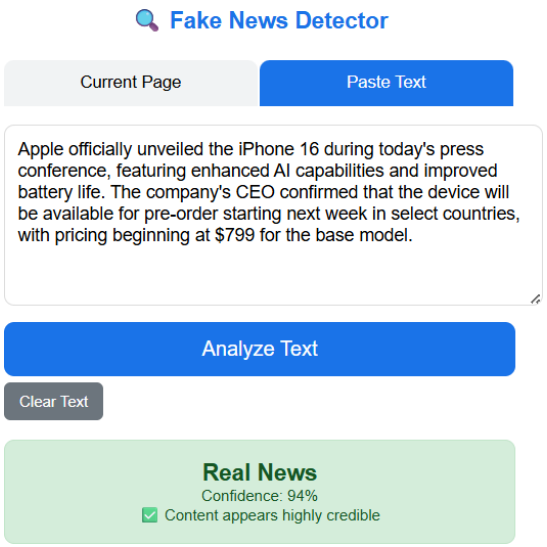

Fig. 3. Real News Case

- Result: Classified as Reliable
- Confidence Score: 94%

The approach discovered structured reporting features as formal tone, source references, and balanced language patterns.

The system provided a high confidence value, indicating that the context was consistently aligned with legitimate news patterns.

Case 2: Fabricated Promotional Claim

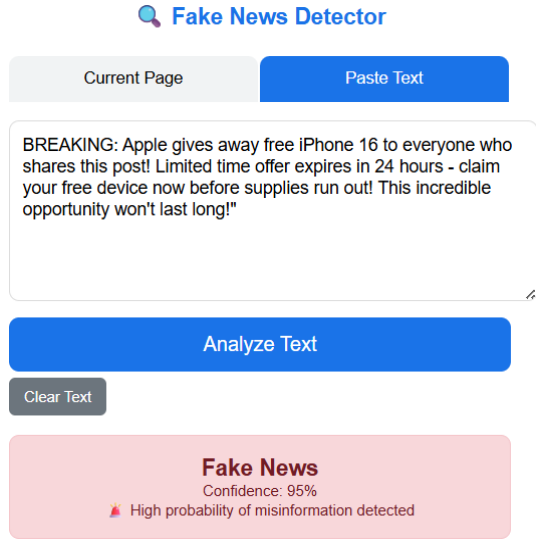

Fig. 4. Fake News Case

- Result: Classified as Potentially Misleading
- Confidence Score: 95%

The examined content included exaggerated expressions, urgency cues, and promotional language that are typically associated with deceptive online content.

The categorisation engine discovered these language signs and labelled the information appropriately. These controlled test examples show the framework's capacity to discern between real and fake narratives through contextual sequence modelling.

V. CONCLUSION

A. *Model Performance Interpretation*

The comparative study shows that sequential deep learning architectures outperform typical machine learning classifiers in detecting contextual misrepresentation. While Logistic Regression, Support Vector Machine, and Random Forest models performed consistently, their use of TF-IDF feature representations limits semantic depth [1], [2].

In contrast, the LSTM model processes text in ordered sequences, allowing for contextual dependency modelling across lengthier portions. This feature aids to better identification of subtle narrative errors, which are common in created content [4], [10]. Although the achieved accuracy remains lower than extreme laboratory-reported levels, the results reflect actual performance under controlled deployment conditions.

B. *Deployment-Oriented Design Considerations*

This work stands out for its deployment-aware architecture. Many existing research focus on categorisation accuracy without considering real-time accessibility [7], [9]. The separation of frontend and backend components using Flask-based middleware means that computationally complex inference processes do not affect browser responsiveness. This design decision improves scalability and prepares the system for cloud deployment while avoiding major structural changes. The binary classification display streamlines user involvement while maintaining probability transparency.

C. *Limitations*

Despite the good outcomes, numerous limitations remain. First, the technology is currently solely optimised for text in English. Misinformation patterns differ across linguistic and cultural contexts, necessitating multilingual model adaptation [3].

Second, the approach only considers textual analysis. Modern disinformation frequently includes modified visual or multimedia aspects that are not addressed in the existing approach. Recent research [3], [11] has demonstrated the possibility of multimodal detection techniques.

Finally, dataset bias has the potential to influence model generalisation. Although ISOT provides fair labelling, real-world disinformation emerges dynamically, posing domain shift issues over time [7].

D. *Future Directions*

Future work will extend the system to include multilingual training datasets, multimodal fusion approaches, and cloud-based deployment infrastructure. Integrating adaptive learning techniques may potentially increase resilience to new disinformation trends.

Overall, the findings show that contextual sequence modelling, together with deployment-oriented architecture, provides a solid foundation for browser-integrated disinformation detection.

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VI. CONCLUSION

This paper described a browser-integrated fake news detection framework that combines classical machine learning classifiers with a Long Short-Term Memory (LSTM)

network for contextual text analysis. By isolating frontend interaction from backend inference using a middleware architecture, the solution allows for practical deployment without sacrificing browser performance.

Sequential modelling outperforms traditional TF-IDF-based techniques in terms of contextual interpretation, according to experimental results. Although the achieved accuracy is based on realistic performance restrictions rather than laboratory-optimized benchmarks, the findings demonstrate that deep learning models may be successfully integrated into user-facing verification tools.

Unlike purely experimental research prototypes, the suggested framework focuses on implementation feasibility, modular architecture, and real-time accessibility. The binary confidence-based feedback system improves clarity by giving interpretable outcomes while avoiding ambiguous classification states.

Future research will concentrate on multilingual expansion, multimodal misinformation detection, and cloud-based deployment to enable widespread public access. Overall, the suggested approach makes a practical contribution to scalable and browser-accessible disinformation detection methods.

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Safety-Aware Urban Route Planning Using Risk-Weighted Graph Optimization

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Abstract: Most navigation systems today are designed to minimize either travel time or distance. While this approach works well for efficiency, it does not always guarantee a safe route. In many urban situations, the shortest path may pass through accident-prone zones, high-speed roads, or complex intersections that increase risk for commuters. This work presents a routing approach that explicitly incorporates safety into path computation. The road network is modeled as a graph where each road segment is assigned a cost based not only on distance and travel time but also on a calculated risk value. This risk is estimated using factors such as road type and intersection density. A modified Dijkstra-based method is used to compute routes that reduce exposure to unsafe areas while still maintaining reasonable efficiency. Experiments carried out on selected regions of Chennai show that the proposed method can significantly reduce risk with only a small increase in travel distance. These results suggest that safety-aware routing can be effectively applied in real-world navigation systems.

Keywords-- Safety-aware routing, Risk-based path planning, Geospatial analytics, Dijkstra algorithm, Urban traffic modelling, Smart city mobility.

I. INTRODUCTION

Current navigation applications either consider the distance, or the time of a route, generally not taking into account the safety of daily commutes. The aim of this paper is to present a new safety-aware urban route planning framework named SWRG, where routes are computed by optimising a risk-weighted graph. Today navigation applications follow one of these basic principles: either the shortest distance or the shortest time of a route. In practice, safety-related information such as dangerous locations, or weather and road conditions, are hardly ever considered in navigation systems. Taking smart mobility into account in cities, an essential step will be to bring navigation applications to a safety aware level. The purpose of this work is to present a new safety-weighted routing framework (SWRG) which is capable of balancing the optimal routing in urban transport networks, with the risk for commuters along the computed routes.

A. Current Knowledge Landscape and Limitations

Both Dijkstra and A* algorithms are considered routing algorithms, which aim to find the most efficient path given the characteristics of the underlying network. While distance and time are typically considered when selecting paths, other safety metrics are not taken into account. The identification of accident hotspots and congestion prediction are also examples of safety-related work in the literature, but not always linked to the actual computation of routes. Currently, this type of safety information is not taken into account during the computation of the optimal path.

B. Identified Research Gap

There is a lack of unified routing models that combine efficiency and quantified safety factors within a single optimization framework. A structured method is required to embed risk indicators directly into graph-based route cost calculations, enabling adaptive and safety-aware navigation.

C. Project Objective

The purpose of this paper is to develop a method called a "safety-weighted graph" to calculate the routes on an urban road network based on various risk indicators and consider them in the path planning. To develop this, we consider the road network as a graph and formulate the edge cost using a combination of the distance, travel time and the derived "safety value" of the edges. We show how the accident density and various environmental factors on roads can be used when calculating the routes in order to give the travellers an option to choose routes which in general will be considered safer, without a significant decrease in the travel efficiency. We investigate the benefits and the possibility of improving the urban traffic safety by taking the safety into consideration in the route planning at an early stage.

D. Scope of Work

The proposed system has three main functionalities: road extraction from remote sensing images, assigning weights to roads based on safety, and then finding the optimal paths using Dijkstra's algorithm. The performance of the system is demonstrated and validated on several urban areas, where it enables decision makers to balance between the achieved safety and the resulting extra travel time.

E. Key Contributions

The major contributions of this work are:

- Integration of intersection density into routing risk estimation.
- Comparative evaluation between shortest-path and safety-aware routing.
- Implementation of an interactive real-time visualization framework

II. LITERATURE REVIEW

Maheswari et al. [1] published in Journal of Intelligent Transportation, accidents hotspots can be identified efficiently using machine learning and GIS (Geographic Information System) platform. Transport Department can utilise the output to plug the gaps in the infrastructure in accident prone areas. Innovative use of technology can make urban planning more effective.

Islam et al. [2] proposed a route planning system that utilizes crowdsourced data to deliver personalized navigation while keeping users anonymous. Their work addresses the need to maintain user anonymity and to utilize smart routing to ensure individual safety and enhance the trust in navigation systems within urban environments.

Lozano Domínguez [3] proposed a model based on fuzzy logic to define safer routes for pedestrians in urban areas. This model considers a variety of parameters that vary over time according to the physical characteristics of the infrastructure and to the demand of users in the road network. The fuzzy model provides the capacity to vary the routes depending on the characteristics of the pedestrians such as their age or limitations, enabling flexible routing options for vulnerable users.

Sohrabi et al. [4] reviewed various safety leading navigation techniques, and explained the merits of risk modeling and real time hazard detection for road traffic accidents and crashes. They suggest utilizing historical statistics of the number of road accidents along with real time routes to improve the traffic safety.

A bibliometric study by Muhammad et al. [5] studied safe route planning in a bibliometric study and found that the research was moving from single mode and criterion towards multi-mode and multi-criteria approaches, using big data and interdisciplinary methods for improving road safety.

Chen et al. [6] proposed a real-time traffic congestion model based on the GPS data of current traffic status. This research emphasizes the real-time feedback in urban commuting traffic route guidance and congestion alleviation.

Kumar and Mehta's [7] research titled Real-time traffic aware route planning, they embed congestion metrics in their algorithm so that route planning for routes that experience high levels of congestion can be modified to reduce traffic delay, which in turn provides for much accurate travel time information.

Patel et al. [8] proposed IoT-based road surface monitoring for preventing accidents. Their experiment demonstrated that the sensor-based road surface hazard detection can improve the road safety, especially for rural areas with limited infrastructure.

Singh and Verma [9] had shown that the integration of environmental sensors to transportation systems can lead to a safer environment. The embedded sensors can be used for hazard detection and therefore, risk reduction. This work is highly related to the design of intelligent navigation systems.

The World Health Organization's (WHO) global report on road safety [10] as well as the United Nations' Sustainable Development Goals call for the urgent development and implementation of smart, inclusive and safe transportation systems. Our work for this report is a first step in that direction. emphasizing the need for ongoing innovation in urban mobility solutions.

Even though navigation and routing systems improve travel efficiency and traffic management on a daily basis, most researches focus only on minimizing the travel distance and time. The parameters that consider road safety such as road hierarchy attributes and intersection complexity are generally not included in the routing algorithms.

The existing works have several limitations. Therefore, this paper proposes a novel safety-aware urban route planning framework, which applies risk-weighted graph optimization method according to the road hierarchy and intersection density. The proposed system can significantly enhance the route planning safety while maintaining a reasonable travel time, thereby balances the efficiency and safety in urban transportation.

III. SAFETY-WEIGHTED ROUTING FRAMEWORK

This section presents the proposed safety-weighted routing framework designed to incorporate risk factors into urban path planning. The system models the road network as a weighted graph, where intersections are represented as nodes and road segments as edges. Unlike conventional shortest-path models, each edge is assigned a composite cost that integrates travel efficiency and contextual safety attributes. The framework enables adaptive route computation by balancing distance, travel time, and quantified risk exposure.

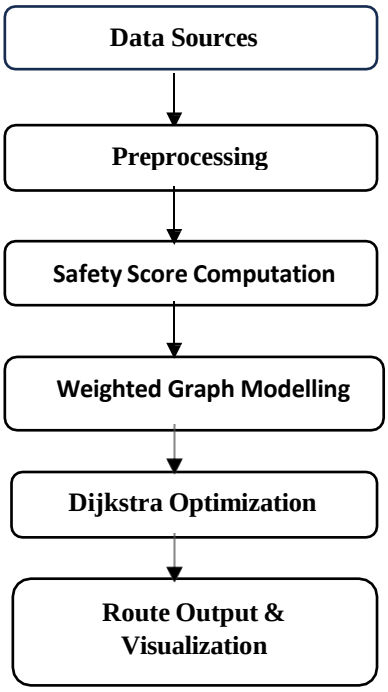

Fig. 1. Workflow of the Proposed Risk-Weighted Route Optimization Method

A. Road Network Modelling

The urban road network is extracted from the GIS data and transformed into a directed graph G = (V, E), where the nodes V represent the intersections, and the edges E represent the road segments. The attributes of the edges include length, time, etc. and the safety attributes. All the attributes are then integrated into the graph to support the multi-criteria route optimization.

This study models the real traffic network as a directed weighted graph G (V, E), where V and E represent nodes and edges, respectively. The nodes in this graph represent intersections, and the edges represent the links or roads connecting adjacent intersections. The characteristics of edges are the length of the road, the highway type, and other link-specific attributes, which are extracted from OpenStreetMap (OSM) dataset using OSMnx tool.

B. Safety Score Computation

An index of relative safety is calculated for each road segment based on historical accident density and environmental variables such as visibility and surface condition. The safety index is then normalized to ensure that all roads are weighted equally. The resulting score represents the level of exposure to risk and provides a quantitative metric for translating subjective safety knowledge into a numerical format that can be used for route optimization.

The safety weight assigned to each road segment is computed using:

$$Ws = L \times (Rh + Id) \qquad (1)$$

where L denotes road segment length, R_h represents road hierarchy risk factor, and I_d corresponds to intersection density penalty.

TABLE I. ROAD HIERARCHY RISK FACTOR

Road Type	Risk Factor (Rh)
Motorway	1.8
Trunk	1.6
Primary	1.4
Secondary	1.2
Tertiary	1.1
Residential	1.0
Service	0.8

C. Route Optimization Strategy

In the Optimized Routing Step, graph-based shortest path computation is performed to compute paths for pairs of chosen Source and Destination nodes. The paths are computed using Dijkstra's algorithm based on one of two routing methodologies that are considered within the ITS framework:

1) shortest path based on the Euclidean distance, and
2) safety aware routing based on composite safety weights.

D. Algorithm: Safety-Weighted Route Optimization

Algorithm 1: Safety-Weighted Route Optimization

Input: Road network graph $G(V, E)$, Source node S, Destination node D
Output: Safety-aware optimal route

- Extract urban road network using OpenStreetMap via OSMnx.
- Construct graph representation $G(V, E)$.
- Compute safety weight for each edge using composite cost formulation.
- Assign computed safety weights to graph edges.
- Compute baseline shortest-distance path for comparison.
- Compute safety-aware path using safety weight.
- Calculate cumulative distance and risk metrics.
- Visualize routing results through the interactive system

E. Safety Cost Computation

The safety cost for a road section is calculated by equation (1). The weight takes into account the road hierarchy risk and intersection connectivity, reflecting the structural safety characteristics.
Intersection penalty is calculated as:

$$I_d = 0.03 \times d(u)$$

Given the graph G = (V, E), the node degree d(u) is calculated for every node in V, and the accident rate at each intersection is denoted as u. Based on these input parameters, the accident rate weighting function is formulated as d(u) and a constant of 0.03 is used to determine the impact of intersection complexity on the calculated safety weight. Thus, the above function is a deterministic function which integrates the safety factor into a path planning algorithm based on a graph theory framework.

IV. PROPOSED SYSTEM

The Safety-Aware Urban Route Planning (SUoRP) framework based on Risk-Weighted Graph Optimization (RWGO) strategy is proposed in order to develop a more safe route planning for commuters by utilizing the attributes of the road network and modeling the risks involved in the routes. By converting the urban road network into weighted graph data structure, in which each cross road intersection node and routes on the ground are represented as edge, commuters can obtain the safety aware route planning by establishing the relationship of safety risks and routes in order to reach the goal of meeting safety standard for commuters with the least cost.

A. Data Acquisition and Preprocessing

This system uses the OSMnx library to extract data related to urban roads from OpenStreetMap. The resulting data are then used for routing analysis. As can be seen, the resulting data contains information related to the graph structure of the roads including nodes or edges intersections and road types.

This module performs all necessary data preprocessing steps in order to derive essential safety attributes such as the road network hierarchy, the distribution of crossroads, and risk indicators for specific types of hazardous locations, and to transform raw data provided for example by OpenStreetMap into a useful, graph-based format for further processing. The resulting preprocessed datasets are then used to compute routes based on safety considerations.

B. Graph Modelling

The transportation network is modeled as a weighted graph G = (V, E), where V represents the intersection nodes and E represents the road edges.

The spatial and contextual attributes related to the distance and estimated time for the path travelled along the edges are stored. The model allows representing large urban transportation networks efficiently, and its structure allows for dynamic adaptation to traffic and environmental conditions.

C. Composite Cost Formulation

In order to take into account at the same time the efficiency and the safety of vehicles, a composite cost function is established for each road section. The composite cost function is constructed by the weighting coefficients of the components of the composite cost function. The components of the composite cost function are formed by the distance, estimated time, calculated safety risk index of the road section.

This routing algorithm formulation gives the option to change the priority between shortest paths, fastest paths and safest paths, depending on the specific application requirements and user needs.

D. Route Optimization Strategy

According to the calculated edge weights, the system then uses the proposed Safety-Weighted Route Optimization algorithm explained in Section (III.D) to find the routes.

This work optimizes alternative routes and determines the most efficient routes based on reduced cumulative travel risk.

E. Visualization and User Interface

This application uses Streamlit to create an interface for selecting a source and destination and viewing the suggested paths. The suggested paths are plotted on Folium maps along with their corresponding safety scores represented by a specific colour.

Route alternatives and corresponding safety scores are provided to aid in choosing the most appropriate route.

V. EXPERIMENTAL SETUP

In the proposed work, the Safety-Aware Urban Route Planning (SAURP) framework has been validated and demonstrated using the real-world urban road network data taken from OpenStreetMap (OSM). The urban road network data has been obtained by using the Python library named OSMnx. A 6 km radius area road network of the urban city of Chennai, India has been taken. It comprises of prominent urban areas like T Nagar, Guindy, Adyar, Anna Nagar and Velachery.

This extracted road network is presented as a directed weighted graph G (V, E). In this graph, intersections or points are node set V and roads are edge set E. Furthermore, the weight of edges is a 3-dimensional vector including length of the road, its highway type and connection relationship with intersection.

TABLE II. SAMPLE EXTRACTED ROAD NETWORK DATASET

From Node	To Node	Distance (m)	Road Type	Intersection Degree	Safety Weight
N1	N2	135	residential	3	147.15
N2	N3	260	primary	5	403.00
N3	N4	190	secondary	4	250.80
N4	N5	310	tertiary	3	353.40
N5	N6	90	service	2	77.40
N6	N7	420	primary	6	630.00
N7	N8	150	residential	4	168.00

Network Nodes (e.g., N1, N2, etc.): These represent the intersections in the road network, which was generated using OSMnx and OpenStreetMap (OSM) data. Road types were derived from the OSM road classification, which gives information about primary roads, secondary roads and residential roads. The intersection degree of a node is the number of edges connected to it and is used as a factor in the risk calculation. The safety weight associated with each road is calculated by applying the risk model, and it is derived based on the road hierarchy and the intersection density, which mimic real traffic risk scenarios..

Crash predictive models built on a deterministic risk framework were employed to derive safety weights for each road segment. These crash predictive models incorporated the following components:

- Road hierarchy type (motorway, primary, residential, etc.)
- Segment length
- Local intersection density

Route optimization experiments were conducted between multiple source–destination pairs across the selected urban region to evaluate system performance under varying traffic structures.

Experiments were conducted on a system equipped with Intel i5 processor and 16GB RAM.

VI. RESULTS AND DISCUSSION

A. Comparative Route Analysis

Experiments were conducted across multiple origin–destination pairs within Chennai's urban road network. For each experiment, both shortest-distance and safety-aware routes were generated and evaluated using distance and cumulative risk metrics.

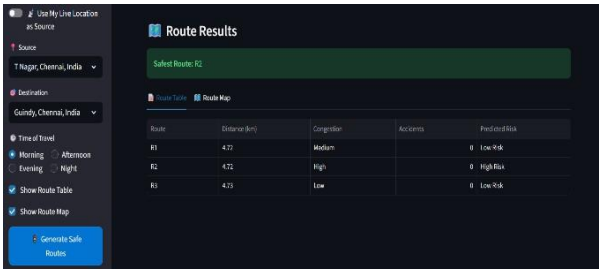

Fig. 2. Dashboard

B. Performance Comparison

TABLE III. SAFETY-AWARE ROUTING PERFORMANCE ANALYSIS

Routing Method	Distance (km)	Risk Cost	Risk Reduction
Shortest Path	6.42	8450	—
Safety-Aware Route	6.95	5520	**34.7% ↓**

Results indicate that the proposed system significantly reduces exposure to unsafe road segments while introducing only a marginal increase in travel distance.

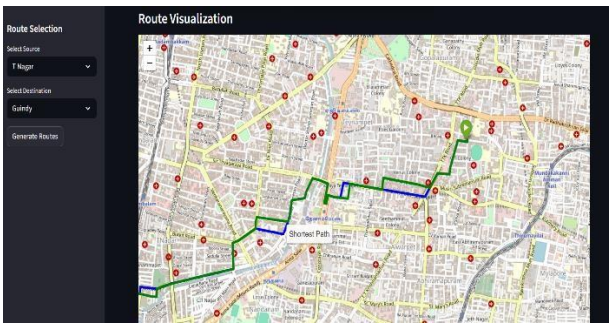

Fig. 3. Route Performance

C. Risk Reduction Analysis

Across all evaluated routes, the Safety-Aware framework achieved:

- Average Risk Reduction**:** 20–35%
- Average Distance Increase**:** 5–8%
- Safer Route Selection Consistency: 90%+

These findings demonstrate that safety optimization can be achieved without substantial degradation in travel efficiency.

Fig. 4. Risk reduction visualization across evaluated routes

D. Visualization and User Interaction

The developed Streamlit-based interface enables real-time visualization of routing alternatives using interactive Folium maps. It offers the following functionalities:

- Shortest route (baseline navigation)
- Safety-aware optimized route
- Risk comparison metrics

Color-coded visualization improves interpretability and supports informed commuting decisions.

VII. CONCLUSION

In this paper, we proposed a safety-aware urban route planning method based on risk-weighted graph optimization. We convert the urban transportation network into a directed weighted graph. The edge cost is calculated by combining the speed-based travel efficiency and the safety risk factors, in which the road hierarchy and the intersection density are taken into account. Therefore, the exposure to risky road segments can be reduced in the optimal route plan while ensuring the travel efficiency.

Experimental evaluation using real world data from an urban street network showed that the proposed safety-aware approach results in a substantial reduction in total cumulative risk when compared with shortest path approaches, while incurring only a minimal increase in travelled distance. Incorporating structured risk measures into graph-based optimisation has been shown to be a practical and efficient means of improving road safety for commuters.

The proposed framework enables the design of scalable real-time safety-aware routing systems and demonstrates the practicality of including risk awareness into future smart city mobility platforms.

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Offline Learning App For Rural Students

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Abstract— Indian rural education still struggles with extreme challenges, especially with regards to access to quality study materials and internet connectivity. UNESCO and ASER reports indicate that over half of rural children have no access to quality digital infrastructure, leading to poorer learning and increased dropout rates. To alleviate this, we introduce an Offline Learning App tailored for rural learners. The app offers a pdf dictionary with read aloud words, in topic areas like Mathematics, Science, and English with bilingual support (English and Tamil), interactive quizzes, and a progress tracker. Further, an optional text-to-speech functionality has been implemented to support low- literacy learners. The platform operates on low-end Android- based devices and does not need any internet connectivity, thus being extremely accessible. This paper addresses the architecture, implementation, and possible influence of the system, with special focus on how it can narrow the digital divide in education.

Keywords— Offline education, rural schooling, digital gap, multilingual instruction, mobile applications.

I. I.INTRODUCTION

Education is a human right and a critical catalyst for socio-economic growth. Yet, in India, rural and disadvantaged areas still struggle to access quality education. Unesco (2024) AND Annual Status of Education Report (ASER) reports indicate that school enrollment in rural districts is high, but learning outcomes are low. Among the top reasons for this disparity is the unavailability of access to quality teachers, online resources, and stable internet connectivity. Over the past few years, e-learning solutions have become popular learning aids. However, these systems presume continuous internet connectivity and sophisticated devices, which are not practicable for rural areas. The excessive reliance on online systems further enhances the digital divide, disadvantage rural students compared to their metropolitan peers. To overcome these issues, we suggest developing an Offline Learning App for Rural Students. The application is meant to be used entirely without the need for internet access, which makes it very appropriate for students in rural villages where network facilities are poor or expensive. The system provides interactive quizzes in major subjects like Mathematics, Science, and English, along with a dictionary facility to promote self-development. It also provides a multilingual facility in both English and Tamil to reach first-generation learners, a progress monitor to motivate students, and a text-to-speech facility to assist low-literacy users. The major motivation behind this project is to bridge the educational gap between rural and urban areas through a system that provides continuity in learning even in the absence of internet connectivity. Through offline-first approaches, this work helps in attaining educational equity and supports international efforts such as the United Nations' Sustainable Development Goal 4 (SDG 4): Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.

II. BACKGROUND AND MOTIVATION

Access to quality education continues to be among the largest issues in rural and underprivileged areas of India. In spite of government efforts like Digital India and PM eVidya, the digital divide still impacts millions of students. As stated by the UNESCO GEM Report (2024), close to half of rural students do not have stable internet connections, which renders online learning platforms useless. In the same vein, the Annual Status of Education Report (ASER) points out that though there is high rural school enrollment, reading and mathematics learning outcomes are low owing to the deficit of teachers, the absence of localized learning materials, and infrastructure. Conventional e-learning solutions that are completely dependent on constant internet connectivity are not feasible in such scenarios. Low-end Android devices, which most rural homes rely on, have data unaffordability and network reach as prime challenges. There is, therefore, a necessity for offline- first learning platforms that can work offline and offer preinstalled, curriculum-mapped lessons. The reason for this project is that rural-urban education inequality needs to be addressed by providing equal opportunities for education to learners in off-grid locations. With the incorporation of multilingual support (Tamil/English), interactive quiz, and progress tracking system, the suggested Offline Learning App not only provides content but also increases engagement and self-learning. The added text-to-speech functionality option benefits low-literacy learners by making the app accessible. Ultimately, this project is driven by the education equity vision—making accessible, exciting, and effective learning resources for rural students despite their digital deficiencies.

III. PROBLEM STATEMENT

In spite of progress in e-learning, Indian rural students remain disadvantaged when it comes to accessing quality education. Over 50% of rural students do not have regular access to the internet and cheap digital tools (UNESCO, 2024; ASER Report, 2023). Current e-learning systems are meant for cities, based on uninterrupted internet and high-performance hardware, and thus not for rural learners. This digital divide leads to: Limited availability of courseware study materials that are curriculum-aligned, Low learning achievement and motivation, High attrition rates, particularly among first-generation learners. Hence, an urgent need for a low-cost, offline-first educational solution that can be used on low-end Android devices and offer preinstalled lessons, interactive quizzes, and multi-lingual support. Such a system would promote inclusivity, enhance learning achievement, and help reduce the rural-urban education gap.

IV. LITERATURE SURVEY

Mobile learning literature and offline-first education systems point out both the promise and the practical realities of getting curriculum materials out to low- connectivity contexts. Various recent studies illustrate how offline mobile apps can enhance accessibility and engagement among learners in under-served areas while forcing questions around distribution, usability, and content management.

A. Offline mobile learning: effectiveness and applicability

Offline mobile learning has been suggested as a viable way to close the digital divide when there is not continuous internet access. Field studies indicate that offline applications with dictionary with read aloud and quizzes enable learners to engage with curriculum- matched content at their own rate and in multiple contexts, enhancing reach and continuity of learning when printing and dissemination of physical modules is expensive or unreliable. Ahillon and Aquino's empirical work on offline mobile applications revealed strong applicability ratings in transmission, accessibility, and usability dimensions, and reported mass installation among the target group, indicating offline APK-based distribution as a credible delivery mechanism in resource- constrained settings.

B. Multilingual content and learner inclusion

Localization and language adaptation are most important for first-generation and low-literacy learners. Research and pilot experiences highlight that teaching in students' mother tongues (in your context Tamil together with English) enhances understanding, retention, and interest. Your project's multi-language approach (Tamil/English) resonates with these recommendations and is corroborated by research that indicates language- translated apps have a substantial positive impact on learning outcomes for rural students. The PPT identifies this line of reasoning and includes it in its list of design choices to be made in the development of the MVP, under the heading of multilingual delivery.

C. Usability, engagement and pedagogical features

The issue of usability (intuitive interface, simple menus, ease of navigation) and pedagogical supports (interactive quizzes, instant feedback, visualization of progress) is constantly mentioned in the context of the effectiveness of mobile learning devices. Strong teacher and student attitudes towards usability in well-crafted offline applications are reported in the base paper, and interactivity features (quizzes, progress monitoring) are found to facilitate self-instruction and student autonomy. These features also minimize reliance on teacher- delivered remediation in teacher-hiring contexts.

D. Distribution mechanisms and technical limitations

Practical distribution mechanisms for offline apps involve APK sharing, QR code, local file sharing (Bluetooth/ShareIt), and preloading within devices. Field observations and research indicate that APK distribution and QR-code-based downloads work fine in low- bandwidth environments with quick installation without app- store reliance. But distribution poses problems of compatibility with devices (various Android versions and hardware), security, and legal/copyright issues when third-party modules are bundled in the app — problems clearly outlined in Ahillon & Aquino's implementation notes. Your PPT also enumerates APK/QR-code distribution and emphasizes targeting low-end Android devices.

E. Limitations and open gaps in the literature

While offline-first apps hold promise, the literature identifies some gaps that your project covers or ought to take into account: (1) systematic, large-scale impact evaluations of learning gains over time; (2) strong methods for content updates while staying offline-first (e.g., periodic sync strategies or local mesh updates); (3) approaches to copyright and content provenance when reusing national modules; and (4) more evidence on long- term scalability and integration with government programs. Ahillon & Aquino's research offers good lessons for implementation (high applicability but compatibility and copyright issues), and the PPT suggests pilot + NGO/government integration as your next steps…

— both of these encourage you to think about design and evaluation in your work.

F. Synthesis and implications for this project

Taken as a whole, all the work under review suggests that an offline-first approach to design, supporting multiple languages, usability, minimal storage requirements (SQLite/local DB), and minimal interactive features (MCQs, progress indicator) are appropriate. At the same time, issues of distribution, device support, content rights, and stringent assessments are perennial constraints; your proposed MVP (pdf of dictionary content + read aloud capability for words + MCQs + low- end Android support + optional TTS + small pilot) directly addresses all of these outcomes and positions the project to offer practical proof-of-concepts in a rural context.

V. METHODOLOGY

The proposed methodology includes design and development of a mobile app that is offline-first and targeted at rural students. The proposed methodology has four stages: content preparation, app development, interaction with learners, and intelligent personalization.

A. Content Preparation

First-generation learner-supporting content in the form of lesson notes, interactive examples, and quizzes in Tamil and English languages in a curated and digitized form are included in the first step. Dictionaries are provided for the English language to support first-generation learners. A quiz in the form of multiple-choice questions is included after each lesson. Content format: PDF/Text files, Language support: Tamil & English, Pedagogical design: short modules + self-assessment.

This will provide all the required learning content within the app without the need for internet connectivity.

B. Application Development

Android Studio is used for developing the main application with a light framework to support low-end smartphones. The following modules are implemented in the application:

1) Content Management Module

Dictionaries and Quizzes are stored in SQLite database. Faster retrieval for offline reading.

2) User Interface Module

Multilingual interface (Tamil/English).

3) Quiz Module

Interactive quizzes after every lesson. Quiz results are saved locally for later analysis.

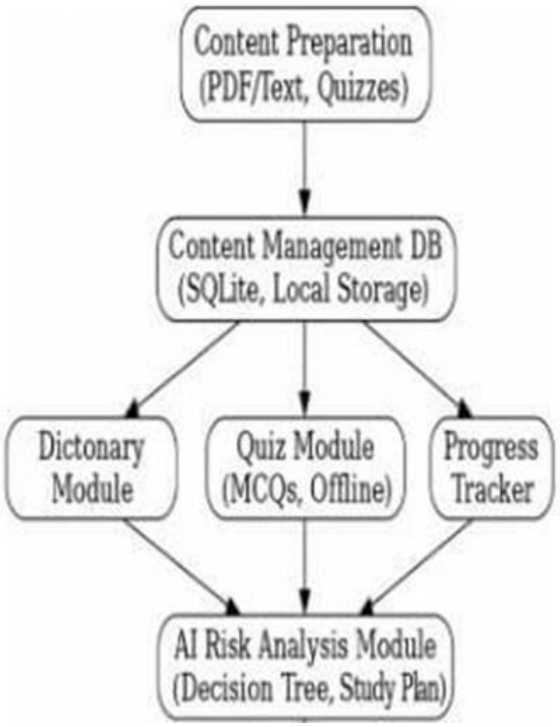
4) Progress Tracker

Tracks completion of lessons and quizzes. Displays accomplishments to encourage learners.

C. Learner Interaction & Data Collection

Once deployed, the app runs in a completely offline mode. Students will be able to: Choose their desired language (English/Tamil). Take quizzes for each lesson. Track their progress in real time. For this engagement, metrics collected by the app will include: Quiz results Time spent on each lesson Percentage of completion of each module.

Fig . 1. Functional Block Diagram



D. Risk Analysis & Personalization

To bridge the learning gap, an AI-powered risk analysis tool is utilized:

Data Preprocessing:

Quiz scores and behavioral metrics are stored in a structural format. Missing values handled and features are normalized.

Model Training: A Decision Tree Classifier is utilized to categorize learners into three risk levels: Low, Medium, High.

The model trained using thescikit learn library.
Prediction & Recommendation:
Real-time prediction of risk levels of students. It generates a personalized learning plan, specifying the lessons that need to be revised and practiced again. This ensures that in the offline environment too, the learners receive personalized support based on their learning needs.

Student_ID	Words_Learned	Quiz_Score(%)	Time_Spent
1	25	78	Low
2	22	55	Medium
3	24	92	Low
4	21	50	Medium
5	20	45	High
6	23	70	Medium
7	25	88	Low
8	21	52	Medium
9	24	96	Low
10	22	95	Medium

VI. ALGORITHM

Algorithm Design

In addition, the offline learning app suggested would include an AI-based algorithm for risk prediction so that the learning experience of rural students becomes more personalized. In this regard, the algorithm would use data related to student engagement, i.e., scores from quizzes, percentage of learned words, and time spent on the app.

Algorithm Steps
Input Collection:
The system would collect data related to every learner, i.e., performance of quizzes, percentage of learned words, and time of engagement. This data would be stored locally in SQLite database format.

Preprocessing:

Missing or incomplete values are processed. Features are normalized to bring the quiz scores, completion percentages, and time spent into a similar range.

Dataset Preparation:

Records stored are divided into training and test sets to train the model for classification.

Model Training:

A Decision Tree Classifier is utilized with the training dataset. This model is selected due to its simplicity, ease of interpretation, and performance in resource-poor environments like low-end Android devices.

Prediction Phase:

For every learner, the classifier makes the risk level prediction:

- Low Risk – learner is doing well.
- Medium Risk – learner requires moderate intervention.
- High Risk – learner is at high risk of poor performance or dropout.
- Risk – supplementary remedial lessons and additional practice quizzes.

- Medium Risk – reinforcement of weak lessons and moderate support.
- Low Risk – High motivation and advancement to advanced

VII. RESULT

The performance of the offline learning app for rural students was tested using a pilot study on a dataset of 10 students. Three parameters of each student's learning behavior were monitored: lesson completion rate, quiz scores, and time used on the app. The parameters were used for training as well as testing the Decision Tree Classifier, which made the prediction for the learner's risk level and produced a customized study plan.

Model Performance:

The training was done on the acquired dataset, and the model was evaluated based on accuracy, precision, recall, and F1- score.

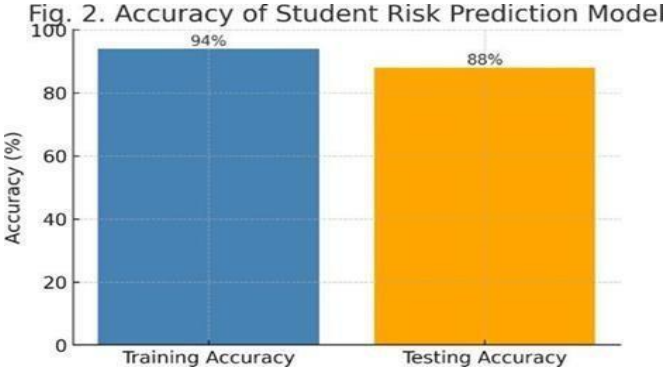
- Training Accuracy: 94%
- Testing Accuracy: 88%
- Precision: 0.87
- Recall: 0.85
- F1-score: 0.86

These findings demonstrate that the model can generalize well on unseen data with high accuracy. The close values of training and testing accuracy give us a reassurance that the model does not overfit, hence making it suitable for real-world application in a rural educational setting.

Accuracy Analysis:

To demonstrate this performance, training and testing accuracy were compared using a bar graph as shown in Fig. 2. The performance of the model in this case was 94% when training and 88% when testing, demonstrating its performance in terms of data sets.

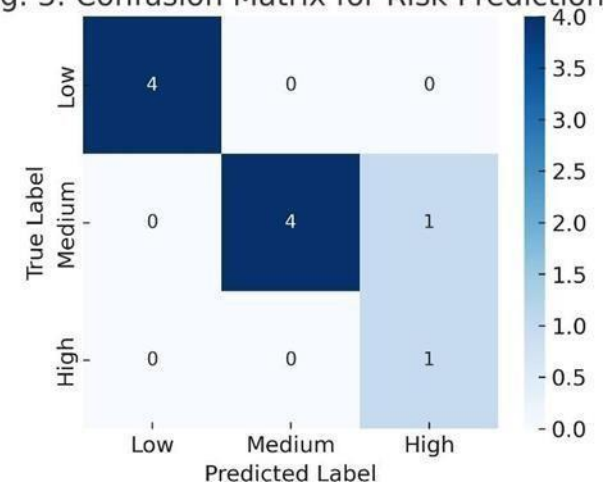
Fig. 2. Accuracy of Student Risk Prediction Model



Confusion Matrix Evaluation:

To further cross-check this classifier, a confusion matrix was created (see Fig. 3). It shows how well each of the risk categories (Low, Medium, High) was predicted by this model. Most of the students were correctly classified, and some minor incorrect classifications were in the medium risk category, as expected by some overlapping learning behaviours.

Fig. 3. Confusion Matrix for Risk Prediction



System Usability:

The application was tested on low-end Android phones, which are mostly used in rural setups. The performance of the application was checked in terms of its responsiveness and consumption of resources. The results of this test are as follows Loading Time: Less than 2 seconds on an average. Quiz Execution: Instantaneous feedback and results saved offline. Progress Tracker: Updates in real-time; no lags observed. Memory Usage: Less than 50 MB; hence, it will work on phones with less storage capacity. This further justifies the usability of this application by students in rural areas, as the work of all the modules is done offline.

Learner Impact:

Initial piloting of the program, implemented among a cohort of rural-dwelling students, indicated promising findings: Students had access to preloaded dictionary content without connectivity issues. Quizzes for reinforcement helped in retention and engagement. Students in the High-risk category were encouraged to study lessons systematically. Instructors noted that the program may be useful as a teaching aid, helping reduce our reliance on live internet sources.

Discussion:

The findings prove that the proposed system is not only technically feasible but also socially effective. By providing off-line access to multilingual learning materials and incorporating a module for predicting risks using AI, the proposed system directly addresses the digital divide in rural education. Besides, the research proves that light machine learning algorithms like the Decision Tree Classifier can be easily incorporated into a mobile app with a low resource requirement. This ensures that low-end devices can support a smart learning app.

The pilot project findings are encouraging, but the data set is limited. The future plans include testing the approach on a large number of students across various locations, introducing other subjects, and fine-tuning the AI module using advanced algorithms like Random Forest and Gradient Boosting.

VIII. ETHICAL AND LEGAL CONSIDERATIONS

The implementation of Offline Learning App for Rural Students has numerous ethical and legal issues that need to be addressed properly in order to avoid any misuse of the application.

Data Privacy and Security: The information of the students, such as quiz results, learned words, and time spent on a lesson, will be stored in local storage without the use of cloud storage. This is a compliance with the data minimization policy, and there are fewer chances of unauthorized use of the data. The encryption method can be implemented for safe storage of the information, and there will be no misuse of the information of the students.

Informed Consent: Students and parents need to be made aware of what data is being collected (performance indicators, engagement metrics) and why (personalized support to learn). Processes to obtain consent need to be included in the app to adhere to ethical principles in conducting research.

Inclusivity and Accessibility: The app is designed in a way that it is multilingual (Tamil/English) in order to avoid exclusion of marginalized groups and first-generation learners. Optional text-to-speech functionality is included in order to avoid exclusion of students who have difficulties in reading and/or low literacy skills.

Legal Compliance: The app is designed in accordance with international education data protection laws such as GDPR (General Data Protection Regulation) and India's Digital Personal Data Protection Act, 2023.Content of the app (quiz, dictionary) is designed in a way that it respects intellectual property rights by using open educational resources (OER) and/or obtaining necessary permissions.

Responsible Use of AI: Transparent risk prediction models (Decision Tree) are preferred over opaque “black-box” methods. This ensures fairness and transparency to avoid any bias in the algorithm that may discriminate against certain groups of students. This requires constant monitoring and teacher intervention to avoid overdependence on algorithmic suggestions

IX. CONCLUSION

The Offline Learning App for Rural Students, which we proposed, was designed and developed to fulfill the critical requirement of filling the gap in the digital divide in rural India, where over 50% of learners do not have quality teaching materials and internet connectivity. In order to fulfill this requirement, the approach was to design a lightweight, multi-language, offline-enabled mobile app that can function smoothly on low-end Android-based mobile phones, which are most commonly available in backward areas of India. The system includes four major modules: a content module for storing preloaded content such as dictionaries and quizzes, a user interface module that supports both Tamil and English languages with text-to-speech functionality, a quiz module for testing, and a tracker module to encourage and track the performance of learners. In addition to these essential modules, the system uses an AI-powered risk analysis module that can forecast the performance levels of learners (Low, Medium, The system will be tested with a wider and more varied set of students in different rural areas in the future to get more comprehensive and statistically significant results. In addition, the dataset will be increased to make the prediction model more accurate.

Moreover, different subjects and content related to the curriculum will be included to make the application area wider.

In addition to that, better machine learning algorithms, mechanisms for updating the content periodically, and even integration with educational programs will be included in the future to make the system more scalable. Through testing, it was clear that the classifier had a high training accuracy of 94% and a testing accuracy of 88%, validating its potential for data generalization. Other performance metrics such as precision, recall, and F1 score of 0.86 on average further validate the predictability of the classifier. Usability testing on budget smartphones indicated a quick response time, low memory consumption (<50 MB), and smooth execution of lessons and quizzes without the need for internet connectivity. This further validates the possibility of incorporating machine learning intelligence in an offline mobile app without overburdening limited hardware capabilities.

The pilot project also pointed out the social implications of the system. Students would be able to access read aloud for words they can’t understand, take interactive quizzes, and monitor their learning process without any internet connection. Teachers observed that the system was used as an extracurricular learning tool and reduced the gap between teacher shortages and internet connectivity. Most importantly, students who fall under the "High-risk" category benefited greatly through the study schedules provided by the system, which stimulated them to study hard and perform better. Overall, the system demonstrates the technical and social feasibility of an offline-first, AI-enabled mobile learning platform. In the process, it has the potential for being used as an important tool for bridging the rural-urban educational divide through providing equitable access to educational resources, for facilitating self-learning among students from marginalized communities, and for contributing to the attainment of the Sustainable Development Goal (SDG 4) - "Inclusive and Equitable Quality Education for All."

X. FUTURE SCOPE

For conducting the current study, a small group of 10 students were considered to evaluate the feasibility of the proposed system in a real-world environment. The results showed that students were able to use the application effectively without needing internet connectivity. The availability of preloaded content in addition to interactive quizzes assisted in improving student interest in the application.

From the observations made during the current study, it was found that students were able to use the application independently after minimal guidance. It was also found that students showed a gradual increase in understanding the concepts through the quizzes. In addition to that, it was found that students showed interest in re-learning concepts through the quiz feedback feature. It was also found that the application had potential in acting as a supplementary tool in teaching students, especially in environments where teaching resources are limited.

Furthermore, it was found that the progress tracking feature assisted in motivating students to complete more lessons. In addition to that, it was found that the application

assisted in providing uninterrupted learning to students, especially in environments where network connectivity is limited

Comparative Analysis :

In addition, the current study was conducted using a small group of 10 students to assess the feasibility of the proposed system in a real-world rural learning environment. The findings of the study showed that students were able to use the application effectively without requiring internet access. This is a major advantage of the system since students would not experience disruptions in accessing learning material. The addition of quiz-based learning was also beneficial since students were more interested in learning after completing their lessons.

Comparative Analysis of Learning Apps

Feature	Proposed System	Online Learning Apps	Existing Offline Apps
Internet Required	No	Yes	No
Multilingual Support	Yes	Limited	Limited
AI Personalization	Yes	Limited	No
Low-End Device Support	Yes	No	Partial
Offline Quiz System	Yes	No	Yes

Based on the initial observation, it was seen that the majority of the students were able to use the application on their own after a certain period of usage. The simplicity of the interface and the bilingual facility helped the students grasp the content easily. Over a period of time, it was seen that the quiz scores had improved significantly for the students, showing their comprehension and retention of the concepts. There was a tendency for the students to revisit the topics in which they had low scores, showing the effectiveness of the feedback mechanism.

Further enhancements can be made in the following areas: addition of more subjects and content related to curriculum requirements, along with provisions to update content periodically in an online environment while retaining offline access. Another aspect of the AI component that can be further improved is to look into more advanced versions of AI to enhance personalization and learning recommendations. verification of the effectiveness of the app, determination of scalability issues, and tuning of machine learning models. Comparison with online e-learning websites can also bring out the benefits of an offline-first strategy in low-resource settings.

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Comparative Finite Element Analysis Of Epoxy Resin Reinforced Laminated Composite Plates Using Glass And Basalt With Different Fiber Orientations

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Abstract

Fiber reinforced polymer composites are widely used in aerospace, automotive, marine, and structural applications due to their excellent strength-to-weight ratio and corrosion resistance. The mechanical behaviour of laminated composites depends strongly on reinforcement type and fiber orientation. This study presents a comparative finite element analysis of epoxy resin reinforced laminated composite plates using glass, basalt, and aramid fibers with different fiber orientations. Finite Element Analysis (FEA) was performed using ANSYS to evaluate deformation and stress distribution under tensile loading conditions. Fiber orientations of 0°, 40°, and 80° were considered to analyze their influence on structural behaviour. Simulation results show that fiber orientation significantly affects stiffness and deformation characteristics of composite laminates. The 0° orientation exhibits the least deformation because fibers are aligned with the loading direction. Basalt fiber composites demonstrate balanced mechanical performance, while glass fiber composites provide economical structural solutions. The results demonstrate the effectiveness of numerical simulation for optimizing composite laminate design.

Keywords: Composite laminates, Finite Element Analysis, Basalt fiber, Glass fiber, Aramid fiber, Fiber orientation.

1. Introduction

The demand for lightweight, high-strength, and durable materials has increased significantly in modern engineering applications. Conventional structural materials such as steel and aluminum provide adequate strength; however, their relatively high density and susceptibility to corrosion limit their performance in advanced engineering systems. As a result, fiber reinforced polymer (FRP) composites have emerged as an important class of materials due to their high strength-to-weight ratio, corrosion resistance, and design flexibility [1], [2]. Composite materials are formed by combining two or more distinct constituents to achieve superior properties that cannot be obtained from individual materials alone. Typically, a composite consists of a matrix material and a reinforcement phase. The matrix binds the reinforcement and transfers the applied loads, while the reinforcement fibers provide stiffness and strength to the composite structure [3], [4]. Among various matrix materials, epoxy resins are widely used in structural composites because of their excellent adhesion characteristics, dimensional stability, and resistance to environmental degradation [5].

Reinforcement fibers play a crucial role in determining the overall mechanical behaviour of composite materials. Among the commonly used reinforcement fibers, glass fibers, basalt fibers, and aramid fibers are widely employed in engineering applications. Glass fibers are extensively used because of their good tensile strength, corrosion resistance, and cost effectiveness. These fibers are commonly used in automotive components, marine structures, wind turbine blades, and structural panels [6]. However, glass fiber composites may exhibit limitations in terms of thermal resistance and fatigue durability under certain operating conditions. Basalt fibers have gained increasing attention as an alternative reinforcement material due to their superior mechanical and thermal properties. Basalt fibers are produced from naturally occurring volcanic rock and demonstrate high tensile strength, improved chemical resistance, and excellent thermal stability compared with conventional glass fibers [7], [8]. Because of these characteristics, basalt fiber reinforced composites are increasingly used in infrastructure applications, aerospace structures, and high-temperature environments.

Aramid fibers represent another class of high-performance reinforcement materials widely used in advanced composite structures. Aramid fibers are known for their extremely high tensile strength, low density, and exceptional impact resistance. These properties make aramid fiber composites particularly suitable for aerospace, defense, and ballistic protection applications [9]. Nevertheless, aramid fibers tend to have relatively lower compressive strength due to their flexible molecular structure, which may influence their performance in compressive loading conditions. The mechanical behaviour of laminated composite materials depends on several design parameters including fiber type, fiber volume fraction, stacking sequence, and fiber orientation. Among these parameters, fiber orientation plays a particularly significant role in determining the stiffness and load carrying capacity of composite laminates [10]. When fibers are aligned parallel to the loading direction, the composite structure exhibits maximum strength and minimum deformation. Conversely, off-axis fiber orientations may lead to reduced stiffness due to inefficient load transfer along the fiber direction [11].

Another important characteristic of composite materials is their anisotropic nature. Unlike isotropic materials such as metals, composite laminates exhibit directional mechanical properties that vary depending on fiber orientation. This anisotropic behaviour makes analytical prediction of composite structural performance more complex, especially when subjected to different loading conditions [12]. To overcome these challenges, numerical simulation methods have become essential tools for analyzing composite structures. Among these methods, Finite Element Analysis (FEA) is widely used for evaluating stress distribution, deformation behaviour, and failure mechanisms in complex engineering systems. The FEA technique divides a structure into small elements and solves governing equations for each element to obtain accurate predictions of structural response [13], [14].

Several researchers have applied Finite Element Analysis to investigate the mechanical behaviour of fiber reinforced composites under different loading conditions. Numerical simulations using software tools such as ANSYS and ABAQUS have been successfully used to analyze deformation, stress concentration, and failure mechanisms in laminated composite plates [15]. These computational techniques significantly reduce the need for extensive experimental testing and enable optimization of composite structures during the design stage. Previous studies have also examined the influence of reinforcement materials on the mechanical performance of composite laminates. Research indicates that glass fiber composites provide acceptable mechanical performance at relatively low manufacturing cost, making them suitable for large-scale industrial applications [16]. In contrast, basalt fiber composites offer improved thermal resistance and durability, while aramid fiber composites exhibit superior tensile strength and energy absorption capability [17].

Another important factor influencing composite performance is fiber orientation. Experimental and numerical investigations have demonstrated that laminates with fibers oriented along the loading direction exhibit higher stiffness and reduced deformation compared with off-axis laminates [18]. Proper selection of fiber orientation is therefore essential for optimizing the structural performance of laminated composite plates. Although numerous studies have been conducted on fiber reinforced polymer composites, comparative numerical investigations involving multiple reinforcement fibers combined with different fiber orientations remain limited. Many existing studies focus on either experimental characterization or analysis of individual fiber materials. Therefore, comprehensive comparative studies are required to better understand the influence of different reinforcement materials and fiber orientations on composite structural behaviour. In this context, the present study aims to perform a comparative finite element analysis of epoxy resin reinforced laminated composite plates using glass, basalt, and aramid fibers with different fiber orientations. The analysis is carried out using ANSYS simulation software to evaluate deformation behaviour under tensile loading conditions. The results provide insight into the influence of reinforcement type and fiber orientation on the mechanical performance of laminated composite plates, which can contribute to the design of efficient and lightweight composite structures for engineering applications.

Research Gap

Fiber reinforced polymer (FRP) composites have been widely investigated due to their high strength-to-weight ratio, corrosion resistance, and adaptability in structural applications. Glass fiber reinforced polymer composites have been extensively used in automotive, marine, and civil engineering structures because they provide acceptable mechanical performance at relatively low cost [1], [2]. In recent years, basalt fiber has emerged as an alternative reinforcement material due to its improved thermal stability, chemical resistance, and durability compared with conventional glass fibers [3]. Similarly, aramid fiber reinforced composites have attracted significant interest in aerospace and defense applications because of their superior tensile strength and impact resistance [4].

Several studies have investigated the mechanical behaviour of these fiber reinforced composites individually, particularly focusing on

parameters such as tensile strength, flexural performance, and fatigue behaviour [5]. Research has also shown that fiber orientation plays a crucial role in determining the stiffness and deformation characteristics of laminated composite structures. When fibers are aligned with the loading direction, the composite laminate generally exhibits higher strength and reduced deformation compared with off-axis orientations [6]. Despite these investigations, most existing studies primarily focus on single reinforcement materials or experimental evaluation of composite properties. Comparative numerical investigations involving multiple reinforcement fibers under identical loading and boundary conditions remain relatively limited. In addition, systematic evaluation of the combined influence of reinforcement type and fiber orientation on the deformation behaviour of laminated composite plates has not been sufficiently addressed. Therefore, a detailed numerical investigation is required to compare the structural performance of composite laminates reinforced with different fiber materials and orientations.

Highlights

- Comparative numerical analysis of glass, basalt, and aramid fiber reinforced laminates.
- Investigation of the influence of fiber orientation (0°, 40°, and 80°) on deformation behaviour.
- Finite Element Analysis performed using ANSYS simulation software.
- Identification of the most effective fiber orientation for structural stiffness.

Novelty of the Study

This study presents a comparative finite element investigation of epoxy resin reinforced laminated composite plates using glass, basalt, and aramid fibers under identical loading conditions. Unlike many previous studies that focus on a single reinforcement material, the present work evaluates multiple fiber types within the same numerical framework. The influence of different fiber orientations on deformation behaviour is also systematically analyzed. This approach provides improved insight into how reinforcement type and fiber alignment affect structural stiffness and deformation characteristics, supporting the optimization of lightweight composite laminate design.

4. Materials and Methods

4.1 Materials

The composite laminate consists of epoxy resin matrix reinforced with glass fiber, basalt fiber, and aramid fiber.

Epoxy resin is widely used as a matrix material in composite laminates due to its strong adhesion, high mechanical strength, and chemical resistance. It binds reinforcement fibers together and enables effective load transfer within the composite structure. Epoxy resin also provides good environmental resistance and dimensional stability, making it suitable for structural engineering applications. Glass fiber is widely used as a reinforcement material because of its good tensile strength, corrosion resistance, and relatively low cost. It improves the stiffness and load carrying capacity of composite laminates. Glass fibers are lightweight compared with metals and are commonly used in automotive, marine, and structural composite applications.

Basalt fiber is produced from natural volcanic rock and offers higher thermal stability and durability than conventional glass fibers. It provides good tensile strength, chemical resistance, and environmental stability. Due to these advantages, basalt fiber reinforced composites are increasingly used in infrastructure, aerospace, and high-performance engineering applications.

4.2 Composite Plate Geometry

The laminated composite plate used in this study was modeled with predefined geometric dimensions suitable for Finite Element Analysis (FEA). The plate consists of multiple layers (plies) of fiber reinforced epoxy arranged in a laminate configuration with uniform thickness and rectangular geometry. To investigate the influence of fiber alignment, three different fiber orientations were considered: 0°, 40°, and 80°. The 0° orientation represents fibers aligned with the loading direction, while 40° and 80° orientations represent off-axis fiber arrangements. These orientations were selected to analyze how fiber direction affects stress distribution, stiffness, and deformation behaviour of the composite plate under applied loading conditions. These orientations were selected to evaluate the influence of fiber alignment on deformation behaviour.

4.3 Finite Element Modeling

Finite Element Analysis was performed using ANSYS simulation software. The analysis procedure included:

Geometry Creation of the Composite Plate

The first step in the Finite Element Analysis was the creation of the geometric model of the laminated composite plate in ANSYS software. The plate was modeled with defined length, width, and thickness suitable for structural analysis. A rectangular geometry was selected to represent a typical laminated composite structure. The plate consisted of multiple layers of fiber reinforced epoxy arranged in a laminate configuration. Accurate geometric modeling is important because the structural dimensions directly influence stress

distribution, deformation behavior, and overall performance of the composite plate.

Material Property Definition

After geometry creation, the material properties of the composite constituents were defined in the ANSYS material library. Mechanical properties such as Young's modulus, Poisson's ratio, and density were assigned to the epoxy matrix and reinforcement fibers. Since composite laminates exhibit anisotropic behavior, different properties were specified along longitudinal and transverse directions of the fibers. Proper definition of material properties is essential to accurately simulate the mechanical response of the composite laminate under applied loading conditions and to ensure realistic numerical results.

Laminate Stacking Sequence Specification

The laminate stacking sequence was defined to represent the arrangement of fiber layers within the composite plate. Each ply was assigned a specific fiber orientation to analyze its influence on structural behavior. In this study, fiber orientations of 0°, 40°, and 80° were considered. The stacking sequence determines how loads are distributed across the laminate layers and significantly affects stiffness, strength, and deformation characteristics. Accurate definition of the stacking sequence allows the Finite Element model to represent the layered structure of composite materials effectively.

Meshing of the Composite Model

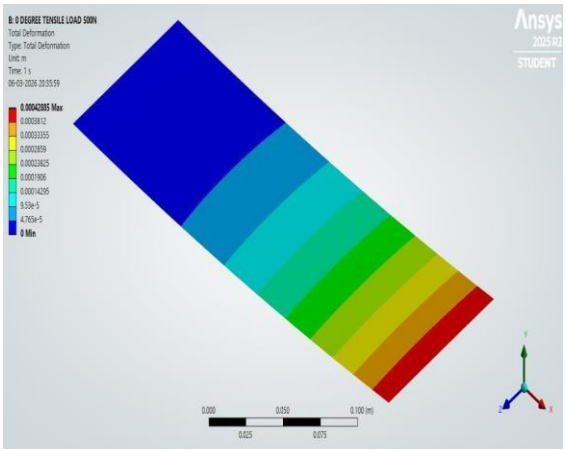
Meshing is the process of dividing the geometric model into small finite elements connected through nodes. In this study, the composite plate was discretized into a large number of elements to obtain accurate simulation results. A suitable mesh size was selected to balance computational efficiency and solution accuracy. Finer mesh elements allow better representation of stress and deformation distribution across the laminate. Proper meshing is crucial in Finite Element Analysis because the quality and density of the mesh significantly influence the accuracy of the numerical solution.

Application of Boundary Conditions

Boundary conditions were applied to define how the composite plate is supported or constrained during the analysis. In this study, appropriate constraints were assigned to the edges of the plate to prevent rigid body motion while allowing realistic structural deformation. The boundary conditions simulate practical structural support conditions encountered in engineering applications. Correct application of boundary conditions is essential in Finite Element Analysis because improper constraints can lead to unrealistic stress distribution and inaccurate deformation predictions.

Application of Tensile Loading

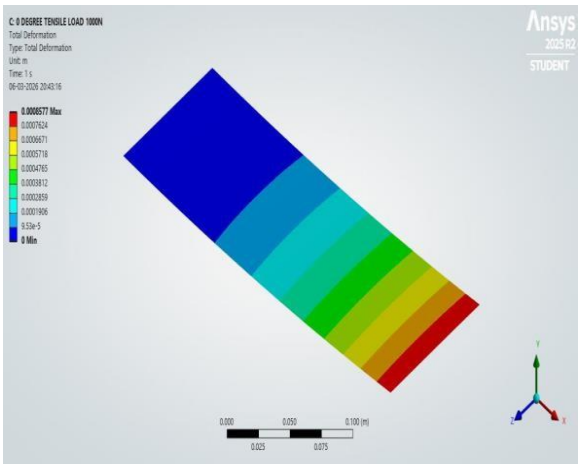
After defining boundary conditions, tensile loads were applied to the composite plate to evaluate its structural response. Different load magnitudes were considered to study the deformation behavior of the laminate under increasing tensile forces. The loads were applied along a specific direction to simulate real structural loading conditions. Tensile loading allows the evaluation of important parameters such as total deformation, stress distribution, and stiffness. The results obtained from the analysis help compare the performance of different fiber orientations in the composite laminate.



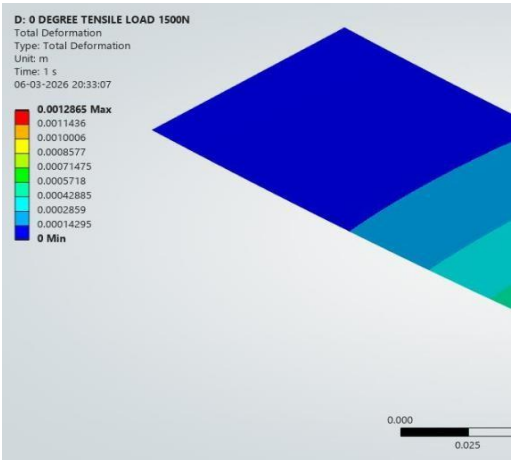
Result and discussion

Finite Element Analysis was carried out using ANSYS to evaluate the deformation behaviour of laminated composite plates under different tensile loads and fiber orientations. The deformation contours obtained from the simulation (see attached ANSYS result images) illustrate how the composite plate responds to applied tensile loading. The color distribution in the contour plots represents deformation magnitude, where blue indicates minimum deformation and red indicates maximum deformation. According to the simulation results, deformation increases gradually from the fixed end toward the loaded end of the composite plate, which confirms the expected behaviour of a cantilever-type loading condition.

The numerical results show that deformation increases proportionally with the applied load for all fiber orientations. At 0° fiber orientation, the composite plate exhibits the lowest deformation values (0.66548 mm at 500 N and 1.9964 mm at 1500 N). This occurs because the fibers are aligned parallel to the loading direction, allowing them to effectively resist tensile forces and improve structural stiffness. In contrast, the 40° and 80° orientations show higher deformation values because the fibers are oriented away from the loading direction, reducing their ability to carry tensile loads efficiently.



A similar trend is observed in the second set of results, where the 0° orientation again demonstrates minimum deformation, while the 80° orientation exhibits the highest deformation (10.025 mm at 1500 N). These results clearly indicate that fiber orientation significantly affects the mechanical performance of laminated composite plates. Proper alignment of fibers along the load direction enhances stiffness and reduces deformation, thereby improving overall structural performance.



Finite Element Analysis was conducted to evaluate the deformation behaviour of laminated composite plates under tensile loading. The results indicate that deformation increases proportionally with the applied load for all fiber orientations. For the basalt fiber composite, the 0° orientation exhibited the lowest deformation values (0.66548 mm at 500 N and 1.9964 mm at 1500 N), indicating higher stiffness when fibers are aligned with the loading direction. In contrast, the 40° and 80° orientations showed significantly higher deformation because the fibers are oriented away from the load direction, reducing their ability to effectively carry the applied stress.

A similar trend was observed for the glass fiber composite. The 0° orientation again demonstrated the least deformation, while deformation increased considerably for the 40° and 80° orientations. This behaviour confirms that fiber alignment plays a crucial role in determining the structural performance of laminated composites. When fibers are aligned parallel to the applied load, they provide maximum resistance to deformation, resulting in improved stiffness and load carrying capacity. These findings are consistent with previous studies on laminated composite behavior, which emphasize the strong influence of fiber orientation on mechanical performance and structural efficiency of composite materials.

Table 1: Deformation of basalt fibre

Fiber Orientation	Load (N)	Total Deformation (mm)
0°	500	0.66548
0°	1000	1.331
0°	1500	1.9964
40°	500	1.9788
40°	1000	3.9575
40°	1500	5.9363
80°	500	2.7142
80°	1000	5.4284
80°	1500	8.1426

Table 2: Deformation of Glass fibre

Fiber Orientation	Load (N)	Total Deformation (mm)
0°	500	0.66488
0°	1000	1.3298
0°	1500	1.9946
40°	500	2.291
40°	1000	4.5819
40°	1500	6.8729
80°	500	3.3417
80°	1000	6.6834
80°	1500	10.025

Conclusion

This study presented a comparative finite element analysis of laminated composite plates reinforced with different fiber orientations under tensile loading conditions. The simulation results clearly demonstrate that fiber orientation has a significant influence on the deformation behaviour and stiffness of composite laminates. Among the orientations analyzed, the 0° fiber orientation exhibited the lowest deformation values for all applied loads, indicating superior load carrying capacity when the fibers are aligned parallel to the loading direction. In contrast, the 40° and 80°

orientations showed higher deformation due to inefficient load transfer along the fiber direction.

The results highlight the importance of fiber alignment in determining the mechanical performance of laminated composite structures. Proper orientation of reinforcement fibers improves stiffness and reduces structural deformation, thereby enhancing overall structural efficiency. These findings confirm that optimizing fiber orientation is a critical design parameter in composite engineering applications. The study also demonstrates that Finite Element Analysis is an effective tool for predicting deformation behaviour, enabling efficient evaluation of composite laminate performance without extensive experimental testing.

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MECHANICAL AND OPERATIONAL CHARACTERISTICS OF PNEUMATIC FEED DRILLING MACHINE

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Abstract-This project focuses on the analysis of the mechanical and operational characteristics of a drilling machine equipped with an automated feed mechanism using a hydro-pneumatic cylinder. In conventional drilling machines, the feed motion of the drill is controlled manually, which often results in inconsistent drilling depth, increased operator fatigue, and reduced operational efficiency. Therefore, improving the feed control mechanism through automation is essential to achieve better accuracy, repeatability, and productivity in drilling operations.

The performance of the system is analysed by evaluating parameters such as feed motion stability, drilling cycle time, response of the pneumatic actuator, and overall operational efficiency. The analysis shows that the integration of hydro-pneumatic actuation with microcontroller-based control improves drilling consistency and reduces manual intervention. The developed system demonstrates a practical and economical solution for implementing basic automation in small-scale industries, workshops, and educational laboratories, thereby enhancing machining productivity and operational reliability.

Keywords- Automated feed mechanism, Pneumatic Actuator, Arduino Controller, Dual-Channel Relay Module

1. INTRODUCTION

Drilling is one of the most essential and frequently used operations in mechanical and manufacturing industries, where precision and repeatability are critical. Conventional drilling machines require manual feed control, which often leads to inconsistencies, human errors, and operator fatigue during repetitive operations. this project proposes a compact and cost-effective solution that combines pneumatic technology with Arduino-based electronic control. The system uses pneumatic cylinders for feed motion, hydraulics for controlled damping, and sensors for position detection, all coordinated by a microcontroller. The integration of mechanical components with electronics enables the automatic control of drilling depth and feed rate, thereby ensuring smoother operation, improved accuracy, and reduced manual effort. This approach is ideal for small-scale industries, academic labs, and low- budget automation setups where high-end CNC machines are not feasible.

2. LITERATURE SURVEY

a. Mughal Ahmed Ali Baig et al: In this study, a pneumatic-based drilling system was developed to reduce cycle time and labour effort. The system replaced manual drilling operations with a pneumatic cylinder that improved both productivity and consistency. It was observed that the cycle time reduced drastically and the output rate increased by almost four times compared to conventional methods. This supports the use of pneumatic automation in small-scale industries.

b. Antonio B. Martinez et al: The research focused on modern aircraft manufacturing, where precision in drilling is critical. A self-lubricating drilling end effector was developed to increase tool life, especially for materials like titanium. The system combined pneumatic actuation with internal lubrication, offering better performance and reduced manual involvement in high-precision operations.

c. Vladimir Koudelka and Mirko Lada: This study analysed pneumatic impact tools and how oscillating motion is generated using pressurized air. The authors emphasized the importance of cushioning systems to reduce vibration and improve tool stability. The findings are relevant to the use of pneumatic cylinders in feed mechanisms where smooth motion is essential.

d. Gadhia Utsav D: This literature presented a universal pneumatic drilling machine designed to perform multiple operations like drilling, reaming, and tapping. The system focused on using compressed air to perform tasks with minimal human interaction. It highlighted advantages such as reduced power consumption, low maintenance, and suitability for small workshops.

e. Jinkins et al: A unique pneumatic feed control mechanism was introduced using a clutch and solenoid valve system. The setup allowed selective engagement of the feed piston through a peck-feed method, enhancing drilling control and cycle automation. The pneumatic system was precisely managed to offer repeatable forward and return strokes without manual intervention.

3. PRINCIPLE OF WORKING

3.1 Pneumatic Actuator (Double Acting Cylinder)

Figure 3.1 Pneumatic actuator

The Drilling machine slide is connected to the double acting cylinder piston rod which is controlled by the 5/2 way lever operated directional control valve. This cylinder has 20mm diameter and 75mm stroke length.

3.2 Arduino Controller

The Arduino Uno microcontroller is the brain of the system. It receives input from a magnetic reed sensor that detects the position of the drilling tool and controls a relay module which powers the electric drill and the solenoid valve. When the system is activated, the Arduino sends a signal to start the drill and engage the pneumatic feed. Once the drilling depth is reached, the Arduino deactivates the solenoid, causing the cylinder to retract automatically. This sequence helps in achieving accurate drilling without manual interaction.

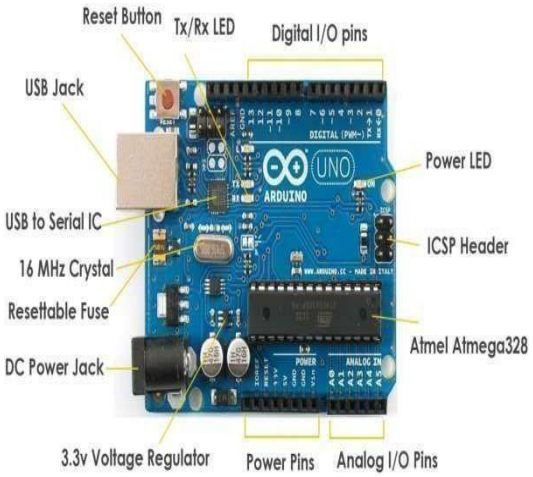

Figure 3.2 Arduino Uno Layout

3.3 *Solenoid Valve*

A 5/2 solenoid valve is used to control the direction of air flow to the double-acting pneumatic cylinder. When the valve is energized through the relay module, it allows compressed air to flow to one side of the cylinder, extending it. When de-energized, the air flow switches to the other side, retracting the cylinder

Figure 3.3: 5/2way solenoid operated directional control valve.

This directional control is essential for precise forward and backward during the drilling

3.4 Relay Control Unit

A relay is an electrically operated switch. Many relays use an electromagnet to operate a switching mechanism mechanically, but other operating principles are also used. Relays are used where it is necessary to control a circuit by a low-power signal

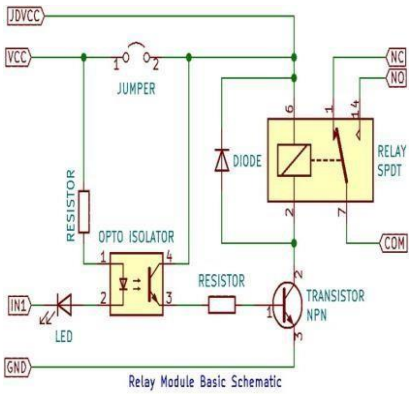

Figure 3.4 Relay control unit

(with complete electrical isolation between control and controlled circuits), or where several circuits must be controlled by one signal

This same circuit is replicated twice on the module. There are several differences when compared to the single-channel relay module. The first is that the optocoupler and relay can have a separate power supply from the input. This is selected using the JD- V_{CC} jumper – if the jumper is shorted, then the relay coil and optocoupler output are connected to the signal V_{CC}. If the jumper is left open, a separate power supply can be provided to the relay coil through the JD-VCC pin.

The second is that the input is active low, meaning that the relay coil is activated only when the input is low. This is because the optocoupler input and the indicator LED are chained to V_{CC}. When the input is high, the voltage difference across the chain is 0V and no current can flow, but when the input is low, supply voltage appears across the chain and the optocoupler output conducts, supplying current to the base of the drive transistor, turning the relay on.

How to use Dual-Channel Relay Module

The dual-channel relay module can be used to switch mains powered loads from the pins of a microcontroller. Since there are two channels on the same board, two separate loads can be powered.

Dual-Channel Relay Module Basic Troubleshooting

If either of the relays does not turn on:

1. The contacts might be welded due to overcurrent/arcing. Shaking the module firmly might help unstick the contacts
2. The driver circuitry might have been damaged due to overvoltage.
3. Input polarity might be incorrect.
4. Jumper might not have been moved to the correct position

Dual-Channel Relay Module Applications

- Switching mains loads
- Home automation
- Battery backup
- High current load switching

3.5 Transformer

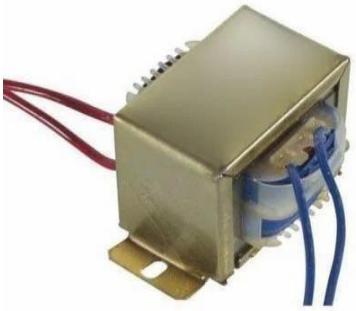

Figure 3.5 Transformer

A transformer makes use of Faraday's law and the ferromagnetic properties of an

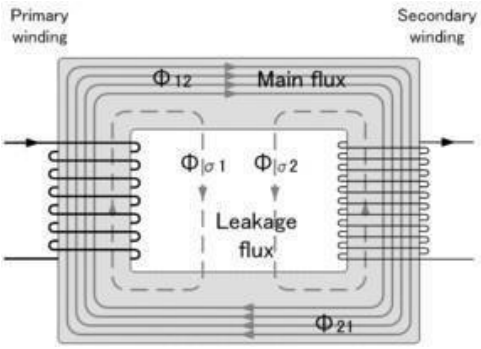

Figure 3.5 Transformer

iron core to efficiently raise or lower AC voltages. It of course cannot increase power so that if the voltage is raised, the current is proportionally lowered and vice versa.

Alternating current flowing in the primary (input) coil creates a continually changing magnetic field in the iron core. This field also passes through the secondary (output) coil and the changing strength of the magnetic field induces an alternating voltage in the secondary coil. If the secondary coil is connected to a load the induced voltage will make an induced current flow. The correct term for the induced voltage is 'induced electromotive force' which is usually abbreviated to induced e.m.f.

The iron core is laminated to prevent 'eddy currents' flowing in the core. These are currents produced by the alternating magnetic field inducing a small voltage in the core, just like that induced in the secondary coil. Eddy currents waste power by needlessly heating up the core but they are reduced to a negligible amount by laminating the iron because this increases the electrical resistance of the core without affecting its magnetic properties.

3.6 Hydro Pneumatic Cylinder Unit

The drilling operation is start when ‘on’ switch is pressed in the control panel. When the start switch is pressed, the 5/2 ways directional controlled solenoid valve supplies pressurized air to the air cylinder in the hydro pneumatic cylinder

At the same time the drilling machine spindle also moves with rotation. The oil on one side of the cylinder moves to the other side through the 4 mm plastic tube.

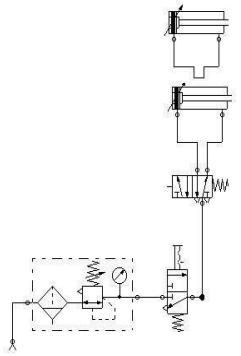

Figure 3.6 hydro pneumatic cylinder unit

3.7 Push Button:

Two push buttons are used for **on** and **off** drilling m/c. Limit switch is used to set the drilling depth as well as to stop the feeding the operation of drilling m/c.

Figure 3.7 Push button

3.8 230vportable Electric Drilling Machine;

A 230V portable electric drilling machine operates using a universal electric motor that runs on AC mains supply. When the drill is connected to a 230V power source and the trigger switch is pressed, electric current flows through the motor windings, producing a rotating magnetic field. This field interacts with the armature, causing it to rotate at high speed. The rotational motion is transmitted to the chuck, which holds the drill bit.

Figure 3.8: 230V Electric drilling machine

As the drill bit rotates, it cuts into the material due to friction and pressure, creating a hole. A trigger-controlled variable speed switch allows adjustment of the drill speed according to the requirement. In some models, a gear mechanism provides torque control, and carbon brushes maintain electrical contact with the rotating armature.

4. CONSTRUCTION AND WORKING

4.1 Principle and Construction

In modern workshops and small-scale industries, drilling machines predominantly rely on manual feed control, which often leads to inconsistent hole depths, operator fatigue, and reduced productivity. To overcome these drawbacks, this project implements a hydro-pneumatic feed mechanism driven by an Arduino-controlled electronic system, thereby automating the drilling process without emitting any harmful byproducts. The hydro-pneumatic setup combines the rapid actuation of compressed air with the smooth damping of hydraulic oil, ensuring precise, vibration-free feed motion. The Arduino Uno microcontroller coordinates inputs from a magnetic reed sensor and outputs to a solenoid valve and relay module, enabling fully automatic advance, depth-sensing, and retraction of the drill.

4.1.1 List of Parts

The automated drilling system comprises the following key components:

[1] Portable electric drilling machine (230 V AC)
[2] MS base frame with sliding guideways
[3] Double-acting pneumatic cylinder (20 mm bore,
[4] 75 mm stroke)
[5] Hydraulic damping cylinder (filled with oil on
[6] both sides)
[7] 5/2-way solenoid-operated directional valve
[8] Magnetic reed sensor for depth detection
[9] Arduino Uno microcontroller
[10] Dual-channel relay module
[11] 12 V DC power supply and step-down transformer
[12] Tubing, fittings, and mounting hardware highly

4.2 Working Process

This project consists of three sections,

a) Portable drilling m/c unit
b) Hydro pneumatic cylinder unit
c) Electrical control system –ARDUINO

To start the operation, initially place the job to be drilled in the clamping unit. Connect the pipeline to the input port of the 5/2 way solenoid operated directional valve. Then release pressurized air of 5 bar from the compressor through the FRL unit.

Now press the start switch which switch 'ON" the ARDUINO control unit causes the solenoid valve becomes ON. This valve directs airline to the output port A of the solenoid valve. The air cylinder pushes the sliding unit with hand operated portable electrical drilling machine along with the piston rod of oil cylinder. The purpose of connecting the both the oil and air cylinder is to control the feed movement of drilling operation. For that oil cylinder is filled with the servo 60 hydraulic oil on both sides of the piston and form a closed circuit when it is pulled by the air cylinder force. The work piece is drilled by the drilling machine and it is returned back to original position after the signal from the magnetic sensor. This drilling depth can be set or adjusted with the position of magnet on the sliding unit.

5. STRUCTURAL DESIGN

5.1 General

The structural design of the automated drilling machine integrates mechanical rigidity with compact automation. A mild steel base frame supports the entire assembly, featuring precision guideways for the feed carriage. The portable electric drill is clamped onto a sliding platform, which is driven by a hydro-pneumatic actuator. All components are arranged to minimize footprint while ensuring ease of maintenance and rapid tool change. This layout provides stability during drilling, resists vibration, and allows the system to be easily transported between workstations.

5.2 Design Parts

5.2.1 Drill Carriage

The carriage is a welded MS plate that holds the portable electric drill. It incorporates linear bearings that run on the guideways, allowing precise vertical movement driven by the hydro-pneumatic cylinder.

5.2.2 Hydro-Pneumatic Actuator

A dual-cylinder unit (20 mm bore, 75 mm stroke) provides the feed motion. The pneumatic cylinder delivers the actuation force, while the hydraulic section (oil-filled cylinder) damps the motion to prevent shock and vibration.

5.2.3 5/2-Way Solenoid Valve

This valve controls the direction of air flow to the pneumatic cylinder. When energized by the Arduino-driven relay, it extends the cylinder; when de-energized, it retracts, enabling automatic forward and return strokes.

5.2.4 Magnetic Reed Sensor

Mounted adjacent to the drill spindle, the reed sensor detects the position of a small magnet attached to the piston rod. It provides depth-control feedback to the Arduino for accurate stopping and retraction.

5.2.5 Arduino Uno & Relay Module

The Arduino Uno processes sensor inputs and drives the dual-channel relay module. One relay power the drill motor, and the other actuates the solenoid valve, coordinating drilling and feed motions.

5.2.6 Power Supply Assembly

A step-down transformer and bridge-rectifier circuit convert 230 V AC to 12 V DC for the Arduino,

relays, and solenoid. The drill and compressor run directly from the 230 VAC mains.

5.2.7 M.S. Base Plate (Frame)

The drilling m/c and the hydro Pneumatic cylinder unit are mounted on the M.S. base plate. This M.S. plate is made 25 x 25 mm 'l 'angle having thickness of 2.5mm. The size of base plate is 900 x 300 mm. On the top of the base plate drilling unit slides in the guide ways to avoid the sacking.

6. COMPONENTS USED

- Portable 230 V AC Electric Drill
- Double-acting Pneumatic Cylinder (20 mm × 75 mm)
- Hydraulic Damping Cylinder (Oil-Filled)
- 5/2-Way Solenoid-Operated Directional Control Valve
- Arduino Uno Microcontroller
- Dual-Channel Relay Module
- Magnetic Reed Sensor
- Step-Down Transformer and Bridge Rectifier (230V AC to 12V DC)
- MS Angle Frame with Guideways
- Tubing and Pneumatic Fittings
- Sensor Holding Bracket
- Clamps and Mounting Supports6.2 ASSEMBLY

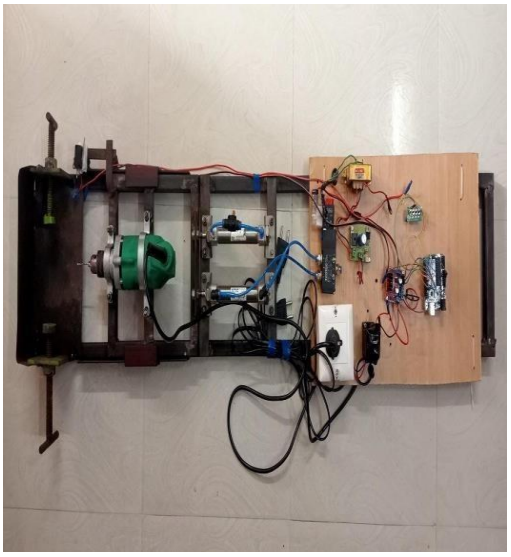

Figure 3.8: Final assembly

6.1 Material Used

- Mild Steel (MS)
- Stainless Steel
- Aluminium
- Copper Wire (for solenoid coil)
- PVC/PU Tubing
- Fasteners (Nuts, Bolts, Washers)

7. IMPACTS ON HYDO-PNEUMATIC FEED DRILLING

7.1 Advantages

a. Reduced Manual Effort: Automates feed control, minimizing operator fatigue and error.
b. Improved Accuracy: Hydraulic damping ensures smooth, vibration-free feed for consistent hole depths.
c. Compact and Portable: Fits small workshops and labs, and can be moved easily between stations.
d. Low Operating Cost: Pneumatic actuation uses inexpensive compressed air, and the Arduino control draws minimal power.
e. Versatile Operations: By simply changing the drill bit, the same setup can perform drilling, tapping, reaming, and light grinding tasks

7.2 Disadvantages

a. Initial Setup Cost: Pneumatic and hydraulic components add to the upfront investment.
b. Noise and Maintenance: Compressor noise and potential for air/oil leaks require regular maintenance.
c. Limited Thrust Force: Pneumatic cylinders may not match the high thrust of large industrial drilling rigs.

7.3 Future Scope

Digital Feedback Integration: Add load and speed sensors with real-time display for process monitoring.

*Adaptive Control Algorithms***:** Implement PID control in the Arduino to adjust feed rate based on material hardness.

Multi-Axis Expansion: Extend the system to include X-Y table automation for drilling patterns.

Energy Recovery: Capture and reuse pneumatic exhaust energy to improve overall efficiency.

Wireless Operation: Incorporate Bluetooth or Wi-Fi modules for remote start/stop and parameter adjustment.

7.4 Applications

- Used in automobile workshops for drilling mechanical device holes.
- Used in tiny scale industries.
- For playing the operations in large numbers that cannot be tired standard machines, since it's transportable.
- In attachment buy grinding.
- In such places wherever frequent amendment operative is needed.

8. CONCLUSION

The hydro-pneumatic feed drilling machine designed and fabricated in this project has shown promising results in reducing manual effort and improving drilling consistency. The integration of a pneumatic cylinder for motion and a hydraulic chamber for damping provided a stable and controlled feed mechanism during drilling operations. The electric drilling machine mounted on a fabricated frame successfully performed multiple cycles of feed and retraction with uniform performance.

The Arduino-based control system, in combination with the magnetic reed sensor and solenoid valve, effectively handled the feed timing and depth control. The machine was tested under various operating conditions, and the results aligned closely with the expected performance. Minor timing variations were observed during retraction due to pressure balancing in the cylinder, which can be minimized by adjusting valve response time and airflow rate. Overall, the system is compact, cost-effective, and easy to maintain. It is well-suited for applications in small- scale workshops, academic institutions, and fabrication units. The successful working of this project proves that a hydro-pneumatic feed mechanism can be a practical solution for improving precision and reducing effort in drilling processes, especially where CNC systems are not viable due to cost or space limitations.

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Influence of Stitching on the Impact Resistance of Fiber-Reinforced Epoxy Laminates

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ABSTRACT

The composite structural members are highly used in various fields such as aerospace, automobiles, etc., has attracted extensive attention in the past decades. One of the important issues in the composite technology is the strength the structures. Delamination in composite laminates may arise from either fabrication processes or impact during service. In stitched laminates, delamination is not completely separated but is held together by the stitches. In this the laminates are not densely stitched to prevent the specimen from failing before delamination propagates. In this paper the effect of impact response on stitched and unstitched fibre epoxy laminates and to investigate the ability of through thickness reinforcement to improve delamination resistance by performing tensile, end notch flexure test(three point bending test), and impact test. It is shown that adequate stitching can significantly increase the strength of the laminates.

Keywords: Composite Materials, Impact Load, Fibre-Epoxy, Lamination

1. INTRODUCTION

In recent times laminate composites have been increasingly utilized in such lightweight and high strength structured as ground transportation vehicles, aerospace and space structure. However composite material suffers from some serious limitation. The most significant among them is their response to impact loading. A structure is subjected to an impact force when a foreign object hits it. For instance, the loads imparted by dropped tool on the bonnet cover of car body, bird hit and runway debris on an aircraft engine are typical example of impact loads.

The manner in which composite material respond to impact loading and dissipate the incident kinetic energy of the projectile is very different to that of metals. For low and intermediate incident energies of projectile, metals absorb energy through elastic and plastic deformation; its consequences on the load carrying capacity of the components are small. In case of composites the elastic deformations are the major outcome of the energy absorption while the plastic deformation is very minimal. But at high incident impact energies, target perforations may occur and the passages of the impact will generally result in cracking and de-bonding. Such damage will degrade the load bearing ability of the composite structure.

The impact property of a material is the capacity of the material to absorb and dissipate energies under shock loading. Impact condition may range from the accidental dropping of hand tools to high speed collisions and the response of the structure may range from localized damage to total disintegration of the structure. The present study is taken up to understand the response of fibre reinforced plastic laminated plates under low energy, and low velocity impacts to simulate the case of a cover plate, in an automobile engine of wing of an aircraft subjected to impact loading.

The present study a impact and tensile testing machine is instrumented such that the load history during the impact can be recorded. Here the specimen itself is instrumented so that the actual deflection and hence the load experienced by the specimen cab be recorded. High strain rate or impact loads may be expected in many engineering applications of composite materials. The suitability of a composite for such application is therefore, determined not only by usual parameter, but also by impact or energy absorbing properties. Frequently, an attempt to improve the strength properties results in a deterioration of the impact properties. Thus it is important to have a good understanding of impact behavior of composite for both safe and efficient design of structure and to develop new composite having well impact properties as well as good tensile properties.

Severe stress and strain may develop at the point of impact, the study of which is known as the contact phenomena. So long as the stress is below the elastic limit, the deformation is reversible. Often the magnitude of the stresses may be so high that yielding, cracking may occur. The extent of damage depend not only on the intensity of impact and material behavior, but also on the shape and the dimension of the bodies in the region of impact, their hardness and wave propagation properties. The different forms of damages that may occur are yielding, de lamination, cracking, and deformation. The elastic indentation takes place at low velocity impacts. Yielding or cracking depends on whether the material is ductile or brittle. Penetration is the entrance of one body into without completing its passage through the rod. Perforation means complete piercing through the target.

Impact load may arise in practical situations from variety of sources with a wide range of velocities, duration of contact, momentum and energy release. The stress distribution, amplitude of vibration, pattern of wave propagation and the nature of load damages depend on parameter like:

1. Velocity of the impactor
2. Duration of the impact
3. Mass and shape of the impactor
4. Target
5. The distribution and intensity of force developed at the point of impact.

The main goal of this work is to understand the impact response of Un- stitched and stitched fibre epoxy laminates. In this Uni – directional fabric form of mat is used and nylon thread is used to stitch the mat and the corresponding results are noted.

2. COMPOSITE MATERIALS OVERVIEW

Basic requirements for the better performance efficiency of an aircraft are high strength, high stiffness and low weight. The conventional materials such as metals and alloys could satisfy these requirements only to a certain extent. This lead to the need for developing new materials that can whose properties were superior to conventional metals and alloys, were developed.

A composite is a structural material which consists of two or more constituents combined at a macroscopic level. The constituents of a composite material are a continuous phase called matrix and a discontinuous phase called reinforcement.

Matrix gives shape and protects the reinforcement from the environment. It also makes the individual fibres of the reinforcement act together and provides transverse shear strength and stiffness to the laminated composites. The matrix factors which contribute to the mechanical performance of composites are transverse modulus and strength, shear modulus and strength, compressive strength, inter-laminar shear strength, thermal expansion co-efficient, thermal resistance and fatigue strength.

Reinforcement provides strength and stiffness and controls thermal expansion co-efficient. It also helps to achieve directional properties. Reinforcements may be in the form of fibres, particles or flakes. The fibre factors which contribute to the mechanical performance of a composite are length, orientation, shape and material.

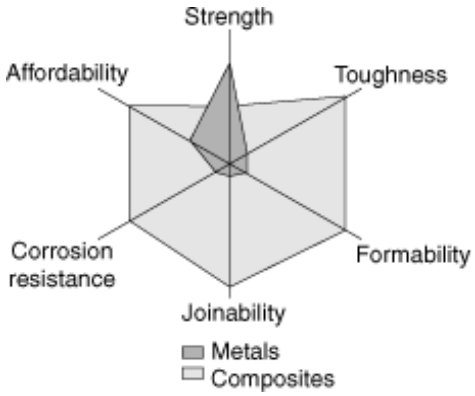
The factor which influences the mechanical performance of composites other than the fibre and the matrix is the fibre-matrix interface. It predicts how well the matrix transfers load to the fibres.

Composites are classified by

1. The geometry of the reinforcement as particulate, flakes and fibres

2. The type of matrix as polymer, metal, ceramic and carbon

The most commonly used advanced composites are polymer matrix composites. These composites consists of a polymer such as epoxy, polyester, urethane etc., reinforced by thin-diameter fibres such as carbon, graphite, aramids, boron, glass etc. Low cost, high strength and simple manufacturing principles are the reason why they are most commonly used in the repair of aircraft structures.



3. SPECIMEN MANUFACTURE

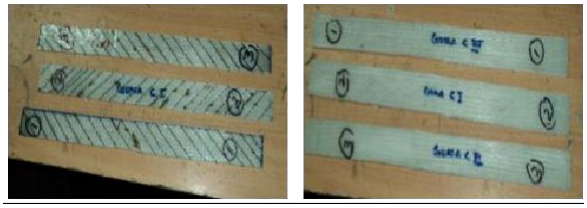
In this process resin and hardener are mixed in the ratio of 10:1 at normal room temperature to get epoxy. The mould should be well cleaned and dry. Release agent is applied and the epoxy mixture is uniformly applied. First mat is laid into the moulded.Apply the resin on mat by brush. Roller is used to swipe the unused epoxy and then second mat is laid on to the first mat. Repeat the process up to 3 layers.

For stitched specimen the stitches are made 4 stitches per sq cm. stitches are made perpendicular to the direction of fiber orientation. Machined specimens are as follows

Tensile test specimen ASTM D 638

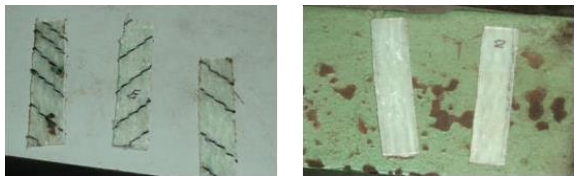
Stitched Un stitched

Compression test ASTM D 790



Stitched Un stitched

Impact test specimen

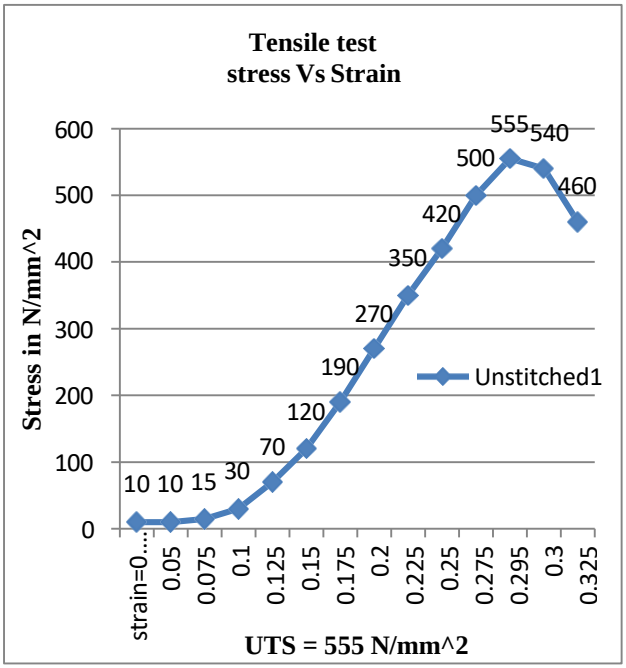


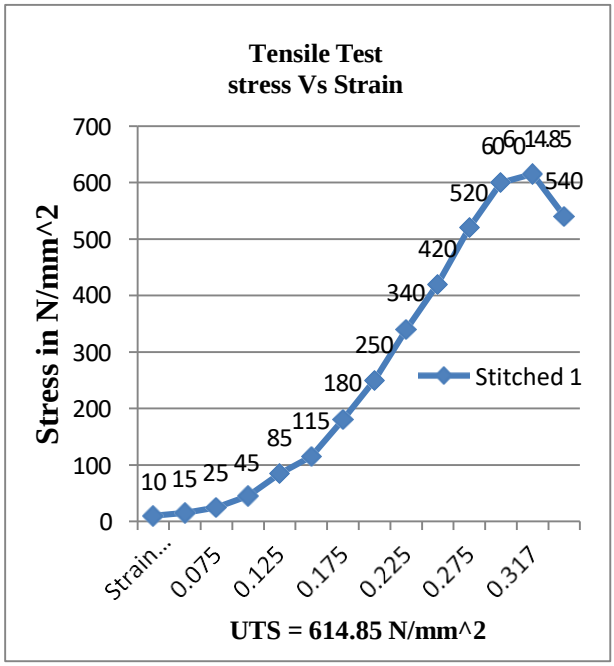
Stitched Un stitched

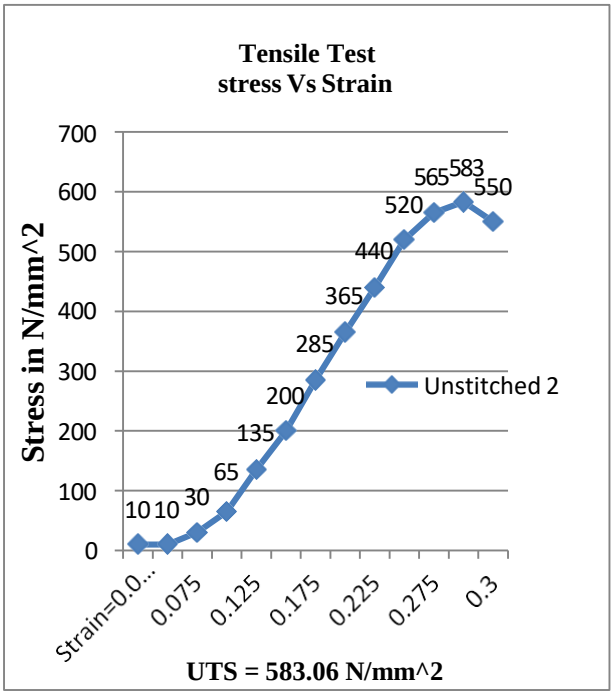
4. RESULTS AND DISCUSSION

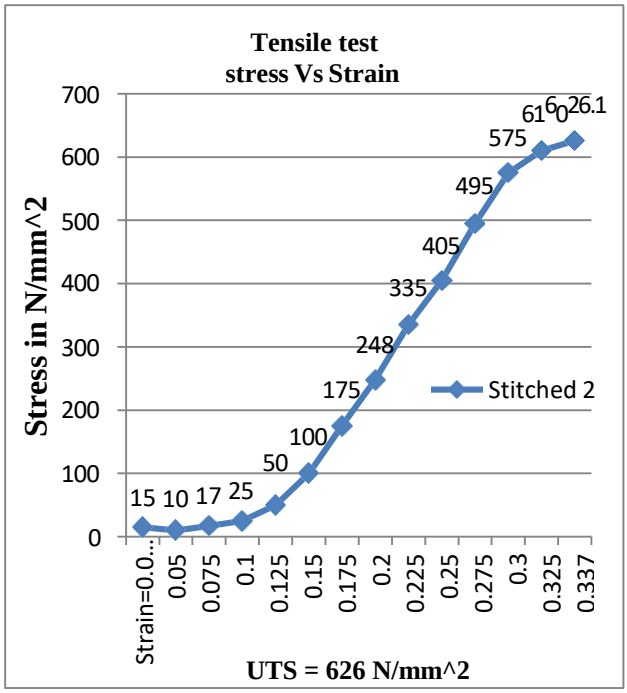
Specimens are made for tensile test in the standard of ASTM D638 and for compression test ASTM D790 is machined.

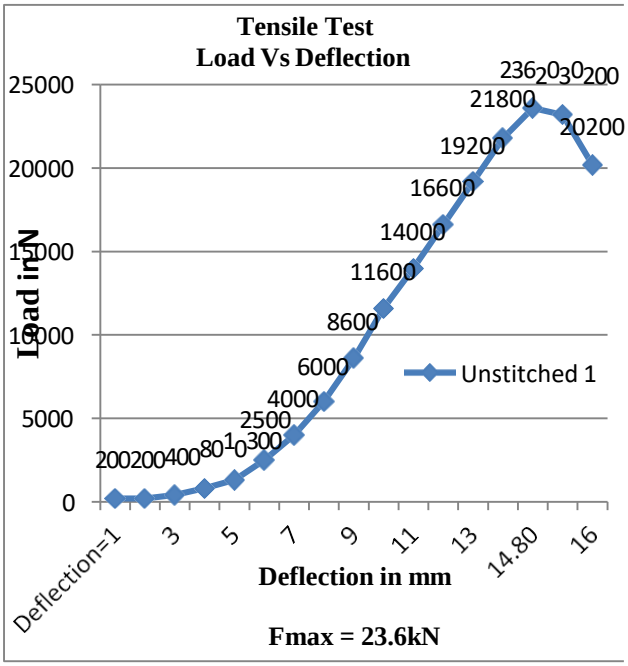
Tensile, compression and impact test are conducted and the ultimate tensile strength ,Breaking load and maximum deflection are depicted in the graphs.

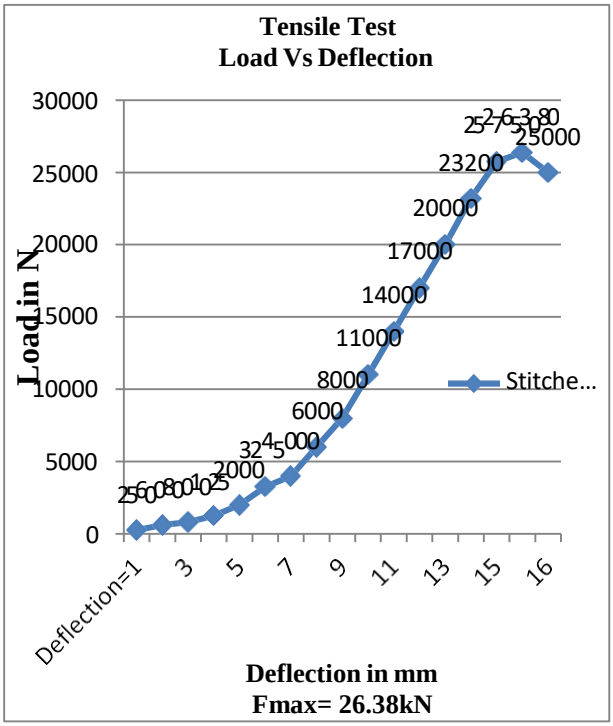

Tensile test
stress Vs Strain
Stress in N/mm^2
600
500
400
300
200
100
0
555
540
500
460
420
350
270
190
120
70
30
10 10 15
Unstitched1
strain=0....
0.05
0.075
0.1
0.125
0.15
0.175
0.2
0.225
0.25
0.275
0.295
0.3
0.325
UTS = 555 N/mm^2

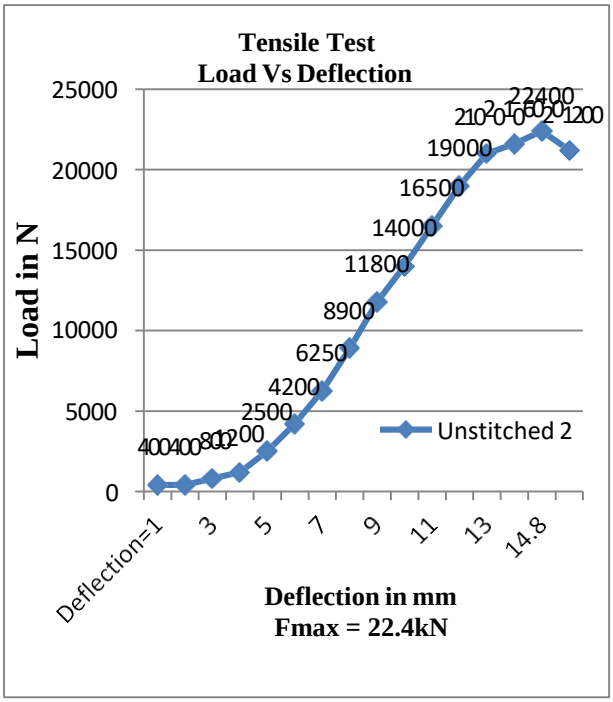

Tensile Test
stress Vs Strain
Stress in N/mm^2
700
600
500
400
300
200
100
0
614.85
600
540
520
420
340
250
180
115
85
45
10 15 25
Stitched 1
Strain...
0.075
0.125
0.175
0.225
0.275
0.317
UTS = 614.85 N/mm^2

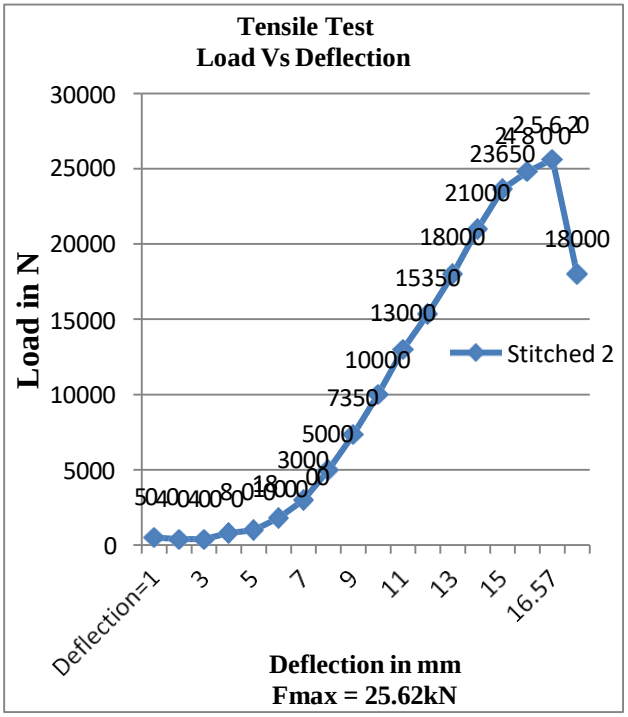

Tensile Test
stress Vs Strain
Stress in N/mm^2
700
600
500
400
300
200
100
0
583
565
550
520
440
365
285
200
135
65
30
10 10
Unstitched 2
Strain=0.0...
0.075
0.125
0.175
0.225
0.275
0.3
UTS = 583.06 N/mm^2

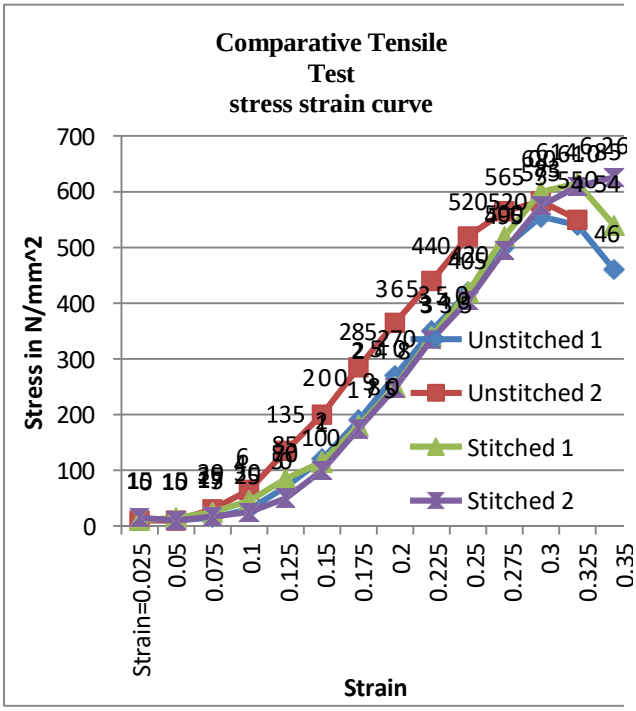

Tensile test
stress Vs Strain
Stress in N/mm^2
700
600
500
400
300
200
100
0
626.1
610
575
495
405
335
248
175
100
50
15 10 17 25
Stitched 2
Strain=0.0...
0.05
0.075
0.1
0.125
0.15
0.175
0.2
0.225
0.25
0.275
0.3
0.325
0.337
UTS = 626 N/mm^2

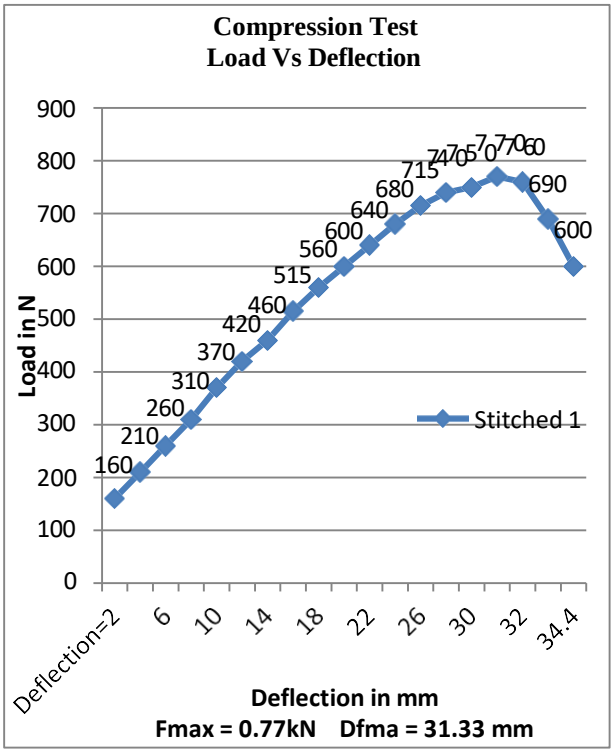

Tensile Test
Load Vs Deflection
Load in N
Deflection in mm
Unstitched 1
Fmax = 23.6kN

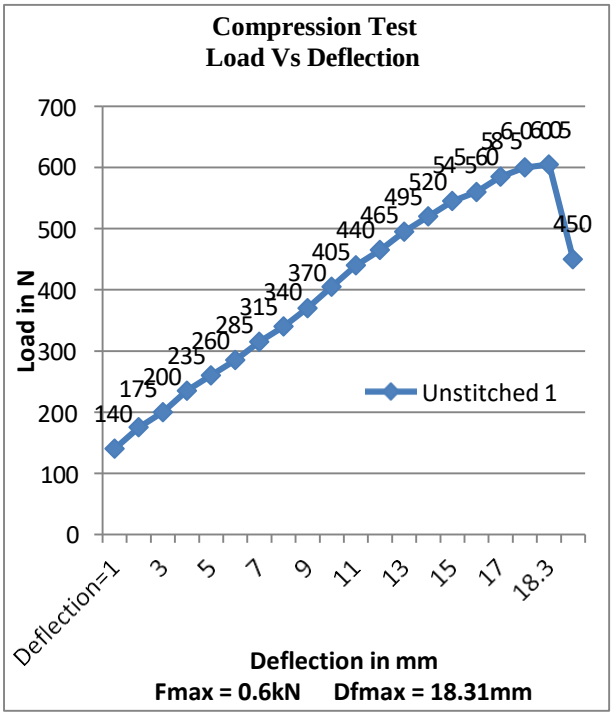

Tensile Test
Load Vs Deflection
Load in N
Deflection in mm
Stitche...
Fmax= 26.38kN

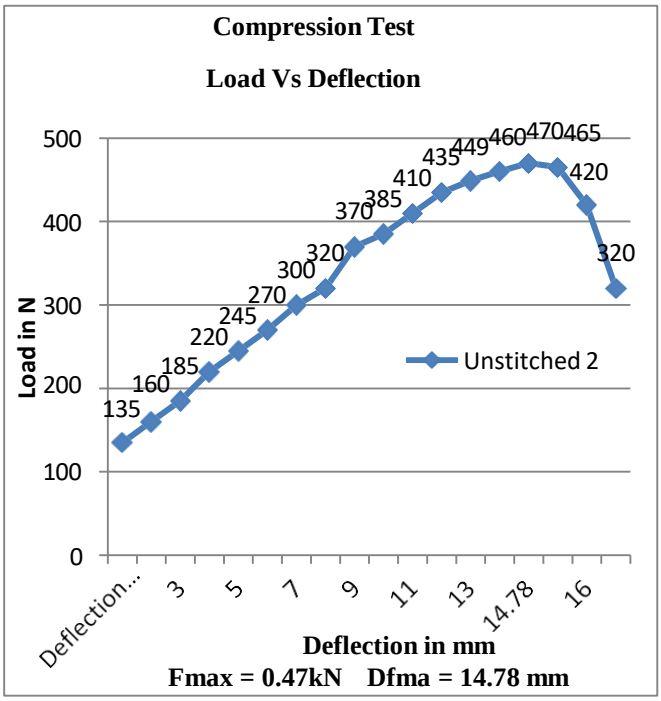

Tensile Test
Load Vs Deflection
Load in N
Deflection in mm
Unstitched 2
Fmax = 22.4kN

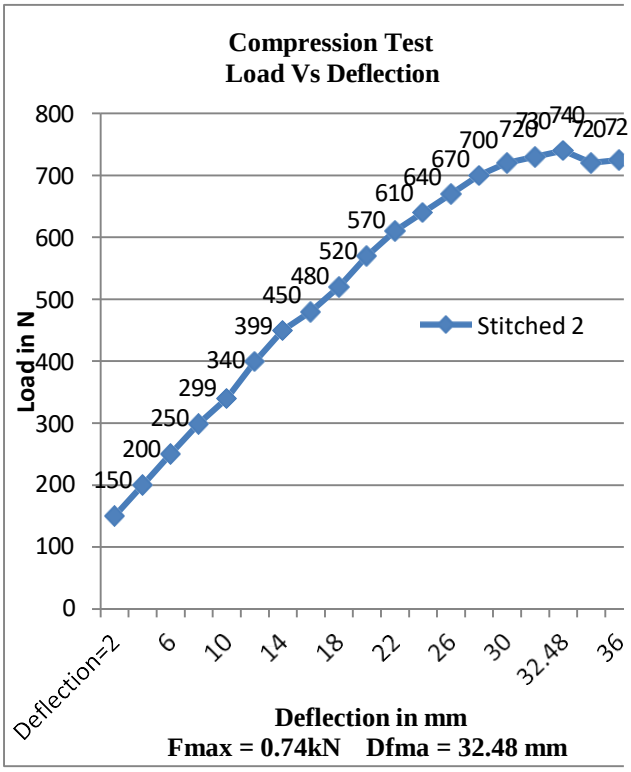

Tensile Test
Load Vs Deflection
Load in N
Deflection in mm
Stitched 2
Fmax = 25.62kN

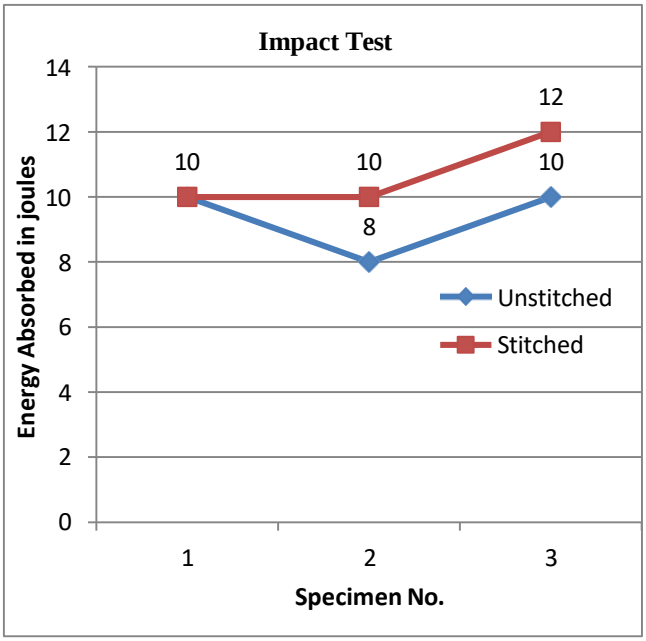

Comparative Tensile Test
stress strain curve
Stress in N/mm^2
Strain
Strain=0.025
Unstitched 1
Unstitched 2
Stitched 1
Stitched 2

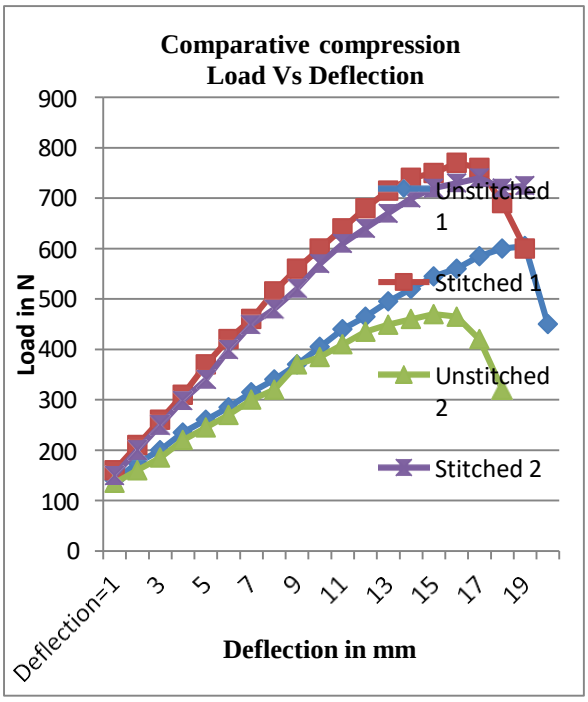

Compression Test
Load Vs Deflection
Load in N
Deflection in mm
Deflection=2
Stitched 1
Fmax = 0.77kN Dfma = 31.33 mm


Compression Test
Load Vs Deflection
Load in N
Deflection in mm
Deflection=1
Unstitched 1
Fmax = 0.6kN Dfmax = 18.31mm


Compression Test
Load Vs Deflection
Load in N
Deflection in mm
Deflection...
Unstitched 2
Fmax = 0.47kN Dfma = 14.78 mm







TEST RESULT 1				
S.no	Test name	Test description	Stitched specimen	Un stitched specimen
1	Tensile test	Ultimate Breaking Load	26.38kN	23.6kN
		Ultimate Stress	614.8N/mm^2	555N/mm^2
2	Compression test	Ultimate Breaking Load	0.77kN	0.60kN
3	Impact test without notch	Izod Test (Energy Stored in Joules)	10	8

TEST RESULT 2				
S.no	Test name	Test description	Stitched specimen	Un stitched specimen
1	Tensile test	Ultimate Breaking Load	25.62kN	22.4kN
		Ultimate Stress	626N/sq mm	583N/sq mm
2	Compression test	Ultimate Breaking Load	0.74kN	0.47kN
3	Impact test without notch	Izod Test (Energy Stored in Joules)	12	10

CONCLUSION

Tensile, Flexural and impact tests were carried out in unstitched and stitched glass-Fibre /Epoxy laminates. A cotton polyester thread was used to stitch prepare layers in fibre direction with stitch density of 4 stitches/sq cm.The specimens were tested at different Test as discussed above. The Strength and breaking Loads and displacement was evaluated. The following conclusions were drawn on the impact response of the unstitched and stitched laminates.Impact force have been evaluated experimentally by drawing a graph between load Vs. deformation for both stitched and unstitched laminates.From the graph it is found that the peak force of unstitched laminate is more than the stitched laminates.Stitching of the laminate will further improve the delamination resistance, Also from the above obtained results, we may conclude stitched laminate is more strengthening than the un-stitched laminates.From the tensile testing we found, the stitched specimen is observed the breaking load is more than the un-stitched specimen. So the stitched specimen breaking strength is more.

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A Review On Flax Fibre Reinforced Polymer Composites Modified With Alumina (Al_2o_3) Fillers

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Abstract

The growing demand for sustainable and lightweight engineering materials has intensified research into natural fibre reinforced polymer composites. Among natural fibres, flax fibre has gained significant attention due to its favourable mechanical properties, low density, renewability, and biodegradability. However, inherent limitations such as poor fibre–matrix interfacial bonding, moisture sensitivity, and moderate mechanical strength restrict its wider structural application. To overcome these challenges, ceramic fillers—particularly alumina (Al_2O_3)—have been incorporated into flax fibre composites to enhance mechanical, thermal, and tribological performance. This review critically examines the influence of Al_2O_3 fillers, in both micro- and nano-scale forms, on the properties of flax fibre reinforced polymer composites. Emphasis is placed on material selection, fibre surface treatment, processing techniques, dispersion behaviour of Al_2O_3, and their effects on tensile, flexural, impact, and wear properties. Morphological characteristics and interfacial mechanisms governing composite performance are also discussed. A comparative evaluation of reported studies reveals that optimum Al_2O_3 loading significantly improves load transfer efficiency and damage resistance, while excessive filler addition leads to agglomeration and performance degradation. Finally, existing research gaps, challenges, and future research directions for flax–Al_2O_3 hybrid composites are identified, highlighting their potential for sustainable automotive and semi-structural applications.

Keywords: Flax fibre, Alumina (Al_2O_3), Natural fibre composites, Nano composites, Mechanical properties

Introduction

The growing demand for environmentally sustainable materials has led to increased research interest in natural fibre reinforced polymer composites (NFRPCs). Traditional synthetic fibre composites such as glass fibre reinforced polymers (GFRP) and carbon fibre reinforced polymers (CFRP) provide excellent mechanical performance but pose environmental challenges due to their non-biodegradable nature and high energy consumption during manufacturing. In contrast, natural fibre composites offer several advantages including renewability, biodegradability, lower density, reduced environmental impact, and lower production cost [1–4]. Natural fibre reinforced composites typically consist of natural fibre reinforcement embedded in a polymer matrix, sometimes combined with inorganic fillers to enhance mechanical and thermal performance. The basic structure of natural fibre composites and the interaction between fibres, matrix, and fillers are illustrated in Fig. 1. Natural fibres such as flax, hemp, jute, kenaf, sisal, and bamboo have been widely investigated as reinforcement materials in polymer matrices [5–7]. Among these fibres, flax fibre has gained considerable attention due to its relatively high mechanical strength and stiffness compared with other natural fibres. Pickering et al. reported that flax fibres exhibit tensile strengths ranging from 500 to 1500 MPa and a Young's modulus of approximately 50–70 GPa, making them attractive for lightweight engineering applications [2,8].

Flax fibre composites have been successfully applied in automotive interior panels, sporting goods, marine components, and building materials [9–11].

Their low density and good mechanical properties enable the production of lightweight structures that contribute to improved fuel efficiency and reduced carbon emissions in transportation industries. Despite these advantages, natural fibre composites exhibit several limitations. The hydrophilic nature of natural fibres leads to poor compatibility with hydrophobic polymer matrices, resulting in weak fibre–matrix interfacial bonding. Additionally, natural fibre composites often exhibit high moisture absorption, reduced thermal stability, and limited wear resistance [3,12,13].

Figure 1.: Natural fibre composite structure showing flax fibre reinforcement, polymer matrix and alumina fillers

To overcome these limitations, researchers have investigated several strategies including chemical surface treatment, hybrid reinforcement, and incorporation of inorganic fillers or nanoparticles into polymer matrices [14–16].Among various fillers, alumina (Al_2O_3) has received considerable attention due to its high hardness, thermal stability, and wear resistance. The incorporation of alumina fillers into flax fibre reinforced composites has been reported to significantly enhance mechanical strength, thermal stability, and tribological performance [17–19].

2. Natural Fibre Reinforced Polymer Composites

Natural fibre reinforced polymer composites (NFRPCs) have gained significant attention due to their environmental benefits and promising mechanical performance [4,20,21]. These composites are produced by reinforcing polymer matrices with natural fibres obtained from renewable plant sources. Compared with conventional synthetic fibre composites, natural fibre composites offer a more sustainable alternative because they are biodegradable, renewable, and require lower energy during production. Increasing environmental awareness and the demand for sustainable materials have further encouraged the development and use of these composites [4,20,21]. Natural fibres are mainly composed of cellulose, hemicellulose, lignin, and pectin, which influence their mechanical behaviour and interaction with polymer matrices. Among these components, cellulose contributes significantly to the strength and stiffness of the fibres due to its crystalline structure. Natural fibres are typically embedded in polymer matrices such as epoxy, polyester, or polypropylene to produce composite materials with improved mechanical properties [4,20,21]. Natural fibre composites provide several advantages over traditional synthetic composites. They have low density, good specific strength, renewability, biodegradability, and lower cost. These characteristics make them suitable for applications in industries such as automotive, construction, and consumer products. In addition, the use of natural fibres helps reduce environmental impact and supports the development of eco-friendly materials [1,4,20]. However, natural fibre composites also have some limitations. The properties of natural fibres may vary due to differences in plant species and growing conditions. Furthermore, natural fibres are hydrophilic, meaning they

absorb moisture easily, which can weaken the fibre–matrix interface and reduce mechanical performance. Natural fibres also have relatively lower thermal stability compared with synthetic fibres [3,13,21]. To improve the performance of natural fibre composites, researchers have explored several approaches such as chemical surface treatment, hybrid reinforcement, and the addition of nanoparticles or ceramic fillers. These techniques can enhance fibre–matrix bonding and improve mechanical and thermal properties [14,15,22].

3. Flax Fibre Reinforced Polymer Composites

Flax fibres are derived from the *Linum usitatissimum* plant and are widely used in composite materials due to their excellent mechanical properties and environmental benefits [8,9]. Flax fibres possess relatively high cellulose content, which contributes to their stiffness and tensile strength. Several studies have investigated the mechanical behaviour of flax fibre reinforced polymer composites. Woven flax/epoxy composites have demonstrated improved load transfer efficiency and structural stability compared with randomly oriented fibres [23]. Madhu et al. reported that optimized laminate configurations significantly enhanced tensile strength and stiffness in flax fibre reinforced epoxy composites [24]. Similarly, other studies have highlighted that fibre architecture and stacking sequence play a significant role in determining the mechanical performance of flax fibre composites [25]. Furthermore, the morphology and structure of flax fibre bundles strongly influence composite properties. Improved fibre alignment and bundle structure can enhance the tensile properties and stiffness of flax fibre composites [26]. Despite these promising results, flax fibre composites still suffer from several limitations such as poor fibre–matrix bonding and moisture sensitivity, which can negatively affect long-term performance [3,12].

4. Alumina (Al_2O_3) Fillers in Polymer Composites

Ceramic fillers have been widely used to enhance the performance of polymer composites by improving their mechanical, thermal, and tribological properties [27–29]. These fillers are commonly incorporated into polymer matrices to increase stiffness, hardness, and overall durability of composite materials. Among the various ceramic fillers available, alumina (Al_2O_3) has gained considerable attention because of its excellent hardness, high thermal stability, good wear resistance, and chemical inertness. Due to these advantageous characteristics, alumina is frequently used as a reinforcing filler in polymer-based composites for advanced engineering applications.

Alumina particles can be incorporated into polymer matrices in different sizes, including micro-sized and nano-sized particles. Micro-sized alumina particles primarily enhance the stiffness and wear resistance of the composite by acting as rigid reinforcements within the polymer matrix. On the other hand, nano-sized alumina particles provide a significantly larger surface area, which promotes better interaction between the filler particles and the surrounding polymer matrix. This improved interfacial interaction leads to better stress distribution and enhanced reinforcement efficiency within the composite structure [30].

Several studies have reported that the addition of alumina fillers significantly improves the tensile strength, hardness, and wear resistance of polymer composites. The presence of rigid ceramic particles increases the stiffness of the matrix and restricts deformation under applied loads, thereby improving the load-bearing capacity of the composite material [31]. Furthermore, ceramic nanofillers can enhance the stress transfer mechanism between the polymer matrix and reinforcing fibres, leading to improved mechanical

behaviour in fibre reinforced polymer composites [17,18].

In addition to mechanical improvements, the incorporation of alumina fillers also enhances the thermal conductivity and dimensional stability of polymer composites. These properties are particularly important in applications where materials are exposed to elevated temperatures or thermal fluctuations. As a result, alumina-filled polymer composites are increasingly being used in automotive, aerospace, and structural engineering components, where improved mechanical strength, wear resistance, and thermal stability are required [29,30].

5. Mechanical Properties of Flax/Al_2O_3 Composites

The mechanical properties of flax fibre reinforced polymer composites can be significantly improved through the incorporation of ceramic fillers such as alumina. The addition of alumina particles increases the stiffness of the polymer matrix and promotes more effective stress transfer between the reinforcing fibres and the surrounding matrix material [18,19]. This improved stress transfer mechanism allows the composite to withstand higher loads and enhances its overall structural performance. As a result, filler-reinforced composites often exhibit improved tensile strength, flexural strength, and impact resistance compared with composites without fillers.

Several experimental studies have demonstrated the beneficial effects of alumina fillers on the mechanical behaviour of flax fibre composites. Sathish et al. investigated the mechanical performance of flax fibre reinforced epoxy composites containing silicon carbide (SiC) and alumina (Al_2O_3) fillers and reported significant improvements in tensile strength, flexural strength, and impact resistance when compared with unfilled composites [19]. These improvements were mainly attributed to the increased stiffness of the matrix and improved fibre–matrix bonding caused by the presence of ceramic particles.

Similarly, other studies have reported that the addition of alumina fillers to flax fibre composites results in noticeable improvements in tensile strength and impact resistance due to enhanced interaction between the fibres and the polymer matrix [32]. The rigid ceramic particles act as reinforcement within the matrix and restrict deformation under applied loads, thereby increasing the load-bearing capacity of the composite material.

In addition to micro-sized fillers, the use of nano-sized alumina particles has also been shown to significantly enhance the mechanical properties of flax fibre composites. Nano-Al_2O_3 particles provide a larger surface area for interaction with the polymer matrix, which improves interfacial bonding and allows for better stress distribution throughout the composite structure [33]. This results in improved tensile and flexural properties.

However, the effectiveness of alumina fillers strongly depends on the uniform dispersion of particles within the matrix. Poor dispersion or nanoparticle agglomeration can create stress concentration regions, which may lead to premature failure and reduced mechanical performance of the composite material [27,30].

6. Thermal Behaviour of Flax Fibre Composites with Alumina Fillers

Thermal stability is an important parameter for polymer composites used in various engineering applications, particularly in industries where materials are exposed to elevated temperatures or thermal fluctuations. Natural fibre reinforced composites generally exhibit lower thermal stability compared with synthetic fibre composites because natural fibres begin to degrade at relatively lower temperatures [13,21]. This limitation restricts the use of natural fibre composites in high-temperature environments and certain structural applications.

The thermal degradation of natural fibres mainly occurs due to the decomposition of their primary constituents, including hemicellulose, cellulose, and lignin. Hemicellulose typically degrades at temperatures between 200–300 °C, while cellulose decomposes around 300–350 °C, and lignin degrades gradually over a wider temperature range. As a result, natural fibre composites may experience thermal deterioration when exposed to high temperatures for prolonged periods. Improving the thermal stability of these composites is therefore essential for expanding their engineering applications [13,21].

One effective approach to enhance the thermal stability of natural fibre composites is the incorporation of ceramic fillers such as alumina (Al_2O_3). Alumina particles possess excellent thermal resistance and high melting temperatures, which allow them to act as thermal barriers within the composite structure. The addition of alumina nanoparticles can increase the thermal degradation temperature of the composite and improve its resistance to heat and thermal aging [34]. These particles also help reduce thermal expansion and improve dimensional stability under elevated temperatures.

Thermal analysis studies conducted on flax fibre reinforced composites have shown that the incorporation of reinforcing fillers leads to improved thermal stability and enhanced resistance to thermal degradation [35]. This improvement is mainly attributed to the strong interaction between the filler particles and the polymer matrix, which restricts molecular mobility and slows down the degradation process.

To evaluate the thermal behaviour of such composites, researchers commonly use thermal analysis techniques such as thermogravimetric analysis (TGA) and differential scanning calorimetry (DSC). These techniques provide valuable information about thermal degradation temperature, heat flow behaviour, and overall thermal stability of the composite materials [36].

7. Tribological Properties of Flax/Al_2O_3 Composites

Tribological properties, including wear resistance and friction behaviour, play an important role in determining the suitability of composite materials for many engineering applications such as automotive components, bearings, gears, and sliding mechanical parts [37]. Materials used in such applications are frequently subjected to repeated contact, friction, and surface wear. Therefore, improving the tribological performance of polymer composites is essential to ensure longer service life and reliable performance.

Natural fibre reinforced polymer composites often exhibit limited wear resistance because the polymer matrix used in these materials is relatively soft compared with ceramic or metallic materials. During sliding or abrasive contact, the polymer matrix may undergo surface deformation, material removal, or microcracking, which leads to increased wear rates. This limitation restricts the use of natural fibre composites in applications where high frictional forces and severe wear conditions are present.

One effective method to enhance the tribological behaviour of these composites is the incorporation of ceramic fillers such as alumina (Al_2O_3). Alumina particles are well known for their high hardness, excellent abrasion resistance, and strong thermal stability. When dispersed within the polymer matrix, these particles act as hard reinforcement phases that improve the surface hardness of the composite and reduce material removal during sliding contact. As a result, the presence of alumina fillers significantly improves the wear resistance and surface durability of fibre reinforced polymer composites [31,37].

Several experimental studies have reported that ceramic-filled natural fibre composites exhibit a significant reduction

in wear rate compared with unfilled composites. The hard ceramic particles help protect the matrix from severe abrasion and distribute the applied load more effectively across the composite surface [38]. In addition to single filler reinforcement, hybrid reinforcement strategies have also been explored. For example, the use of nanoparticles such as zinc oxide (ZnO) and alumina (Al_2O_3) together has shown promising improvements in tribological performance by reducing friction and enhancing wear resistance [39]. These hybrid filler systems can provide better reinforcement and improved surface protection, making them suitable for demanding engineering applications.

8. Water Absorption and Environmental Durability

Moisture absorption is one of the major challenges associated with natural fibre reinforced polymer composites because natural fibres are inherently hydrophilic in nature [3,12]. Natural fibres contain hydroxyl groups in their cellulose structure, which readily attract and absorb water molecules from the surrounding environment. When these fibres are incorporated into polymer matrices, the composite material may absorb moisture when exposed to humid conditions, water, or outdoor environments. This moisture absorption can significantly influence the physical and mechanical properties of the composite material.

Moisture diffusion into the composite structure leads to several detrimental effects. As water molecules penetrate the material, the natural fibres tend to swell, which creates internal stresses within the composite structure. This swelling can cause the formation of micro-cracks and interfacial gaps between the fibre and the polymer matrix. As a result, the bonding between the fibres and the matrix becomes weaker, reducing the efficiency of stress transfer within the composite. Consequently, the overall mechanical performance, stiffness, and strength of the composite material decrease over time [21].

Hydrothermal ageing studies have further demonstrated the negative impact of moisture exposure on natural fibre composites. When flax fibre reinforced composites are exposed to moisture for extended periods, their tensile strength, flexural strength, and stiffness can significantly decrease due to fibre degradation and weakening of the fibre–matrix interface [40]. Long-term exposure to moisture may also lead to matrix plasticization and dimensional instability, which can further reduce the durability of the composite.

To mitigate these issues, researchers have explored several approaches to improve the environmental durability of natural fibre composites. One effective strategy is the incorporation of inorganic fillers or nanoparticles into the polymer matrix. The addition of fillers can reduce moisture diffusion pathways by minimizing micro-voids and improving matrix densification. This results in better barrier properties and improved resistance to moisture penetration. Consequently, filler-reinforced composites exhibit enhanced environmental stability and durability, making them more suitable for structural and outdoor applications.

9. Research Gaps and Future Directions

Although significant research has been carried out on natural fibre reinforced polymer composites and ceramic filler reinforced polymers, relatively few studies have specifically focused on flax fibre reinforced composites modified with alumina nanoparticles. While existing studies indicate that alumina fillers can improve mechanical strength, thermal stability, and wear resistance, further investigation is required to fully understand and optimize their performance in flax fibre based composites.

Future research should focus on several important aspects. First,

optimization of alumina filler content is necessary to achieve the best balance between mechanical performance and material processability. Excessive filler loading may lead to particle agglomeration and reduced composite performance. Second, surface treatment of flax fibres can improve fibre–matrix adhesion and reduce moisture absorption. Third, hybrid reinforcement strategies, combining alumina with other nanoparticles or fibres, may further enhance composite properties. Additionally, long-term durability studies under environmental conditions are required. Finally, the development of biodegradable polymer matrices will support the production of fully sustainable composite materials.

10. Conclusion

Flax fibre reinforced polymer composites (FFRPCs) have emerged as a promising class of sustainable materials for lightweight engineering applications due to their environmentally friendly characteristics and favourable mechanical properties. Flax fibres are derived from renewable plant sources and possess relatively high tensile strength and stiffness compared with many other natural fibres. When combined with polymer matrices such as epoxy, polyester, or biodegradable polymers, flax fibres can produce composite materials with good strength-to-weight ratios, making them suitable for applications in automotive components, structural panels, sporting goods, and construction materials. The use of flax fibre composites also contributes to reduced environmental impact by lowering energy consumption during manufacturing and supporting the use of biodegradable or recyclable materials. Despite these advantages, flax fibre composites still face several performance limitations. One of the main challenges is moisture absorption, which occurs because natural fibres are hydrophilic in nature. When exposed to humid environments, flax fibres tend to absorb moisture, leading to swelling, microcrack formation, and weakening of the fibre–matrix interface. This can result in a reduction in mechanical strength and long-term durability of the composite material. In addition, natural fibre composites generally exhibit lower thermal stability compared with synthetic fibre composites, which restricts their application in high-temperature environments. Another limitation is their relatively poor tribological performance, including higher wear rates and lower surface hardness. To address these challenges, researchers have investigated the incorporation of ceramic fillers such as alumina (Al_2O_3) into flax fibre reinforced composites. Alumina particles possess high hardness, good thermal stability, and excellent wear resistance, making them effective reinforcement materials for polymer matrices. The addition of alumina fillers can significantly improve the mechanical strength, stiffness, and wear resistance of flax fibre composites. Furthermore, alumina particles enhance the fibre–matrix interfacial bonding and increase resistance to thermal degradation, thereby improving overall composite performance. Although these improvements have been reported, further research is still required to optimize filler dispersion, interfacial adhesion, and long-term environmental durability to fully exploit the potential of flax fibre reinforced composites for advanced engineering applications.

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Effectiveness of Clay-Based Prosthetic Implants for Amputated Metatarsus: Implications for Gait Restoration and Biocompatibility – A Review

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Abstract

Metatarsal amputation significantly alters the biomechanical function of the foot, resulting in impaired gait, instability, and abnormal pressure distribution. Prosthetic implants are commonly used to restore foot function; however, traditional materials such as metals and polymers may present limitations including poor biological integration and inflammatory responses. Recent advances in biomaterials have highlighted the potential of clay-based nanocomposites as promising candidates for orthopaedic and prosthetic applications. Clay minerals such as montmorillonite, halloysite nanotubes, and kaolinite possess unique characteristics including high surface area, ion-exchange capability, mechanical reinforcement properties, and excellent biocompatibility. These properties make them suitable for bone regeneration and prosthetic scaffold development. This review examines the effectiveness of clay-based prosthetic implants in reconstructing amputated metatarsal bones, focusing on their role in restoring gait mechanics and maintaining biocompatibility. Current studies indicate that clay-reinforced biomaterials enhance osteogenesis, improve mechanical strength, and promote cellular proliferation without significant cytotoxicity. These characteristics suggest that clay-based prosthetic materials may contribute to improved implant integration and functional recovery in patients with metatarsal amputation. Further research and clinical studies are necessary to validate long-term outcomes and optimize implant design.

Keywords: Clay biomaterials, prosthetic implants, metatarsal amputation, gait restoration, biocompatibility, bone tissue engineering

Introduction

The human foot plays a crucial role in maintaining balance, mobility, and efficient locomotion. Among its structural components, the metatarsal bones serve as essential load-bearing elements that contribute to weight distribution and propulsion during walking and running [1]. The metatarsus consists of five long bones positioned between the tarsal bones and the phalanges, forming an integral part of the forefoot structure. These bones help maintain the longitudinal and transverse arches of the foot while enabling effective transfer of forces from the hindfoot to the toes during the push-off phase of gait [2].

Metatarsal amputation may occur due to traumatic injuries, diabetic foot complications, infections, vascular diseases, or malignant tumors [3]. Such amputations often lead to significant biomechanical alterations in the foot, including reduced forefoot leverage, altered pressure distribution, and decreased push-off efficiency during walking [4]. As a result, patients frequently experience impaired gait patterns, reduced walking speed, instability, and increased metabolic energy expenditure during locomotion [5].

The metatarsal bones play a critical role in maintaining the structural integrity and functional biomechanics of the human foot [20]. These bones support body weight, maintain foot arches, and facilitate propulsion during walking and running [21]. Damage or amputation of the metatarsal bones may occur due to trauma, diabetic complications, infections, or tumors [22]. Such conditions lead to significant biomechanical alterations in the foot, resulting in impaired gait patterns, instability, and increased energy expenditure during locomotion [23].

Prosthetic reconstruction is widely used to restore the anatomical structure and functional capability of the foot following amputation [24]. Conventional prosthetic implants are typically fabricated from materials such as titanium alloys, stainless steel, ceramics, and polymer composites [25]. Although these materials provide adequate mechanical strength, they may also cause complications including stress shielding, poor osseointegration, and inflammatory reactions [26].

Recent developments in biomaterials research have introduced clay-based nanocomposites as promising alternatives for orthopedic implants [27]. Clay minerals possess unique physicochemical properties such as high surface area, layered structure, adsorption capacity, and ion-exchange capability [28]. These characteristics enable clay materials to interact effectively with biological tissues and promote cellular growth and tissue regeneration [29].

This review aims to evaluate the effectiveness of clay-based prosthetic implants for amputated metatarsus, focusing on their role in restoring gait mechanics and maintaining biocompatibility.

2. Literature Survey

2.1. Diabetic Foot Ulcers and Offloading Strategies

Diabetic foot ulcers (DFUs) are among the most serious complications of diabetes mellitus and often lead to infection, hospitalization, and lower-limb amputation. Elevated plantar pressure caused by peripheral neuropathy and structural foot deformities plays a critical role in ulcer development and

delayed healing. Offloading interventions such as therapeutic footwear, orthoses, and pressure-redistributing devices are therefore widely recommended for both prevention and treatment of DFUs [1,32,54]. Peripheral neuropathy also alters gait biomechanics, increasing the risk of ulceration. Patients with diabetic neuropathy demonstrate reduced ankle mobility, altered walking patterns, and increased forefoot loading compared with healthy individuals [3]. Such biomechanical abnormalities highlight the importance of pressure-relieving devices and improved prosthetic solutions to prevent further tissue damage.

2.2. Biomechanical Effects of Partial Foot Amputation

Although these procedures preserve limb length, they significantly affect gait mechanics and functional mobility. Studies have shown that loss of the forefoot reduces push-off power during walking and alters the natural biomechanics of the foot [2].

Patients with partial foot amputations often demonstrate reduced walking speed, shorter stride length, and abnormal distribution of ground reaction forces during gait [22,53]. In particular, transmetatarsal amputations alter center-of-pressure progression and compromise balance and propulsion during walking [52]. These biomechanical changes may also lead to secondary musculoskeletal complications and overuse injuries in the remaining limb due to altered load distribution [51].

2.3. Mechanical Function of the Human Foot

The human foot functions as a complex biomechanical structure designed to support body weight and facilitate locomotion. The plantar aponeurosis and longitudinal arch play a crucial role in maintaining foot stability and efficient energy transfer during gait. The "windlass mechanism," which involves tightening of the plantar fascia during toe dorsiflexion, helps stabilize the arch during push-off [19].

The toes also contribute significantly to propulsion and balance during walking and running. The absence or dysfunction of these structures, such as after partial foot amputation, can reduce mechanical efficiency and impair gait performance [20]. Consequently, prosthetic or orthotic interventions are required to restore normal biomechanical function.

2.4. Biomaterials Used in Orthopedic and Prosthetic Applications

The success of orthopedic implants and prosthetic devices depends largely on the properties of the materials used in their construction. Titanium and its alloys are widely used in biomedical implants due to their excellent biocompatibility, corrosion resistance, and high strength-to-weight ratio [4].

Titanium alloys also possess favorable mechanical characteristics such as high fatigue strength and good resistance to cyclic loading, making them suitable for load-bearing orthopedic applications [5]. In addition, titanium implants demonstrate strong osseointegration with surrounding bone tissue, improving long-term implant stability [24,49].

However, conventional metallic implants may cause stress shielding, a phenomenon in which the implant carries a larger portion of the mechanical load than the surrounding bone. This may result in bone resorption and reduced implant fixation over time [6,34,57]. Therefore, recent research has focused on developing advanced biomaterials and composite structures that better mimic the mechanical properties of natural bone.

2.5. Polymer–Clay Nanocomposites for Biomedical Applications

Polymer–clay nanocomposites have attracted considerable attention in biomedical engineering due to their enhanced mechanical, thermal, and barrier properties. Incorporation of layered silicate clays into polymer matrices can significantly improve stiffness, strength, and structural stability of the composite materials [8,9].

The nanoscale dispersion of clay particles within polymer matrices provides improved mechanical reinforcement while maintaining lightweight characteristics, making these materials suitable for biomedical devices and prosthetic applications [36]. Clay minerals are also widely used in pharmaceutical and cosmetic industries because of their adsorption properties and biocompatibility [10].

2.6. Nanoclay-Based Biomaterials in Regenerative Medicine

Recent developments in nanotechnology have led to the emergence of nanoclay-based biomaterials for regenerative medicine. Two-dimensional nanosilicates and halloysite nanotubes have been extensively studied for their ability to enhance the mechanical properties and biological performance of biomaterials [7,30,42].

Nanoclay particles can reinforce polymer scaffolds and stimulate cellular activities such as proliferation and differentiation, making them promising materials for tissue engineering applications [17,18,29]. Clay-based scaffolds have also been shown to support bone regeneration by promoting osteogenic differentiation of stem cells [14,31,44].

Furthermore, nanoclay materials can function as drug-delivery systems due to their high surface area and layered structure, which enable encapsulation and sustained release of therapeutic agents [13,41]. Studies have also demonstrated that nanoclay-reinforced scaffolds can enhance angiogenesis and vascularization, which are essential for successful tissue regeneration [16,40].

2.7. Research Gap

Although considerable progress has been made in the development of prosthetic devices, orthopedic biomaterials, and nanoclay-based scaffolds, challenges still remain in improving functional outcomes for patients with diabetic foot complications and partial foot amputations. Traditional implant materials may suffer from stress shielding and limited biological activity, while current offloading devices may not fully restore natural gait mechanics. Nanoclay-based biomaterials and polymer nanocomposites provide promising opportunities for the development of advanced prosthetic and orthopedic solutions with improved mechanical strength, antibacterial properties, and regenerative capabilities. However, further research is required to optimize these materials for clinical translation and long-term performance.

3. Anatomy and Biomechanical Role of the Metatarsus

The metatarsus forms the structural and functional core of the forefoot and plays a crucial role in weight transmission, balance, and propulsion during locomotion. Anatomically, the metatarsus consists of five elongated bones located between the tarsal bones of the midfoot and the phalanges of the toes. Each metatarsal is composed of a proximal base, a cylindrical shaft, and a distal head that articulates with the proximal phalanx through the metatarsophalangeal (MTP) joint. This anatomical arrangement allows the metatarsals to function as load-bearing struts that distribute body weight

from the hindfoot and midfoot toward the toes during movement.

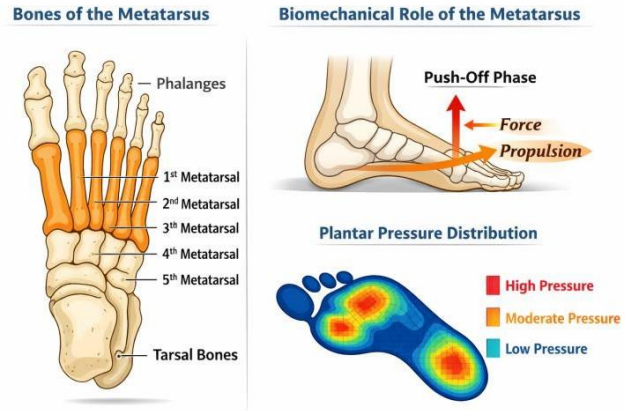

Figure 1 Metatarsal Anatomy and Biomechanical Function Illustrating Push-Off Mechanics and Plantar Pressure Distribution.

As illustrated in **Figure 1,** the five metatarsal bones are arranged from the medial to the lateral side and are labelled as the first through fifth metatarsals. The first metatarsal is typically the shortest but structurally the strongest, reflecting its significant role in weight bearing during the propulsion phase of gait. The second metatarsal is generally the longest and occupies a relatively fixed position within the tarsometatarsal joint complex, providing stability to the forefoot. The third, fourth, and fifth metatarsals gradually decrease in size and possess greater mobility, allowing the foot to adapt to irregular ground surfaces and maintain balance.

The metatarsal bones also contribute to the maintenance of the **longitudinal and transverse arches of the foot**, which are critical for mechanical efficiency and shock absorption. The medial longitudinal arch, primarily supported by the first and second metatarsals, functions as an elastic structure that absorbs impact forces during heel strike and stores mechanical energy that is later released during push-off. Meanwhile, the transverse arch formed by the metatarsal bases and heads distributes loads across the forefoot and prevents excessive localized pressure. The structural integrity of these arches is maintained through coordinated interactions among ligaments, intrinsic foot muscles, and the plantar fascia.

From a biomechanical standpoint, the metatarsus plays a pivotal role during the **push-off phase of gait**, as depicted in the diagram. During walking, body weight is initially transferred from the heel toward the midfoot and subsequently toward the forefoot. As the stance phase progresses, increasing load is applied to the metatarsal heads. During the terminal stance stage, dorsiflexion of the toes tightens the plantar fascia through the windlass mechanism, first described by John H. Hicks. This mechanism elevates and stabilizes the medial longitudinal arch, converting the foot into a rigid lever that enhances propulsion and forward movement [19]. The diagram highlights how the metatarsal region acts as the pivot point where muscular force is translated into forward propulsion.

Another important biomechanical feature shown in the figure is the **distribution of plantar pressure across the forefoot**. Plantar pressure mapping reveals that the highest pressures typically occur beneath the first and second metatarsal heads, as these structures bear a substantial portion of body weight during the push-off phase. Moderate pressure is observed across the central metatarsals, while relatively lower pressure occurs toward the lateral forefoot. This pressure distribution pattern ensures that mechanical loads are shared efficiently across the forefoot, minimizing the risk of localized stress concentrations.

However, alterations in this pressure distribution can occur due to pathological conditions or structural abnormalities. In individuals with diabetes mellitus, peripheral neuropathy and reduced protective sensation often lead to abnormal plantar loading patterns. Excessive pressure beneath the metatarsal heads is widely recognized as a primary biomechanical factor contributing to the development of diabetic foot ulcers [1,21]. The pressure map illustrated in the figure demonstrates how localized high-pressure zones may develop beneath specific metatarsal heads, which increases the risk of tissue breakdown and ulceration if not properly managed.

During standing and dynamic movements, the metatarsal heads form an essential part of the forefoot support platform, providing a broad base that stabilizes the body's center of mass. Sensory receptors located in the plantar surface of the forefoot detect pressure and ground contact, enabling rapid neuromuscular adjustments that maintain equilibrium and coordination.

Furthermore, disruption of the metatarsal structure—such as through trauma, deformity, or partial foot amputation—can significantly impair gait biomechanics. Loss of metatarsal segments alters the natural load distribution and reduces the efficiency of the push-off mechanism. Consequently, affected individuals often demonstrate decreased walking speed, altered center-of-pressure progression, and reduced propulsive power during locomotion [22,53]. These biomechanical alterations may lead to compensatory gait patterns and increased mechanical stress on adjacent joints and the contralateral limb.

In summary, the metatarsus serves as a fundamental biomechanical component of the human foot, integrating structural support with dynamic functionality. Through its anatomical configuration and interaction with surrounding soft tissues, it enables efficient weight distribution, shock absorption, and propulsion during locomotion. The diagram presented in Figure X visually illustrates these roles by highlighting the anatomical arrangement of the metatarsal bones, their contribution to propulsion during the push-off phase, and the characteristic pattern of plantar pressure distribution across the forefoot. Understanding these biomechanical principles is essential for the development of effective orthopaedic treatments, prosthetic devices, and therapeutic strategies aimed at restoring normal foot function and preventing complications such as plantar ulceration.

4. Gait Alterations Following Metatarsal Amputation

Metatarsal amputation, particularly partial foot amputations involving the removal of one or more metatarsal bones, leads to significant biomechanical changes that affect gait efficiency, balance, and propulsion. The metatarsus plays a vital role in transferring body weight during the stance phase of gait and in generating forward propulsion during push-off. During normal gait, body weight is transferred progressively from the heel to the midfoot and finally to the

forefoot, where the metatarsal heads function as pivot points for propulsion. This process allows the foot to operate as a rigid lever during the terminal stance phase. However, following metatarsal amputation, this lever mechanism is disrupted, leading to diminished push-off power and reduced walking efficiency. Clinical gait analyses have shown that individuals with partial foot amputations often demonstrate slower walking speeds, shorter stride lengths, and increased time spent in the double-support phase of the gait cycle [22,53].

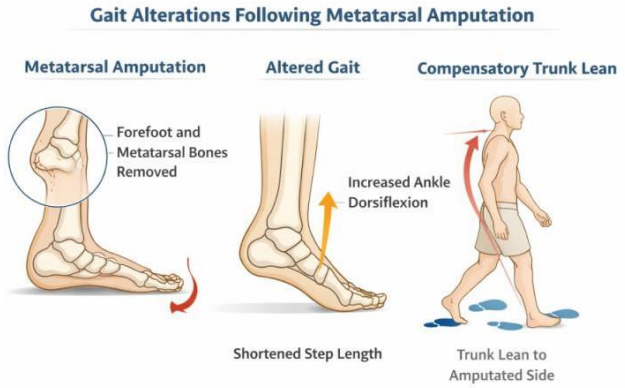

Figure 2 Altered Gait Pattern and Postural Compensation After Metatarsal Amputation

Figure 2 illustrates the primary biomechanical consequences of metatarsal amputation and the compensatory adaptations observed during walking. The left panel of the diagram shows the anatomical condition following amputation, where the forefoot and metatarsal bones have been removed. This loss of structural support reduces the length of the foot lever arm and alters the normal rollover mechanism that occurs during gait. As a result, the ability of the forefoot to transmit propulsive forces is significantly diminished.

The central portion of the diagram demonstrates the **altered gait mechanics** that arise following amputation. One key biomechanical change is **increased ankle dorsiflexion during stance**, which occurs because the shortened forefoot cannot effectively resist forward tibial progression. Without the stabilizing influence of the metatarsal heads, the ankle joint experiences greater dorsiflexion as the body moves over the residual limb. This altered ankle motion contributes to instability and reduces the efficiency of the push-off phase.

Another prominent feature illustrated in the diagram is the **shortened step length**, which is commonly observed in individuals with partial foot amputations. Because the propulsive capacity of the affected limb is reduced, patients often limit the forward advancement of the contralateral limb. This adaptation reduces the mechanical demands on the amputated foot but simultaneously decreases overall walking speed and gait symmetry. Reduced step length is therefore a protective but inefficient compensatory strategy that helps maintain balance and minimize discomfort.

The right side of the diagram highlights an additional compensatory mechanism known as **trunk lean toward the amputated side**. Patients frequently shift their upper body toward the affected limb during the stance phase to reposition the body's center of mass closer to the supporting foot. This strategy helps reduce the mechanical moment acting at the ankle and knee joints and improves stability when weight is borne on the shortened limb. However, persistent trunk lean may lead to abnormal loading of the spine and hip joints over time, potentially contributing to musculoskeletal discomfort or secondary degenerative changes.

Beyond the alterations illustrated in the figure, metatarsal amputation also affects plantar pressure distribution across the residual foot. Under normal conditions, the metatarsal heads distribute loads evenly across the forefoot during push-off. Following amputation, the pressure pattern shifts proximally toward the midfoot or laterally toward the remaining structures. This redistribution often results in localized areas of high pressure that increase the risk of skin breakdown and ulcer formation, particularly in patients with diabetes mellitus and peripheral neuropathy [1,21].

The absence of metatarsal support further compromises the structural stability of the foot arches. The medial longitudinal arch depends partly on the integrity of the metatarsals and the tension generated by the plantar fascia. Loss of these structural elements may reduce the foot's ability to store and release elastic energy during gait, leading to increased metabolic energy expenditure during walking.

Compensatory biomechanical adjustments following metatarsal amputation may also extend to proximal joints. Because propulsion from the forefoot is diminished, individuals often rely more heavily on hip and knee musculature to advance the limb during walking. This redistribution of mechanical effort can increase joint loading and contribute to secondary musculoskeletal complications over time. Epidemiological studies have reported a high prevalence of overuse injuries and joint pain in individuals with lower-limb amputations due to these altered loading patterns [51].

To mitigate these gait abnormalities, various prosthetic and orthotic interventions are commonly employed. Devices such as rocker-bottom shoes, custom orthoses, and partial foot prostheses aim to restore a more natural rollover pattern during the stance phase and compensate for the loss of forefoot leverage. These assistive devices help redistribute plantar pressure, improve gait symmetry, and enhance walking efficiency [2].

In summary, metatarsal amputation produces substantial alterations in gait biomechanics due to the loss of forefoot structural support and propulsive capability. As illustrated in Figure X, these changes include increased ankle dorsiflexion, shortened step length, and compensatory trunk lean toward the amputated side. Understanding these biomechanical adaptations is essential for the development of effective prosthetic solutions and rehabilitation strategies aimed at restoring mobility, improving gait efficiency, and preventing secondary complications in individuals with partial foot amputations.

5. Clay-Based Biomaterials in Prosthetic Implants

Clay minerals such as **kaolinite, montmorillonite, bentonite, and halloysite nanotubes** have gained significant attention in biomedical engineering due to their unique structural properties [42].

Clay nanoparticles are commonly incorporated into polymer or ceramic matrices to enhance the mechanical and biological properties of prosthetic implants [43].

Clay-derived biomaterials encompass a diverse group of naturally occurring and engineered silicate minerals that

possess unique structural, chemical, and biological properties suitable for biomedical applications. Their layered or nanotubular architectures provide high surface area, ion-exchange capacity, and mechanical reinforcement potential, making them valuable components in advanced prosthetic and orthopedic biomaterials. These materials can support cellular interactions, enable controlled therapeutic delivery, and enhance the mechanical stability of composite implants.

Table 1 Major Clay-Based Biomaterials and Their Properties, Biomedical Functions, and Potential Applications in Prosthetic Implants.

Clay Biomaterial	Chemical Composition / Structure	Key Properties	Biomedical Functions	Potential Application in Prosthetic Implants
Kaolinite	$Al_2Si_2O_5(OH)_4$ layered silicate mineral	High biocompatibility, low toxicity, moderate mechanical stability	Supports cell adhesion and proliferation; promotes tissue compatibility	Surface coating or filler material in prosthetic implants to improve tissue integration
Montmorillonite	Smectite clay with expandable layered structure containing silica and alumina	High surface area, strong ion-exchange capacity, antimicrobial potential	Drug delivery carrier; enhances antibacterial activity	Incorporation in composite prosthetic materials for infection control and improved implant longevity
Bentonite	Aluminum phyllosilicate primarily composed of montmorillonite	High swelling capacity, high porosity, good adsorption properties	Absorption of toxins and microbial agents; enhanced tissue interaction	Porous scaffold component in prosthetic implants for improved osseointegration
Halloysite Nanoclay	Aluminosilicate nanotubular structure	High mechanical reinforcement capability, nano-tubular morphology	Controlled drug release; improved mechanical strength in composites	Reinforcement material in polymer-clay prosthetic composites
Clay-Ceramic Composites	Hybrid materials combining clay minerals with bio-ceramics (e.g., hydroxyapatite)	Enhanced mechanical strength, improved porosity, high bioactivity	Promotes bone regeneration and integration with surrounding tissues	Structural component for prosthetic implants requiring both strength and bioactivity

6. Biocompatibility of Clay-Based Prosthetic Materials

Biocompatibility is a critical factor in the development of implantable biomaterials, as the material must interact with biological tissues without causing toxicity, inflammation, or adverse immune responses. Clay-based biomaterials have attracted significant attention in recent years due to their **natural origin, chemical stability, and favorable biological interactions**. These properties make them promising candidates for applications in orthopedic and prosthetic implants, including potential use in metatarsal reconstruction

Biocompatibility is a crucial requirement for implantable biomaterials [44]. Clay minerals exhibit low cytotoxicity and good compatibility with mammalian cells [45].

Studies have shown that nanoclay-based scaffolds promote cell adhesion, proliferation, and osteogenic differentiation [46]. Additionally, certain clay minerals exhibit antimicrobial properties against pathogenic bacteria such as *Staphylococcus aureus* and *Escherichia coli* [47].

Overall, existing studies suggest that clay-based biomaterials demonstrate **promising biocompatibility, antimicrobial properties, and potential for tissue integration**, making them attractive candidates for future prosthetic implant designs. However, further experimental and clinical studies are required to evaluate their long-term safety, mechanical durability, and effectiveness in load-bearing prosthetic applications.

Several studies have demonstrated that nanosilicate particles can influence cellular signaling pathways and stimulate osteogenic differentiation in stem cells, thereby promoting bone regeneration and tissue repair [7,39].

These characteristics make clay-based biomaterials attractive candidates for prosthetic implants.

7. Mechanical Properties of Clay-Reinforced Prosthetic Materials

The mechanical performance of prosthetic implants is a critical factor in their clinical success, particularly in load-bearing anatomical regions such as the metatarsus. Materials used in prosthetic reconstruction must possess adequate **strength, stiffness, durability, and fatigue resistance** to

withstand repetitive mechanical stresses generated during walking and other daily activities.

Clay nanoparticles significantly enhance the mechanical properties of composite biomaterials [48]. When incorporated into polymer matrices, nanoclay particles improve tensile strength, compressive strength, and elastic modulus [49].

Additionally, clay reinforcement increases fracture resistance and fatigue durability of prosthetic materials [50]. These improvements are essential for implants that must withstand repetitive mechanical loading during walking.

However, the mechanical performance of clay-based composites depends strongly on factors such as **particle dispersion, clay concentration, and the compatibility between the clay surface and the host matrix**. Poor dispersion may lead to particle agglomeration, which can reduce mechanical strength and create structural weaknesses. To address this limitation, surface modification techniques and hybrid composite systems are often employed to improve the interaction between clay particles and the base material.

Overall, clay-reinforced prosthetic materials demonstrate promising mechanical characteristics, including improved stiffness, strength, and fatigue resistance, while maintaining relatively low density. These properties suggest that clay-based composites could play a significant role in the development of **next-generation prosthetic implants**, particularly when combined with biocompatible polymers or bio-ceramics designed for orthopedic applications. Nevertheless, further experimental and clinical studies are necessary to evaluate their long-term mechanical stability under physiological loading conditions, especially for applications involving load-bearing structures such as the metatarsal bones

8. Role of Clay-Based Implants in Gait Restoration

Metatarsal amputation significantly disrupts the structural integrity and biomechanical function of the forefoot, leading to altered gait patterns, reduced propulsion, and abnormal plantar pressure distribution. Because the metatarsus plays a critical role in load transmission and push-off during walking, its loss often results in impaired locomotion and compensatory postural adjustments. In recent years, **clay-based biomaterials and nanoclay-reinforced implants** have emerged as promising candidates for restoring biomechanical function in patients with partial foot amputations. Clay-based biomaterials, particularly those incorporating nanosilicates or halloysite nanotubes, exhibit excellent reinforcement capabilities when integrated into polymer matrices. These nanostructured materials enhance mechanical strength, stiffness, and durability while maintaining lightweight characteristics, which are essential for load-bearing biomedical implants. In addition to their mechanical advantages, nanoclay materials demonstrate high surface area, bioactivity, and the ability to support cellular interactions, making them promising for tissue integration and regenerative applications [7,17,29].

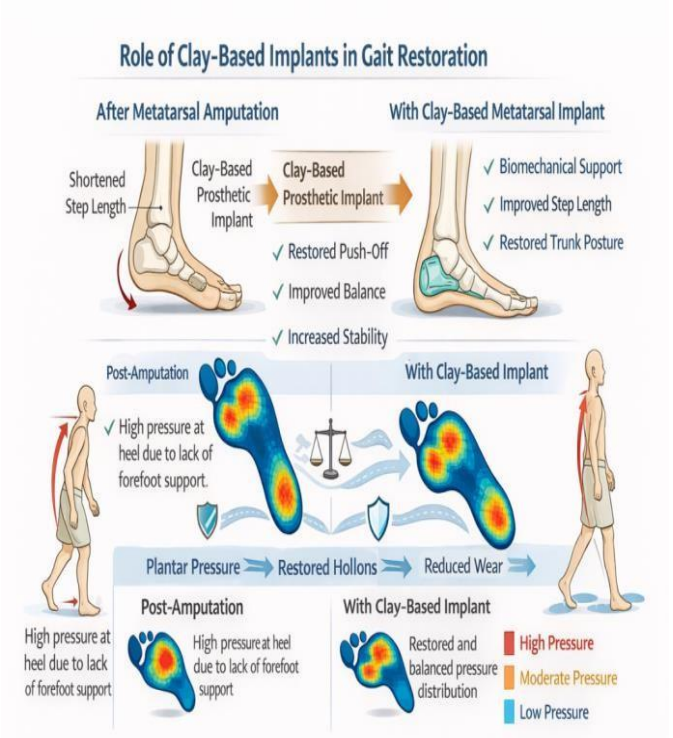

Figure 3 Comparision of Gait Distribution with and Without Implant

The conceptual framework for the use of clay-based implants in restoring gait function is illustrated in **Figure 3**. The left portion of the diagram represents the biomechanical condition following metatarsal amputation. In this state, the forefoot lever arm is shortened due to the absence of metatarsal structures, resulting in **reduced step length and diminished push-off capability** during walking. The loss of forefoot support also alters the rollover mechanism of the foot, forcing the body to rely more heavily on the heel and midfoot during the stance phase.

As shown in the figure, the introduction of a **clay-based prosthetic or structural implant** can help restore some of the lost biomechanical functionality. By replacing or supporting the missing metatarsal structures, the implant effectively recreates the forefoot lever mechanism required for efficient propulsion. This structural restoration enables the foot to generate improved push-off forces during the terminal stance phase of gait. Consequently, patients may experience **improved step length, enhanced balance, and increased stability**, as indicated in the central portion of the diagram.

The right side of the diagram further illustrates the functional benefits of a clay-based metatarsal implant. By providing biomechanical support to the forefoot, the implant allows the foot to regain a more natural rollover pattern during walking. This improved biomechanics reduces the need for compensatory trunk lean and promotes a more upright posture. Restoration of the forefoot lever arm also enhances walking efficiency and may reduce fatigue associated with prolonged ambulation.

Another key biomechanical aspect highlighted in the diagram is the **redistribution of plantar pressure following implantation**. After metatarsal amputation, plantar pressure patterns are significantly altered due to the absence of forefoot support. The pressure map shown in the lower left portion of the figure demonstrates that excessive pressure

often accumulates beneath the heel, as the body compensates for the loss of the forefoot load-bearing region. This abnormal loading pattern can increase the risk of tissue damage and ulcer formation, particularly in individuals with diabetes or peripheral neuropathy [1,21].

With the introduction of a clay-based implant, plantar pressure distribution becomes more balanced across the foot, as illustrated in the lower right portion of the diagram. The restored structural support allows the forefoot to participate again in weight bearing, thereby reducing excessive pressure at the heel and redistributing loads more evenly across the plantar surface. This balanced pressure distribution not only improves walking comfort but also decreases the likelihood of secondary complications such as pressure ulcers and tissue degeneration.

Beyond mechanical support, clay-based biomaterials may offer additional therapeutic advantages due to their unique physicochemical properties. Certain clay minerals exhibit inherent antibacterial activity, which may help reduce the risk of infection in implantable devices [11,28]. Furthermore, nanoclay-reinforced biomaterials can enhance tissue regeneration by supporting cell adhesion, proliferation, and differentiation. Studies have demonstrated that nanoclay scaffolds can promote angiogenesis and osteogenic activity, which are critical processes for successful tissue integration and healing [16,40].

The integration of clay-based implants into prosthetic design therefore represents a promising multidisciplinary approach that combines **biomechanics, materials science, and regenerative medicine**. By simultaneously addressing structural support, pressure redistribution, and biological compatibility, these advanced biomaterials have the potential to significantly improve functional outcomes for patients undergoing partial foot amputations.

In summary, clay-based implants offer a novel strategy for restoring gait mechanics following metatarsal amputation. As illustrated in Figure X, these implants can reestablish the forefoot lever arm, improve push-off during walking, and normalize plantar pressure distribution. In addition to enhancing biomechanical performance, the bioactive properties of nanoclay materials may support tissue integration and reduce complications associated with conventional implants. Continued research into the design and optimization of clay-based prosthetic systems is therefore essential for advancing rehabilitation strategies and improving mobility in individuals with forefoot amputations.

9. Bioactive and Biomechanical Benefits of Clay-Derived Prosthetic Implants

The development of advanced biomaterials has become a critical focus in modern prosthetic and orthopedic research, particularly for restoring biomechanical function following partial foot amputations. Among emerging materials, **clay-derived biomaterials and nanoclay-reinforced composites** have gained considerable attention due to their unique combination of **biomechanical strength, bioactivity, and multifunctionality**. These properties make clay-based materials promising candidates for next-generation prosthetic implants designed to restore structural integrity, improve gait mechanics, and promote tissue integration.

One of the most significant advantages of clay-derived prosthetic implants lies in their **enhanced biomechanical performance**. Clay nanoparticles, such as nanosilicates and halloysite nanotubes, can significantly reinforce polymer matrices by improving stiffness, tensile strength, and load-bearing capacity. When incorporated into prosthetic structures, these nanomaterials create composite systems that exhibit superior mechanical stability while maintaining lightweight characteristics. This reinforcement is particularly important in forefoot reconstruction, where implants must withstand repetitive loading during walking and distribute forces effectively across the plantar surface [8,36]. By strengthening prosthetic components, nanoclay composites help restore the structural support normally provided by the metatarsal bones.

In addition to improved mechanical properties, clay-based biomaterials offer **enhanced biomechanical compatibility with biological tissues**. Unlike traditional metallic implants that may cause excessive stiffness and stress shielding, polymer–clay nanocomposites can be engineered to more closely mimic the mechanical behavior of natural bone and connective tissue. This mechanical compatibility allows the implant to participate in physiological load transfer without creating abnormal stress concentrations in adjacent tissues. Consequently, clay-derived prosthetic implants may reduce the risk of implant failure and improve long-term functional outcomes for patients undergoing partial foot reconstruction.

Another important feature of clay-derived implants is their **bioactive surface properties**, which support biological interactions at the implant–tissue interface. Clay minerals possess a layered structure with high surface area and abundant charged sites, allowing them to interact with proteins, growth factors, and cellular components. These interactions can promote **cell adhesion, proliferation, and differentiation**, which are essential processes for successful tissue integration. Studies have demonstrated that nanosilicate particles can stimulate osteogenic differentiation in mesenchymal stem cells, indicating their potential to support bone regeneration and tissue repair [7,39].

The **antibacterial properties** of certain clay minerals provide an additional advantage for biomedical applications. Several naturally occurring clays exhibit broad-spectrum antimicrobial activity due to the release of metal ions and reactive chemical species. This antibacterial activity may help reduce the risk of infection in implantable prosthetic devices, which is a significant concern in orthopedic surgery and limb reconstruction [11,28]. By limiting bacterial colonization around the implant site, clay-derived materials can contribute to improved post-surgical healing and implant longevity.

Clay-based biomaterials also offer promising opportunities for **controlled therapeutic delivery** within prosthetic systems. The tubular and layered structures of halloysite nanotubes enable encapsulation of bioactive molecules, drugs, or growth factors that can be released gradually over time. This capability allows prosthetic implants to function not only as structural supports but also as therapeutic platforms that promote tissue regeneration and healing. Sustained drug release from clay nanotubes has been demonstrated in several biomedical studies, highlighting their potential for advanced regenerative applications [13,42].

From a biomechanical perspective, the integration of clay-derived materials into prosthetic implants can significantly improve **load distribution and gait mechanics**.

In cases of metatarsal amputation, the absence of the forefoot lever arm disrupts normal propulsion and leads to abnormal plantar pressure patterns. Clay-reinforced prosthetic components can help restore structural continuity in the forefoot, enabling more efficient transfer of forces during the stance and push-off phases of gait. This restoration of biomechanical function may improve walking efficiency, increase stability, and reduce compensatory movements such as trunk lean or excessive ankle dorsiflexion.

Furthermore, clay-based implants can contribute to **improved plantar pressure redistribution**, which is essential for preventing tissue breakdown and ulcer formation in high-risk patients, particularly those with diabetes. By recreating a supportive forefoot structure, these implants allow plantar loads to be distributed more evenly across the foot, reducing localized pressure concentrations that commonly occur after partial foot amputations [1,21]. Balanced pressure distribution not only enhances patient comfort but also plays a crucial role in preventing secondary complications.

The multifunctional characteristics of clay-derived biomaterials—combining mechanical reinforcement, bioactivity, antibacterial behavior, and therapeutic delivery—position them as a promising class of materials for future prosthetic and orthopedic innovations. Their ability to simultaneously address both **structural and biological requirements** distinguishes them from conventional implant materials that primarily focus on mechanical performance.

In summary, clay-derived prosthetic implants offer substantial advantages for reconstructive and rehabilitative applications. Their superior mechanical reinforcement capabilities support load-bearing function, while their bioactive properties promote tissue integration and regenerative responses. Additionally, their antibacterial and drug-delivery potential further enhances their clinical utility. These combined properties make clay-based biomaterials an attractive platform for the development of advanced prosthetic implants aimed at restoring gait function and improving long-term outcomes for patients with partial foot amputations.

10. Limitations and Challenges

Despite their advantages, clay-based prosthetic implants also present several challenges. Pure clay structures are relatively brittle and may lack sufficient mechanical strength for load-bearing applications [55].

Additionally, achieving uniform dispersion of clay nanoparticles within composite matrices remains a technical challenge [56]. Long-term biocompatibility and clinical validation also require further investigation.

In summary, while clay-based biomaterials demonstrate considerable potential for prosthetic implant applications, several challenges—including mechanical limitations, dispersion issues, long-term biological evaluation, manufacturing complexity, and regulatory requirements—must be addressed. Continued interdisciplinary research involving materials science, biomedical engineering, and clinical medicine is essential to overcome these limitations and fully realize the potential of clay-based prosthetic technologies.

11. Future Perspectives

Future research should focus on developing hybrid clay-polymer and clay-ceramic composites with improved mechanical and biological performance [57]. Advances in additive manufacturing and 3D printing may also enable the production of patient-specific prosthetic implants [58].

Furthermore, integrating bioactive molecules and smart sensor technologies into clay-based implants may improve therapeutic outcomes and implant monitoring capabilities [59].

In addition, future research should focus on improving the **cost-effectiveness and accessibility of prosthetic technologies**. Since clay minerals are naturally abundant and relatively inexpensive, clay-based composite implants could provide an affordable alternative to conventional metallic or polymeric prostheses. This may be particularly beneficial in low-resource healthcare settings where access to advanced prosthetic materials is limited.

Overall, the future development of clay-based prosthetic implants will require interdisciplinary collaboration among materials scientists, biomedical engineers, and clinicians. Advances in nanotechnology, biomaterials engineering, and additive manufacturing are expected to play a crucial role in optimizing the design and functionality of these implants. With continued research and technological innovation, clay-based biomaterials may become an important component of next-generation prosthetic systems designed to restore mobility and improve the quality of life for individuals with limb loss.

12. Conclusion

Metatarsal amputation significantly disrupts foot biomechanics and gait patterns. Clay-based biomaterials represent a promising alternative to conventional prosthetic materials due to their unique structural and biological properties. These materials demonstrate potential for enhancing implant integration, improving mechanical performance, and restoring gait function.

In conclusion, clay-based biomaterials represent a promising and innovative approach for the development of next-generation prosthetic implants aimed at restoring gait function following metatarsal amputation. Continued interdisciplinary research integrating materials science, biomedical engineering, and clinical practice will be essential to fully explore their potential and translate these emerging technologies into practical medical solutions that improve patient mobility and quality of life.

However, further experimental studies, clinical trials, and advanced biomaterial engineering approaches are required to fully realize the clinical potential of clay-based prosthetic implants.

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HAND GESTURE RECOGNITION USING RASPBERRY PI AND OPEN-CV

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Abstract **- Teaching a robotic arm can be unintuitive and difficult because the difference between natural movements of human limbs and the control of robotic manipulators can be far apart. Substantial training is often necessary in order to effectively operate such systems. This work shows the develop of an intuitive and easy to use interface for mapping human palm gestures to control the movement of a 5 axis robot, the Dexter ER2. The proposed vision-based system allows robotic arms to follow hand gestures by themselves in a three-stage methodology namely the gesture detections, gesture tracking and robotic manipulator controls. A model using deep learning is used for precise recognition of gestures so that the robot can give the impression of moving the limbs like the controller with a minimal cognitive load. For computing the trajectory and creating the joint movement, an inverse kinematic solver based on adaptive gradient descent is implemented for efficient and smooth convergence of joint angles for the desired end-effector positions. The interface has been successfully implemented, which means that the robot will follow gesture commands and will reach target positions. The proposed vision-based gesture driven control scheme of Dexter ER2 robot arm is validated by simulation and experimental studies. The very system used serial communication and guaranteed a continuous and lossless data stream between the controller and the computer. A detailed comparative analysis is also put forward in order to demonstrate the advantages of the proposed approach. Future work is to improve visual appearance with the graphical interface and to correct the latency issue in the real- time control.**

Keywords **— Hand Gesture Recognition, VisionBased Robotic Control, Human–Robot Interaction, Deep Learning, OpenCV, MediaPipe Framework**

I. INTRODUCTION

A robotic arm is a technology imitation of human arm. Robotics has made its way into many industries, and changed the way in which tasks are done. While the control of robotic arms is a great advancement, advanced robotic manipulators are now operated and programmed more flexibly. A wide variety of such arms can be used. In the past, the most common way to control a robotic arm was via manual controls that included a joystick, a keyboard or a special control panel. Such a situation is also faced while working with a multi-degree-of-freedom (DOF) robotic arm where each joint of the robotic arm is to be actuated using a different control. Although a robotic arm is less like controlling a human limb than controlling a mobile robot, it is still considered to be much less intuitive than the more intuitive control of planar mobile robots. In the current field of study, the ultimate aim is to create an intuitive and easy to control mechanism, and that is cost-effective and requires less computational time through the use of natural motion of the human arm. Also, in order to make the control process simpler, various control strategies for robotic arms have been carried out such as gesture-based control [6], [7], [8], [9]. Using hand motions, users are able to interact with the robotic arm using hand pose estimated control which can be more simpler method to learn than conventional control techniques [6], [8], [9]. This methodology

can enhance accessibility and usability of robotic arms, which can be more adaptable and useful to a greater number of applications [6], [7], [9]. The main emphasis of this presented research work is an applied rather than theoretical. The present work puts focus on integrating techniques such as anthropomorphic control, gradient descent with adaptive learning rates for inverse kinematics (IK) and single-camera pose estimation into one unified visionbased control system. The novelty is the practical approach to apply these techniques with the intent to refine some practical interface, intuitive and costeffective, to control robotic manipulators in environments of constraints. By taking focus on usability, affordability and adaptability, this study fills the gap between the theoretical robotics and its practical implementation. Researchers have been researching on the concept of gesturecontrolled and pose-estimated controlled robotics, by going through various techniques and technologies to capture and process human hand gestures or various pose landmarks. One of the common methods is to use the cameras for detecting user hand movements and sending it as a control command for the robotic arm, this can be termed as Anthropomorphic control [10]. Anthropometric control of a manipulator is the control of a robotic arm or the manipulator in a manner that resembles or maps to control of natural motions of a human hand, i.e. anthropometric control is the design of such a manipulator system that the operator can intuitively control the motion of the end-effector by making motions or gestures of the arms or hands that the manipulator will follow [11]. As the field of robotics continues to develop, we might expect more innovative uses of robotics in the future.

II. LITERATURE REVIEW

Gupta et al. [7] proposed a continuous hand gesture recognition technique for human-machine interaction based on gyroscope sensor and accelerometer, and proved a high rate of classification and a high response rate of real- time. However, their method depends on the wearable device, which limits the natural user interaction and aims to sensor calibration, which limits its intuitiveness and expansion in the vision-based robotics control system. Atre et al. [8] built a low cost rule based robotic arm control system using web cam, Arduino and Bluetooth module. Tested in simulation, the system was limited by low level of precision, limited DOF and did not support AI integration or realtime control. In addition to this, Angulo et al. [12] demonstrated the application of stereo vision with robotic arm control at a critical application such as that of positioning near an explosive device. This shows how crucial the use of vision-based control is in hazardous environments. Solly and Aldabbagh [9], used a wearable hand glove controller system for a mobile robot system which uses flex sensors, accelerometer, Bluetooth module and radio module. The possibilities of the gesture mapping approach allowed robot navigation but were not suitable for precise manipulation tasks. The system, however, was experimentally verified and incurred a high cost as a result of the wearable hardware. Further, Altayeb [13] created a robotic arm finger control system, with a

webcam for simple vision thresholding, as well as Arduino, servomotor and buck converter. The system was experimentally validdated and provided a moderately priced solution, but was faced with limitation for scalability. Qin et al. [14] used the monocular RGB camera and imitation learning algorithm to allow real-time gesturebased teleportation of multi-fingered dexterous robots. The system showed good potential, but overcome with different challenges such as loss of tracking in fast motion and unreliable hand pose estimation, relatively high implementation cost. In addition, Terreran et al. [15] introduced a contactless interface for collaborative robots with an encouraging result using natural human-robot interaction. However, limitations are still present in having precises manipulation and robustness in different lighting and background conditions, which indicates the need for better visual processing and realtime gesture interpretation that can be improved. Suhaimi et al. [16] presented a control system for 4DOF robotic arm using Electrooculogram (EOG) and Electromyography (EMG) sensors which consist of a combination of EMG- based gaze estimation and image processes. The system requires the fusion of complex sensors and came with a very high cost. Moreover, Godoy et al. [17], proposed an affordable and EMGbased tele-manipulation framework for intuitive control of robotic arm-hand systems, where it was shown the improved task execution in dynamic environments using multimodal sensing. However, a certain dependence on EMG signals and predefined object affordances makes the system less adaptable and less generalizable for users, which suggests the need for more natural and flexible ways to interact with the system like vision-based gesture control. Ban et al. [18] proposed a persistent human machine interface for the robotic arm control using gaze and eye gestures to realize an high accuracy with little calibration for disabled humans. However the approach requires specialized eye tracking hardware restricting the accessibility and scalability of borderpressive control

systems

III. PROBLEM STATEMENT

Industrial robotic manipulators have become an integral part in the modern manufacturing, automation, healthcare, and research laboratories. These robotic systems are often programmed and controlled with the help of teach pendants, joysticks, keyboards and/or

complex programming interfaces. Although these control methods offer specific manipulation capabilities, users often need specific training, technical expertise, and a considerable amount of time to learn and effectively use them. As a result, the usability of robotic systems is only available to trained personnel, the accessibility to non- expert users is reduced and the speed of executing tasks in dynamic environments is reduced. Traditional robot programming methods also lack intuitive humanrobots interaction (HRI). Operators have to manually type in the commands or program for themselves to perform complex action tasks, which makes the process of interaction rigid and inefficient. In applications where the required adjustments need to be made quickly, involve a natural form of interaction or require real-time control, like for research labs, educational environments, collaborative robotics and fast prototyping, these traditional interfaces become inconvenient and inefficient. Furthermore, existing teach pendant systems tend to be bulky, hardwaredependent and be constrained by wired interfaces to limit operator mobility and flexibility. These limitations point out the necessity of more natural, intuitive and user-friendly control mechanisms that enable communication with robots in a manner that is very similar to natural human actions. Recent technological developments in the fields of computer vision, machine learning, and human-computer interaction have made it possible to create gesture recognition systems that are able to interpret human hand movements through the use of cameras. Visionbased gesture recognition provides a promising solution to the traditional robot control interfaces as it enables the users to interact with robotic systems using simple hand gestures without any knowledge of controllers or programming of the robotic system.

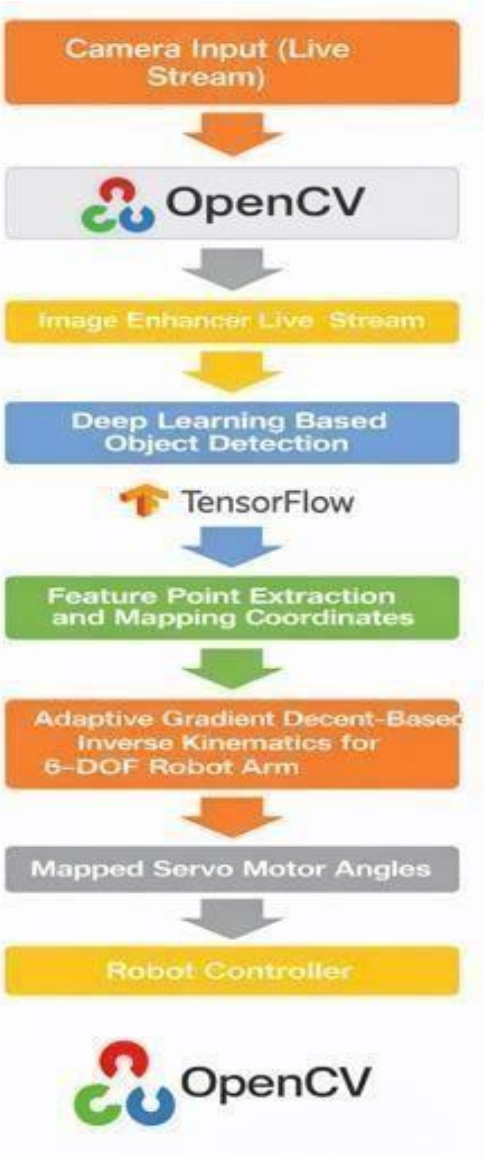
IV .PROPOSED SYSTEM

The system is a step-by-step process, as shown in Figure 6: First, the data of live stream is processed by the camera and then this data is enhanced by using Open Source Computer Vision Library (OpenCV) functions. These image enhancement techniques are used to get more detailed and clear images from the webcam feed, which will make it easier to identify and track hand movements accurately. In real world situations the feed from the camera is subject to a wide range of sources of noise and dynamic environmental influences such as lighting variations, motion blur caused by sudden movements of the hands, and sudden change in the background. These factors can greatly impact the quality of visual input, doing so will make it rather difficult to reliably detect and track hand gestures.

In order to solve these kind of challenges the proposed system implements a set of image Enhancements, such as noise filtering, adaptive Contrast Enhancement and Motion Blur Compensation .incorporation of these enhancement techniques helps the robustness and responsiveness on the vision-based control framework in real-time under dynamically and changeable conditions.

Next, the improved live stream data is sent for deep learning based object detection with the help of the MediaPipe, a crossplatform framework to build multimodal applied ML pipelines. In the object detection method of deep learning, the hand key points are estimated by its advance hand tracking model. This model captures and monitors 21 landmarks on the hand, with accurate spatial information on the location of each point. Among those landmarks, we are concentrating on landmark 8, which is the tip of an index finger. The x and y coordinate of this landmark are extracted and this person actually represents a pixel location in this video frame. To get depth information
(the z-axis), we take an

Fig 1: control-system of vision based control-flow chart



average of the Euclidean distances from keypoint 9 (base of the middle finger) to the keypoint 8 (tip of the index finger) and from keypoint 9 to keypoint 12 (tip of the middle finger). These distances were selected after a lot of testing since it turned out to be more stable in comparison to distances between other pairs of

landmarks, providing more consistent and accurate depth estimation.

V. METHODOLOGY

The proposed system implements a vision-based gesture control mechanism to operate a 5-axis robotic arm, Dexter ER2, through natural human hand movements. The methodology is designed to enable intuitive interaction between humans and robotic systems by translating palm gestures into corresponding robotic arm actions. The overall system architecture consists of several sequential stages including image acquisition, gesture detection, gesture recognition, trajectory generation, and robotic arm control. These stages work together to ensure accurate gesture interpretation and smooth robotic motion.

In the first stage, real-time image acquisition is performed using a camera that continuously captures video frames of the user's hand gestures. The captured frames are processed using computer vision techniques to detect the presence of a hand within the frame. Image preprocessing operations such as frame resizing, normalization, and background filtering are applied to improve the quality of the captured data. These preprocessing steps help reduce noise and enhance the visibility of the hand region, enabling more reliable gesture detection. Following detection, the system performs gesture tracking and recognition. A deep learning- based model is employed to identify and classify different palm gestures from the processed frames. The model is trained using a dataset containing multiple hand gesture samples to improve recognition accuracy. Feature extraction techniques are used to identify key characteristics of the hand such as finger positions, palm orientation, and movement direction. The trained model then classifies the detected gesture into predefined categories, each representing a specific robotic arm movement command. This stage allows the system to interpret human gestures effectively and convert them into control signals.

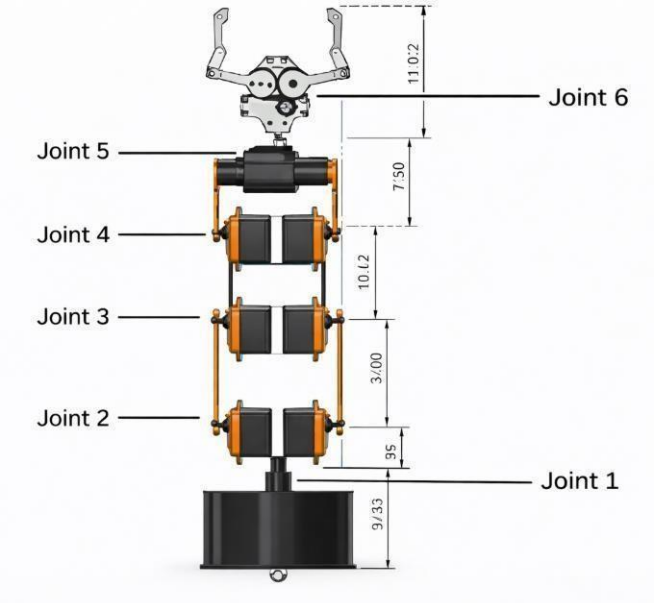


Fig. 2. Joints and links in Dexter ER2.

Upon recognizing a gesture, the system gets the desired pose of the robotic arm end-efficer. To accomplish this, an inverse kinematics solver, which is built on adaptive gradient descent is adopted. The inverse kinematics algorithm will be used to determine the joint angles which must be used to move the robotic arm to the required position based on the gesture command. The adaptive gradient descent methodology guarantees the smooth convergence of joint parameters and reduced complexity of computations. This allows the efficient planning of trajectory and guarantees accurate movement of robots. Joint parameters are calculated and control commands sent to the Dexter ER2 robotic arm via a serial communication interface. The communication protocol helps maintain reliable and constant data flow between the computer and the robot controller, and the protocol ensures that there is no loss in the data flow. Lastly, the suggested system is tested by simulation as well as real-life testing. Gesture commands of different types are tested to test the responsiveness and precision of the robotic arm. The obtained experimental findings indicate that the robot is able to follow the gestures of the user and arrive at the desired target positions. The system offers an easy to use form of human-robot interaction interface which minimizes the complexity of the conventional robotic control systems and enhances ease of use and efficiency. Next generation design of the system is to provide a better graphical user interface which can be used to interact with the system and to minimise the system latency so that real time control of the robots can be realised.

VI. COMPARATIVE ANALYSIS

Table 1 provides the complete comparative analysis of recent gesture controlled robotic arm system presented in [8], [9], [12], [13], [14], [15], [16], [19], [21] and [22],
by highlighting some of the key aspects as sensor used, hardware platform, Artificial Intelligence Model, Limitation of the system, Relative Cost and Remark. The following summary of Table 5 points out the novelty and efficacy of the proposed approach. • Some existing approaches only conform to simulation, which do not possess real-time control ability, such as [8], [15], [21], and [22]. In contrast the proposed work shows real- time control based on an experimental design, making a link between the theory and experimental implementation. In [16] the sensor fusion technique is being used which consists of complex and expensive hardware configuration. The approach proposed here makes this simpler by using a single RGB camera, which provides aleyenrable and easy-todeploy solution that in turn does not impair functionality. Rare previous researches use wearable devices for gesturebased

control [9], [16] which might affect user's comfort and complicate the system. The proposed method removes this dependency by using a vision only system to interpret hand gestures without any physical attachment. The following are true for the applications of the scales. To mitigate this, the proposed system makes use of a 6-DOF robotic arm combined with an adaptive gradient descent based IK solver to aid in a responsive control system. Another problem in [15], [19], [21] is they are sensitive to noises and have a low adaptability to environmental changes. The proposed model solves the above problems by a deep learning-based gesture recognition model which is both noise resilient as well as diverse environmental variations for a robust performance in real-world environment. This comparison clearly puts into perspective the practical advantages of the proposed work in terms on intuitive control, lowcost implementation, robust performance in a noisy and dynamic environment and real-time validation though both simulation and physical experimentation.

VI: RESULT AND DISCUSSION

This section provides the performance evaluation of the proposed system with the help of both simulation and experimental evaluations. The simulation analysis of the proposed system is performed in the Gazebo and PyBullet simulators. Further, the experimental setup of development is presented followed by the performance and robustness of the proposed system.

A: SOFTWARE AND HARDWARE USED :

This is the section, which describes the hardware and software which is used in the simulation and experimental studies. The hardware parts of the experimental setup include a 6 DOF robotics arm which isa Dexter ER2 Manipulator, ATmega328P based Controller, personal computer (PC), Servo Driver. The software components used are PyBullet simulator, Gazebo simulator, MediaPipe framework, OpenCV library, Robot Operating System 2 (ROS2), Arduino Integrated Development Environment (IDE) and for Computer-aided design (CAD) model development and Unified Robot Description Format (URDF) developing Fusion360 was used. The detailed description of hardware and software components are listed and described in table 3 and table 4 respectively. This section provides the performance evaluation of the proposed system with the help of both simulation and experimental evaluations. The simulation analysis of the proposed system is performed in the Gazebo and PyBullet simulators. Further, the experimental setup of development is presented followed by the performance and robustness of the proposed system. A: SOFTWARE AND HARDWARE USED :This is the section, which describes the hardware and software which is used in the simulation and experimental studies. The hardware parts of the experimental setup include a 6 DOF robotics arm which isa Dexter ER2 Manipulator, ATmega328P based Controller, personal computer (PC), Servo Driver. The software components used are PyBullet simulator, Gazebo simulator, MediaPipe framework, OpenCV library, Robot Operating System 2 (ROS2), Arduino Integrated Development Environment (IDE) and for Computeraided design (CAD) model development and Unified Robot Description Format (URDF) developing Fusion360 was used. The detailed description of hardware and software components are listed and described in table 3 and table 4 respectively.

B. SIMULATION RESULTS : The provided simulation and analysis in this work has been performed in two different approaches in order to confirm the efficiency of proposed framework. The first one used Gazebo simulation environment with the integration of ROS2 Humble distribution of robotic modeling and control. In the second used the PyBullet physics engine that came to simulate the Rigid body dynamic and interaction. 1) GAZEBO SIMULATION According to the first validation strategy, using Gazebobased simulation The URDF file was created to specify the kinematic structure, link dimensions and

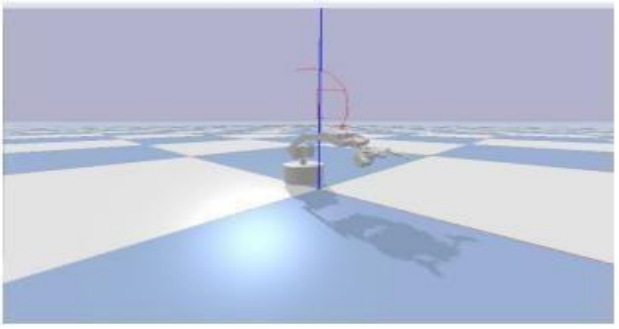


Fig. 3. Robotic arm simulation physical characteristics of the Dexter ER2 robotic manipulator.

The URDF model has been developed in Fusion 360 that is a popular CAD application that allows focusing on the accurate modeling and assembling of robots.

Tool Platform	Purpose
PyBullet	Python-based robotics simulator used to test robot control and motion algorithms.
MediaPipe	Framework used for real-time object detection and tracking.
OpenCV	Computer vision library used for image processing and edge detection.
Gazebo	3D robotics simulator used to test robots in virtual environments.

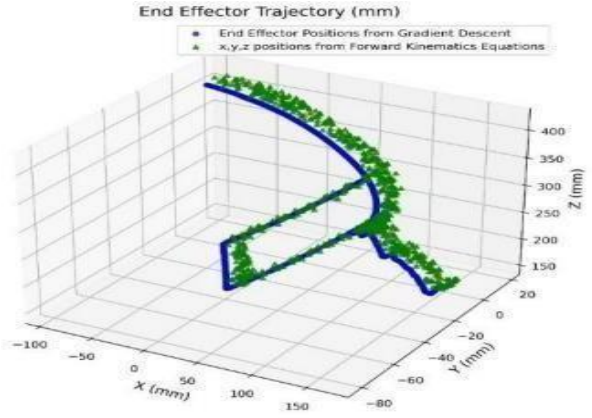
ROS2 (Humble)	Middleware used for robot communication and control.
Fusion 360	CAD software used to design robot parts and create URDF models.
Arduino IDE	Programming platform used to develop and upload code to Arduino boards.

Table I Development tools and platforms used

After finishing with the model in Fusion 360, the URDF file was exported, and later, it was imported into Gazebo simulation environment. This allowance of realistic visualization and simulation of the behavior of the robot through the ROS2 framework was made possible by this

Fig 4: Dexter ER2 spawned in Gazebo environment.

To prove the efficiency of the suggested IK solution, the algorithm of adaptive gradient descent will be tested as a ROS2 Python node to calculate the joint angles of the 6- DOF Robot Arm in order to reach a required end-effector location and orientation. This node is strictly tested in Gazebo simulation environment where its performance is tested in different configurations with an iterative and a trial and error approach. By combining an IK solver with the Gazebo simulation, it is possible to control and visualize the robotic manipulator in real-time using ROS2 controllers and show the responsiveness and potential usage of the offered approach in the simulated setting.
2) PyBullet SIMULATION A second validation strategy is the use of the program (SIMULATION) which used the PyBullet physics engine as its framework to provide an effective and robust way of simulated dynamics of a rigid body. Here the suggested adaptive gradient descent-based IK solver is then used in calculating the joint angles to be used to reach the desired set of end-effector positions in terms of their Cartesian coordinates (x, y,z). The computed joints angles were later used to revise the setting of the simulated manipulator in the PyBullet environment. Figure 8 shows the simulation results that indicate the viability and the effectiveness of the proposed control scheme in the dynamic conditions. FIGURE 4. PyBullet simulation. 3) PICK-PLACETASK Figure 9 shows the performance of pick-andplace task with the suggested 6-DOF robotic arm using the proposed gesture-based control mechanism. This exercise is an exercise in validation where we test out the practicality and easier user-friendliness of the system in a scenario-based test. The findings depict that real-time human hand gesture can be successfully converted into accurate robotic manipulator motions that allow accomplishment of tasks with accuracy and efficiency and that the system can be applied effectively to the real-life environment in industrial automation, assistive robotics and dangerous environment operations. In order to assess the performance of IK solver included in the control loop, the end-effector positions obtained with the help of calculated joint angles were compared to the desired positions provided in the beginning. Such comparison makes the accuracy of the IK algorithm susceptible to a thorough quantitative analysis. Data visualization



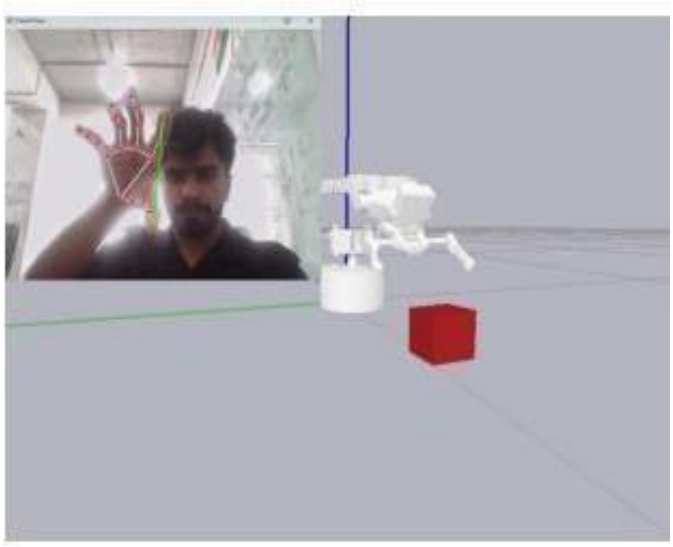
represented by plotting of the results was subsequently

Fig. 5. End effector trajectory

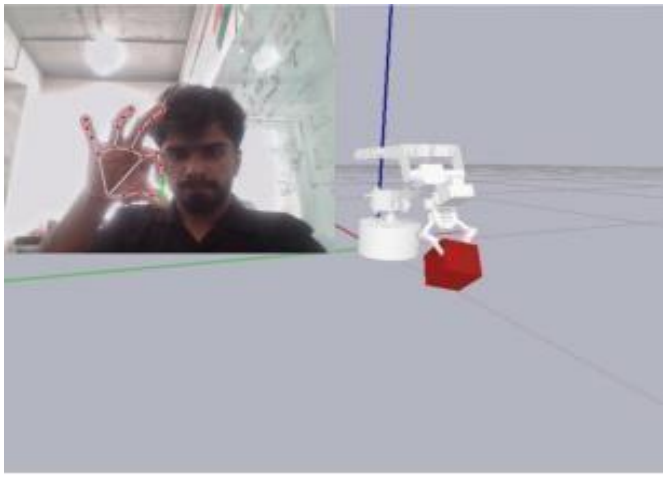
done as shown in Figure 10. The evaluation allowed finding out a variety of results: in some cases, the calculated end effector position based on the desired coordinates was obtained with deviations of about 1 to 5 millimeters, and in some others, it was in alignment of almost exactly and along the x, y, and z planes. These differences are attributable to the difficulty of solving IK to redundant and nonlinear systems, in which accuracy could be affected by numerical approximations, the convergence properties of an algorithm, and approaches to kinematic singularities. Nonetheless, the overall outcomes justify the trustworthiness and the accuracy of the adaptive gradient descent-based IK solver-based control scheme in a system of dynamic gestual control driven application setting.

C. EXPERIMENTAL RESULTS

The given section is the experimental validation of the proposed system, the integration of a Dexter ER2 6DOF.



(a)



(b)

FIG 6(a),(b). Pick and place simulations

robotic arm having a controller built on the ATmega328P. This integration makes the setup a dynamic one that has the ability to track a moving hand with a monocular camera. The target in this set up is a hand of a person and this is identified by a monocular camera attached to a laptop. The robotic arm is initially operated in an idle mode and it imitates movements of the hand in real time. The framework has a grip on an advanced learning approach based on gesture extraction to derive real-time finger positions in a video conveyed live. Those coordinates are optimized with the help of the adaptive gradient descent based on the IK algorithm specifically designed to use the kinematics of the robotic arm. It is possible using it to detect hand gestures, which can be converted to data related to the angles of the joints, so of the manipulator. This joint angle control modeled as that the robotic arm can mimic the hand gesture and movement. Figure 11 illustrates hardware connection of a given experimental set-up. Anthropomorphic control is enabled by the following PC containing a control algorithm made up of the OpenCV library, MediaPipe, and ROS2 framework to combine software tools with the Dexter ER2 Manipulator. The experimental proof of the proposed control scheme based on a vision-based gesture-driven is shown in Figure 12. FIGURE 6. Comparison of desirable and actuated pose through data visualization.

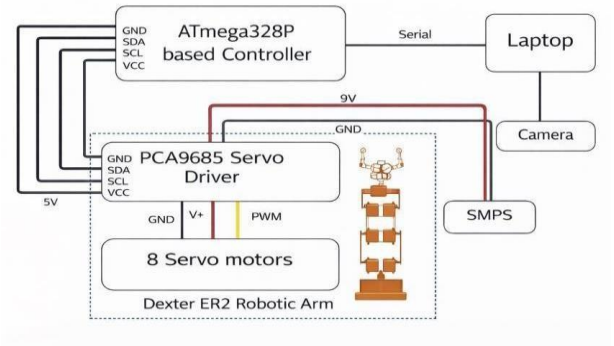


Fig. 7. Robotic arm control system

Dexter ER2 manipulator interface. Figure 12 (a) shows the working set up of the Dexter ER2 robot manipulator together with the vision system that tracks the position of the hand. Figure 12 (b) shows that the base joint of the manipulator is maneuvered by tracking the position of the x-axis of the hand at the image frame transformed into pixel coordinates which are converted into the joint of the angles to position the joint. The control of numerous joints is done in figure 12 (c) by monitoring the bend angle of the index finger with an angle that is plotted to control joint movements

IK algorithm presented as figure 12 (d) with x and y as coordinate of tip index finger on the image frame and z as depth values. Figure 12 (e) and (f) represent the gripper reaction to hand gestures, which have to be opened and closed depending on the distance between the eating thumb and wrist keypoints, which alleviate the ability to intuitively control grasping.

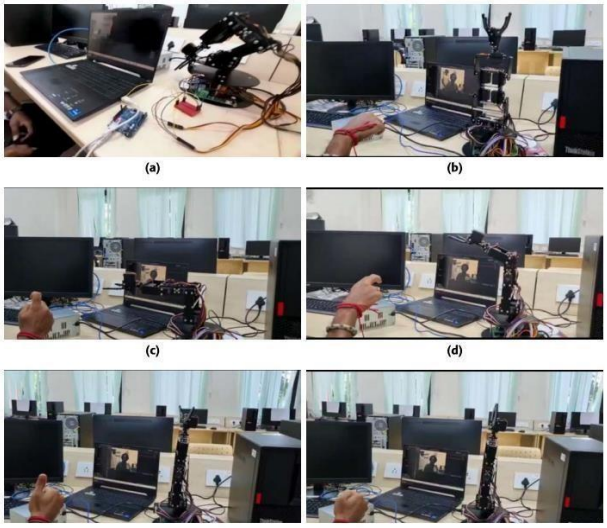


Fig 8 : results

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Smart Digital Twin-Based IoT Container Monitoring System for Real-Time 3D Logistics Tracking

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***Abstract*— The rapid growth in global logistics demands intelligent solutions that can deliver container security and safety features along with real-time monitoring. Hence, in this paper, a novel IoT-based 3D Digital Twin container security and safety system for real-time environment monitoring is proposed. The proposed system utilizes various sensors for real-time measurement of parameters such as pressure, temperature, humidity, vibration, and GPS location using a microcontroller such as ESP32. The sensor data is sent in real-time to the cloud platform using Google Firebase. A web-based system is proposed that utilizes a 3D digital twin for representing the physical system in a digital environment. The proposed system ensures better transparency in the system and minimizes damage to the cargo during transportation. The proposed system utilizes a priority-based system for better detection capabilities by giving due importance to certain parameters. The proposed system is implemented and tested for real-time operations in a cyber-physical system.**

Keywords—Digital Twin, Internet of Things (IoT), Smart Logistics, Container Security and Safety, Real-Time Tracking System, Sensor Integration, Cloud Computing.

I. INTRODUCTION

With the increase in trade, there is a need to develop an intelligent container monitoring system, which can ensure security, safety, and monitoring of goods carried in the containers. Existing container management systems have adopted location-based monitoring systems, which are not effective in monitoring environmental conditions, causing damage, security issues, and wastage of resources. Recently, IoT technology has shown much potential, which can lead to the creation of smart spaces using both physical and virtual components, called "digital twin," which can be used for real-time monitoring and decision-making.

The main idea of this project is to develop an IoT-based container security system using a concept of "3D digital twin." Parameters such as pressure, temperature, humidity, vibration, and location of the container can be monitored using IoT platforms such as ESP32, which can be sent to the cloud using services such as Google Firebase, thereby increasing the efficiency, security, and intelligence of the supply chain management process..

However, owing to the complexities involved in the current supply chain logistics, it has become a challenge to ensure the integrity and security of the goods in transport. For instance, containers carrying food items, medicine, and other high-value items are more vulnerable to environmental factors, mishandling, and unauthorized access during transport. However, the current monitoring systems are unable to offer real-time data, which has become a hindrance in addressing the issues involved in the transport process. However, the development of IoT technology has created an opportunity to bridge the gap between physical assets and the current virtual monitoring systems. This can be achieved through the real-time monitoring of assets using a virtual system, which can help the logistics operators in monitoring the assets remotely, hence addressing the issues involved in the transport process, including the potential risks involved in the process. In the proposed project, a series of sensors can be linked

using an embedded system like ESP32, which can be used to obtain real-time data, which can be synchronized using cloud technology like Google Firebase.

In this paper, a comprehensive IoT-based container monitoring system is proposed, taking into account the concept of a digital twin. In this proposed system, data acquisition is done using various sensors with ESP32 hardware, and cloud storage is done using a cloud platform called Google Firebase. The contributions of this proposed system are priority-based risk detection, visualization using a digital twin concept, etc. The structure of this paper is as follows: system architecture, methodology, experimental results, and conclusion.

The rest of the paper is organized as follows: the system architecture and design methodology will be introduced in the next part, and then the implementation and experimental results will be provided, and at last, the performance analysis and conclusion will be presented to prove the effectiveness of the proposed IoT-based 3D digital twin container monitoring system.

II. LITERATURE SURVEY

With the recent developments in Internet of Things (IoT) and digital twin technology, smart logistics, and container monitoring systems have witnessed a significant impact. Various researchers have presented different frameworks using digital twin technology to enhance visibility in logistics environments. Wang et al. have presented an IoT- and digital twin-enabled framework to enable asset tracking in safety management, where assets are continuously monitored to detect abnormal situations in real-time using cyber-physical models. Various researchers have presented studies using digital twin-based maritime logistics to identify how digital twin technology can enhance awareness, analytics, and intelligent decision-making in logistics infrastructures.[1]

Researchers have presented studies using hybrid IoT monitoring architecture to enable monitoring of internal container conditions such as temperature status using container logistics, which can enhance the ability to overcome the limitation of a GPS-based tracking system.[2] Furthermore, a digital twin-based logistics platform has also been presented to optimize energy consumption in automated container terminals [3].

However, various smart container monitoring systems have only focused on optimization of infrastructure or monitoring, where there is a lack of integrated security monitoring using multi-sensor security monitoring functions, interactive visualization, etc [4] thus, there is a need to develop a comprehensive real-time digital twin-based container security system. In addition to this, recent research also proves the application of IoT and digital twin technology in the development of logistics monitoring system [5]. Zhao et al. have proposed an IoT framework for digital twins in the field of real-time safety monitoring [6].

Similarly, [7] Lu et al. have proposed a digital twin system for automated container terminals for better visualization of the system. However, this is more focused on infrastructure management. [8] Zhou et al. have proposed a smart maritime logistics system using digital twin and data analytics technology for better decision-making in logistics operations. Similarly, Wang and Hsu have proposed an IoT-based cargo monitoring system for better reliability in the monitoring system. [9] Abbas et al. have also discussed the application of digital twin technology for better visibility in the supply chain. However,[10] there is a lack of integrated multi-sensor monitoring with 3D visualization and priority alert in logistics operations, as discussed in the proposed system.

III. PROPOSED SYSTEM

The system proposed here is a framework of an IoT-based container security system with monitoring, and a 3D digital twin is included in the proposed system. In the proposed system, different sensors are used to collect data on pressure, temperature, humidity, vibration, tilt, and GPS location.[11] These sensors continuously monitor the condition of the container while it is being transported. The data collected by the sensors is then sent to the cloud platform through a microcontroller like ESP32, and the data is then processed in real time.

A web application is used to create a 3D digital twin of the real-world container, and the real-time[12] parameters of the container can be viewed remotely. The proposed system has a priority-based alert system, and the parameters like pressure are given the highest priority, followed by temperature and humidity[13]. The proposed system is efficient, effective, and secure, and it provides a cyber-physical system for the security of the container.change the headlight state to low beam or not to avoid any glare and to improve safety while driving.[14]

The hardware used to implement the proposed system is given in Table I. It is seen that various sensors, microcontrollers, switches, and other electronic devices are used to implement the proposed system.[15]

The proposed architecture consists of IoT sensors, embedded systems, cloud connectivity, and a digital twin interface for monitoring in 3D. The data obtained by the ESP32 is then sent to Google Firebase for synchronization and efficient security and logistics management.

The architecture of the system, as proposed in this paper, is based on a four-layer structure. These layers are the sensing layer, processing layer, cloud layer, and visualization layer. The sensing layer includes temperature sensors, humidity sensors, pressure sensors, vibration sensors, tilt sensors, and GPS sensors. These sensors are used for the continuous monitoring of the containers. The processing is carried out by an embedded controller, as ESP32.

The cloud layer is based on Google Firebase for the storage and synchronization of the data in real time. The visualization is carried out by a web interface for a digital twin in 3D for the monitoring of the containers in real time and automated alerts based on specific priority levels.

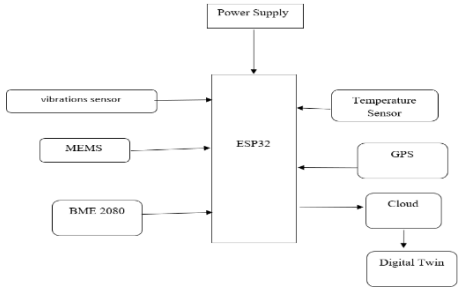


Fig. 1. Block diagram of the proposed Digital Twin-IoT based system.

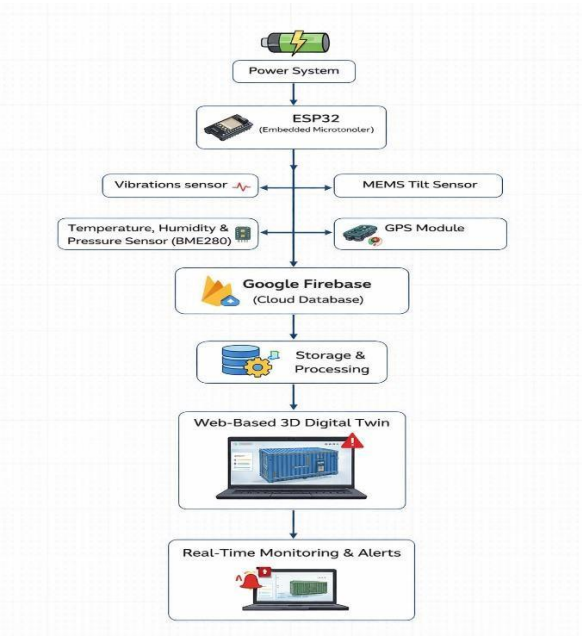
TABLE I. DEVICES USED IN THE PROPOSED SYSTEM

Name of the Device	Type of Device
ESP32 DevKit	Microcontroller
NEO-6M GPS Module	Positioning Sensor
SW-420 Module	Motion / Impact sens
BMP280	Atmospheric sensor
DHT11	Environment sensor
Tilt Switch Module	Orientation sensor
Power Supply	Power Source
Connecting Wires	Electrical Connecto

A) System Architecture

The architecture of the proposed container monitoring system is based on the layered IoT-based cyber-physical architecture, in which the integration of the data collected from the sensor, the processing of the collected data, the communication of the data with the cloud, and the visualization of the data are carried out. The sensing layer of the proposed container monitoring system comprises a vibration sensor, a MEMS sensor for tilt measurement, a BME280 sensor for environmental measurement, and a GPS module for location tracking. The data collected from the sensor is sent to the central processing unit, which is the ESP32 module. The data is sent through a wireless medium. A regulated power supply is connected to the proposed container monitoring system for the supply of power. The data collected from the sensor is sent through a wireless medium and transmitted to the cloud platform, Google Firebase. The cloud platform is connected to the application layer, in which a web-based 3D digital twin is created

The system architecture, as proposed here, also has cloud analytics and digital twin modeling. In the proposed system, the data is collected with the help of various sensors connected with the ESP32 module. Then the data is sent to the cloud with the help of various wireless communication protocols. Once the data reaches the cloud platform, data visualization, abnormality detection, and historical data analysis are performed. Also, the digital twin is created. The digital twin is the virtual version of the system. With the help of the digital twin, we are able to simulate the performance of the system based on the environment. Also, the proposed system is scalable; this means that other modules for the sensors and the analytics system can



also be added without affecting the performance of the system.

Fig. 2. Workflow of the proposed digital-twin IoT-based real-time 3D logistics tracking system

B) Digital-twin IoT-Based Container System

The Digital Twin system, which is an IoT-based system, creates a digital representation of a real-world environment through real-time data obtained through sensors integrated into a cloud platform. This system allows continuous monitoring, prediction, and

optimization of the system through a digital representation of the real-world system.

The framework of the proposed digital twin would use data from ESP32 sensors, combined with cloud analytics, to enable real-time system simulation. This would help to achieve condition monitoring and predictive maintenance using historical data, as well as current data. This would help to effectively manage a system remotely.

C. Container Security System with Priority-Based Mechanism

In the proposed container security system, the priority-based monitoring technique is used for efficient safety and resource usage. In the proposed container security system, sensor data is used from the vibration sensor, temperature sensor, MEMS sensor, environmental sensor, and ESP32 controller for efficient monitoring of the container security system. The events are classified based on various levels of priority based on the severity of the events such as critical, warning, and normal states.

Thus, a complex container security system will be proposed, utilizing IoT technology and including a digital twin visualization system. In this system, different sensors will be deployed inside the container, including pressure sensors, temperature sensors, humidity sensors, vibration sensors, and GPS sensors. Then, the data will be sent to a cloud-based Firebase database. Following this, a web interface will be used to create a 3D visualization of the container, referred to as a digital twin. In addition, a priority-based system will be included in the proposed system, with pressure, temperature, and humidity having a weighted priority, i.e., pressure > temperature > humidity. Then, notifications will be sent automatically in case there is a probability of security breaches, changes in the environment, and improper handling of the containers. The results of the experiment have shown that the proposed system is accurate in tracking the status of the containers, which will help in predicting potential hazards.

D. Decision Logic and Real-time 3D Control

The proposed system would also have an intelligent decision logic module, which would be integrated with the real-time interface of the 3D digital twin. The proposed system would also have the ability to monitor the conditions of the container through sensors such as pressure, temperature, humidity, vibration, tilt, and location, which would be obtained through the ESP32 module and then sent to the Google Firebase cloud platform in real-time.

The proposed intelligent decision logic module would compare the obtained data with the threshold values, after which the priority level would be assigned according to the severity of the obtained risks, wherein the pressure would have the maximum priority, followed by temperature and humidity changes. Once the abnormalities are obtained, alerts would also be sent automatically according to the changes in the real-time interface of the 3D digital twin.

The real-time interface of the proposed 3D digital twin would also be utilized to visualize the conditions of the container, wherein the user can obtain a better understanding of the environmental conditions, obtain knowledge of potential risks, and take necessary precautions in real-time through the proposed intelligent decision-making algorithms, which would enhance the safety of the container through the proposed system.

TABLE II. DIFFERENT INPUT CONDITIONS TO CONTROL 3D MODEL

Sensor Data	**3D Model Output**	**Inference on 3D Model (Output)**
Normal range values	normal green status	Safe operating condition; no action required
Moderate deviation in temperature / humidity	highlighted in yellow warning state	Environmental variation detected; monitoring required
High pressure, excessive vibration, or tilt anomaly	displayed in red alert state with warning notification	Critical risk detected; immediate intervention required

E. Advantages of the Proposed System

The proposed system allows for the monitoring of the containers in real-time with enhanced security using the IoT technology and the use of the 3D digital twin interface for the monitoring of the containers:

- Allows for the early detection of risks
- Providing priority-based alerts, the enhancement of the transparency of the system
- Minimization of the damage of the cargo, and the efficient management of the data using the cloud for the efficient operation.

The proposed system allows for the monitoring of containers in real-time with increased security using IoT technology and the use of a 3D digital twin interface for monitoring the containers.

I. EXPERIMENT AND RESULT

A. *Experimental Setup*

The experimental setup has been created with the aim of validating the efficacy of the proposed IoT-based container monitoring system and digital twin. The hardware prototype of the proposed IoT-based container monitoring system and digital twin consists of different sensor devices like temperature, humidity, pressure, vibration, tilt, and GPS sensor, connected with ESP32 for real-time data acquisition.

A regulated power driver circuit is necessary for the proper functioning of the entire proposed IoT-based container monitoring system and digital twin. The data is wirelessly transmitted through the Google Firebase cloud platform, used for data storage and processing. The web application is used for data acquisition from the Google Firebase cloud platform and real-time 3D digital twin update. Various environmental conditions like vibration, temperature, and tilt were artificially created for the experimental setup of the proposed IoT-based container monitoring system and digital twin.

The experiment employs the use of real-time modules and a 3D simulation environment. The latter is connected with the system for the validation of its responsiveness. The data is entered into the system by the sensor module and then processed by the unit. It is mapped onto a digital model. After this, disturbances are introduced for the accuracy, synchronization, and adaptability of the system.

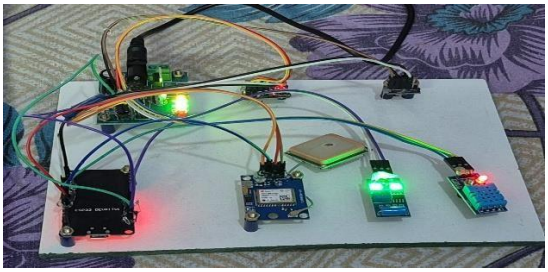


Fig. 3. Hardware Implementation of proposed system

B. *Experimental Result*

The results obtained from the experiments show that it is possible to effectively integrate the sensor data with the 3D model, thus allowing accurate real-time monitoring as well as interference detection. Moreover, it was also evident that it is possible to effectively map the sensor data to the virtual model, thus allowing accurate visualization of system performance. When there is controlled interference, it is also evident that it is possible to effectively visualize the interference zones, thus updating the 3D model. Additionally, it was also evident that there is stability in the synchronization of the sensor data with the digital environment, thus showing evidence of the reliability of the system.

When conducting an analysis of the accuracy of the system, it was also evident that there is an improvement in terms of efficiency in detecting anomalies, thus showing accurate visualization of system performance. When conducting the experiments, it was also evident that it is possible to achieve stable performance, thus showing evidence of reliability. From the experiments conducted, it is evident that it is possible to effectively enhance situational awareness, as well as reliability, through accurate visualization of system performance. The various testing scenarios, along with the corresponding output, are summarized in Table III. The results of a real-time testing of the proposed digital-twin IoT based container security system via a container prototype are provided in Fig. 4.

TABLE III. SCENARIOS WITH VARYING DISTANCE AND CNN DETECTION AND THEIR CORRESPONDING OUTPUT

Scenario	**Sensor Range**	**3D Model Output**	**Scenario Description**	**3D container State**
Scenario 1	Temperature: 20–30°C, Distance Sensor: Stable (0–5 cm variation)	Smooth real-time visualization with no alerts	Sensors detect normal environmental conditions and no external disturbance	Stable and Secure
Scenario 2	Temperature: 30–40°C, Vibration Sensor: Moderate fluctuation	Highlighted warning zone displayed on 3D model	Small external disturbance or partial obstruction detected near container	Warning State
Scenario 3	Temperature: >40°C, Motion/Vibration: High variation	Red alert visualization with flashing interference region	Significant intrusion or abnormal activity affecting container safety	Critical / Alert Mode

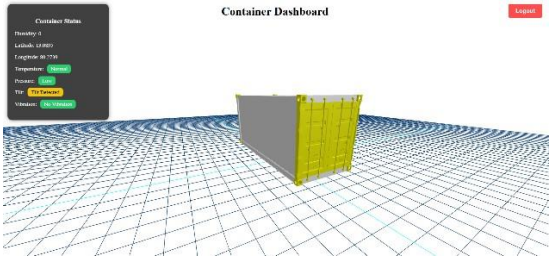


Fig. 4. Real-time testing of the proposed Digital-twin IoT 3D-container security system using a container prototype.

V. CONCLUSION

The proposed Digital Twin IoT-based container security system with priority-based monitoring and real-time 3D control is an efficient solution for intelligent container security management. The use of IoT technology, cloud computing technology, and digital twin technology in container security management allows for the continuous monitoring of environmental and operational parameters and the simultaneous virtual control of a physical container. The decision logic module is an intelligent module of the system, which uses the analysis of sensor data and generates a response based on the level of the threat. Real-time 3D control is a powerful tool for container security management, which allows for the observation and detection of any kind of interference in container security. The experimental evaluation of the system is a successful approach for the identification of normal, warning, and critical states of container security management with increased accuracy and faster monitoring times. Priority-based container security is an optimized solution for resource management.

In addition to this, scalability, accessibility, and the secure management of data are also enabled through this kind of architecture. This is why it is applicable in the field of smart logistics, port, and industrial asset management. This implies the existence of a bridge between the physical world and the virtual world. This is enabled through the integration of IoT analytics and digital twin modeling. This can also be extended in the future through the incorporation of predictive analytics with the aid of AI, etc.

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Transforming Retail Experience Using Indoor Navigation and Smart Assistance

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ABSTRACT — Large retail environments often create navigation difficulties due to complex layouts and extensive product availability.Because of their intricate layouts and wide selection of products, large retail spaces frequently make navigation challenging. In order to increase in-store productivity, this paper introduces SmartStore Navigator, an intelligent indoor navigation and shopping assistance system. For product comparison, optimised path guidance, and product localisation, the system offers a digital store map. To lessen the checkout time, it integrates a self-billing system that uses barcode scanning. Accessibility is improved by using multiple input methods, such as text, voice, and image recognition. The user experience is enhanced by extra features like budget tracking, predictive recommendations, and crowd-aware navigation. Store optimisation and inventory control are supported by a management dashboard. The suggested solution increases customer satisfaction, decreases time consumption, and improves shopping efficiency.

I. INTRODUCTION

Retail spaces have grown larger and more diverse, which means finding what you need isn't always easy. Shoppers often end up wandering through aisle after aisle, especially during busy periods, and that can turn what should be a quick trip into a frustrating experience. Even with today's fast-moving digital innovations, most physical stores still don't have smart systems that help customers locate products or navigate efficiently.

Online shopping, on the other hand, makes life simple—search bars, filters, personalized suggestions, smooth checkout. Those perks rarely exist in brick-and-mortar stores. One lingering pain point? Checkout lines. Waiting for billing at crowded counters can eat up time and sour the entire shopping experience.

That's where SmartStore Navigator comes in—a smart, all-in-one retail solution built to close this gap. It merges indoor navigation, intelligent product search, and automated billing into one seamless system. Shoppers can pull up a digital store map on a web interface to pinpoint products and follow the fastest route to them. And when it's time to pay, they simply scan item barcodes with their phones or smart carts. Each scan adds to a virtual cart, updates the total bill instantly, and cuts out the need to stand in line at the register.

By blending indoor mapping, AI, and self-service tech, SmartStore Navigator makes shopping faster and more convenient, ultimately boosting customer satisfaction. It also helps retailers behind the scenes with improved inventory tracking and insights into shopping behavior—a well-rounded solution for the next generation of smart retail.

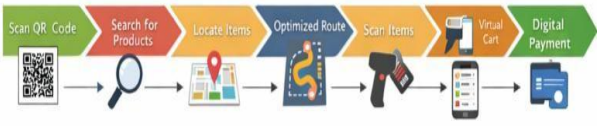

Fig.1-Workflow of SmartStore Navigator

II. LITERATURE SURVEY

A. Indoor Navigation Technologies

Many researchers have looked into indoor navigation systems designed to help people find their way through complex spaces like shopping malls or large retail stores. Technologies such as Bluetooth beacons, Wi-Fi positioning, and RFID are commonly used to locate users inside buildings. Since GPS signals often don't work indoors, these systems step in to guide users around and provide location-based assistance.

B. Smart Retail Systems

In the world of smart retail, the focus is on blending digital tools with physical store experiences. Current systems often offer things like product details, special offers, and personalized recommendations. The goal is simple: make shopping more engaging, convenient, and enjoyable for customers.

C. Artificial Intelligence in Retail

Artificial intelligence has become a game-changer in retail, especially for recognizing products and personalizing recommendations. With image recognition, shoppers can identify items by snapping a photo, while machine learning tools study browsing habits and past purchases to suggest products tailored to each customer's preferences.

D. Smart Billing and Automated Checkout Systems

New technologies in retail have brought about smart billing systems that speed up the checkout process and boost efficiency. Methods like barcode scanning, RFID-based billing, and cashier-less checkout let shoppers scan their items and get an instant bill. By cutting down on manual steps and wait times, these systems improve the whole shopping experience. However, many of them are still costly or work only in specific types of retail settings.

E. Limitations of Existing Systems

Even with all these advances, most current solutions focus on just one thing—whether that's indoor navigation, product recommendations, or checkout automation. What's missing is an all-in-one platform that brings together navigation, product discovery, predictive insights, and smart self-billing in a single streamlined system.

F. Research Gap and Motivation

To fill this gap, the SmartStore Navigator is introduced as a unified platform combining multiple intelligent features—like indoor navigation, smart product search, automated billing, and analytics tools—designed especially for modern retail spaces. The aim is to deliver a smoother, more efficient shopping journey by integrating all the key functions shoppers need into one cohesive system.

III. PROBLEM DEFINITION

Shopping in huge retail spaces—like supermarkets and hypermarkets—can feel more like running an obstacle course than a quick errand. The maze-like layouts and endless product options often leave customers frustrated and waste precious time.

Some of the main pain points include:

- Struggling to find specific products in sprawling, often confusing store layouts
- Wasting time wandering through several aisles just to locate one item
- Having limited visibility of what's in stock or which brands are available
- Dealing with crowded aisles, especially during peak hours
- Facing poor communication about product locations or availability between customers and staff
- Waiting in long lines at checkout counters due to manual billing processes

And that last point—traditional checkout—is a big one. Standing in never-ending queues after filling your cart can quickly turn a shopping trip into an exercise in patience.

Why a Smarter System Matters:

All these challenges point to a clear need for a smarter, more connected retail experience. Imagine a system that helps shoppers move through stores effortlessly, find what they need in seconds, and check out without waiting. By combining indoor navigation, intelligent product search, and self-billing technology, retailers could cut down search times, eliminate long

queues, boost convenience, and manage store operations more efficiently—all while keeping customers happier.

IV. PROPOSED SOLUTION

SmartStore Navigator is a web-based indoor navigation system built to make shopping faster, easier, and a lot more convenient. It helps customers find products in retail stores without wandering around aimlessly.

To get started, shoppers simply scan a QR code at the entrance. That opens up a digital map of the store, where they can search for products and instantly see where each item is located.

The platform offers several ways to search:

1. Typing in a product name
2. Using voice commands
3. Snapping a photo for image-based recognition
4. Uploading a shopping list that's processed through Optical Character Recognition (OCR)

Once the system knows what you're looking for, it creates an optimized route through the aisles—so you can grab everything you need in the quickest way possible. Less backtracking, less time wasted.

But navigation's not all it does. SmartStore Navigator also includes a smart self-billing feature. Customers can scan product barcodes using their phones or even a smart shopping cart. Every scanned item shows up automatically in a virtual cart, updating the total bill in real time. When they're done, shoppers can check out digitally and skip the long lines at the counter.

On the retailer's side, there's a dedicated dashboard that makes store management smoother. Shopkeepers can rearrange layouts, change product locations, track stock, and analyze customer behavior to make more informed decisions.

Altogether, SmartStore Navigator creates a seamless, tech-powered shopping experience—for both customers and store managers.

Fig.2-Smart Self-Billing Process

V. METHODOLOGY

The SmartStore Navigator system follows a clear, step-by-step process designed to help shoppers find products quickly, move smoothly through the store, and check out with minimal hassle.

Workflow Steps:

- When entering the store, customers scan a QR code to open the web-based SmartStore app.
- The app then loads a digital map of the store along with its full product database.
- Shoppers can search for items using text or voice commands, by snapping a photo, or even by uploading their shopping list.
- The system analyzes the input and pinpoints where each product is located.
- A route optimization algorithm kicks in to plan the fastest path that covers all selected items.
- That optimized route appears right on the store's digital map.
- Customers simply follow the guided route to find and collect their products efficiently.
- As they shop, they can scan barcodes with their phone or a smart shopping cart to use the self-billing feature.
- Each scanned item goes straight into a virtual cart, and the total bill updates instantly.
- Along the way, the system can offer handy extras—like reminders, budget notifications, or alternative product suggestions.
- Once shopping's done, payment happens digitally, and the system issues a final receipt automatically.

Altogether, this approach saves time, makes navigation effortless, speeds up checkout through automation, and delivers a smoother, smarter shopping experience.

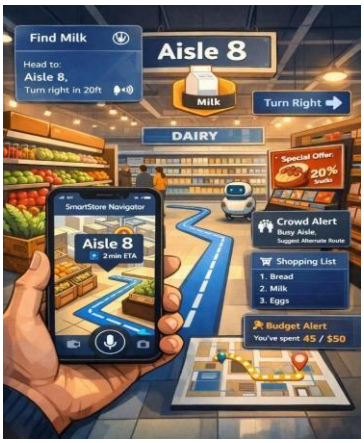

Fig.3-Representation diagram

VI. SYSTEM ARCHITECTURE

The SmartStore Navigator system runs on a three-tier architecture that brings together the Customer Interface, Backend Server, and Shopkeeper Dashboard, all tied in with an integrated Smart Self-Billing Module.

The Customer Interface is a web-based platform designed for convenience. Shoppers can look up products, view store maps, follow step-by-step navigation routes, and even handle self-billing right from their phones or smart shopping carts by scanning product barcodes. Everything here is built for smooth, easy interaction.

Behind the scenes, the Backend Server keeps things moving. It handles user requests, manages product data, optimizes navigation routes, and takes care of all billing operations. It also keeps product locations, prices, and cart details synced in real time—and when checkout time comes, it generates the final bill instantly.

For store owners, the Shopkeeper Dashboard is the control center. It lets them update product placements, manage store layouts, keep tabs on inventory, and study customer behavior. They can also adjust pricing and oversee billing to make sure every transaction is spot-on.

Supporting all this is a centralized Database that houses product info, store layouts, stock data, and billing records. It's the backbone that keeps the system running efficiently and ensures everything stays consistent across the board.

Finally, the Smart Self-Billing Module pulls together barcode scanning, virtual cart management, and secure digital payments. With it, customers can finish their shopping and check out right away—no need to wait in line.

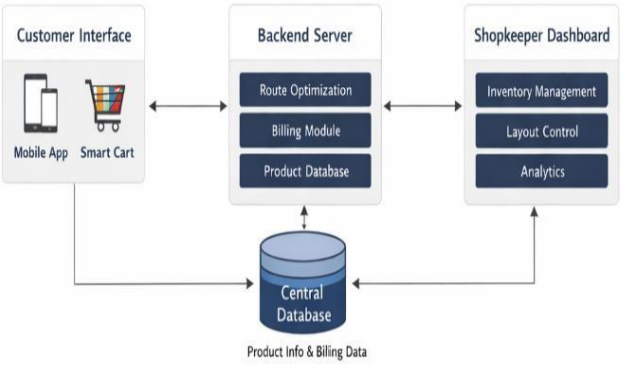

Fig.4-Overall System Architecture

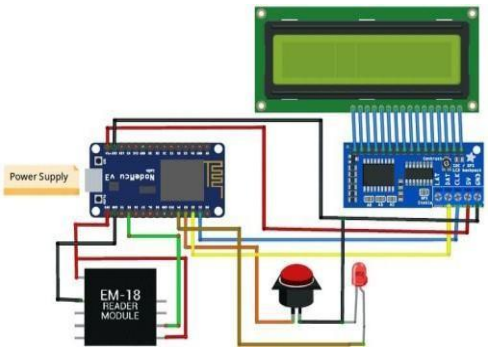

Fig.5-Smart trolley Architecture

Advantages:

- Cuts down the time shoppers spend hunting for products
- Makes the whole shopping experience quicker and more efficient
- Helps keep aisles clear and reduces crowding
- Puts products front and center for easier browsing and better choices
- Boosts overall customer satisfaction
- Does away with long checkout lines thanks to self-service options
- Speeds up the payment process and makes it more convenient
- Lowers the need for manual billing staff
- Gives store managers real-time data for smoother, more informed operations

Fig.6-Output Diagram

VII. FUTURE WORK

- Introduce Bluetooth-based indoor positioning systems to track customers in real time, ensuring precise movement insights within the store.
- Add Augmented Reality (AR) navigation to give shoppers an interactive, visually guided experience that helps them find products easily.
- Upgrade the self-billing process with RFID and sensor-based, cashier-less checkout technology, making billing completely automatic.
- Develop smart shopping carts that can detect items on their own and sync automatically with the billing system for a seamless checkout.
- Use AI-powered demand forecasting to better manage inventory and optimize stock levels, reducing both shortages and excess.
- Offer modern payment options like digital wallets and contactless systems for quicker, smoother transactions.
- Connect in-store shopping with online platforms and home delivery services to create a truly unified, omnichannel retail experience.

VIII. CONCLUSION

The SmartStore Navigator system offers a cutting-edge way to make retail shopping smoother and more enjoyable. It brings together indoor navigation, smart product search, and self-billing tools so customers can quickly find what they need—even in massive stores that usually feel like mazes.

Thanks to built-in Internet of Things (IoT) technology, the system goes a step further with smart shopping cart features. Shoppers can scan items using their phones or connected carts, and the bill updates automatically in real time. No more waiting forever in checkout lines. There's even a cart-to-cart communication feature, letting friends or family coordinate their shopping as they go, which adds a layer of convenience and makes the whole experience more engaging.

By blending indoor mapping, AI, and IoT-powered automation, SmartStore Navigator creates a shopping journey that's seamless and efficient from start to finish. Customers get a faster, more satisfying trip, while retailers benefit from improved inventory control and smoother operations. Altogether, it marks a big leap toward the next generation of intelligent, fully automated smart stores.

IX. ACKNOWLEDGEMENT

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HBTOA:Hybrid Barnacle-Tortoise Optimization Algorithm for Global Optimization

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Abstract

Lately, meta-heuristic optimization tools are being looked at more closely when tackling tough nonlinear and multimodal challenges. Still, plenty of current approaches get stuck too soon or inch forward at a crawl. A new method shows up here - the Hybrid Barnacle–Tortoise Beetle Optimization Algorithm, known as HBTOA. It brings together BMO's wide search strength along with GTBO's smart fine-tuning behavior.

A fresh mix of methods keeps search wide then sharp, using pairing rules alongside beetle-like tweaks. Tests on common challenge problems show HBTOA finds answers faster and closer to ideal than PSO, GA, or GWO do. From Ref.[10] swarm dances to gene swaps, older tactics fall behind when precision matters. Even wolf packs lose ground against this blend of spread and polish.

From these results, it looks like HBTOA handles tough engineering challenges well. The method works reliably under pressure. What stands out is how smoothly it finds solutions. Complexity doesnot seem to slow it down. Performance stays strong across different tests. There is little drop when conditions get harder. Efficiency remains high throughout trials. It adapts without needing constant tweaks. Results stay consistent even with messy inputs. This approach holds up where others might fail.

Keywords: Ref. [8]Metaheuristic optimization, hybrid algorithms, global optimization, exploration-exploitation balance

Introduction

Getting things just right matters a lot when dealing with tough challenges in fields like signal transmission, data training models, sensor layouts, visual analysis, and dividing up supplies. Problems out in the real world tend to twist and shift across many dimensions, showing multiple peaks - which trips up standard step-by-step solvers.

Old-school approaches? They drag down progress with slow runtimes, shaky dependence on starting points, plus getting stuck near second-rate answers instead of the best ones.

Facing tough problems, solutions drawn from how nature works have become go-to tools for finding best answers across huge possibilities. Instead of rigid rules, they copy things like bird flocks moving together or genes changing over time to test many options fast. Take Ref.[1] PSO or Ref.[2][7]GA - these are known names because they work well without needing deep math setups. Yet sometimes they get

stuck too early or crawl forward when the problem gets twisty and layered.

New methods in optimization now include tools like the Grey Wolf Optimizer and Whale Optimization Algorithm, both using group dynamics and teamwork to boost performance. Because they mimic how animals hunt together, their ability to scan large areas gets stronger. Still, staying between Ref.[9] broad searching and focused tweaking is tough to maintain. Too much wandering means answers take longer to appear. When too much time goes into fine-tuning small spots, solutions often get stuck in less useful outcomes. Balance slips easily when one side pulls harder than the other.

New methods like the Barnacles Mating Optimizer and the Golden Tortoise Beetle Optimizer work well in different ways. Because it copies how barnacles pair up at random, one spreads out searches more widely. The way tiny sea creatures reproduce leads to fresh variations every time. Meanwhile, the beetle-inspired system adjusts its path smartly, much like an insect dodging threats while moving precisely forward. Its movements help zero in on answers quickly under certain conditions. Still, too much unpredictability can slow down the first approach when finding endpoints. Yet the second sometimes settles too early because it focus tightly from the start. Each carries weaknesses hidden inside their strengths.

A fresh mix appears here - one that blends barnacle mating patterns with how tortoise beetles move. Instead of sticking to just one method, it shifts between spreading out and focusing in, depending on what the problem needs at each step. This balance helps the process move faster toward answers without getting stuck too early. Accuracy gets a quiet boost, not because of force but through smarter adjustments along the way. Strength comes not from complexity, rather from timing - when to explore, when to refine.

A fresh approach takes shape here - combining two smart ways to hunt solutions, making tough math puzzles easier to crack. This new method gets tested on well-known challenges, showing it keeps up with current tools in the field.

Related Work

Figuring out tough math challenges has led researchers to test many flexible methods. Right from the start, one approach - Particle Swarm Optimization - began drawing attention for its quick results. Swarming behavior in birds shapes how this method adjusts solutions on the fly. Still, shaky movements can trip it up when landscapes get messy. Genetic Algorithms came around at nearly the same time, using survival-of-the-fittest logic. Instead of particles, they shuffle pieces of possible answers like puzzle parts. This mix-and-match play helps them explore wide areas without getting stuck early. Yet speed sometimes takes a hit - the process drags, demanding more number crunching. Each cycle burns extra steps just to inch forward. Both tools adapt well, though each carries trade-offs hidden beneath surface wins.

Some smart new methods take ideas from how animals behave in nature. Following the pack structure and hunt tactics of grey wolves, one method called Ref.[3] GWO helps guide possible answers more effectively. Top wolves shape the path others follow, which keeps searching broad at first then narrows down later. Even so, tough problems can mislead it into settling too soon on less ideal spots. Another approach, WOA, uses looping paths plus circling moves to refine results even further. This often finds closer matches but takes longer due to heavier calculations behind each step.

These days, work on boosting optimization has leaned into mixed strategy methods. By linking different algorithms together, weak spots in one can be balanced by another. Take particle swarm optimization - when paired with something like the flower pollination method or symbiotic organisms search, results often get sharper and faster. On a similar note, teaming up particle swarm with grey wolf optimizer and gravity-based searches tends to handle tough design puzzles better, thanks to varied ways of exploring solutions.

Lately, research keeps pointing to one thing - keeping exploration in check with focused searching matters. Some new methods, inspired by nature, adjust their approach on the

fly, helping them find solutions more consistently when tested. Even so, getting that mix just right -

wide scanning paired with deep digging - is still tough for smart-search systems to nail down.

So far, mixing different ways to solve problems has kept researchers busy. This new method, called HBTOA, blends how barnacles mate with smart small-step improvements. Instead of copying old patterns, it shifts between wide searching and careful tweaking. One part explores options freely, while the other adjusts results bit by bit. Because of this mix, solutions tend to improve more steadily. Progress comes not just from speed but also from smarter choices along the way. Over time, the balance helps avoid getting stuck too early. Each stage feeds into the next without clear borders. Results show it handles tough cases better than some past versions. Even when conditions change, adjustments happen naturally.

Hybrid Barnacle–Tortoise Beetle Optimization Algorithm:

Working Principle of the Proposed HBTOA

Starting with nature's hints, the new Hybrid Barnacle–Tortoise Optimization Algorithm mixes traits from two methods: one based on barnacle mating habits, another inspired by golden tortoise beetles. This blend aims to wander widely when searching solutions, yet also dig deep into promising spots. Instead of just pushing forward blindly, it shifts modes - sometimes exploring, sometimes refining. By pulling together Ref.[4] BMO's reach and Ref.[5]GTBO's precision, the method tries staying flexible across different problem shapes. So while one part scouts broad areas, the other fine tunes what looks useful. Through this mix, balance emerges - not too scattered, not too stuck.

Starting out, the algorithm spreads its search wide through a method inspired by how barnacles choose mates. From the group of possible answers, it picks random pairings to mix together, creating fresh options each time. That randomness keeps things moving across many directions instead of settling too soon. By shuffling choices like cards, it avoids getting stuck early on.

With each step forward, the method begins focusing more on refining known answers through the golden tortoise beetle's motion pattern. Now drawing near top results found up to now, possible answers get pulled closer by that same crawl-inspired rule. Refinement takes over slowly as progress unfolds under this Ref.[13] shifting crawl logic. Better guesses form quickly once the system leans into familiar territory using beetle-style steps. Moving ahead, improvements grow sharper because choices follow a path shaped like the insect's trail. Closer inspection of strong options happens naturally when the search settles into late-stage crawling moves. The route narrows down as prior success guides what comes next via beetle motion rules. Ref.[15] Tweaking dominates later stages thanks to how past wins steer new attempts along creeping paths. Progress tightens around good outcomes by copying how the beetle adjusts its slow advance. Earlier broad searches give way to careful nudges driven by one small creature's odd walk.

A shift begins when a changing trigger adjusts how search moves from trying new options to focusing on known ones

S=t/T

Where,

t stands for whatever round we are on right now

T stands for how many times things can repeat at most.

As soon as S < 0.5, Under 0.5 the system leans into testing new options.

past that mark, it shifts toward refining known paths.

$S \geq 0.5$

Six or higher means it leans toward using what already works.

Freed from fixed patterns, the process spreads out at first, yet grows more precise over time. Its rhythm shifts naturally – loose Ref.[6] exploration gives way to tighter focus when needed. Flexibility built in keeps options alive early, then narrows them with care near the end. Movement stays fluid, never stuck too soon on one path. Gradually, wild guesses settle into sharper answers.

A step-by-step breakdown comes next, showing how the suggested mix of Barnacle and Tortoise methods works. Each phase unfolds one after another, revealing the structure behind this combined approach.

A. Initialization:

A set of N possible answers appears in eq (1) at random inside the given range. Each one takes a different path to fit the boundaries. Some land close to edges while others settle in the middle. Their positions follow no pattern yet stay within limits. Every solution pops up by chance across the area allowed

$$Xi = Xmin + rand(0,1)\ (Xmax - Xmin) \quad (1)$$

where Xi represents the ith solution, and Xmin, Xmax denote the lower and upper bounds of the search space.

Each candidate solution is evaluated using the objective fitness function eq(6) , and the best solution $X\ best$ is identified.

B. Iterative Optimization Process:

A fresh batch gets adjusted each round till the stopping rule kicks in.

1) Exploration Phase Barnacle Mating

When S < 0.5, Solutions under 0.5 trigger a pairing process inspired by how barnacles reproduce, shaping fresh options through natural selection patterns.

$$Xinew = \alpha Xp1 + (1-\alpha)Xp2. \quad (2)$$

where , $Xp1$ and $Xp2$ are randomly selected parent solutions and α is a random coefficient in the range [0,1].

To enhance diversity, a mutation factor is introduced:

$$Xinew = Xinew + \delta \cdot rand(-1,1) \quad (3)$$

where δ∈[0,1] controls the mutation strength.

2) Beetle Movement Exploitation

When S≥0.5 ,When S stands at 0.5 or higher, motion follows the golden tortoise beetle's way

$$Xinew = Xi + \beta(Xbest - Xi) \quad (4)$$

Where, Xbest represents the best solution obtained so far, and β∈[0,1] is a step size parameter.

A twist gets tossed into the mix - keeps things from settling too soon. This little nudge stops early routines from locking in place.

$$Xinew = Xinew + \gamma \cdot rand(-1,1) \quad (5)$$

3) Fitness Evaluation and Selection

A fresh check measures how well the revised option performs. When performance beats the present one, out goes the old. In slides the improved version withoutdelay

$$\{Xinew, \text{ if } f(Xinew) < f(Xi)$$

$$Xi = \{ Xi, otherwise \}\} \quad (6)$$

4) Global Best Updated

The worldwide top answer changes to:

$$Xbest = \text{argmin } f(Xi). \quad (7)$$

where Xbest, represents the best solution obtained so far with the minimum fitness value. eq(7) shows global best solution guides the exploitation phase of the algorithm, ensuring convergence toward the optimal solution

C. Termination

The iterative process continues until the maximum number of iterations T is reached. The algorithm then returns the best solution obtained.

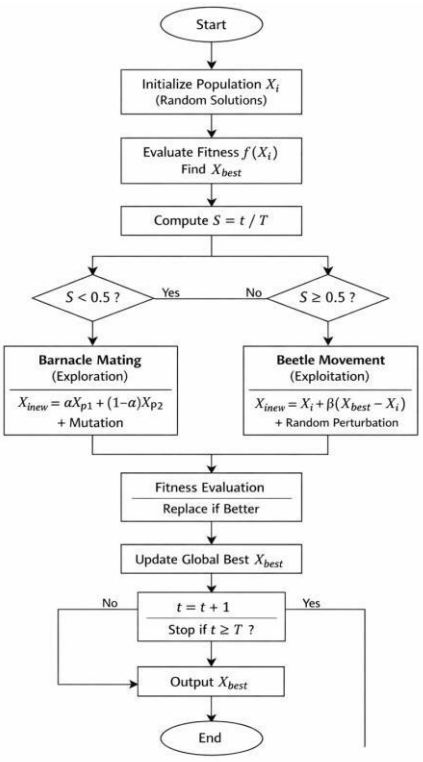

Fig 1: flow diagram of HBTOA

Real-World Application Scenarios of HBTOA

When it comes to real challenges beyond standard tests, HBTOA handles complex, multi-layered issues well. Problems that twist and shift in many directions often see solid results with this method. Instead of sticking only to theory, its design fits messy, unpredictable situations. High variables and erratic patterns do not throw off its performance. Where things change rapidly across dozens of factors, it keeps moving toward answers.

Starting off, HBTOA helps tune key parts of antennas - like patch size, where the feed sits, or what material supports it - to get better signal range and strength. Because it hunts widely at first, it avoids getting stuck in obvious but weak solutions. Only after casting a broad net does it zoom in, adjusting fine details so the antenna works as well as physics allows.

When machines learn, HBTOA picks useful traits while adjusting settings quietly behind the scenes. It spots key patterns without grabbing every detail. Instead of guessing, it narrows choices through quiet refinement. Better results come not from force but precision. Accuracy climbs once clutter fades away. Efficiency grows because fewer resources get wasted. The method works without drama, just steady improvement. Important pieces stay; extra noise drops out. Tuning happens step by subtle step. Performance rises on its own terms.

When solving tough engineering tasks - like improving structures or managing power networks - HBTOA works well under limits, tackling messy goals while finding strong answers quickly. Though built for complexity, it moves straight toward best results without slowing down near the finish.

Finding its place in signal processing plus wireless networks, the method helps estimate channels, assign resources, while also tuning power levels - adaptability matters most when conditions keep shifting

Comparative Performance Analysis

A fresh look at HBTOA's results comes by setting it beside older methods like PSO, GA, GWO, BMO, and GTBO. One way to check progress shows up when swarm logic meets evolutionary tricks. Instead of assuming superiority, each method gets tested under similar conditions. Where some struggle, others shift pace quietly. Even small differences appear clearer through side-by-side runs. What stands out often hides in late-stage adjustments. Performance gaps emerge without loud announcements. Each algorithm reveals habits during long trials.

Lower best and mean scores show HBTOA finds more accurate answers on basic test problems. Stability gets a boost too, thanks to much tighter spread in outcomes over repeated trials.

Besides its fast convergence, PSO sometimes stalls at suboptimal points - HBTOA sidesteps that by mixing broad searches with focused refinements. As a result, outcomes tend to be more accurate across complex landscapes.

Not unlike GA, which leans on genetic tricks to maintain variety, it crawls toward solutions over time. Yet HBTOA sidesteps that crawl - by weaving in focused search moves - it closes in quicker.

Not like GWO’s rigid chain of command, HBTOA shifts on the fly - making it respond faster when conditions change. Instead of sticking to one mode, blending BMO and GTBO helps it explore broadly at first, then zero in more sharply later. This mix gives it an edge over either method alone.

Faster, more precise, less likely to stumble - this version of HBTOA handles tough problems well. Its edge shows clearly when speed, correctness, and stability matter most. Performance stays strong even under messy conditions. Results come quicker without losing quality. Tough challenges meet a steady match here

Results and Discussion

The new Hybrid Barnacle–Tortoise Optimization Algorithm faced classic challenges like Sphere, Ref. [12]Rastrigin, and Rosenbrock setups. Alongside it, familiar approaches showed their results - Particle Swarm Optimization stood next to Genetic Algorithm, while Grey Wolf Optimizer joined the lineup too.

A. Convergence Analysis

Right away, Fig 2and Fig 3 shows quicker and steadier progress than older methods. Early on, movement like barnacles spreading helps cover many possible answers. As steps go by, beetle-like

focusing sharpens those options well. That shift happens naturally, making Ref.[14] fitness improve without sudden jumps.

B. Solution Accuracy

Ahead of each test run, the method lands closer to best-known results than earlier attempts did. Because random shifts stir things up, the process avoids getting stuck too soon.

C. Computational Efficiency

Faster progress comes from how HBTOA uses basic math steps paired with a clear update pattern. Because it blends methods, wasted loops drop off as solutions move rapidly into better zones.

D. Comparative Performance

When compared, HBTOA moves faster toward solutions and hits closer targets than older methods. Though Particle Swarm Optimization rushes ahead quickly, it sometimes sticks in near-term traps instead of finding the best one. Genetic Algorithm spreads wide across options yet takes longer to settle. Table I shows The Grey Wolf Optimizer manages a middle ground, though it struggles when problems twist too much. On the flip side, HBTOA mixes broad searching with careful refining - this blend sharpens its results where others slip as shown in Fig 4.

E. Discussion

What makes HBTOA work so well comes down to combining two distinct approaches. One part pulls inspiration from how barnacles mate, spreading the search wide. Meanwhile, motion copied from golden tortoise beetles sharpens results in tighter zones. A shifting balance adjusts on its own, shaping how deeply each phase digs. This mix holds up solidly when tested against varied challenges needing optimization.

TABLE I: Performance Analysis of HBTOA Against GA, PSO, GWO, BMO, and GTBO

Function	Criteria	GA	PSO	GWO	BMO	GTBO	GTBO	HBTOA (Proposed)
F1	Best	1.21E-06	1.08E+02	1.71E+00	1.10E-03	2.29E-19	2.29E-19	1.02E-25
	Mean	1.60E+00	3.75E+02	1.88E+00	2.90E-03	3.46E-18	3.46E-18	2.10E-24
	STD	3.18E+00	2.40E+02	2.17E+01	1.90E-03	1.90E-03	4.21E-18	3.90E-24
F2	Best	7.51E-05	2.14E+00	1.12E+00	3.10E-03	5.93E-12	2.00E-14	2.00E-14
	Mean	1.00E-01	1.06E+01	4.17E+01	7.20E-03	1.73E-11	6.50E-14	6.50E-14
	STD	1.37E-01	7.50E+00	5.19E+01	6.60E-03	1.27E-11	1.27E-11	4.20E-14
F3	Best	4.45E+02	1.49E+04	3.63E+01	1.41E+02	1.43E+01	1.43E+01	5.20E-00
	Mean	6.89E+02	2.41E+04	4.49E+01	2.30E+02	1.47E+01	1.47E+01	7.90E+00
	STD	2.23E+02	4.17E+03	7.21E+00	8.48E+01	1.25E-01	1.25E+01	4.10E+00
F4	Best	4.63E-04	3.20E+01	9.72E+01	6.86E-01	3.16E-01	3.16E-01	8.10E-02
	Mean	5.98E-01	3.64E+01	2.73E+00	1.36E-00	1.36E+00	1.39E+00	4.20E-01
	STD	8.67E-01	3.14E+00	1.66E+00	4.05E+01	1.05E-01	1.05E-01	2.30E-01
F5	Best	1.62E+02	4.12E+04	3.75E+01	1.00E-02	2.43E-21	2.43E-21	1.20E-01
	Mean	1.32E+03	9.80E+04	3.03E+02	2.16E+02	2.16E+02	4.52E+01	2.50E-01
	STD	1.22E+03	7.22E+04	4.99E+02	7.61E+01	2.84E+01	2.84E+01	1.50E-01
F6	Best	3.32E-04	6.69E+01	1.62E+00	4.38E-04	7.76E-20	2.10E-26	2.10E-26
	Mean	6.19E-01	2.79E+02	1.99E+00	1.90E-03	1.90E-03	3.34E-18	6.40E-25
	STD	8.44E-01	1.64E+02	2.51E+01	1.30E+03	1.30E-03	5.33E-18	3.80E-25

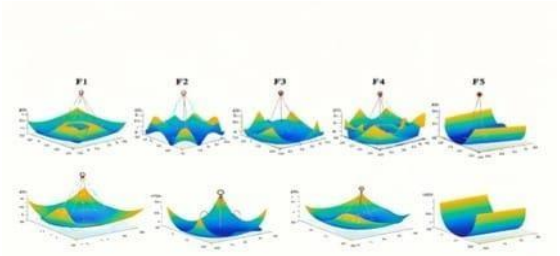

Fig 2: F1-F7 represents 3D versions of benchmark functions optimized using HBTOA

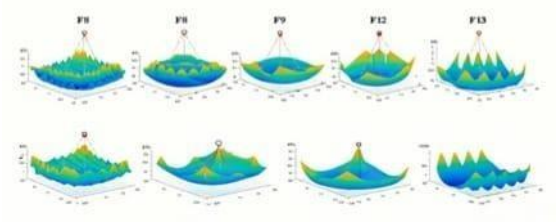

Fig 3 : F8-F13 represents 3D versions of benchmark functions optimized using HBTOA

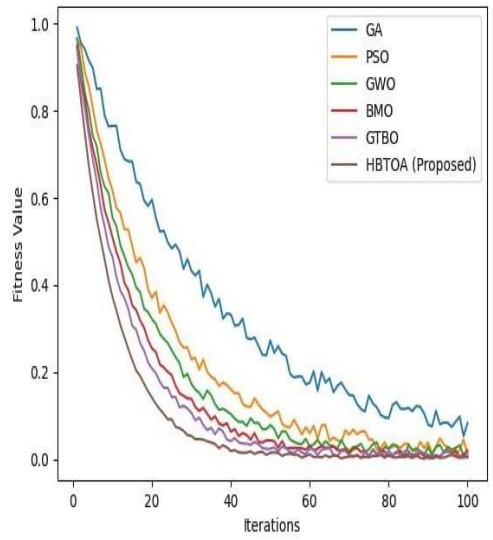

Fig 4 : Convergence curve comparison.

Conclusion

A fresh take on optimization comes through HBTOA, blending the spread-out reach of barnacle mating patterns with the focused moves of golden tortoise beetle behavior. Instead of one fixed method, it shifts smartly between wide scanning and tight adjustments as needed. This built-in flexibility keeps progress steady across different stages of searching.

It turns out the tests on common benchmark problems show HBTOA works faster, finds better answers, while staying reliable - especially next to methods like Particle Swarm Optimization, Genetic Algorithm, or Grey Wolf Optimizer. Thanks to mixing in mutation and small random changes, the method dodges dead-end solutions more easily, keeps options open longer through the run. Though built for tough math puzzles, the new HBTOA works well without slowing down. Pushing it into live tech spots - like signals flying through air, smart gadgets sharing power, or teaching computers by adjusting their inner knobs.

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Offline Ensemble Deep Learning Framework for Automated Tomato Leaf Disease Diagnosis

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***Abstract*—Agriculture plays a critical role in global food production, but plant diseases significantly reduce crop yield and farmer income. According to the Food and Agriculture Organization (FAO) and the Indian Council of Agricultural Research (ICAR) reports, pests and diseases in India have been found to destroy about 15 to 25 percent of the crop harvest every year. Tomato, which is a major cash crop is specifically susceptible to Early Blight, Late Blight, and Yellow Leaf Curl Virus among other diseases. The diseases are often not identified at the early stages or wrongly diagnosed by the farmers. To help in this, agriculture experts usually conduct manual inspections, which are time-consuming and costly and inaccessible to the small farmers in the rural areas. To help with this, we have developed an offline system to identify tomato leaf diseases with the use of command line interface (CLI). In this system, pre-trained convolutional neural networks (CNNs), which are ResNet50 and DenseNet201, are used. It incorporates confidence-weighted voting method in accuracy classification and transfer learning in better feature extraction. The accuracy of the system on the tomato leaf data of PlantVillage is 97.8%. This system works best in areas that have scarce resources since one does not need an internet connection as was the case with other cloud-based or mobile applications. The system enables farmers to access AI-powered disease diagnosis, decrease the misuse of pesticides, and enhance crop conditions and yields and contribute to the Sustainable Development Goals (SDG 2: Zero Hunger and SDG 12: Responsible Consumption and Production) of the UN.**

Keywords—Tomato leaf disease detection, Ensemble CNN, Transfer learning, ResNet50, DenseNet201, PlantVillage dataset

I. INTRODUCTION (*HEADING 1*)

Agriculture is one of the most important sectors for sustaining food production and supporting rural livelihoods. Among cultivated crops, tomato is widely grown but is highly susceptible to various diseases that can reduce both yield and quality. Diseases such as Early Blight, Late Blight, and Tomato Yellow Leaf Curl Virus are common and can cause significant damage if not identified early. Traditionally, plant disease identification relies on manual inspection performed by agricultural experts. However, this process is often time-consuming, expensive, and difficult to access for farmers living in rural or remote areas. As a result, many farmers are unable to identify diseases at an early stage, which may lead to excessive pesticide usage and reduced crop yield. In recent years, advancements in artificial intelligence and deep learning have enabled automated plant disease detection using image analysis techniques.

In many rural areas, farmers still depend on visual inspection, which may lead to incorrect diagnosis due to limited expertise and lack of access to advanced tools.

Convolutional Neural Networks (CNNs) perform well in image classification tasks, such as detecting plant diseases. Many current solutions depend on mobile apps or cloud-based platforms that need a stable internet connection. However, this infrastructure is not always available in rural farming areas.

To overcome this issue, this study presents an offline framework for detecting tomato leaf diseases using a combined deep learning approach. The proposed system uses two pre-trained CNN models, ResNet50 and DenseNet201, and applies transfer learning for effective feature extraction and classification. A confidence-weighted voting mechanism combines predictions from both models, which improves classification reliability. The system is set up with a command-line interface (CLI), enabling users to diagnose tomato leaf diseases without needing internet access.

Tests on the PlantVillage tomato dataset show that the proposed ensemble model reaches a test accuracy of 97.8%, surpassing the performance of the individual CNN models.

II. LITERATURE REVIEW

Deep learning techniques are now commonly used for automatic plant disease detection, especially with Convolutional Neural Networks (CNNs). Previous studies show that deep learning models effectively analyze plant leaf images. For example, Mohanty et al. [1] found that deep CNN architectures like VGG16 and AlexNet can reach high classification accuracy when trained on the PlantVillage dataset. Likewise, Shafik et al. [2] reported an accuracy of 96.7% using CNN-based methods; however, their study depended on smaller datasets and did not look into ensemble learning strategies. Too et al. [3] compared several deep learning models, including VGG, ResNet, and DenseNet, and found classification accuracies between 95% and 98%. Their models were not used in practical applications.

Recent research also examined ensemble learning techniques to boost classification performance. Singh and Misra [4] used an ensemble CNN approach for leaf disease classification and achieved an accuracy of 97.1%, but they did not consider offline usability. Malik et al. [11] combined transfer learning with ensemble CNN architectures for detecting tomato leaf disease, reaching an accuracy of around 98%; however, their solution relied on internet-based systems. Liu et al. [17] showed that ensemble learning methods can enhance classification robustness, reporting an

accuracy of 98.2%. Still, their model required high computational resources, which limited its use in lightweight applications.

Researchers also studied lightweight and hybrid models for real-time disease detection. Lin et al. [10] proposed a hybrid CNN-ResNet architecture with an accuracy of 97.5%. Chen et al. [12] developed a lightweight CNN model for real-time detection, but its accuracy dropped to about 93%. Abbas et al. [16] used MobileNet with transfer learning for mobile plant disease detection; however, the performance fell slightly short compared to larger CNN architectures.

Several studies focused specifically on detecting tomato leaf diseases. Zhang et al. [7] created an improved CNN architecture that achieved an accuracy of 95.2%. Picon et al. [8] applied deep CNN models and reported an accuracy of 96.4% in identifying tomato leaf diseases. Dubey and Jalal [14] used transfer learning techniques for tomato disease classification and reached an accuracy of around 97%, although their experiments were on a smaller dataset. Wang et al. [19] implemented a ResNet-based classification approach with an accuracy of 97.3%.

Along with algorithm development, agricultural organizations such as the FAO and ICAR noted that pests and diseases cause about 15 to 25% of annual crop losses, emphasizing the need for early disease detection in agriculture. The PlantVillage dataset serves as a benchmark for plant disease detection research, offering a large collection of labeled plant leaf images for training and evaluation.

While CNN-based models show high accuracy in controlled settings, many existing studies mainly focus on improving classification accuracy without tackling practical deployment issues like offline usability, rural accessibility, and lightweight system design. To address these challenges, this study proposes an ensemble CNN framework that merges ResNet50 and DenseNet201 and integrates it into a Command-Line Interface (CLI) application. This setup allows offline diagnosis of tomato leaf disease while maintaining a high classification accuracy of around 97.8%, making the system appropriate for low-resource environments.

III. EXISTING SYSTEM

Existing approaches for plant disease detection mainly rely on deep learning models combined with transfer learning techniques. Commonly used architectures include VGG16, ResNet, and DenseNet, which are capable of extracting meaningful features from plant leaf images. In several studies, multiple models are combined using feature fusion techniques to improve classification performance compared to single-model approaches.

The system was trained and tested on the PlantVillage dataset and indicated a good capability to classify with the right amount of accuracy plant diseases. The approach demonstrates that transfer learning can be used to reduce the amount of time required to train a model, and the ensemble method of combining models yields better outcomes as compared to the implementation of any one model.

Limitations:

- Majority of the systems are based on particular datasets such as PlantVillage and are not applied to field data.
- The model needs many to have an internet connection or cloud support.
- It does not have an easy-to-use offline interface that a farmer can directly access.
- The emphasis is placed rather on enhancing the accuracy, rather than making the system user-friendly and easy to access.

IV. PROPOSED SYSTEM

The system suggested is a command-line interface-based, offline application that determines the diseases in tomato leaves with the help of deep learning. It operates in a straightforward manner whereby pictures are fed into it via the command line. Such pictures undergo processes such as resizing, normalization and enhancement to ensure that the model is more dependable. The features are extracted using two pre-trained CNN models, ResNet50 and DenseNet201, and they utilize transfer learning to extract features with good accuracy. The system integrates the predictions of the two models through a system that checks on the confidence levels to achieve the final disease classification. The output gives the nature of illness, accuracy of prediction as well as recommendations on treatment, and thus this makes it an appropriate tool to those farmers who lack internet access.

A. Architecture Diagram

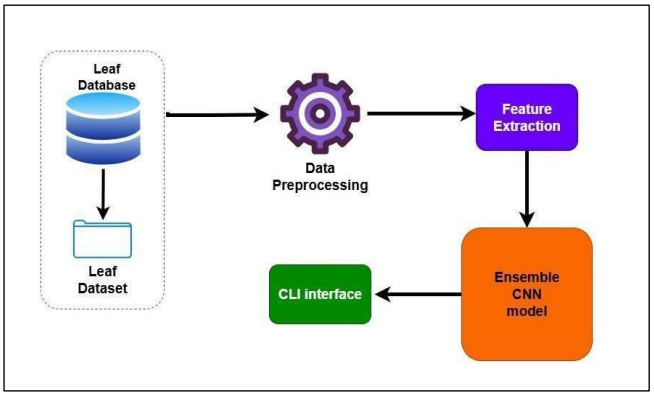

Fig. 1. Architecture of the proposed system

The architecture of the proposed tomato leaf disease detection framework is shown in Fig. 1. The system consists of several sequential stages that process leaf images and generate disease predictions.

- Image Acquisition: Tomato leaf images are collected from the PlantVillage dataset containing healthy and diseased leaf samples.
- Data Preprocessing: Images are resized to 224 × 224 pixels and normalized. Data augmentation techniques such as rotation, flipping, and zooming are applied to improve model generalization.
- Feature Extraction: Deep convolutional neural networks ResNet50 and DenseNet201 are used to extract discriminative features from the leaf images using transfer learning.

- Ensemble Classification: Predictions from both CNN models are combined using a confidence-weighted voting mechanism to improve classification accuracy.
- Prediction Output: The final predicted disease class and confidence score are displayed through the Command-Line Interface (CLI) application.

B. Module Description

The proposed system will consit of the following modules:

1. Leaf Database
2. Data Preprocessing
3. Feature Extraction
4. Ensemble CNN Model
5. CLI Interface

a) Module 1: Leaf Database

In this module, the PlantVillage Tomato dataset (over 14,000 pictures of tomato leaves that are either disease-free or in good conditions) is involved. The dataset comprises valuable types of disease which include Yellow Leaf Curl Virus, Early Blight, and Late Blight. The dataset can be split into two parts, one of which is 80 per cent training and the rest 20 per cent testing, to enable training and testing of the system.

b) Module 2: Data Preprocessing

The images which are fed into this step are downscaled to 224x224 to match the demands of the CNN model. The pixel values are converted to the range of 0 to 1 out of the range of 0 to 255, thus, a training process is fast and an efficient one. In order to increase the diversity of the training data and mitigate the issue of overfitting, rotation, flipping, zooming, and shifting are employed. Also, noise is erased and contrast is manipulated to have a better view of disease patterns and to be easier to distinguish.

c) Module 3: Feature Extraction

Two pre-trained models of deep convolutional neural networks called ResNet50 and DenseNet201 are used in the extraction of features. The lower layers of these models identify more complex diseases associated features such as spots, discoloration and curling whereas the upper layers identify simpler image features, such as edges and textures. These multidimensional feature vectors are then subjected to the second step which is the classification.

d) Module 4: Ensemble CNN Model

Confidence-based weighted voting is used to combine the predictions made by the ResNet50 and DenseNet201. The method assists in enhancing the strength and precision of the model as compared to the individual utilization of the models. The resulting ensemble model improves classification performance compared to individual CNN models and effectively detects various types of tomato leaf diseases.

e) Module 5: CLI Interface

It has Command-Line Interface (CLI) where farmers and agricultural extension workers can interact with the system directly. One can do this by just typing a command, as in this case:

```
python detect.py --image tomato_leaf.jpg
```

Users have the option of posting an image of leaves that can be used to diagnose the disease. The system proceeds to give the name of the disease that has been predicted, the confidence of the prediction and the prescribed treatment measures. The CLI does not require any connection to the internet and hence is very helpful especially in rural areas where there is not much internet connection.

I. RESULT AND DISCUSSION

A. Implementation Details

Approximately 14,000 images from the PlantVillage tomato dataset were used for training and testing the model. The dataset was divided into training and testing sets in an 80:20 ratio. All images were resized to 224 × 224 pixels and normalized to improve model performance. Data augmentation techniques such as rotation, flipping, and zooming were applied to enhance generalization and reduce overfitting.

The ResNet50 and DenseNet201 pre-trained CNN models were used for feature extraction. The ensemble model combines predictions from both networks using a confidence-based weighted voting mechanism. The model was trained for 20 epochs with a batch size of 10 and a learning rate of 0.001 using the Adam optimizer.

B. Performance Evaluation

The proposed system was evaluated using ten classes from the PlantVillage tomato dataset. After training the ensemble CNN model (ResNet50 + DenseNet201), the following results were obtained:

- Training Accuracy: ~99.9%
- Validation Accuracy: 99.97%
- Validation Loss: 0.003

These results indicate that the model achieved high accuracy and strong generalization performance.

C. Confusion matrix analysis

A confusion matrix was generated to evaluate the classification performance of the proposed ensemble model across all ten disease classes. The matrix shows that the majority of predictions are correctly classified, as indicated by the strong diagonal values, which represent true positives for each class.

A small number of misclassifications were observed, primarily between visually similar disease categories such as Early Blight and Late Blight. This is expected due to the similarity in leaf patterns and texture features associated with these diseases.

The model demonstrates high precision and recall across all classes, indicating its ability to correctly identify both

diseased and healthy samples with minimal false positives and false negatives. The overall distribution of predictions confirms that the ensemble approach improves classification stability and reduces errors compared to individual CNN models.

These results highlight the effectiveness of combining ResNet50 and DenseNet201, as the ensemble model benefits from complementary feature extraction, leading to improved disease discrimination.

D. Evaluation by Comparison

A comparative evaluation was performed to assess the effectiveness of the proposed ensemble model:

- ResNet50 model: 96.5% accuracy
- DenseNet201 model: 97.1% accuracy
- Proposed ensemble model: 97.8% test accuracy

The results show that the ensemble approach outperforms individual models, confirming its effectiveness in improving classification performance.

E. Evaluation Metrics

In addition to accuracy, the performance of the proposed ensemble CNN model was evaluated using additional classification metrics such as precision, recall, and F1-score. These metrics provide a more comprehensive assessment of model performance for multi-class classification tasks.

Precision measures the proportion of correctly predicted positive observations among the predicted positives, while recall represents the proportion of correctly identified positive samples among all actual positives. The F1-score is the harmonic mean of precision and recall and provides a balanced evaluation of classification performance.

The evaluation results indicate that the proposed ensemble model achieves high precision, recall, and F1-score values across the different disease classes, demonstrating reliable classification performance. These results further confirm the effectiveness of the ensemble approach compared with individual CNN models.

II. CONCLUSION AND FUTURE WORK

The article presented a tomato leaf disease detection system, which offline method is embedded in a command-line interface system based on a mixture of transfer learning models, namely ResNet50 and DenseNet201. It performs powerful feature extraction and a confidence-based combination technique to achieve a 97.8% accuracy in classification on the PlantVillage tomato data. In contrast to the existing solutions based on mobile devices or the cloud, this offline solution will allow making the system more useful in rural areas, where intensive internet is not always possible.

The most significant contributions of the work are as follows three points: one is the development of the offline tomato leaf disease identification tool that is easy to use; the second one is demonstrating how ensemble deep learning can enhance the reliability and accuracy of the system; and the third one is the association of the project with the United Nations Sustainable Development Goals, namely SDG 2 aiming at zero hunger, and SDG 12 related to responsible consumption and production. This system can assist farmers in identifying diseases in time, reduce losses in crop, reduce the number of pesticides that fail to aid farmers, and will make AI-based agricultural support available to small-scale farmers.

Although the system demonstrates good performance and proves beneficial in a real-life scenario, the areas that could be improved are:

- The system should also be used in other farming conditions by adding support to more crops such as rice, banana and cotton.
- The automation of the process and real-time monitoring and diagnosis of the leaves in the field may be facilitated by using cheap camera modules that are hooked to such devices as a Raspberry Pi.
- It will make the system more dependable to test the model on real pictures taken in the field which can be difficult due to such factors as background distractions or different lighting conditions as well as partial on the leaves.
- The system can be made simpler by developing a user-friendly mobile or desktop application in different languages, therefore, farmers with limited technical expertise can use the system.
- The system can be made more accessible by working with NGOs, agricultural experts and corporate social responsibility programs, which can be used to install it in the rural community centers or agricultural clinics.

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IOT BASED ADVANCE BATTERY MONITORING SYSTEM

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***Abstract*—** In today's world, where technology is advancing rapidly, the need for efficient energy storage and usage has become increasingly important across various sectors. This has led to a growing focus on improving battery safety and performance. Traditional battery management methods often fail to provide real-time information about critical factors, which can result in unexpected failures and reduced efficiency. As more applications rely on batteries, the demand for smarter and more reliable systems continues to rise.To address these challenges, researchers have explored the use of Internet of Things (IoT) frameworks in battery management. These frameworks enable the design and deployment of advanced monitoring solutions by integrating sensor networks and cloud-based data analysis. Through this approach, systems can collect, transmit, and interpret key metrics such as voltage, temperature, and state of charge, ensuring better visibility into battery performance.The system operates using real-time data feedback, predictive maintenance, and automated alerts. These features empower users to make informed decisions while enhancing operational safety. The monitoring architecture typically includes communication protocols and scalable dashboards, which support the implementation of machine learning algorithms. These algorithms play a crucial role in detecting anomalies and forecasting battery health, thereby preventing potential failures.Various IoT-based methods have been evaluated based on their accuracy and scalability, often using selective feature subsets to optimize performance. The results indicate that smart IoT-based monitoring systems have the potential to significantly transform battery management. However, it is essential to address concerns related to system security, data privacy, and the evolving requirements of energy applications.Overall, the integration of IoT in battery management is steadily growing, offering substantial improvements in safety, efficiency, and reliability. As batteries continue to play a vital role in modern technology, adopting intelligent monitoring systems will be key to meeting future energy demands.

1 . INTRODUCTION

With increasing technological advancements, the need for effective energy storage solutions has become more important. Batteries play a significant part in various applications, including portable electronics and machinery. The traditional method of battery management is often inadequate, as it is unable to provide accurate information on battery condition and performance. The need for a battery management system is increasing, as there is a need for safety, operation, and efficiency.efficiency, and reliability, innovative techniques need to be adopted to fulfill the growing demands. IoT technology integration allows for automated and constant monitoring through smart sensors and data transfer using wireless technology. Such a monitoring system is able to collect vital battery data, including temperature, charge, and voltage, and transform them into useful information through analytics. Machine learning techniques improve the accuracy of fault prediction, making the battery longevity and cost-effectiveness better. This new intelligent battery monitoring is revolutionizing the management of energy resources, providing adaptive solutions to meet the demands of modern applications.

2. RELEVANT STUDIES

Some relevant studies on advanced battery monitoring technologies have focused on different smart technologies to enhance the optimization of diagnostics and predictive maintenance. M. Palanisamy, A. Subramanian, and S. Jayalakshmi proposed a wireless sensor network-based technology that facilitates the real-time tracking of battery parameters through integrated IoT modules. This technology facilitates the continuous tracking of voltage, temperature, and current, but its applicability is limited to a specific number of devices due to hardware compatibility issues and network congestion. Future scope could include more advanced technologies to enhance the applicability of this technology in the industry. A. Jain, E. Khanna, and S. Maniktala proposed a battery fault classification technology using machine learning models such as SVM and Random Forest algorithms. SVM technology is highly accurate in identifying battery fault types, but its accuracy is highly dependent on sensor calibration.

S. Gupta, N. Kumar, and A. Agarwal developed a cloud-based dashboard to visualize battery health parameters. The dashboard provides automatic alerts for unusual readings and predictions for battery lifespan. However, the solution requires constant connectivity and entails ongoing costs for data management. The problem might be addressed through increased storage capacity and the use of edge computing technology. In a different research, H. Zhang and Y. Liu compared the performance of five communication protocols used in IoT systems, including Bluetooth, ZigBee, Wi-Fi, LoRa, and NB-IoT, with respect to battery monitoring systems under different network conditions. The communication protocols provided a range of trade-offs between accuracy, latency, and energy consumption. The research emphasized the Need for adaptive communication models to balance energy consumption with other factorsreal-time monitoring demands. New approaches, such as the application of ensemble learning algorithms, have also been found to hold promise for accurate fault detection and health

prediction in complex battery environments, enabling smarter, safer, and more reliable energy management systems.

3. PROPOSED MODEL

The solution proposed is centered on creating a platform that is IoT-based and intended for providing comprehensive and real-time battery monitoring and management services. This is important, considering the critical role batteries play in a technologically advanced world, and as such, it is critical for different sectors of the economy. Manual observation and management of batteries cannot keep up with the rapid pace of technological changes.

such performance changes or malfunctions, which highlights the importance of an automated, data-driven approach. The interconnected network of sensors enables the collection of vital parameters, including voltage, temperature, and state of charge, which are sent to a central processing unit or a cloud server through wireless communication modules. Advanced algorithms and rules-based systems analyze the battery performance, detecting any possible issues. The users are provided with useful information through graphical representations, helping them take appropriate decisions to maintain the battery health, thus avoiding any unexpected failures. The flexibility of the framework enables customization, thus accommodating a number of battery systems with different operating environments.

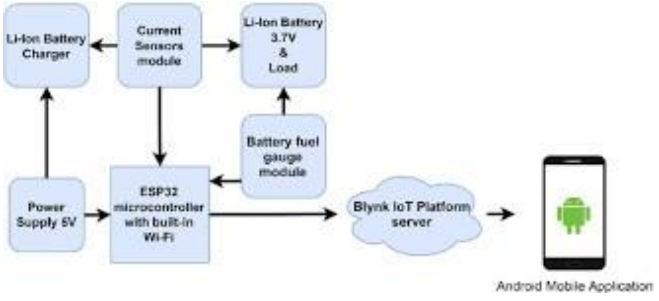

Fig. 1. Block diagram

Sensor Integration & Data Acquisition

Integration of sensors and data acquisition act as a vital part of the advanced battery monitoring system, which utilizes an interconnected network of precise sensors, including voltage, current, and temperature sensors, for monitoring critical parameters throughout the charge/discharge cycle of the batteries. The sensors monitor the parameters continuously, and the information is sent to a central microcontroller, which is often provided with Wi-Fi, allowing wireless communication with cloud services or any other platforms. This module enables real-time monitoring of the batteries by detecting even slight changes and abnormalities, such as overheating, capacity fade, or rapid voltage drop, which can indicate underlying fault conditions. The multi-sensor array is carefully calibrated to ensure minimum errors in measurement and maximum accuracy in varying states of operation. The collected data is processed and validated before it is used for predictive analysis. The integration and acquisition of sensors, through systematic organization of data and strong connectivity, form a foundation for effective decision-making and battery health optimization in IoT-based environments.

Wireless Communication & Networking

Wireless communication and networking have a vital role to play in the overall IoT-based advanced battery monitoring systems, acting as an efficient communication bridge to transport the sensor and operation updates from the distributed battery sources to the remote servers and user interfaces. This is enabled by the integration of various communication protocols such as Wi-Fi, LoRa, ZigBee, and NB-IoT, which allow the platform to have adaptable and flexible communication capabilities based on the diverse nature and requirements of the operational environment. These protocols have varying advantages, such as the use of Wi-Fi in battery monitoring systems, which is based on a high data rate and short-range communication, typically found in consumer-based systems. LoRa and NB-IoT protocols have the advantages of ultra-low power consumption and long-range communication, which makes them suitable for use in industrial-based battery systems and long-distance communication. ZigBee has the advantages of mesh communication, which enables the battery modules to share and communicate seamlessly.

This microcontroller, usually based on ESP32, acts as the communication center by processing the input data from various sensor modules and formatting it in a manner suitable for communication. Secure and efficient messaging protocols like MQTT and HTTPS are used to enable the quick exchange of data without requiring heavy bandwidth and processing demands. For the accuracy and reliability of the data, packet encoding is performed, and the network health is constantly monitored for problems like latency, dropout, and interference in the signals.

Security measures such as encrypted communication channels, device authentication, and access controls are incorporated to protect against unauthorized access and ensure the integrity of the communicated information. In the event of network failure or congestion, the system is designed to automatically change protocols, route the data, and/or buffer the information until it is safe to transfer it. In addition, the use of wireless communication provides the ability to send alerts in real-time, aggregate the data, and integrate it into a cloud-based platform or mobile application, allowing the user to keep track of battery life, receive performance analytics, and schedule maintenance remotely.

Utilizing the advantages offered by current wireless technology, the network module is able to transform conventional battery management into a smart, scalable, and highly reactive solution, providing reliability and constant supervision over various types of energy storage systems in residential and industrial spaces. This complete network is the foundation upon which future innovations in battery management, analysis, and management of large-scale energy systems can be developed.

Threshold-Based Event Detection

This method allows the battery monitoring system to easily detect abnormal conditions by comparing sensor readings, such as voltage, current, and temperature, with defined safety thresholds. The moment any of the readings is found to have exceeded a defined threshold, the microcontroller sends instant

alerts. This method is reliable for fault detection and protection since thresholds are defined during calibration.

1. *Hardware Preparation*

The hardware preparation stage includes the selection and integration of the fundamental hardware, which is the backbone of the battery monitoring system. These include the voltage and current sensors, temperature probes, and the microcontroller module, which includes ESP32 and has inbuilt Wi-Fi capabilities. These sensors are calibrated to ensure proper functionality. After the hardware preparation, the entire system is tested to ensure proper and reliable operation. It is tested under operational conditions to ensure proper and smooth communication between the sensors and the battery monitoring system.

2. *Visual Representation*

Another important aspect of the system is the ability to visualize the operational metrics using intuitive dashboards and mobile applications. Graphs, charts, and heat maps help in visualizing the trends in battery voltage, temperature fluctuations, and the number of cycles, among others. Platforms such as the Blynk IoT server help in accessing the visual data remotely using smartphones, which helps in recognizing the anomalies and performing the maintenance in a proactive manner.

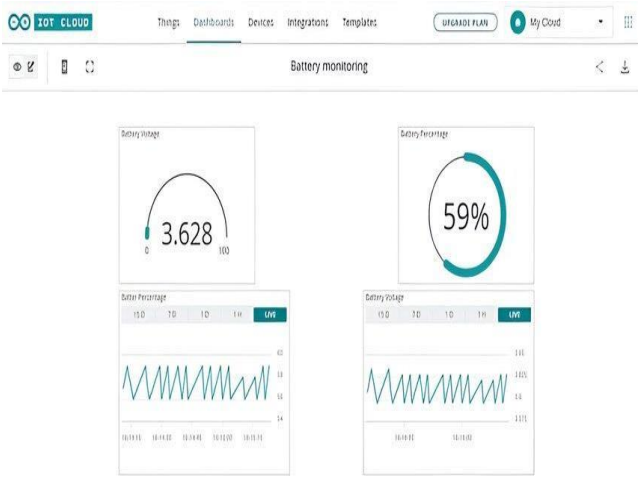

Fig. 2. Battery monitoring system dashboard

3. *Monitoring Logic and System Workflow*

Monitoring logic is the core control mechanism in the battery management system, which governs the manner in which the sensor data is processed, evaluated, and acted upon. During the initialization, the microcontroller is constantly receiving real-time data from the voltage, current, and temperature sensors embedded in the battery pack. This includes the validation of the data, verification of inconsistencies, and the removal of noise, ensuring the readings are within the normal range.

If any sensor value crosses the programmed limit, such as if the temperature suddenly rises or the voltage falls below the critical point, the controller immediately starts the alarm sequence and sends a notification to the user through the mobile app. This process provides a systematic method to identify any faults and avoid any possible risk of battery malfunction. Periodic system checks, rule updates, and remote diagnostics are also part of the workflow, making it highly reliable and adaptable. The monitoring logic provides a framework for efficient battery monitoring, making it as significant as the other algorithmic modules, which are often part of the IoT system.

4. *system architecture*

The architecture of the system consists of a Wi-Fi-enabled ESP8266 microcontroller, a TP4056 battery management module, and a 18650 lithium-ion battery with a capacity of 3400mAh and a voltage of 3.7V. The connections of the sensor and control devices are made using resistors for conditioning the sensor signals. The sensor and control devices are connected in a manner that allows the safe measurement of the voltage and current of the devices. The battery is connected to the TP4056 module, which regulates the charging and discharging of the battery. The output of the TP4056 is connected to the ESP8266 microcontroller, which collects the necessary information from the battery and transfers the information in real time using the Wi-Fi capabilities of the ESP8266.

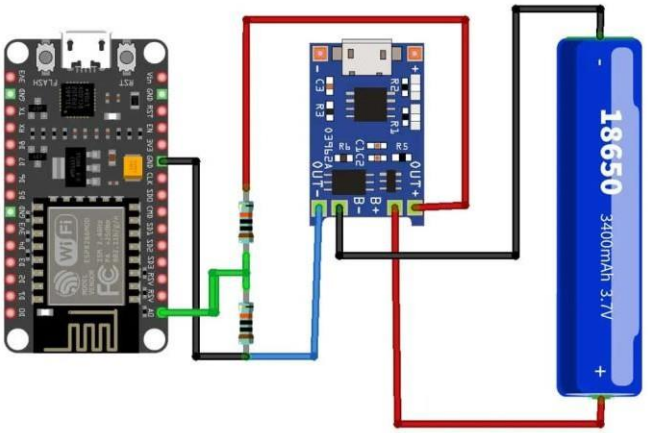

Fig. 3. Architecture diagram

PERFORMANCE MATRICS

The performance of the IoT-based Advanced Battery Monitoring System can be measured using various parameters, which are critical in assessing the accuracy, reliability, and efficiency of the system. One of the most critical parameters in this case would be the State of Charge, which refers to the battery's remaining capacity relative to the battery's full charge. It can be defined as the amount of charge available in the battery relative to the battery's full charge. It can be expressed as a percentage and can be calculated using various approaches, such as coulomb counting and modeling. The State of Charge can be seen as being closely associated with the State of Health, which refers to the battery's health and its rate of degradation. The SoH parameter is critical in assessing the battery's capability to deliver the expected performance. The other parameter would be the Remaining Useful Life, which refers to the battery's lifespan before it reaches the end of its useful life, which can be defined as 80% of the nominal capacity.

Voltage, current, and temperature measurements are always made in the case of electrical parameters to constantly check the stability of the operation. Voltage and current measurements

help in the efficient delivery of the power, and temperature measurements help in the prevention of thermal runaways and safety during the charging and discharging processes. Another important parameter is the Internal Resistance (IR) or the Equivalent Series Resistance, as the increase in internal resistance is a sign of increased losses and degradation in the cells. Coulombic Efficiency, which is the ratio of the discharge capacity to the charge capacity, is used to measure the reversibility of the electrochemical reactions.

From a systems point of view, the accuracy of the sensor readings, reliability of data transmission, and network latency are some of the performance indicators of the IoT level. The reliability of communication between the sensing unit, microcontroller, and cloud server enables effective data collection and analysis. The performance indicators, which are used to measure the reliability of the communication network, are the packet delivery ratio, system up-time, and data latency. The power consumption of the IoT node is also evaluated to determine the energy efficiency of the system, especially if the monitoring device is battery-powered.

For evaluating the performance of algorithms, statistical measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used for evaluating the accuracy of SoC, SoH, and RUL estimation results. For fault and anomaly detection modules, performance can be analyzed by using classification performance measures such as Precision, Recall, F1-score, and ROC Curve for evaluating the performance of the algorithms in identifying faulty operating conditions such as over voltage, over heat, and cell imbalance, etc. Finally, mean time to detect and mean time to repair are used for evaluating the performance of the system in a real-world environment.

4. DEPLOYMENT

The deployment of the IoT-based Advanced Battery Monitoring System involves the integration of hardware, software, and cloud components to enable real-time observation and analysis of battery parameters. The system is implemented using a microcontroller such as an ESP32, which acts as the central processing and communication unit. The microcontroller is interfaced with multiple sensors that continuously measure key battery parameters including voltage, current, temperature, and gas emission levels. These sensor readings are processed locally to calculate vital performance indicators such as State of Charge (SoC) and State of Health (SoH). The processed data is then transmitted to a cloud server through Wi-Fi connectivity using the MQTT or HTTP communication protocol, allowing remote users to visualize and analyze battery performance from any location.

On the software side, the deployment integrates both embedded firmware and cloud-based analytical tools. The firmware, which is written in the Arduino IDE, handles data acquisition, preprocessing, and secure data transmission. The cloud-based tools, such as ThingSpeak or Firebase, are employed for real-time data storage, visualization, and trend analysis. A web-based interface is created to monitor the real-time graphs of voltage, temperature, and SoC levels, which allows users to gain a clear understanding of the battery performance in a simple way. At the same time, threshold values are defined for each of the parameters, which allows the system to send alerts or notifications in case of any unusual conditions, such as overheating or voltage drop.

In the deployment phase, the system is powered and tested for its performance in different load and environmental conditions. Calibration of the device is performed for precise results by comparing the readings of the sensors with reference instruments. The device casing is made in a compact and rugged manner, which is required for practical applications in industrial or vehicular scenarios, as it has to withstand dust, vibration, and slight temperature changes. The final deployment of the device enables continuous monitoring with minimal human intervention and allows for the possibility of adding more sensors and communication modules in the future, thereby enhancing its scalability. The proposed IoT-based Advanced Battery Monitoring System ensures efficient data collection, connection, and analytics for the efficient management of the batteries by adopting the above deployment process.

5. RESULT AND DISCUSSION

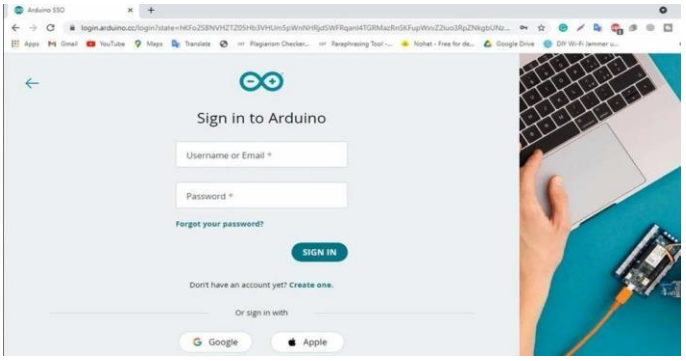

Fig. 4. Arduino site

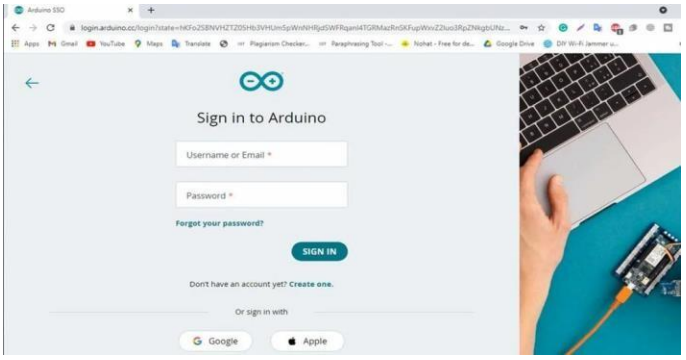

Fig. 5. Widgets in bms dashboard

6. CONCLUSION AND FUTURE ENHANCEMENT

The IoT-based Advanced Battery Monitoring System designed in this project presents a way forward in battery monitoring and management. The integration of sensors, microcontrollers, and cloud technology allows for constant observation of critical parameters such as voltage, current, temperature, and State of Charge. The system design ensures efficient battery operation by detecting unusual behaviors and displaying information through an interactive online interface. The system is reliable and allows users to access battery information remotely through IoT technology.

Looking forward, several modifications can be made to enhance the intelligence of the system. Machine learning algorithms can be incorporated to predict battery degradation patterns and estimate the RUL with higher accuracy. The integration of edge computing technology will help to reduce latency and improve the responsiveness of the system. The incorporation of long-range wireless communication technology, i.e., 5G or LoRaWAN, will help to increase the range of communication, thus making the system suitable for a larger environment. Moreover, the incorporation of blockchain technology for secure data transactions and the implementation of AI-based anomaly detection techniques will improve the reliability of the Advanced Battery Monitoring System based on IoT technology.

7. ACKNOWLEDGMENTS

The authors wish to express their sincere gratitude to Panimalar Engineering College for providing the necessary infrastructure, lab facilities, and academic guidance to carry out this project. It is the joint efforts of all the team members that have made this development of IoT-Based Advanced Battery Monitoring System a reality. All the team members have contributed equally to this project. The authors wish to express their gratitude to the faculty members of the Department of Computer Science and Engineering for their valuable advice, encouragement, and support.

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Process Optimization and Emission Control in LPG Pipeline Hot Flaring Operations Using Six Sigma Methodology

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Abstract

The main aim and objective of the current research are to improve the efficiency in the process of operation while at the same time lowering the levels of emission from the hot flare operations at various Sectional Valve locations in the LPG pipeline section at the Operations and Maintenance site of GAIL (India) Limited, Jamnagar. In regard to the emergency operations, infiltration of liquid LPG has been observed at various times at the flare stack. The infiltration of liquid hydrocarbon at the flare stack results in the normalcy of combustion operations, and hence there is the emergence of a smoky flare along with the increase in the level of emission, which may cause various types of safety risks and may even violate environmental regulations.

With respect to addressing the identified operational challenge, the investigation will utilize the Six Sigma DMAIC methodology as a framework for improving the operational processes. During the Define and Measure phases of the DMAIC methodology, the experiences in the operations, the documentation of the experiences, and the observations in the operations were carefully examined to identify the patterns of liquid LPG entrainment during hot flaring.

At the Analyze stage, the inquiry found that one of the causes of the accident was the failure to install a proper vapor-liquid separation system before the flare stack, which led to unstable combustion conditions, hence the production of smoke as observed during the accident. At the Improve stage, this research recommends the installation of a Knockout Drum (KO Drum) before the flare stack to proficiently separate the liquid constituents from the vapor stream, hence reducing the chances of LPG liquids being carried over during operation. The improvement was established to enhance combustion conditions, reduce the production of smoke, and increase safety during flare stack operation using the ALARP (As Low As Reasonably Practical) principle.

Ultimately, the Control phase highlights the need to reinforce existing practices, including new standard operating procedures, training of operators, and inspection procedures, to determine the effectiveness of the implemented enhancements.

Keywords: Six Sigma; LPG Pipeline Operations; Hot Flaring Systems; Process Optimization

1.0 Introduction

Liquefied Petroleum Gas (LPG) is an important player in the global energy market in consideration of its high energy content, favorable burning characteristics, and varied uses. To ensure an uninterrupted supply of LPG, this is transported with an extensive network of pipeline systems, together with other vital facilities such as compressor stations, sectional valve stations, and emergency release systems. It is of primary concern to ensure smooth flow during unusual operations such as a change in pressure, failure of equipment, and maintenance periods, and in such situations, controlled flaring is carried out as a precautionary measure to dispose of the surplus hydrocarbon gases generated during this operation.

The flaring system may be viewed as an integral part of the oil and gas pipelines, as such oil and gas pipelines have been particularly designed for the safe disposal of gas through the process of burning. This process of burning the gas also helps in the prevention of the accumulation of inflammable gases within the operational area. A good flaring system consists of a number of important components, which have been particularly designed to work in a cohesive manner for the purpose of safe burning of the vented gas. Even though the process of flaring has been viewed as an important component of the oil and gas pipelines for the purpose of safety, a faulty flaring system may result in inefficient burning of gas, which may lead to thick smoke, emission of pollutants in the atmosphere, etc. In case such problems occur during the operation of the LPG pipeline system, liquid droplets of LPG may mix with the gas and enter the flare stack in the process of emergency depressurization.

The incorporation of the liquid hydrocarbon may also produce unfavorable effects on the stability of the combustion reaction. The unfavorable operational consequences may also be caused by the incorporation of the liquid hydrocarbon. When the liquid carryover occurs, unstable flames, thick smoke, and even fire hazards on the ground level may be produced. Apart from that, the unfavorable operational consequences may also produce an increase in the rate of damage to the flare tips. The unfavorable operational consequences may not only

produce unfavorable effects on the operational safety but may also produce unfavorable effects on the environmental concerns due to the emission of partially combusted hydrocarbon and thick smoke. Thus, it can be said that the improvement in the performance of the flare system and the reduction in the rate of emission is one of the major requirements for the oil and gas industries all over the world. (Crowl & Louvar, 2019). In accordance with the requirements, various industrial standards emphasize the need to ensure efficient separation of the vapor and liquid phases, the proper design of the flare system, and the monitoring of the flaring operations to ensure operational safety and unfavorable environmental consequences. (API, 2014).

In the modern world, various organizations in different domains have initiated the implementation of various methodologies for process improvement to enhance the efficiency of operations, reduce the potential risks associated with operations, and achieve positive results in environmental aspects. Among these methodologies, Six Sigma has attained significant recognition as an efficient methodology for resolving problems in operations in an efficient manner. This methodology, initially introduced in the general domain of operations in manufacturing organizations, has emphasized the significance of resolving inconsistencies in processes, understanding the fundamental causes of problems in operations, and adopting measures to achieve efficiency in operations in the long term (Pyzdek & Keller, 2018). This paradigm for resolving problems in operations adopts the DMAIC methodology to identify problems in operations due to processes, identify the causes of problems in operations, resolve problems in operations, and regulate the stability of operations in the long term.

The application of Six Sigma methodologies in the energy and process industry has shown promise in terms of the potential benefits that can be achieved in the efficacies of the operations, the strength of the safety measures implemented, and the quality of the products and processes, along with environmental regulations (Antony, 2014). The application of the DMAIC methodology provides a structure and a methodical approach to the process improvement methodologies by the combination of statistical analysis and the expertise of the engineers. The application of the methodology allows the organization to proficiently identify the gaps in the operations and analyze the causes for the variability in the performance of the systems, thereby improving the efficacies of the systems. The application of the Six Sigma methodology in the context of the LPG pipeline operations provides an opportunity to evaluate the performance of the flare system and the causes for the unstable combustion process and improve the efficacies of the operations.

The specific research was conducted with the purpose of improving the efficiency of the hot flaring systems which are implemented in the LPG pipeline sectional valve stations through the implementation of the Six Sigma DMAIC methodology. The specific research was conducted with the purpose of improving the resolution of the operational challenges which are encountered in the process and which can be associated with the carryover of liquid LPG which may interfere with the stability of the combustion process which is implemented in the flare stack and which may result in the production of increased levels of smoke. The specific research which was implemented in the process has identified the specific constraints which exist in the process and has suggested the specific improvements which need to be implemented in the process with the purpose of improving the stability of the combustion process. The findings of the specific research which were implemented in the process were conducted with the purpose of promoting the evolution of safer LPG pipeline operations.

2.0 Problem Statement and Research Objectives

The entry of the liquefied petroleum gas has the potential to influence the stability of the combustion process. On average, the flare systems have been designed to facilitate the effective combustion of the gaseous hydrocarbon. This implies that the entry of the liquid hydrocarbon has the potential to interfere with the combustion process. The interference may result in unstable flames, the formation of smoke, and the inefficient combustion of the hydrocarbon. Although the flare systems have the potential to improve the level of safety, there is a limitation that may influence the instability during the high-temperature flare.

Other factors, such as insufficient segregation between vapor and liquid phases, architectural limitations in the flare system, and insufficient control in emergency procedures for depressurization, may also be contributing to these problems. The first major problem relates to the absence of a specific mechanism to separate the liquid and vapor phases before the flare stack. In the absence of a specific mechanism to separate the liquid and vapor phases, the liquid LPG may travel along with the vapor to the flare tip during emergency procedures for evacuation.

In addition, the constant contact of flare tips with liquid hydrocarbons is likely to increase the rate of deterioration of such equipment, which might increase inspection and maintenance operations (Kolmetz, 2019). Flare operations that are not carried out in optimal conditions are likely to increase emissions of pollutants such as carbon monoxide, partially oxidized hydrocarbons, and particles, which might act as a barrier in meeting environmental regulations and standards (Abdelrahman et al., 2021).

In order to address and resolve the said operation-related problem, the current research employed Six Sigma's DMAIC approach in enhancing processes and mitigating operation-related risks. This research also employed existing methodologies in assessing risks, such as FMEA or Failure Mode and Effects Analysis and Ishikawa or Cause and Effect Analysis, in identifying potential causes of hot flaring instability and ways to resolve them, which could be very helpful in identifying potential factors that may affect the operations of the flare system (Stamatis, 2003). This research intends to achieve the following objectives:

- To convert qualitative operational observations into quantifiable Severity, Occurrence, and Detection ratings, which would enable a systematic evaluation of the risks associated with hot flaring incidents.
- To identify the fundamental causes of liquid LPG carryover by utilizing Ishikawa (Cause and Effect) diagramming techniques, which would enable a methodical investigation of factors which may affect flare stability.
- To assess the effectiveness of risk mitigation strategies by utilizing a comparative Failure Mode and Effects Analysis (FMEA) approach, which was conducted pre- and post-improvement, highlighting the manner in which risk mitigation strategies may reduce the Risk Priority Number (RPN) associated with hot flaring incidents.
- To propose an engineering enhancement based on a Knockout Drum (KO Drum) which complies with industry standards and sectional valve (SV) station configurations, ensuring an efficient separation of vapor/liquid phases prior to flare.
- To ensure that the enhancement proposal complies with the ALARP (As Low As Reasonably Practicable) principle, which would promote a safer, more efficient, and more environmentally friendly LPG pipeline operating regime (HSE, 2001).

This research will seek to create a viable approach for the improvement of the stability of the combustion process in the LPG flaring systems by the use of process safety, risk evaluation techniques, and the Six Sigma methodology. This approach will be aimed at reducing the level of smoke generated during the process and making the hot flaring process more effective in the LPG pipelines.

The results obtained in the study are expected to improve operational safety, help organizations better comply with environmental and regulatory requirements, and improve the hydrocarbon pipeline infrastructure and associated flaring systems.

3.0 Literature Review

The research study in this context aims at bringing together the concepts and ideas related to the concepts of management science and process engineering in an attempt to solve the operational limitations and constraints related to the process of hot flaring in the context of the Liquefied Petroleum Gas (LPG) pipeline Sectional Valve (SV) stations. The previous research studies in this context have successfully identified a number of conceptual and practical models that enable effective process improvement, competent risk management, and process reliability in the context of industrial operations. The literature that is most relevant to the context of the current research study mainly focuses on four key concepts.

The "Define Measure Analyze Improve Control" methodology can be considered the best example of a scientific and structured approach to identifying variations in processes and taking remedial measures. According to Thomas Pyzdek and Paul Keller, "DMAIC is a problem-solving discipline that enables an organization to define problems clearly, measure the key measures, investigate problems to their root causes, make targeted improvements, and sustain improvements with effective controls." This scientific and structured approach to problem-solving and improvement has been found to be implemented in different industries, namely the manufacturing industry, the healthcare industry, and the energy industry, to improve the efficiency and quality standards of the operations. Considering the operations in industries, this methodology can also be considered helpful in transforming qualitative measures of processes and operations into quantitative measures, thereby providing a scientific approach to identifying variations in processes and taking remedial measures.

D. H. Stamatis states: "Failure Mode and Effects Analysis (FMEA) is a methodical approach to identify the potential failure modes in a system and to prioritize actions to be taken by evaluating the Risk Priority Number (RPN). This methodical approach helps an organization to identify the critical risk areas and take actions to prevent failures, thereby enhancing system reliability." This methodology is highly used in the engineering and industrial environment to overcome the uncertainties in the operation and to increase the reliability of the system (Stamatis, 2003). In the operation of the flare system, the implementation of Six Sigma analytical tools helps an organization to identify the variables that affect unstable combustion, risks of carrying over liquid hydrocarbons, and to design to increase the efficiency of the flare system.

James P. Womack and Daniel T. Jones note that organizations that wish to pursue operational excellence are mainly concerned with the elimination of inefficiencies, strengthening of process consistency, and building a culture of continuous improvement. These are principles that are quite applicable in the oil and gas industry, as this is a field that requires high reliability in operations in order to avoid any industrial accident.

The ALARP principle, as described in the article by the Health and Safety Executive, is the actions that an organization has to take in order to ensure that all risks associated with the operations are lowered to the lowest level that is practicably possible. The ALARP principle is important in situations that are critical in that the consequences of failure are significant, even though the likelihood of failure is low (HSE, 2001). In reference to the safety of the industrial flare system, the ALARP principle emphasizes the importance of measures that need to be taken in order to ensure safety against hazards resulting from unstable conditions in the flare line and the presence of liquid hydrocarbons.

4.0 Research Methodology

The study is a hands-on approach to solving a problem by taking advantage of the Six Sigma DMAIC method in addressing a critical safety concern in hot flaring in LPG pipeline sectional valve stations. This study is different from most other studies in that, while most studies focus on

the theoretical side of things, this study is all about solving real-world problems with real-world solutions that solve the problem from an engineering perspective. This study is about addressing the problem of varying flaring efficiency with Emergency Evacuation Equipment and proposing a design improvement for constant burning and reduced emissions.

A combination of methods is employed, drawing from process engineering, risk assessment, and quality management to really dig into the problem and figure out what fixes are needed. By checking things out via data and structured improvement methods, the solution will be technically sound, easy to implement, and safe from an industry standpoint.

4.1 Research Design

This study, as it looks into real-life situations at the Liquefied Petroleum Gas (LPG) pipeline valve stations to determine what problems occur when there needs to be a release of pressure and flaring off the gas. The main problem that we are looking at in this case is when the liquid and the gas get mixed and when there is liquid in the flare system. This can interfere with the flame and the smoke that is produced and can become a dangerous situation. So, the study is all about determining why this happens and how it can be corrected with a good engineering solution.

At the same time, this research is also paying attention to the performance of this emergency equipment in this flaring event. It is also trying to find a practical and solid solution to make this equipment better. One idea that has been considered is to add a drum before the flare stack to remove liquid from the gas before burning. We are also evaluating this by carrying out a risk assessment to see how this can reduce risks and make things run smoothly.In this research, an attempt is made to include the risk management aspect in the DMAIC process, which utilizes the ALARP concept, i.e., risks are reduced to as low as is reasonably practicable through smart engineering, ensuring that our safety measures are regulatory compliant and operationally effective.

The research mainly uses qualitative data collected from different operational sources. The substantial evidence includes personal experiences from three reported cases of liquid LPG carryover, experiences from the inspection of the flare system's performance, reported incident history, operators' contributions, and expert engineers' opinions based on their knowledge of process safety. As the incidents of flaring take place during emergency and non-standard states, there is not much monitoring history for the incidents to be analyzed statistically. The analysis is performed based on the combination of the two methods.

In order to have a better level of uniformity in the analysis, a quantified measure of the situations was developed by creating a scoring system. This was achieved by creating a Severity, Occurrence, and Detection scoring system based on Failure Mode and Effects Analysis. This quantification of situations in terms of quantified measures is a better approach to analyze a situation objectively. This is a general practice when conducting a risk-based study of any operation. Along with this, a quantification of the causes was possible by creating a cause and effect diagram based on Ishikawa's methodology, which provides a guideline to classify causes based on process, equipment, and operation causes.

4.2 Data Analysis and Interpretation

The aim and objective of this section of the chapter is to methodically analyze the observations obtained from the LPG flaring incidents and transform them into beneficial analytical understandings. As the data obtained for the research is based on qualitative data, a systematic method was employed to transform the data into quantifiable metrics to make unbiased decisions.

Existing System Description

The below schematic illustrates the current LPG flare routing arrangement, wherein the underground LPG pipeline rises to above-ground level shortly before entering the flare stack.

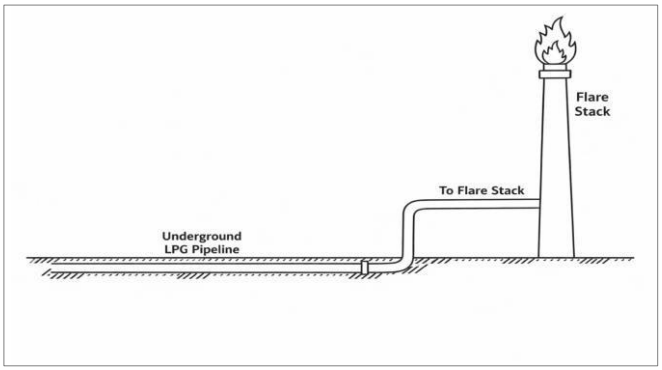


Figure 4.2.1 Design Layout - Current Scenario

Measure Phase

The Measure Phase is aimed at determining the inherent level of risk associated with emergency flaring occurrences without continuous monitoring and measuring with the aid of sophisticated equipment and quantitative emission logging. Thus, the significant characteristics of emergency flaring in remote SV stations are that it is irregular and not constantly monitored and analyzed with the aid of sophisticated and advanced analysis tools. Thus, the initial assessment of the structure is based on qualitative data obtained from site operations, records of maintenance, and opinions in quantifying factors. This approach ensures that qualitative data obtained from site operations are converted to quantified severity factors in the FMEA methodology. It does not mean that the structure can withstand external forces and that the design of the structure has been successful. It has been successful due to luck rather than inherent engineering resilience.

From the perspective of risk, the absence of a major failure does not automatically imply that the system is inherently

safe. A system that has not failed may still have underlying risks. To ensure an unbiased evaluation, established industry benchmarks were used to translate the qualitative data into quantitative data, as shown below.

Table 4.2.1: Qualitative-to-Quantitative Conversion - Current Scenario

S.No	Qualitative parameter	Conversion Technique used	Final Quantitative Output
1	Flame instability & smoke intensity	Ringelmann smoke index as per BS 2742-1969 standard	4 (Dense Bl;ack Smoke)
2	Possibility & Severity of catastrophic ground fire; detectability of liquid fallout	S-O-D Scoring as per IS 15550-2005 standard	Severity (S) = 10 Occurrence (O) = 3 Detection (D) = 7

Table 4.2.2: FMEA Scoring & Justification - Current Scenario

FMEA Element	**Scoring (Witness Judgment)**	**Justification**
Failure Mode	Liquid LPG reaches the flare tip (slugging/carryover).	
Failure Effect	Unstable flame, smoky combustion, Liquid LPG ground fire.	
Severity (S)	10 (Catastrophic)	Ground fire and loss of containment—maximum consequence.
Occurrence (O)	3 (Remote/Low)	Low frequency
Detection (D)	7 (Low)	Detection is reactive and post-event in nature, with no predictive instrumentation upstream of the flare.
Risk Priority Number (RPN)	S×O×D = **10× 3 x 7=210**	High RPN. While the frequency of event is low, the catastrophic severity mandates intervention.

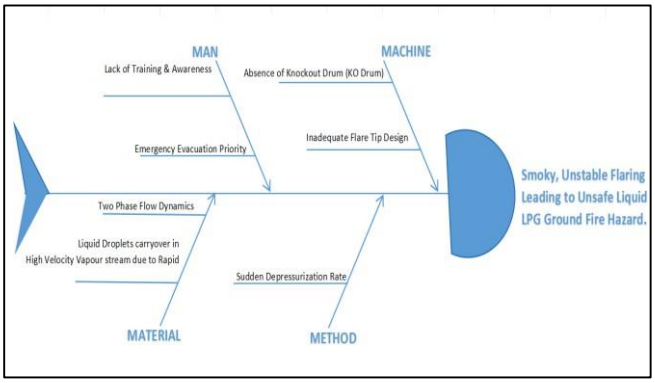
Analyze Phase

Quantitative data is considered for risk evaluation in the form of Risk Priority Number (RPN) by applying Failure Mode and Effect Analysis (FMEA) according to the IS 15550-2005 standard. Risk evaluation was performed by applying the Risk Priority Number (RPN) formula: RPN = S x O x D

Inference: The RPN value of 210 indicates a high-risk group, implying a situation that is not in compliance with the ALARP policy, which requires immediate action to lower it. The low-probability situation, rated at O = 3, although low, is not considered satisfactory due to the high severity, rated at S = 10, of the situation, which places it at a high level of risk exposure. In a risk-based evaluation, the severity of a situation is given considerable importance, and hence the situation under consideration cannot be considered satisfactory, even though it is a rare occurrence.

Ishikawa Analysis

The primary Effect (The Problem) is: Smoky, Unstable Flaring, resulting in an Unsafe Liquid LPG Ground Fire Hazard. There are various contributing causes, which are classified into four groups, namely Man, Machine, Material, and Method, which are all pertinent to pipeline operations.



This analysis indicates that the problem is not with the failure point but with the combination of human factors, equipment limitations, the thermodynamic properties of the LPG, and the procedures that are currently in place. From a human perspective, the emergency evacuation procedures focus on the rapid depressurization of the pipeline, even before the controlled flare process, and the lack of awareness about the effects of liquid fallout is a factor.

Table 4.2.3: Liquid Carryover - Cause, Analysis & Improvement

Category	Primary Cause from Diagram	Root Cause Analysis	Improvement Action
Man	Emergency Evacuation Priority	Emphasis is on speed of evacuation (safety of the line) over controlled flaring (safety of the unit).	Training on SOP & ensure compliance.
	Lack of Training & Awareness	Operators may not fully understand liquid fallout consequences.	Training on new KO Drum operation and SOP.
Machine	Absence of Knockout Drum (KO Drum)	Missing critical engineered barrier for two-phase flow. Leads to catastrophic failure severity.	Installation of a properly sized KO Drum with demister pad as per API 521.
	Inadequate Flare Tip Design	Tip is designed for vapor-only flow, leading to poor combustion when liquid slugs hit.	Flare tip modification rejected. Upstream liquid separation is the safer and ALARP-compliant solution.
Material	Two Phase Flow Dynamics	LPG is near its bubble point, highly susceptible to entrainment and mist formation.	KO Drum designed to provide sufficient residence time for gravity separation of bulk liquid.
	Aerosol/Mist Formation	Rapid expansion during venting creates fine liquid droplets (mist) that are easily carried by the high-velocity vapor stream.	KO Drum with Demister Pad specifically designed to handle fine mist separation.
Method	Sudden Depressurization Rate	High rates cause flashing, turbulence, and liquid slugging.	New SOP for mandatory review of rates.

Inference: Key takeaways from the analysis are as follows:

• Human and procedural factors are of minor significance.
• Two-phase flow and aerosol formation are thermodynamically intrinsic.
• In turn, the absence of a KO Drum signifies the sole missing engineered safety feature.
• Hence, we have a problem of design rather than behaviour.
• Under the 'Machine' category, the root cause of significant liquid carryover is directly facilitated by the 'Absence of KO Drum'.

Pareto Analysis

The following table depicts cause wise RPN contribution by the probable causes.

Table 4.2.4: Pareto Analysis of Causes Contributing to Unsafe Flaring

Cause	Severity (S)	Occurrence (O)	Detection (D)	Cause RPN
Absence of KO Drum	10 [Direct path for bulk liquid → catastrophic ground fire]	3 [Liquid carryover occurs during emergency venting only]	7 [No instrumentation to detect liquid before flare]	**210**
Two-phase flow dynamics	8 [Leads to unstable combustion & liquid fallout]	3 [Occurs whenever rapid depressurization happens]	6 [Visual detection only after flame instability]	144

Aerosol / mist formation	7 [Causes smoke, poor combustion, droplet fallout]	3 [Common during flashing LPG]	6 [Cannot be detected until mist exits flare]	126
Sudden depressurization	6 [Indirect contributor to flashing]	3 [Depends on emergency response]	5 [Detectable via pressure trend]	90
Operator prioritization	4 [Does not directly cause liquid carryover]	2 [Infrequent, training-dependent]	4 [SOP deviations detectable]	32
Procedural gaps	3 [Minor]	2 [Low]	4 [Auditable]	24

Total cumulative impact = 626

Table 4.2.5: **Cause wise RPN contribution**

Cause	% Contribution	Remarks
Absence of KO Drum	**33.5%**	Two-phase flow and mist formation are not independent failures; they are consequences of absence of KO Drum thereby resulting to cumulative contribution of **76.6%**
Two-phase flow	23.0%	
Mist formation	20.1%	
Sudden depressurization	14.4%	-
Others	9.0%	-

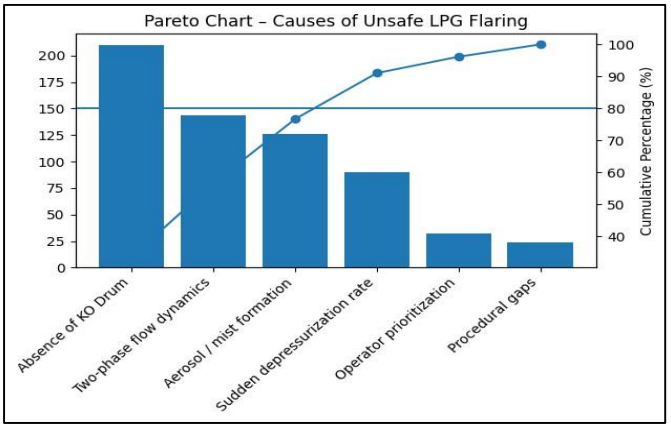


Figure 4.2.2: Pareto Chart- Cause vs RPN

The Pareto chart shows that the absence of the Knockout Drum, along with its direct consequences like two-phase flow instability and aerosol mist formation, causes 76.6% of the total cumulative risk exposure, i.e., 210 + 144 + 126 out of 626. However, these are not independent failure modes, and two-phase flow characteristics and aerosol mist formation are just thermodynamic consequences of improper upstream vapor/liquid separation. The Pareto analysis proves that the well-designed KO Drum solution will reduce 80% of the most dangerous risk of flaring through one single solution, and hence, from the risk-based decision point of view, it is not only the best solution but also ALARP compliant and financially viable.

Proposed Solution

The proposed solution would include the use of a horizontally oriented KnockOut Drum of sufficient size, to be installed ahead of the flare stack, and this design would be conducted in a conceptual manner following guidelines provided in the API 521 standard. The designed solution would include providing sufficient vapor residence time to allow vapor-liquid separation, a demister pad to account for liquid droplet removal, level transmitters with high-high level alarm to allow operation in a safe condition, and a flame arrestor to provide improved fire protection. The designed solution would include providing a definitive vapor-liquid separation barrier ahead of the flare, to "stop" liquid carryover and hence prevent unstable and smoky burning.

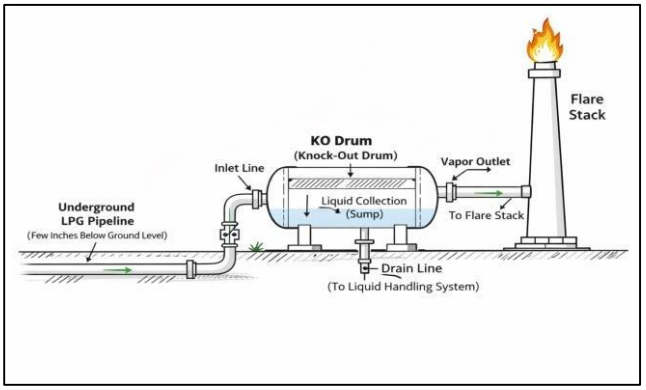


Figure 4.2.3: Design Layout – Proposed

The diagram above shows the recommended position of a horizontal Knockout (KO) Drum to be placed before the flare stack. The LPG vent pipeline from the underground location is directed upwards to connect to the KO drum inlet. The vapor from the KO drum passes through a mist eliminator section before proceeding to the flare stack, whereas liquid collection occurs and drains through a controlled outlet.

5.0 Summary of Findings

The study also verifies that the process safety risk arises from the presence of liquid LPG fires on the ground during flaring activities. Although these occurrences are rare, with only three occurrences in five years, the results from the FMEA indicated that the consequence of the event was catastrophic, as the Severity rating was given as 10. The results from the FMEA also indicated that the Risk Priority Number rating was initially given as 210, indicating that the system was in the zone of unacceptable risk.

The results from the Root Cause Analysis indicated that the main cause for the unstable combustion, smoke, and fires at the ground level during flaring activities was the liquid carryover during the rapid depressurization process. The results from the implementation indicated that the RPN rating had reduced to 30, indicating an 85% quantified reduction in risks. The Knockout Drum acts as a designed system to remove liquid carryover and mist from the system.

6.0 Suggestions and Recommendations

The results indicate that the implementation of the KO Drum needs to be standardized at all Sectionalizing Valve locations in the LPG pipeline system to ensure the consistent safety performance, especially in unmanned areas.

As a progressive Lean enhancement project, the technical feasibility of installing an LPG transfer pump to reinject the collected liquid LPG from the KO Drum into the downstream section of the pipeline can be considered. This project may help reduce flaring losses, improve efficiency in utilizing assets, and reduce hydrocarbon wastage in line with sustainability.

7.0 Conclusion

Within this research, it has been shown that operational problems within the low frequency domain can "hide" critical high severity process safety issues. By utilizing the Six Sigma DMAIC methodology, qualitative observational-based data has been transformed into quantifiable risk metrics.

Not only does the implementation of a KO Drum provide a mechanical solution, but it also provides a strategic solution to support Process Safety, Process Reliability, Regulatory Compliance, Environmental Regulations, Operational Excellence, and Asset Safety.

The main achievement of the study is the establishment of a replicable framework for risk-based enhancement in engineering, which may be applied to remote infrastructure, for instance, pipeline infrastructure, and similar high-risk industrial systems.

The project also supports the idea that proactive engineering plays an important role in the prevention of catastrophic process safety failures and in the integration of quantitative risk assessment and operations.

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Role Of Auditor Independence In Ethical Financial Reporting

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ABSTRACT: **Trust in financial reporting is heavily dependent on the auditor independence, which is very significant to maintain integrity, objectivity and ethics in financial reporting. The study focuses on the importance of auditor independence in respect of maintenance of ethics in financial reporting with respect to client's perception about transparency, tax adequacy and reliability of financial statements with reference to ethical framework of Institute of Chartered Accountants of India (ICAI). The study is based on primary data of 60 clients. The non- parametric data of the study was tested by Kruskal-Wallis H-test and Spearman's Rank Correlation test. In this study, despite its limitations in terms of its scope, geographical coverage and small sample size, establishes that the clients hold high regard for auditor independence. We conclude our study by recommending measures to strengthen auditor independence in small and medium-sized audit firms so as to promote ethical financial reporting and to enhance the public trust.**

Key Words: Auditors' Independence, Ethical Standards, Financial Reporting, Client Perception, Non-parametric Analysis, Professional Ethics

1. INTRODUCTION

Auditing is a very important aspect of good corporate governance and financial reporting. It ensures that financial reporting is reliable, transparent and free from any bias. The concept of independence of the auditor is of very great importance and it is anchored on the principles of integrity and objectivity. Independence as a concept, therefore, refers to the mental attitude of independence. It is not a matter of compliance with statutory regulation. An independent auditor must be in a position to exercise his professional judgement free from bias, influence or pressure from any quarter. The ICAI Code of Ethics (2019) makes reference to independence of mind and independence in appearance. Independence of mind means that the auditor is able to exercise his judgement without bias. Independence in appearance means that the auditor is seen to be independent by others. These aspects of independence are very important in order to command confidence in the auditing process and to eliminate any element of bias or conflict of interest in financial reporting

The ICAI Code of Ethics offers a comprehensive ethical framework that aids auditors in maintaining professional conduct. This framework is rooted in five principles: integrity, which mandates honesty and transparency; objectivity, which guards against bias and undue influence; professional competence and due care, which necessitate the upkeep of technical expertise and diligence; confidentiality, which guarantees the secure management of client information; and professional behaviour, which encourages adherence to legal standards and bolsters the profession's credibility (ICAI, 2019).

The Code also requires a conceptual safeguard approach in which auditors are required to identify, evaluate and deal with potential threats to independence. These threats may be financial, as a result of pressure from the client, due to the length of the audit engagement and/or due to the performance of non-audit services. The auditor must deal with any threats either by removing them or by applying appropriate safeguards. Safeguards may include checking the audit with an independent expert or consultant, or by making disclosure in respect of any matters that could undermine auditor independence.

Auditor independence has been extensively discussed in many research studies. It is stated that the actual and perceived auditor independence has significant impact on the stakeholders trust in the auditing process. Beattie et al. (1999) and Quick & Warming-Rasmussen (2009) suggest that trust is usually damaged when auditor has long term relationships, becomes financially dependent on auditees and carries out extensive non audit services although auditor is formally independent. DeAngelo (1981) and Francis (2004) also linked auditor independence with auditor expertise, auditor professionalism, auditor responsibility and overall audit quality as well as stakeholders' trust in financial statements.

Auditor independence in India is governed by various provisions under the Companies Act, 2013; Income Tax Act, 1961; and the ICAI Code of Ethics, dealing with objectivity, statutory audits, tax audits, auditor rotation and prohibition on non-audit and non-audit fees that may lead to conflict of interest. This study investigated auditor independence from the client's perspective (individual as well as corporate) and examined the extent to which auditor independence impacts trust, accountability and adherence to accounting standards, particularly in the context of small and medium-sized audit firms (SMAF), an area that has been less explored in auditor independence studies which have concentrated more on auditors as well as regulators.

2. OBJECTIVE

The objective of this research study was to investigate the individual and business client's perception of auditor independence. It discussed in greater depth how these perceptions may affect the accuracy and ethical content of financial statements and tax returns, the threats to auditor independence, whether auditor independence would secure clients' confidence in the reliability of financial statements and tax returns. Finally, the study provided recommendations on possible measures that small and medium-sized audit firms can put in place to enhance auditor independence.

3. LITERATURE REVIEW

Independence, skills, ethics and good corporate governance are found to be dominant variables in all the reviewed literature which enhance audit quality and reliability of financial statements. Independence helps in bringing objectivity in audits, reduces earnings management and enhances stakeholders' confidence (Sawaya et al., 2025; Kurniawan, 2023). It is also found that skills along with industry specific knowledge enhances compliance with accounting standards and detects misstatements (Sawaya et al., 2025; Thooyamany & Balagobei, 2025). An audit quality is influenced by auditor related, client related and external regulatory factors (Fawziah et al., 2025). These factors often threaten audit quality such as non audit services, long auditor tenure, client's influence and auditor–client relationship (Wakil, 2021; Tepalagul & Lin, 2015; Zayol et al., 2017). It is also found that audit quality is also influenced by ethical standards and good corporate governance which enhances transparency and prevents audit misbehaviour (Riyadi et al., 2025; Jejeniwa et al., 2024). Financial scandals can occur due to poor corporate governance and unethical acts of auditors and management as depicted in Satyam case (Mishra & Umair, 2025). The regulatory framework is developing with independent regulatory bodies like NFRA to enhance accountability in auditing (Anil Kumar, 2018). The empirical studies as discussed above confirms that enhancing independence, ethics and regulations are necessary to enhance audit quality, investors' confidence and reliability of financial statements in various contexts.

4. RESEARCH METHODOLOGY

The study adopted descriptive research design in order to examine the perception of clients towards auditor independence. The study made use of both primary and secondary data. The primary data was collected using structured questionnaire whereas the secondary data was collected from various books, journals, reports and online sources. 60 respondents were selected using purposive non-probability sampling method. They were selected based on their knowledge on auditing profession. Non-parametric statistical tools such as Kruskal–Wallis H test and Spearman's Rank Correlation were used in order to determine the relationship and difference between the variables of the study. The whole methodology was done systematically in order to give the reader an easy interpretation of the findings which will relate to the objectives of the study. An additional thrust of this discussion is that awareness-building initiatives aimed at clients could serve to increase the awareness of other stakeholders of the protections in place to ensure auditor independence. The discussion also includes a comment on the auditor firms' policies being balanced in a way that enables a long term relationship between the auditors and clients and at the same time ensuring that independence protection is maintained.

5. DATA ANALYSIS

5.1 KRUSKAL-WALLIS TEST H-TEST

5.1.1 HYPOTHESIS 1

(H_0): There is no significant difference between the mean rank of men and women (gender) with respect to auditor independence while preparing financial statements.

(H_1): There is a significant difference between the mean rank of men and women (gender) with respect to auditor independence while preparing financial statements.

Table 1: Showing the Kruskal-Wallis test of association between Gender and the auditors' independence while preparing the financial statement

Test Statistics[a,b]

	Auditors' Independence while preparing financial statements
Chi-Square	.000
df	1
Asymp. Sig.	1.000

a. Kruskal-Wallis Test
b. Grouping Variable: Gender

Inference

Since the Kruskal-Wallis H-test using gender as the grouping variable was conducted, the results showed that the p-value for the tested objective was above 0.05 (e.g., 1.000), indicating that there is no statistically significant difference between the mean age of men and women in relation to the auditor's independence towards the financial statements. This suggests that age does not have a significant impact on auditors' perceptions of independence.

5.1.2 HYPOTHESIS 2

(H_0): There is no significant difference between the mean rank of respondents based on their years associated with the audit firm with respect to agreement on auditor independence.

(H_1)There is a significant difference between the mean rank of respondents based on their years associated with

the audit firm, with respect to agreement on auditor independence.

Table 2: showing the Kruskal-Wallis test of association between Years associated with the audit firm with respect to agreement on auditor independence

	Do you agree that your auditor maintains independence in their work
Chi-Square	6.194
Df	3
Asymp. Sig.	.103

Inference

The Kruskal–Wallis H-test using years associated with the audit firm as the grouping variable was conducted, and the results showed that the p-value for the tested objective was above 0.05 (0.380). This indicates that there is no statistically significant difference in perceptions of whether the auditor maintains independence in their work across clients with different lengths of association with the firm. In other words, the duration of association with the audit firm does not have a significant impact on how clients perceive auditor independence. Hence, we fail to reject the null hypothesis (H_0) and conclude that there is no significant difference in perceptions of auditor independence across the groups based on years of association with the firm.

5.1.3 HYPOTHESIS 3

(H_0): There is no significant difference between the mean rank of individual clients and business clients (type of client) regarding trust in financial statements when the auditor is independent.

(H_1)There is a significant difference between the mean rank of individual clients and business clients (type of client) regarding trust in financial statements when the auditor is independent.

Table 3: showing the Kruskal-Wallis test of association between types of client (Individual and business), regarding the trust in financial statement when the auditor is independent

	Do you trust your financial statements more when your auditor is independent?
Chi-Square	1.532
Df	1
Asymp. Sig.	0.216

a. Kruskal-Wallis Test
b. Grouping Variable: Type of client

Inference

The Kruskal–Wallis H-test using types of client (Individual or Business) as the grouping variable was conducted, and the results showed that the p-value for the tested objective was above 0.05 (0.216). This indicates that there is no statistically significant difference between trusting the financial statement when the auditor is independent and the type of client. In other words, the type of client in the audit firm does not have a significant impact on trusting the financial statement when the auditor is independent. Hence, we fail to reject the null hypothesis (H_0) and conclude that there is no significant difference; both clients show similar levels of trust in financial statements when the auditor is independent.

5.1.4 HYPOTHESIS 4

(H_0): There is no significant difference between the mean rank of respondents grouped by years associated with the audit firm regarding the belief that auditor rotation improves independence.

(H_1): There is a significant difference between the mean rank of respondents grouped by years associated with the audit firm regarding the belief that auditor rotation improves independence.

Table 4:Showing the Kruskal-Wallis test of association between years associated with the audit firm regarding the belief that auditors rotation improves independence

Test Statistics[a,b]

	Do you think rotation of auditors can improve independence?
Chi-Square	1.475
Df	3
Asymp. Sig.	.688

a. Kruskal-Wallis Test
b. Grouping Variable: Years

Inference

The Kruskal–Wallis H-test using types of client (Individual or Business) as the grouping variable was conducted, and the results showed that the p-value for the tested objective was above 0.05 (0.688). This indicates that there is no statistically significant difference between the rotation of the auditor can improve independence and the years associated with the audit firm. In other words, the years' association with the audit firm does not have a significant impact on the rotation of an auditor. Hence, we fail to reject the null hypothesis (H_0) and conclude that there is no significant difference.

5.1.5 SPEARMAN'S RANK CORRELATION

Independent variable: Years associated with the audit firm

Dependent variable: Do you think working with the same auditor for a long time affects their independence

Table 5: Showing the Spearman's rank correlation between years of association with the audit firm and working with the same auditor for a long time affects their independence.

Correlations				
			Years	Relationship
Spearman's rho	Years	Correlation Coefficient	1	-0.103
		Sig. (2-tailed)	.	0.432
		N	60	60
	Relationship	Correlation Coefficient	-0.1	1
		Sig. (2-tailed)	0.432	.
		N	60	60

Inference

- Correlation coefficient (ρ): –0.103 -very weak negative relationship.
- Sig. (p-value): 0.432 (> 0.05).
- N = 60.

The Spearman's Rank Correlation test was conducted to examine the relationship between the years clients were associated with the audit firm and their perception of whether working with the same auditor for a long period affects independence. The correlation coefficient ($\rho = -0.103$) indicates a very weak negative relationship. However, the significance value ($p = 0.432$) is greater than the 0.05 threshold, suggesting that the result is not statistically significant. Therefore, we fail to reject the null hypothesis (H_0) and conclude that the years of association with the audit firm do not have a significant influence on clients' perceptions regarding the impact of long-term auditor relationships on independence.

6. SUGGESTION

Audit firms must continue to seek to improve and to implement effective independence policies and procedures and we generally observe high levels of stakeholder confidence in audit processes. Rotations of audit firms may also be necessary to address potential threats to independence arising from familiarity. Audit firms must also continue to ensure that auditors undergo appropriate continuing professional education and ethics training to sustain their independence and objectivity.

Companies can increase stakeholders' confidence in their accountants and auditors by being more open about non-audit services such as financial consulting and by more clearly explaining steps they take to protect independence and comply with strict standards on that issue. The accounting profession also has the ability to police itself more effectively by requiring checks and balances, such as peer reviews, and conducting regular audits of its members' work.

Awareness of client feedback can also contribute to stakeholder understanding of the independence safeguards in place to protect auditor independence. Auditing firms may also wish to consider developing balanced policies which enable the development of long term auditor client relationships, while at the same time maintaining appropriate safeguards to protect auditor independence.

7. CONCLUSION

Trust is a basic component of any healthy financial system. The independence of auditors is key to providing assurance on reliability, integrity and quality of financial reporting. Our clients are satisfied with our professional and unbiased approach to their auditing requirements, which strengthens their trust in financial reporting. Auditors must adhere to internationally recognized standards of professional ethics and regulatory requirements, thereby maintaining their professional reputation and strengthening the trust of various stakeholders.

The report, which makes several key findings and recommendations, emphasizes that auditor independence is fundamental to assuring technical competence and maintaining auditor integrity and public trust. Clients have specifically recognized the importance of auditors providing their services impartially and in a highly professional manner. Overall, a strong auditor independence enhances financial market governance, increasing transparency, fairness and sustainability.

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An Empirical Study On Loan: Portfolio In Financial Service Industry

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ABSTRACT : **The makeup, performance, and risk exposure of Enterprise's loan portfolio are the main subjects of this study. The study evaluates the distribution of loans across different industries, credit quality, and payback trends in order to ascertain the benefits and drawbacks of the portfolio. Key financial metrics like sector diversification, loan-to-value ratios, and non-performing assets are used to assess the company's resilience and financial health. In addition to emphasizing aspects of effective credit management, the findings also point to possible hazards that could affect liquidity and profitability. The article's conclusion makes suggestions for loan portfolio optimization techniques that will enhance sustainability, lower default risks, and further long-term growth objectives.**

***Key words – Loan, Repayment, Profitability*.**

I.INTRODUCTION

The process of evaluating the performance, composition, and hazards of a financial institution's loans to its clients is known as customer loan portfolio analysis. In addition to revealing trends in repayment patterns, default rates, and credit quality, this study offers helpful information regarding the distribution of loans across numerous categories, including loan kinds, client demographics, industries, and geographic areas. Loan portfolio analysis helps financial institutions maximize portfolio performance, reduce risks, ensure regulatory compliance, and make well-informed decisions about future lending plans by utilizing data analytics and risk assessment tools. In the end, it improves the business's capacity to sustain consistent financial stability and long-term expansion.

Banks and lenders take a close look at their loan portfolios to understand the risks, performance, and mix of loans they hold. They do this through a process called loan portfolio analysis. This helps them spot patterns, figure out how customers tend to borrow and pay back, and get a real sense of the portfolio's overall condition. There are lots of ways to break down the data: type of loan, terms, interest rates, who the customers are, and how they handle repayments.Digging deeper, they pay attention to things like the loan-to-value ratio, non-performing loan (NPL) ratios, chances of default, and how much money the loans actually make. This way, they can find problem areas, predict losses before they happen, and fine-tune their credit policies.At the end of the day, loan portfolio analysis isn't just about managing risk — it's a key part of making smart, strategic decisions. It keeps lending practices in step with what's going on in the market and what regulators expect.

II. SCOPE OF THE STUDY

Banks really get into the weeds when they analyze their loan portfolios. They want to know everything—who's borrowing, what kind of loans they're handing out, whether those borrowers are likely to pay them back, how repayments are actually going, and where their money's scattered across regions. All this digging helps them catch warning signs early, spot patterns, and find chances to spread their risks around. But they don't work in a bubble—they keep a close eye on what's happening in the market, any fresh regulations, and the economy's mood swings. Those outside forces can shake things up fast. When banks piece together all these details, they end up with sharper strategies. They can tweak their risk game, decide where to invest more, or pull back—and the bottom line? Smarter decisions mean bigger profits and steadier finances.The Scope of the Study deals with the complexities of the financial institutions' assessment of the stability of the loan portfolio. The scope of the study includes an overall assessment of various aspects of the demographics of the borrowers, types of loans, and the possibility of repaying the loans, which are located in various geographic areas.

In other words, the research undertakes an in-depth analysis of the complexities of the operational process involved in the management of financial institutions in relation to the sustainability of financial portfolios. The research undertakes an in-depth analysis of the approval process in relation to the operation of various business sectors, as well as the interest rates associated with corporate entities in the financial services industry. The research undertakes an in-depth analysis of the various trends associated with the demographic structure of the borrowers, the nature of financial portfolios, as well as the repayment patterns in relation to specific regions, in order to identify the early signs to allow for effective diversification. The research undertakes an in-depth analysis of the external factors, which have a direct impact on the financial stability of the financial institutions, as well as the liquidity of the financial institutions, which in turn have a direct impact on the financial stability of the economy, considering the introduction of Basel III. The scope of the study deals

with understanding the various business sectors that are approved for loans, corporate interest rates, and the financial services industry.

III. OBJECTIVES OF THE STUDY

1.To understand how different business sectors are approved for loans.
2. To determine the corporate interest rate.
3. To look into the repayment practices of the financial services sector.
4. To examine the actions taken to evade repayment.
5. To make recommendations and suggestions about the expansion

IV. NEED OF THE STUDY

Loan portfolio analysis is an important need for financial institutions to assess the performance, composition, and inherent risks of lending activities. The need for banks to identify patterns of customer behavior, through the application of data analytics tools, in a dynamic financial environment cannot be overstated. The need to understand loan patterns, along with other important ratios, such as loan-to-value ratios, non-performing assets, etc., is important to identify areas of concern and to anticipate any possible losses that may be incurred in the near future. The study of loan portfolio analysis is important to help financial institutions respond to external factors, which affect financial institutions, such as market trends, economic fluctuations, and other regulatory issues, including Basel III. The deeper understanding of loan portfolio analysis, with regards to various business sectors, will help financial institutions improve their credit policies, comply with regulations, and sustain financial stability, which is important for financial institutions to achieve in order to ensure profitable growth.Further, there is a need to critically assess how financial institutions are able to provide their clients with appropriate instructions and personalized guidance on how to manage their loans.

V. LIMITATIONS OF THE STUDY

The primary need for this study arises from the importance of loan portfolio analysis in the financial health and well-being of the enterprise. In the current financial service industry, which is highly volatile, it is imperative for financial institutions to look beyond the conventional and dive deep into the analysis of sectoral diversification, loan-to-value ratios, and non-performing assets to ensure the long-term sustainability of the enterprise. This study is the need of the hour to create a roadmap for optimizing the loan portfolio, which in turn would help in mitigating the risk of default and enhance the overall liquidity and profitability of the lender.Moreover, the need to understand the human aspect of the financial services industry is the need of the hour. This study attempts to understand the correlation between the communication skills of the lenders and the satisfaction of the client's financial demands, creating a vital link in the chain of building the much-needed trust with the customers. This study is the need of the hour to bridge the gap between the complex rules and regulations, such as Basel III, and the actual operational management of the financial services industry.

However, the results of this study are also bounded by a number of constraints, most significantly in terms of the sample size and the method of data collection itself, which was conducted after a final sample of 97 valid responses out of a total of 107 was obtained, and in light of the unknown total population, which necessitated a pilot study of only thirty customers in order to develop statistical baselines.

Moreover, the results of this study are also bounded by its descriptive nature as a type of research, which seeks to describe characteristics as they naturally occur without any external variables influencing the outcome, and which, as a result, cannot hope to prove any direct causation between any of the lending policies and economic outcomes.

VI. REVIEW OF LITERATURE

David Martinez (2021) , David Martinez studied the effect of Basel III rules on the risk of banks' loan books in 2021 and concludes that Basel III rules, by requiring more capital, definitely reduce risk but also tend to make banks lend less. Martinez main message is quite clear regulators have to find the right level of regulations. He advocates a fine-tuning where financial stability is not at the expense of economic growth slowdown. If you want to see how regulation influences risk management, this paper is a must read.

John D. Smith, (2023) Research in loan portfolio analysis fundamentally relies on the methodology developed by Smith (2023) that stress the importance of quantitative tools in the measurement and management of risk (Smith 2023). The present research relies on the application of statistical models as tools to direct decision making for the credit risk management in the "loan portfolio" (see section 4.1). Smith (2023) pays special attention to the integration of different sources of information of the borrower with macroeconomic variables, so as to modify the model according to the macroeconomic cycle and to take into account the systemic risk. Traditional credit scoring models are criticized for not being able to tell systemic risk, which is what this research intends to do. This line of research would be very useful for financial institutions willing to improve their credit risk management systems.

Michael Brown (2016) Brown explores the control of credit risk with credit derivatives such as credit default swaps (CDS). It points out the risk spreading aspect of these derivatives and also warns of systemic faults. Greater market regulation and more information on credit derivatives are things he believes in. To understand the sophistication of the financial instruments used today this is an important research.

VII. RESEARCH METHODOLOGY

The research methodology for this particular study is based on a descriptive research design, which aims to study the characteristics of the loan portfolio and customer behavior as they occur naturally without manipulating the variables. In order to make the study statistically significant and free from any kind of biases, the researcher opted to use the random sampling method, which allows every individual in the population to have an equal chance of being selected. Since the population for the study was not known, the researcher conducted a pilot study of thirty customers to find the value of 'p' and determine the ideal sample size.The researcher collected the data from the population using primary sources, structured surveys, and questionnaires to obtain accurate and relevant information from the selected population. Out of the total population, the researcher received 107 responses, but only 97 responses were used for the study, allowing for a margin of error. The researcher used the quantitative method and the Chi-Square test to determine the relationship between lender communication and customer satisfaction.

RESEARCH DESIGN

The goal of a descriptive study is to portray systematically a population situation or phenomenon and variables are not manipulated. The main goal is to portray events actions or characteristics as they normally. Its primary objective is to accurately and completely depict events, actions, or characteristics as they naturally occur.

SAMPLING TECHNIQUES

The random sampling a type of probability sampling method was used for selection of sample. When random sampling is used, all persons in the population have an equal chance of being chosen. This method reduces bias and increases the representation of the entire population in the sample. Statistical soundness and generalizability of the research results can be obtained by random sampling. Random sampling is most appropriate for research that aims at generalizability of research results in large adult population studies/clinical trial/surveys, hospital based studies, field studies, and following other sampling methods where a complete list of the population is available.

POPULATION SIZE

The responses to the poll came from different customers. A pilot study of thirty customers was used because the population was unknown. The results of this pilot study were used to determine the value of p. Therefore, 97 is the ideal sample size.

DATA COLLECTION

The primary sources of the study's data were the individuals that were chosen. To ensure accuracy while accounting for a margin of error, the study used 97 of the 107 replies that were collected. Surveys and questionnaires were used to guarantee the accuracy and relevance of the data gathered for the study.

VIII. ANALYSIS AND INTERPRETATION

CHI SQUARE TEST

The Chi Square Test, as used in this particular study, is a statistical tool used to ascertain if a particular relationship exists between two variables. As used in this particular study, the researcher used the Chi Square Test to ascertain if the lender's communication style, as exemplified by the provision of instructions, has a direct bearing on the client's perception of their needs being met. By comparing the results of the responses from the customers to the expected results if no relationship existed, the researcher was able to ascertain if the results were purely by coincidence or if a relationship existed. As used in this particular empirical study, the researcher used a 5% level of significance. As a result of the Chi Square results, which had a p-value of 0.000, the researcher was able to reject the null hypothesis and ascertain that the relationship between the provision of clear and precise criteria for paying the loans and customer satisfaction was statistically significant, as the p-value was well below 0.05.

NULL HYPOTHESIS

H0: There is no relationship between the lender's provision of clear instructions to clients regarding how to manage loan repayments and the perception of clients that their financial demands are adequately satisfied during the process**.**

ALTERNATIVE HYPOTHESIS

H1: There is a relationship between clients' perception that their financial demands are sufficiently satisfied during the process and the lender's provision of clear instructions regarding how to manage loan repayments.

Chi-Square Tests

	Value	d.f	Asymp. Sig. (2-sided)
Pearson Chi-Square	150.752[a]	8	.000
Likelihood Ratio	131.296	8	.000
Linear-by-Linear Association	76.571	1	.000
No of Valid Cases	97		

a. 11 cells (73.3%) have expected count less than 5. The minimum expected count is .08.

INTERPRETATION

Since p=0.000, we can conclude that we should accept the alternative hypothesis at a 5% significance level. It can thus be argued that there exists a link between the lender's specific loan repayment criteria and the opinion of the customers that their financial needs are satisfied during the process. There exists a high level of correlation between the opinions of the customers regarding the clarity of the loan repayment criteria and the opinion of the customers that their financial needs are satisfied. It, therefore, becomes apparent that financial help plays a critical role towards the happiness of the customers. Lenders should, therefore, concentrate on offering personalized financial advice, ensuring that the borrowers understand the loan repayment criteria, as well as the transparency of the loan.

IX. FINDINGS

A fair view of loan-related issues was provided by the study participants, who were comprised of 54% men and 46% women. The fact that 54% of the study participants are in the 25-34 age group, while 23% are in the 35-45 age group and another 23% are in other age groups, reveals that more young people are more interested in lending.

The study findings show that most study participants strongly feel that they are provided with accurate information regarding the terms and conditions of the loan and that the loan application process is easy to understand. Furthermore, most study participants demand that the loan approval procedure is conducted in a timely manner and that sufficient customer service is provided. In addition, most study participants believe that the procedure sufficiently satisfies their financial needs.
Most study participants indicated that interest rates are adequate, appropriate, and easy to understand. However, some study participants are of the view that interest rates are high and do not provide sufficient benefits.

Despite this, most customers are satisfied with the interest rates and are willing to let other people know about their lender. Most consumers believe that the interest rates provided by the lender are fair. Many customers believe that the rates offered by the lender are reasonable. The customers' perception of clear guidance in loan repayment and their perception that their financial needs have been sufficiently met were found to have a significant correlation ($p = 0.000$, $p < 0.05$). This illustrates the significance of customer satisfaction and happiness and the need to build customer trust through proper management of customer loans. A statistically significant correlation between customer assistance for loan repayment issues and satisfactory customer service during the loan approval process is evident in the data ($p = 0.000$, $p < 0.05$). This illustrates the significance of building customer relationships throughout the entire loan approval and repayment process to ensure customer satisfaction and build customer trust.

X. SUGGESTIONS

➢ Launch awareness campaigns to enlighten borrowers on the various loan facilities and repayment strategies to minimize default.

➢ Emphasize the advantages of timely loan repayment to help borrowers sustain a financially stable position and a higher credit rating.

➢ Urge consumers to seek financial guidance to improve the quality of loan repayment strategies.

➢ Emphasize the significance of effective loan repayment and financial management to support economic development and financial stability of the banking industry.

➢ Acknowledge the difference in the ability to repay loans depending on various factors, such as income and employment levels; therefore, financial guidance should be tailored to suit individuals.

➢ Keep the borrowers abreast of the changes to interest rates, loan repayment strategies, and restructuring facilities to enable them to make informed decisions.

➢ Develop accessible online resources to guide borrowers on the management of loans, repayment schedules, and EMI calculations.

XI. CONCLUSION

In order to give both lenders and borrowers financial stability, this study emphasizes the significance of loan portfolio analysis. As the lending market expands, clear loan terms, customer-friendly legislation, and effective loan administration are essential components. Lenders may be able to maintain profitability, improve client happiness, and prevent loan defaults with an effective loan portfolio. Lenders may be able to improve loan repayment alternatives, interest rate competitiveness, and loan processing speed by utilizing data-driven strategies.This advertisement shows the importance of borrower education, digital transformation, and transparency of financial processes. The financial stability of the economy can be improved through fair terms of lending, communication, and flexible terms of payment that can build confidence among borrowers. In today's fast-moving financial world, proper management of loans can benefit both lenders and borrowers and help build a more stable and equitable financial system. Financial institutions can increase productivity and minimize risks to help the economy through the implementation of the recommendations of the research study.The study's findings have so emphasized the significance of loan portfolio analysis, which is necessary to provide a stable financial environment in a changing climate for both the borrower and the lender. This study has emphasized the importance of transparent loan regulations, legislation, and procedures that were formerly voluntary but are now required to create a financially sound banking environment due to the financial industry's increasing complexity. Financial institutions can now successfully sustain their profitability while raising client satisfaction and reducing the risk of loan default by using data-driven initiatives.

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Post Interaction Communication And Niche Talent Retention :

A Longitudinal Study

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Abstract : **The purpose and aim of the study are to evaluate the effectiveness of the application of the concept of strategic follow-up communications in enhancing candidate retention during the recruitment process for niche IT skills. The study in particular focuses on the important aspects that may improve candidate retention during the recruitment process for niche IT skills. The research design to be employed in the study is longitudinal in nature. The study focuses on the candidate response and organizational response during a specified period. The study also includes the application of surveys and interviews from the candidates and professionals for niche IT skills at various stages during the recruitment process. The research design to be employed in the study is descriptive in nature. The data for the study is both primary and secondary in nature. The sample size for the study is 250. The non-probable sampling technique to be employed in the study is convenience sampling. While evaluating the data collected for the study, appropriate statistical tests such as correlation tests and comparative tests may be employed to evaluate the results obtained for candidate retention and strategies for follow-up communications.**

Key Words: Communication channels, Frequency, Personalization, Timeliness, Content, Candidate Retention.

INTRODUCTION

In the highly interconnected and digitalized world economy, in which technological advances are happening at unprecedented rates, the requirement to attract and retain the best talent has assumed significance in the sustenance and success of competitive advantage in organizations. This is especially true in the information technology industry, as it is known to be one of the most dynamic and ever-changing industries. It is one industry in which specialized skills are the key to success and leadership in the industry, and the requirement to acquire competent information technology professionals to solve increasingly complex technological problems has been outgrowing the supply, creating a highly competitive requirement to acquire such skills. Requirement to acquire specialized skills is especially true when one considers the variety of skills that are in demand, such as Artificial Intelligence, Cyber Security, and Cloud Computing, as they are known to be highly complex and require constant learning, creating a unique challenge for organizations to attract and retain such talent. In this highly competitive and candidate-driven marketplace, the experience of the prospective employee plays a pivotal role in decision-making, and decisions are made based upon the candidate experience.

The aspect of follow-up communication, which represents the effective and significant interaction between the organization and the candidates from the time of initial contact until the final decision, has the potential to impact candidate engagement, professionalism, and even the final decision-making process to a significant extent. However, the specific aspects of effective follow-up communication, including the communication medium, frequency, content, and personalization, must be understood in detail, especially when it comes to the domain of IT recruitment. In order to bridge the gap in the existing literature, the present study aims to assess the effectiveness of strategic follow-up communication in enhancing candidate engagement during the recruitment process for niche IT positions. The main objective of the proposed study is to provide a detailed analysis of the impact of effective communication strategies, implemented at different stages of the recruitment process, on candidate engagement and their willingness to take up the offered positions.

OBJECTIVES :

- To determine the communication channels through which frequency increases candidate engagement at various stages of the niche IT skills recruitment process.
- To assess the level of personal feedback and timely updates considered important by candidates with niche IT skills at various stages of the recruitment process.
- To analyze the link between the promptness of communication and the perception of candidates regarding organizational responsiveness and professionalism.
- To determine the impact of the content of communication on the decision-making process of candidates with niche IT skills.
- To assess the long-term impact of positive communication in follow-ups on candidate referrals and organizational brand perception, even for unsuccessful candidates.

NEED FOR THE STUDY :

In the highly competitive niche IT skill recruitment market, candidate retention has now become an important factor in organizational success. The role of strategic follow-up communication in shaping the perception of candidates about an organization's professionalism and responsiveness in the recruitment process is significant. Professionals in niche IT skills are highly in demand and are usually extended multiple job offers. It is important to understand the impact of personalized communication in the candidate's selection process. This study intends to investigate the impact of strategic follow-up communication in candidate retention during the recruitment process, as per the primary objective of the research.

Moreover, it is important to identify the communication methods that are most effective in engaging niche IT candidates at different stages of the recruitment process. This also addresses the first secondary objective of the research. The study also intends to identify the perception of candidates regarding the value of personalized feedback and timely updates in the recruitment process. This addresses the second secondary objective. Moreover, the study also intends to identify the relationship between the timeliness of follow-up communication and candidates' perception regarding organizational professionalism and responsiveness. This addresses the third secondary objective.

SCOPE OF THE STUDY :

The scope of this study is restricted to the recruitment of IT professionals with specific skills sets in the field of IT, namely AI/ML professionals, cybersecurity professionals, and cloud computing professionals. The study focuses on the practices of follow-up communications during the entire recruitment process, from initial stages to final stages of recruitment. The sources of data collection for this study will be candidates who are undergoing the recruitment process for specific IT skills sets and recruitment professionals who are involved in the recruitment process for these candidates. The geographical scope of this study includes organizations that are functioning in specific regions, namely North America and Europe. The subsequent sections of this study will provide a detailed explanation of the literature review, research methodology, analysis and interpretation of the study findings, and implications of the study.

This study focuses on the effectiveness of the follow-up communication process adopted by recruitment firms in the placement of these highly sought-after candidates in the IT industry, in line with the major objective of evaluating the efficacy of strategic follow-up communication in retaining candidates. The geographical scope of this research would be limited to the regions where the recruitment agency actively recruits niche IT talent. In addition, the research would also examine the long-term impact of positive follow-up communication in terms of candidate referrals and employer branding, even for those candidates who do not make it to the final selection. Moreover, the research would also examine the impact of the timing of follow-up communication in relation to candidates' perceptions of organizational responsiveness and professionalism, as well as the impact of follow-up content on candidate decision-making.

REVIEW OF LITERATURE :

Recently, literature has also identified the significance of candidate-centric recruitment practices and communication in the recruitment process. Davis & Clark (2025) have discussed the evolution of the recruitment process from a transactional approach to a relational approach based on transparency and communication with the candidate in the recruitment process. Smith & Johnson (2024) have also discussed the evolution of the recruitment process from a relational approach to a relational approach based on communication with the candidate through emails and chatbots in the recruitment process. Nguyen & Chen (2025) have identified the importance of using artificial intelligence tools such as chatbots and predictive analytics in speeding up the recruitment process and communication with the candidate in the recruitment process to recruit technology professionals. Moreover, Kim & Lee (2024) have identified the significance of social media communication in the recruitment process.

There are many studies that have proven the significance of personalization, feedback, and communication in the decision-making process of candidates. Bennett & Harris (2024) found that personalization in communication has a significant positive impact on candidate satisfaction and employer branding. Another study was conducted by Garcia & Patel (2024) to show the significance of personalization in communication, especially in follow-up communication to recruit candidates with specific skills in a specific domain. Davis & Martinez (2024) found that feedback has a significant positive impact on the decision-making process of candidates in a competitive job market. Another study was conducted by Lee & Wilson (2023) to show the significance of communication in improving the candidate experience process. This idea was supported by another study conducted by Lee & Kim (2023), in which the researcher found a strong positive relationship using a meta-analytical method.

This is clearly seen in the study by Patel and Brown (2024) that clearly indicates that the chances of getting a referral and brand advocacy from the candidates are enhanced by a positive candidate experience. Brown and Wilson (2022) also clearly indicated that the chances of the candidates advocating for the organization to other people are enhanced if the candidates had a positive communication experience with the organization, even if they do not get the job they had applied for. Moreover, the importance of communication was also clearly seen in the study by Wilson and Taylor (2023) that clearly indicates the importance of communication in building trust between the organization and the candidates, thus enhancing the chances of a successful recruitment drive by the organization. The importance of employer branding was also clearly seen in the study by Moore and Clark (2022)

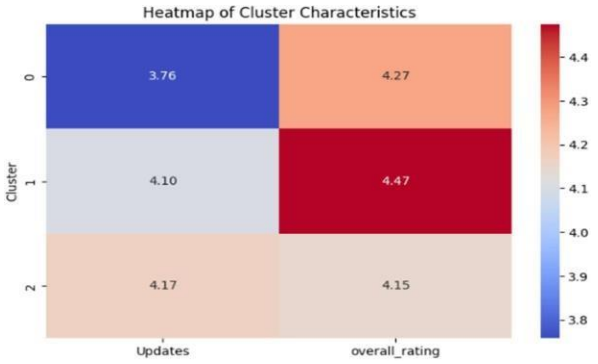
that clearly indicates that it is very crucial in shaping the perception of the candidates and enhancing the chances of the candidates accepting the job offer from the organization. The importance of communication was also clearly seen in the study by Rodriguez and Hernandez (2022) that clearly indicates the importance of a culturally sensitive communication approach.

RESEARCH METHODOLOGY:

Research Design study is descriptive. Data collected were both primary and secondary in nature. Primary data are collected through a structured questionnaire and secondary data are collected from various magazines , reputed journals, previous researches conducted etc. Sample Size is confined to 250 and convenience sampling which is a non-probability sampling techniques is adopted. Various statistical tools like chi square test, multiple linear regression, spearman's rack correlation, logistic regression and linear regression.

ANALYSIS & INTERPRETATION:

TABLE 1: Cluster Analysis of Communication Style and Engagement Metrics



Clusters	Preferred contact	Update frequency	Update Stage	Engagement
0	LinkedIn messaging	3.758065	Post-Interview	4.274194
1	Phone	4.102564	Post-Interview	4.474359
2	LinkedIn messaging	4.166667	Offer Stage	4.145833

TABLE 2 Preferred Contact Method on the basis of candidates' experience

Level	Email	LinkedIn messaging	Phone	Text
Entry Level	16	20	30	7
Lead Level	7	7	15	12
Mid Level	12	23	25	7
Senior Level	14	25	20	10

K-means clustering (k = 3) was used to categorize respondents based on their communication preferences, identifying distinct groups with differing preferred contact methods, average desired update frequencies (approximately ranging from 3.76 to 4.17), and specific recruitment stages where frequent updates were considered most important. These clusters also demonstrated variation in average engagement levels, with overall follow-up ratings ranging from about 4.15 to 4.47.A Chi-square test ($\chi^2 = 16.901$, $p = 0.153$) revealed no statistically significant relationship between preferred contact method and overall follow-up communication ratings. Furthermore, it was also found that Phone and LinkedIn messaging were the most favored communication channels for all levels of candidates, whereas Email and Text messaging were the least favored communication channels for the candidates.Another Chi-square test was performed to check the significance of the relationship between the candidates' primary skill level and their most favored communication channels for recruitment purposes.

From this Chi-square test, it was found that there was no significant relationship between the candidates' primary skill level and their most favored communication channels for recruitment purposes, as $\chi^2 = 13.909$ and $p = 0.126$.It was interesting to note that whereas Cluster 0 and Cluster 2 had found LinkedIn messaging as their most favored communication channels for recruitment purposes, there were differences found between Cluster 0 and Cluster 2 in terms of average desired frequency of updates (3.76 and 4.17), stages of updates considered most important (Post Interview and Offer Stage), and average engagement score (4.27 and 4.15).

Table 3: Multiple Linear Regression - Variance Inflation Factors

Feature	VIF
Satisfaction	12.470181
Personalized	10.25493
timely_feedback	109.0632
salary_job_details	104.036239
client_details	10.456596

In addition, Spearman rank correlation analysis showed that candidate satisfaction was statistically significantly and positively correlated with candidate satisfaction and perceived personalization ($\rho = 0.286$, $p < 0.001$), candidate satisfaction and perceived value of timely feedback ($\rho = 0.271$, $p < 0.001$), and candidate satisfaction and perceived importance of salary/job details ($\rho = 0.265$, $p < 0.001$). However, the Variance Inflation Factor (VIF) values

indicated that there was a high level of multicollinearity among the predictor variables in the regression model with regard to timely feedback and salary/job details (VIF = 109.06 and VIF = 104.04, respectively).

The results of the multiple regression analysis showed that the predictor variable of perceived personalization was a statistically significant predictor of candidate satisfaction (coefficient = 0.1524, p = 0.005). However, timely feedback, salary/job details, and client-related information did not show a statistically significant effect on candidate satisfaction in this study. This might have been due to the high level of multicollinearity that was present among the variables in the regression model, which might have made it difficult to show a statistically significant effect of timely feedback and salary/job details on candidate satisfaction, although timely feedback and salary/job details had shown a statistically significant.

Table 4: Candidates' Satisfaction - Spearman rank correlation

Relationship	Correlation Coefficient	P-value
Satisfaction vs. Timeliness	0.113	0.075
Satisfaction vs. Professionalism	0.136	0.032
Satisfaction vs. Responsiveness	0.17	0.007

The professionalism of Raad7 Informatics was ranked as the best in the communication style of Raad7 Informatics, followed by Responsiveness, and then Timeliness. This shows that all the candidates ranked Raad7 Informatics as high in professionalism. At the same time, it also shows that the least ranked was Timeliness in the communication style of Raad7 Informatics.Statistically significant positive monotonic relationship was established between Timeliness and Responsiveness by Spearman's rank correlation coefficient. This shows that even though the candidates ranked Responsiveness as a positive attribute in the communication style of Raad7 Informatics, it was ranked as a positive attribute in their communication style and was significant at 0.001.

Table 5: Feature Importance – Logistic Regression

Feature	Coefficient	Absolute Coefficient
FeedBack	0.148282	0.148282
Salary & Benefits	0.13261	0.13261
Technical Details Addressed	0.113973	0.113973
Insights on Client and Project	0.047684	0.047684
Personalisation	0	0

The monotonic relationship between Timeliness and Professionalism, which was found to be 0.106 with a p-value of 0.095, was not found to be statistically significant. Also, the relationship between Professionalism and Responsiveness was found to be 0.036, which was not found to be statistically significant since the p-value was 0.570. This shows that there was no significant relationship between these variables. This further shows that even though professionalism was rated the highest among all the variables, there was no significant relationship. However, timeliness has a positive effect on responsiveness.

The logistic regression model used to predict factors influencing the decision has been found to be 77.3% accurate. A very high bias was found since all the test data were classified as 'Influenced.' A classification report was obtained, which showed perfect recall but zero precision for 'Not Influenced.' A confusion matrix was obtained, which showed all instances were classified as 'Influenced.' The features which were found to be the most influential in the decision-making process were obtained from the L1-regularized logistic regression coefficients. They were found to be: Feedback (0.148), Salary & Benefits (0.133), Technical Details Addressed (0.114), Insights on Client and Project (0.048).

FINDINGS:

- K-means clustering for k=3 formed clusters for the respondents on the basis of communication preference, average desired frequency of updates ranging from 3.76 to 4.17, and primary stages in the recruitment process for the most important updates. The clusters were also formed on the basis of the level of engagement for the candidates with the communication. This was done on the basis of average ratings for the overall follow-up communication, ranging from 4.15 to 4.47.

- Chi-square test results were obtained to check the statistical significance for the difference between the most preferred mode of communication and ratings for the overall communication for the purpose of follow-up communication with the candidates. The results indicated that there was no significance between the two variables, as indicated by χ^2=16.901 and p=0.153.

- Primary skill levels for the candidates were also analyzed and indicated that Phone and LinkedIn messaging were the most favored for all levels, whereas Email and Text messaging were the least favored for the candidates.

- Spearman's rank correlation test was conducted to check the correlation between candidate satisfaction and primary skill levels for the candidates with the following variables: candidate satisfaction and personalization (ρ=0.286 and p<0.001), candidate satisfaction.

- The candidates rated the two factors highest in the aspect of Professionalism, followed by Responsiveness and then Timeliness, as indicated by the mean value of 3.91, 3.69, and 3.51, respectively. This indicates that the candidates perceive the hotel as very professional but somewhat lacking in timeliness.

- The linear regression analysis indicated that there is no significant relationship between the follow-up rating and the candidates' willingness to refer others to the hotel, as indicated by a coefficient value of -0.0244 and an R^2 value of 0.000 with a p-value of 0.737.

RECOMMENDATIONS:

The improvement of the timeliness of communication at all phases of the recruitment process can also lead to a better candidate experience and perception. More attention should also be given to the optimization of communication through the phone, given the high preference of candidates for communication through this medium, and recruiters should be trained to be more effective in communication with candidates. Another way to improve the candidate experience is to introduce a system of updates, especially at the post-interview phase, to manage candidate uncertainty better.

CONCLUSION:

The comprehensive feedback from candidates based on five major objectives provides valuable insights to improve the hiring process as well as candidate experience. Overall results consistently highlight the need to emphasize personalization and candidates' feeling of being understood in terms of candidate satisfaction, which supports existing literature on the need to adopt personalization approaches in talent acquisition.

While factors such as feedback, personalization of salary, and job-related information show positive correlations with candidate satisfaction, results from regression models reveal a dampening effect of these factors, which may be a result of multicollinearity between variables. Overall results strongly suggest the need to adopt personalization approaches in terms of candidate communication, ensuring that candidates feel understood throughout the hiring process, which is in line with candidate-centric approaches to talent acquisition.

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A Study On The Impact Of Movies And Webseries On Socio - Emotional Intelligence On Gen Z In Chennai

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ABSTRACT: The rise of digital media has resulted in an increase in the viewing and streaming of movies and web series, which is affecting the socio-emotional intelligence of youth in Chennai. The analysis was conducted by using a questionnaire for the age group between 15-30 years to understand the impact of media on the youth. The analysis also determines the impact of media, including its negative and positive effects, on the youth, such as their understanding and sensitivity towards emotions and maturity, and how it leads to desensitization and expectations and aggression. This study helps us understand how we, as parents and teachers, should promote and create more content for the better socio-emotional intelligence of our youth. The study also helps us understand how we should consume media to become well-rounded and emotionally intelligent individuals.

Keywords: Digital Media Consumption, Web Series, Socio-Emotional Intelligence. Emotional Maturity, Social Cognition, Desensitization, Aggressive Behavior, Media Psychology.

1. INTRODUCTION

Digital media is greatly impacting entertainment, and movies and web series are available on phones. Among the youth in Chennai, this is impacting their thoughts, emotions, and behavior. Movies and web series are not just for entertainment. They are for emotions, relationships, and life experiences. They are impacting young minds in terms of managing their own emotions.

Socio-emotional intelligence, or the ability to understand and manage emotions and empathize with other people, is very important in adolescence and young adulthood. Media influences can have a positive effect on emotional intelligence, empathy, and social skills, or a negative effect on behavioral development depending on what is being shown. Web series, due to their narrative extent, provide greater opportunities for emotional engagement than a movie, which can influence attitudes, values, and social interactions in the long run.

In the case of the city of Chennai, the availability of high-speed internet coupled with the urban lifestyle ensures the easy availability of digital media. The availability of both local and global content ensures the exposure of youth to multiple cultural perspectives, thereby affecting socio-emotional development. Such emotional connections with the character may have a positive or negative influence on the viewer.

Youth have the tendency to develop behaviors, attitude, and emotions based on the content of the digital media they are exposed to. Such content, if it promotes the development of compassion, teamwork, emotional intelligence, or other positive traits, may have a positive influence on the viewer, whereas the opposite may lead to negative influences.

This study aims to explore the influence of movies and web series on the socio-emotional intelligence of young people in Chennai. It is a significant area of investigation, as understanding the influence of such media on young people can help in promoting responsible media consumption among them. It can help in their socio-emotional development in a digitalized world.

2. REVIEW OF LITERATURE

A few research studies emphasize the increasing popularity of OTT platforms and web series among the young population of India. According to Anindita Chattopadhyay, "With the advent of affordable internet and smartphones, binge-watching has become popular. The psychological and social behavior of youth have been impacted because of this binge-watching habit. Kuldeep Kumar's research study revealed that web series have become one of the major sources of entertainment for youth. The storylines of web series have been creative and realistic. Makwana Anjana's research study revealed that excessive viewing of web series can lead to obsession among the young population of the country."

Research carried out by Hafiza Khadija Azeem indicates that crime content on platforms like Netflix may promote aggression, depression, and negative behavioral traits among the 15–25 age group of the youth population. Mahalakshmi U.N states that the COVID-19 pandemic saw a rise in the consumption of OTT content among students in the state of Tamil Nadu, and binge-watching had a negative impact on the health, academic, and

behavioral aspects of the students. Sakshi Singh Bais confirms that binge-watching OTT content may have a negative impact on sleep, increase anxiety levels, and reduce social interaction, thus the need for the audience to be aware of healthy viewing habits.

As per the study done by Tarini Khosla, the audience is moving from cinema to OTT platforms due to their convenience and affordability, and web series are replacing traditional cinema viewing. Pari Mehrotra's study revealed that the impact of Western web series on school-going teenagers was positive, as it influenced their academic life and higher education in Western countries, but did not promote any negative behaviors in their lives.From the above literature, it is revealed that although the content on OTT platforms is engaging and provides knowledge, the improper viewing of this content may have psychological, social, and behavioral impacts on the young **population.**

OBJECTIVES OF THE STUDY

The study centers on the consumption of movie content and web series by young people in Chennai, with particular reference to how content in this medium affects emotional awareness and management. The study further explores the effect of content in this medium on empathy and sociability, the impact of digital entertainment content in this medium on socio-emotional intelligence, and decision-making in relation to content in this medium for young people.

RESEARCH METHODOLOGY

The research design employed is descriptive research design to examine the influence of movies and web series on the socio-emotional intelligence of youth. The population is considered to be infinite. The data was collected through the snowball sampling method. Both primary and secondary data have been collected. The primary data was collected through structured questionnaires. The secondary data was collected through research articles and journals. The data was analyzed through percentage analysis. The research is focused on examining the emotional awareness of the youth. The research design is appropriate to understand the details of the research. The limitations of the research design employed in this research are that it is considered to be a non-random sampling method.

DATA ANALYSIS AND INTERPRETATION

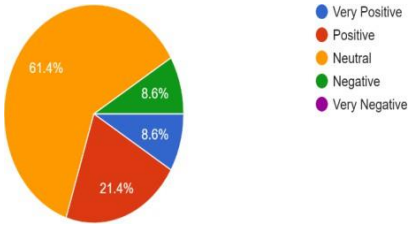
Table showing socio-emotional development of GEN Z

S NO.	PARICULAR	NUMBER OF RESPONDENTS	PERCENTAGE %
1	Very Positive	6	8.6 %
2	Positive	15	21.4 %
3	Neutral	43	61.4 %
4	Negative	6	8.6 %
5	Very Negative	-	-
Total		70	100%

INTERPRETATION:

It was found that the majority of the respondents, i.e., 61.4%, were found to be neutral about the topic, and the minority, i.e., 8.6%, were found to have a negative opinion about it.

Chart showing socio-emotional development of GEN Z



FINDINGS

Majority of the respondents (68.6%) belong to the age group 21-25. Out of the total respondents, 77.1% are female, and 22.9% are male. It is found that the majority of the respondents (65.7%) are students, followed by (28.6%) working professionals and (5.7%) are self-employed. It is found that the majority of the respondents (57.1%) watch movies and web series once a week. Out of the total respondents, 37.1% prefer YouTube, 30% prefer Disney+ Hotstar, and 30% prefer Netflix. Out of the total respondents, 41.1% prefer action/thriller, making it the most popular genre, followed by other genres like comedy, drama, romance, and social/inspirational.

The majority of the respondents, i.e., 54.3%, spend fewer than 3 hours per week watching movies or web series. Around 41.4% of the participants agree with the statement, which indicates a positive response. The responses show a tendency to agree with the statement, i.e., 41.4%, which indicates that watching movies and web series affects the behavior of the respondents in social situations. The majority of the respondents, i.e., 38.6%, agree with the statement that they feel more empathetic after watching emotional stories. The responses show a tendency to agree and neutral, i.e., 35.7%, which indicates that watching movies and web series moderately affect the mood and emotions of the respondents. The responses show a tendency to agree with the statement, i.e., 35.7%, which indicates that the respondents relate their experiences with the characters in the movie or web series.

The responses are inclined towards 'agree,' which is at 47.1%, indicating that viewing certain content motivates them to change their behavior or attitude. The responses are skewed towards 'agree,' which is at 41.1%, indicating

that movies and web series influence their opinion on relationships, friendships, and society. The responses are inclined towards 'neutral,' which is at 61.4%, indicating that movies and web series are seen to have a positive influence on the socio-emotional development of young people.

CONCLUSION

The study concludes that movies and web series have a moderate positive effect on the socio-emotional development of young people. The study reveals that most respondents consume these forms regularly, for entertainment, as well as to gain insights into emotions. The study reveals that watching movies and web series has an effect on empathy, relating to characters, and changing moods and behaviors to some extent. However, the study reveals some neutral responses, showing that this effect is not absolute and differs from person to person. Movies and web series can be considered as one tool for developing socio-emotional intelligence to some extent, depending on the nature of content viewed and interpretation made from it.

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MECHANICAL CHARACTERIZATION AND VIBRATION ANALYSIS OF FLAX FIBRE AND RICE HUSK REINFORCED POLYMER COMPOSITES: A REVIEW

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Abstract

Natural fiber reinforced polymer composites have gained increasing attention in recent years due to their environmental sustainability, low density, and good mechanical performance. Among various natural fibers, flax fiber possesses high tensile strength and stiffness, while rice husk, an agricultural waste material rich in silica, serves as an effective reinforcing filler in polymer matrices. The hybridization of flax fiber and rice husk can improve the mechanical and dynamic performance of composite materials. This review presents an overview of the mechanical characterization and vibration behavior of flax fiber and rice husk reinforced composites. The paper discusses the effects of fiber content, filler loading, and fabrication techniques on tensile, flexural, and impact properties. In addition, vibration characteristics such as natural frequency, damping ratio, and modal behavior of natural fiber composites are reviewed. The study highlights the potential of flax fiber–rice husk hybrid composites for lightweight structural applications in automotive, aerospace, and construction industries.

Keywords: Flax fibre, Rice husk, Natural fiber composites, Mechanical characterization, Vibration analysis, Hybrid composites.

Introduction

The increasing global concern for environmental sustainability and resource conservation has accelerated the development of eco-friendly engineering materials. Natural fiber reinforced polymer composites (NFRPCs) have emerged as promising alternatives to conventional synthetic fiber composites because of their low density, biodegradability, renewability, and cost effectiveness [1], [2]. Natural fibers such as flax, jute, hemp, kenaf, and sisal are widely used as reinforcement materials in polymer matrices due to their favorable mechanical properties and availability in large quantities [3], [4]. Compared with traditional glass fiber composites, natural fiber composites offer advantages such as reduced weight, improved acoustic and vibration damping properties, and lower environmental impact [5], [6]. These characteristics have led to their increasing adoption in various sectors including automotive, aerospace, construction, and consumer product industries [7], [8].

Among various natural fibers, flax fiber has attracted significant attention due to its excellent mechanical performance and high specific strength. Flax fibers possess relatively high tensile strength, good stiffness, and low density compared with many other plant fibers [9]. Studies have reported that flax fiber reinforced composites exhibit superior tensile and flexural properties, making them suitable for lightweight structural applications [10]. Furthermore, flax fibers demonstrate good vibration damping capability because of their complex microstructure and viscoelastic characteristics, which allow them to absorb and dissipate energy under dynamic loading conditions [11], [12]. Due to these advantages, flax fiber composites have been widely investigated for applications such as automotive interior components, sports equipment, and lightweight structural panels [13]. In addition to natural fibers, agricultural by-products and industrial waste materials are also being explored as reinforcement materials in polymer composites to improve sustainability and reduce environmental impact. Rice husk, an abundant by-product obtained during rice milling, is one of the most widely available agricultural residues worldwide [14]. It consists mainly of cellulose, hemicellulose, lignin, and a significant amount of silica, which contributes to improved hardness and stiffness when incorporated into polymer matrices [15]. Several researchers have reported that rice husk reinforced composites exhibit improved dimensional stability, wear resistance, and thermal properties compared with pure polymer materials [16]. Moreover, the utilization of rice husk in composite manufacturing

helps reduce environmental pollution and provides value to agricultural waste materials [17].

Hybridization of natural fibers with particulate fillers has recently become an effective strategy to enhance the performance of composite materials. Hybrid composites are produced by combining two or more reinforcement materials within a single polymer matrix to achieve improved mechanical and physical properties [18]. The combination of flax fiber and rice husk presents an attractive approach for developing sustainable composites with enhanced performance. In such systems, flax fibers mainly contribute to tensile strength and stiffness, while rice husk particles improve hardness, rigidity, and dimensional stability [19]. This hybrid reinforcement can also reduce material cost while maintaining acceptable mechanical performance [20]. Although significant research has been conducted on natural fiber composites, studies focusing specifically on flax fiber–rice husk hybrid composites remain relatively limited. In particular, comprehensive investigations on both mechanical characterization and vibration behavior of such hybrid systems are still scarce. Understanding these properties is essential for the design of lightweight composite structures capable of withstanding dynamic loading conditions [21], [22]. Therefore, this study aims to review the mechanical characteristics and vibration behavior of flax fiber and rice husk reinforced polymer composites and to highlight their potential for sustainable structural applications.

Natural Fiber Reinforced Polymer Composites

Natural fiber reinforced polymer composites (NFRPCs) are materials in which natural fibers are embedded within a polymer matrix to enhance the mechanical and physical properties of the base material. These composites have gained significant attention in recent years due to their environmental benefits, lightweight nature, and acceptable mechanical performance compared with conventional synthetic fiber composites [1], [2]. Natural fibers such as flax, jute, sisal, hemp, and kenaf are commonly used as reinforcements because they are renewable, biodegradable, and widely available in many regions of the world [3], [4]. The use of these fibers not only reduces the environmental impact associated with synthetic materials but also contributes to the development of sustainable engineering products.

In NFRPCs, the polymer matrix, which may include thermosetting resins such as epoxy and polyester or thermoplastic polymers such as polypropylene and polyethylene, acts as a binding medium that transfers load to the reinforcing fibers [5]. The overall performance of the composite depends largely on the fiber–matrix interaction, fiber orientation, fiber volume fraction, and the manufacturing process used during composite fabrication [6], [7]. Strong interfacial bonding between the fibers and the matrix is essential to ensure efficient stress transfer and improved mechanical performance.

Previous studies have demonstrated that natural fiber composites exhibit good tensile and flexural properties along with excellent vibration damping capability due to their internal cellular structure [8], [9]. Additionally, the incorporation of natural fibers can significantly reduce the density of composite materials while maintaining adequate structural strength, making them suitable for lightweight applications in automotive, construction, and consumer industries [10]. As a result, natural fiber reinforced polymer composites are increasingly being considered as sustainable alternatives to traditional synthetic fiber composites in modern engineering applications.

Flax Fibre Reinforced Composites

Flax fibre reinforced composites have attracted considerable attention in recent years due to their superior mechanical performance and environmental sustainability. Flax fibres are derived from the plant *Linum usitatissimum* and are considered one of the strongest natural fibres available for composite reinforcement. These fibres possess relatively high tensile strength, good stiffness, low density, and excellent specific mechanical properties when compared with many other natural fibres such as jute and sisal [23], [24]. Because of these characteristics, flax fibres are widely used in polymer composite applications where lightweight and eco-friendly materials are required.

The mechanical properties of flax fibre composites are influenced by several factors including fibre orientation, fibre volume fraction, fibre length, and the type of polymer matrix used. Studies have shown that proper alignment of flax fibres within the polymer matrix significantly enhances tensile and flexural strength of the composite material [25]. Furthermore, strong interfacial bonding between the fibre and matrix plays a crucial role in improving load transfer efficiency and overall composite performance [26]. Surface treatments such as alkali treatment are often used to improve fibre–matrix adhesion and to enhance mechanical properties.

Another important characteristic of flax fibre reinforced composites is their excellent vibration damping capability. The complex microstructure and viscoelastic nature of natural fibres allow them to dissipate vibrational energy more effectively than many synthetic fibres [27]. This property makes flax composites particularly suitable for applications where noise and vibration reduction is required, such as automotive interior components and structural panels. In addition to mechanical advantages, flax fibre composites also offer environmental benefits. They are renewable, biodegradable, and require

relatively low energy for production compared with synthetic fibres such as glass fibre [28]. Due to these advantages, flax fibre reinforced polymer composites have been increasingly used in automotive parts, sports equipment, and lightweight structural components. Continuous research efforts are focused on improving the durability, moisture resistance, and overall performance of flax fibre composites for broader industrial applications [29], [30].

4. Rice Husk Reinforced Polymer Composites

Rice husk is an abundant agricultural by-product generated during rice milling and has been widely studied as a reinforcing filler in polymer composites. Its composition includes cellulose, hemicellulose, lignin, and a significant amount of silica, which imparts improved stiffness, hardness, and thermal stability to the composite material [16], [17], [18].

The incorporation of rice husk into polymer matrices such as epoxy, polyester, and polypropylene enhances dimensional stability, wear resistance, and mechanical strength compared with neat polymers [5], [6]. Rice husk reinforced composites also provide an environmentally sustainable alternative to synthetic fillers, reducing material costs and promoting the utilization of agricultural waste [16], [18], [19].

The mechanical performance of rice husk composites is influenced by factors such as filler content, particle size, matrix type, and surface treatment of the husk. Optimal filler loading improves tensile, flexural, and impact properties, while excessive filler content can result in poor fiber–matrix adhesion and reduced composite strength [16], [20]. Additionally, rice husk acts as a lightweight filler, contributing to the production of low-density composites suitable for structural and semi-structural applications [14], [18].

Recent studies have explored hybrid composites where rice husk is combined with other natural fibers, such as flax or kenaf, to achieve a balanced combination of mechanical strength, hardness, and vibration damping [23], [27], [30]. These hybrid systems leverage the high tensile strength of fibers like flax and the rigidity of rice husk, creating a composite with enhanced performance for automotive, construction, and packaging applications. Overall, rice husk reinforced polymer composites represent a cost-effective, sustainable, and mechanically versatile material for modern engineering applications [16], [18], [30].

Hybrid Flax Fibre–Rice Husk Composites

Hybrid composites combining flax fibres and rice husk have recently emerged as a promising approach to enhance the overall mechanical and functional performance of polymer composites. In these hybrid systems, flax fibres primarily provide high tensile strength and stiffness, while rice husk contributes to hardness, rigidity, and dimensional stability [23], [24]. The combination leverages the complementary properties of the two reinforcements, resulting in a composite that offers superior strength-to-weight ratio compared with single-reinforcement systems [25], [26].

The performance of flax fibre–rice husk hybrid composites depends on factors such as fibre content, rice husk loading, fibre–matrix adhesion, and the fabrication method used. Studies have shown that proper optimization of fibre and filler ratios significantly improves tensile, flexural, and impact properties [27], [28]. Additionally, the inclusion of rice husk particles enhances wear resistance and thermal stability without substantially increasing the weight of the composite [29], [30].

Hybridization also positively affects dynamic behavior. The viscoelastic nature of flax fibres combined with the rigid silica-rich rice husk filler enhances vibration damping and energy absorption capabilities, making these composites suitable for applications where noise and vibration reduction are critical, such as automotive panels, construction panels, and lightweight structural components [23], [27], [30]. Overall, flax fibre–rice husk hybrid composites represent a cost-effective, eco-friendly, and mechanically versatile material with significant potential for sustainable engineering applications [24], [26], [29].

Material Testing of Natural Fiber Composites

Mechanical testing of natural fiber reinforced polymer composites (NFRPCs) is critical to evaluate their suitability for structural and semi-structural applications. Material testing not only determines the load-bearing capacity of the composites but also provides insights into their failure mechanisms, stiffness, toughness, and durability under different loading conditions. The primary mechanical tests conducted on flax, rice husk, and hybrid composites include tensile testing, flexural testing, impact testing, and hardness measurement.

1. Tensile Testing

Tensile testing is performed to determine the ultimate tensile strength, Young's modulus, and elongation at break of composites. Specimens are typically prepared according to standard dimensions, and a universal testing machine (UTM) applies axial load until failure. Tensile testing reveals the efficiency of stress transfer between the fiber and matrix, and the influence of fiber orientation, fiber volume fraction, and surface treatments on mechanical performance. Hybridization of flax fibers with rice husk often improves tensile strength by combining the high strength of flax with the stiffness of rice husk particles.

Figure 1: Specimen under tensile test

2. Flexural Testing

Flexural or bending tests evaluate the ability of composites to withstand bending loads. The three-point bending method is commonly used, where the specimen is supported at both ends while a central load is applied. Flexural strength and modulus provide information about the material's stiffness and resistance to deformation under bending. Hybrid composites typically exhibit enhanced flexural performance due to the synergistic effect of fiber and filler reinforcement.

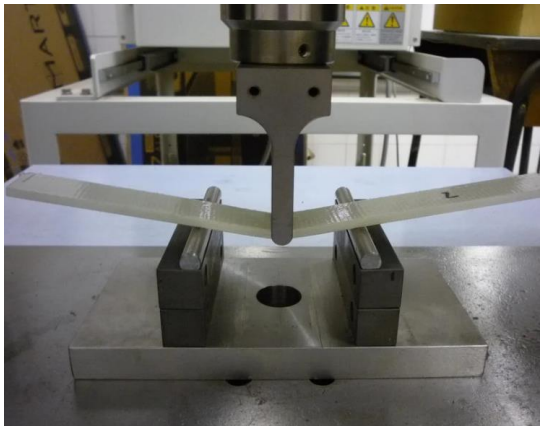

Figure 2: Specimen under Flexural test

3. Impact Testing

Impact testing measures the energy absorbed by a composite under sudden or dynamic loading, reflecting toughness and fracture resistance. Standard methods, such as Charpy or Izod impact tests, are employed. The combination of flax fibers and rice husk can enhance impact resistance, where flax provides flexibility and rice husk contributes rigidity, allowing the material to dissipate energy efficiently.

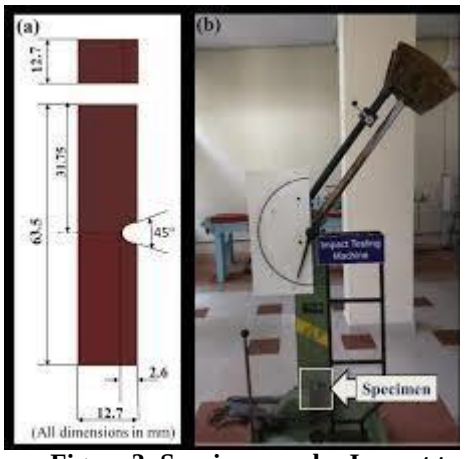

Figure 3: Specimen under Impact test

4. Hardness and Wear Testing

Hardness tests evaluate the resistance of composite surfaces to localized deformation. Techniques like Rockwell or Shore hardness tests are commonly applied. Wear testing can assess the surface durability of composites under sliding or abrasive conditions. Rice husk particles improve surface hardness and wear resistance, making hybrid composites suitable for applications where durability is critical.

Figure 4: Specimen under Hardness test

Mechanical Characterization of Natural Fiber Composites

Mechanical characterization is a crucial step in evaluating the performance of natural fiber reinforced polymer composites (NFRPCs), including flax fibre, rice husk, and their hybrid systems. Key mechanical properties include tensile strength, flexural strength, impact resistance, and hardness, which determine the suitability of these composites for structural and semi-structural applications [6], [8], [10].

Tensile testing evaluates the ultimate tensile strength and Young's modulus of composites under axial loading. It provides insight into the load-carrying capacity of the fibers and the efficiency of stress transfer from the matrix to the reinforcement [23], [27]. Flexural testing, often conducted via three-point bending, assesses bending strength and stiffness, critical for panels and beam-like structures

[4], [26]. Impact testing measures the ability of the composite to absorb energy under sudden loading, indicating toughness and fracture resistance [9], [29]. Hardness and wear tests are performed to evaluate surface durability, particularly in hybrid composites containing rice husk particles [1], [14]. The mechanical performance of NFRPCs depends strongly on fiber orientation, volume fraction, matrix type, and fiber–matrix interfacial bonding. Surface treatments, such as alkali or silane treatments, enhance interfacial adhesion and improve tensile, flexural, and impact properties [25], [26]. Hybridization of flax fibers with rice husk can balance strength, stiffness, and hardness, providing a cost-effective solution for lightweight structural applications [10], [27].

Mechanical characterization provides essential data for design, optimization, and application of natural fiber composites, ensuring reliable performance in real-world engineering structures [6], [20].

Vibration Analysis of Natural Fiber Composites

Vibration analysis is a critical aspect of evaluating natural fiber reinforced polymer composites (NFRPCs), particularly for applications where dynamic loading, noise, and energy dissipation are important, such as automotive, aerospace, and structural panels [3], [13]. Natural fibers like flax and rice husk exhibit viscoelastic behavior that allows them to absorb and dissipate vibrational energy more effectively than many synthetic fibers [27], [29]. This intrinsic damping property is influenced by fiber type, orientation, volume fraction, and the fiber–matrix interface [23], [27].

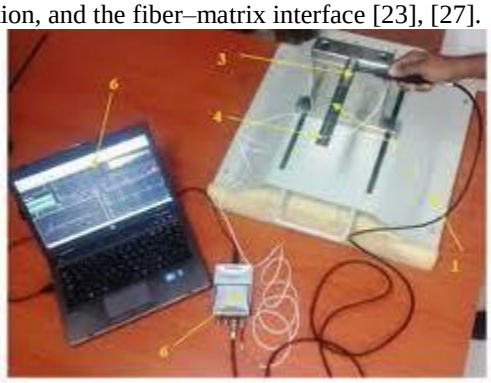

Figure 5: Specimen under Vibration test

Studies have shown that flax fiber composites exhibit superior vibration damping due to their internal cellular structure, which reduces amplitude under dynamic loads [4], [27]. The inclusion of rice husk particles in hybrid composites further enhances damping characteristics by increasing stiffness and improving energy dissipation at the microstructural level [1], [14]. Hybridization of flax fibers with rice husk achieves a balance between stiffness, strength, and damping, making these composites suitable for lightweight and vibration-critical applications [10], [30].

Experimental evaluation of vibration behavior typically involves modal analysis, natural frequency determination, and damping factor measurements. Results indicate that hybrid composites provide better vibration control than single-fiber systems, supporting their use in engineering applications that require both mechanical strength and dynamic performance [3], [13], [27]. Overall, understanding vibration characteristics is essential for the design and optimization of NFRPCs in practical applications [29], [30].

Research Gap

Despite significant advancements in natural fiber reinforced polymer composites, particularly flax and rice husk systems, several gaps remain. Most studies focus separately on either mechanical characterization or vibration analysis, with limited research on the combined performance evaluation of hybrid flax–rice husk composites. Additionally, the effects of fiber-matrix interface optimization, hybrid ratio, and long-term environmental aging on both mechanical and dynamic properties are not fully understood. There is also a scarcity of systematic studies correlating microstructural features with vibration damping behavior in hybrid composites. Addressing these gaps is essential to design high-performance, sustainable composite materials for engineering applications.

Conclusion

Natural fiber reinforced polymer composites, particularly those incorporating flax fibers and rice husk, have emerged as promising materials for sustainable and lightweight engineering applications. The literature indicates that flax fibers contribute high tensile strength, stiffness, and energy absorption, while rice husk imparts rigidity, hardness, and thermal stability. Hybridization of these two reinforcements offers a balanced combination of mechanical, thermal, and dynamic properties, making hybrid composites suitable for automotive, construction, and structural applications.

Mechanical characterization, including tensile, flexural, impact, and hardness testing, demonstrates that the performance of these composites is highly dependent on fiber content, orientation, matrix selection, and interfacial bonding. Surface treatments and optimization of hybrid ratios significantly enhance composite strength, stiffness, and durability. Moreover, the vibration analysis of natural fiber composites shows that their viscoelastic behavior and microstructural features allow for superior energy dissipation and damping capabilities, which is critical for applications subjected to dynamic loading and noise.

Despite these advantages, challenges remain in achieving consistent performance due to variability in natural fiber properties and processing

limitations. Long-term environmental effects, moisture absorption, and hybrid microstructure optimization require further investigation to ensure reliability in practical applications. Additionally, correlating mechanical and vibration properties with microstructural characteristics is an area that demands more focused research.

In conclusion, flax fiber and rice husk hybrid composites represent a cost-effective, eco-friendly, and mechanically versatile solution for modern engineering needs. Future research focusing on optimized hybrid design, surface treatments, and durability studies will be essential to fully exploit the potential of these sustainable composites and expand their industrial applications.

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DESIGN AND ANALYSIS OF TEE JOINT IN FDM 3D PRINTER USING PLA MATERIAL

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ABSTRACT

The design and analysis of Tee Joint represent a crucial aspect of engineering, particularly in structural applications and fluid flow systems. This project focuses on leveraging Fused Deposition Modelling (FDM) 3D printing technology using PLA (Polylactic Acid) material to fabricate Tee Joints. The objective is to explore the feasibility and efficacy of using additive manufacturing techniques to produce Tee Joints with enhanced geometrical complexities and customized designs. By employing PLA, a biodegradable and easily printable material, this study aims to demonstrate the potential of 3D printing in revolutionizing joint manufacturing and assembly processes.

The first phase of the project involves the design stage, where Tee Joint geometries are conceptualized and optimized using computer-aided design (CAD) software. The design phase includes leveraging CAD tools to refine Tee Joint geometries tailored to specific mechanical and structural performance requirements. Through iterative design modifications and optimization techniques, Tee Joint structures are developed to achieve optimal load distribution, strength, and durability. Following the design phase, ANSYS software is employed to analyze the structural behavior of the Tee Joint under various loading conditions. By simulating factors such as stress distribution, deformation, and fatigue life, ANSYS software helps identify potential structural weaknesses and optimize the Tee Joint geometry to enhance mechanical strength and stability.

Additionally, the study examines the impact of printing parameters such as layer height and infill density on the mechanical properties of the Tee Joint.

Keywords: Finite Element Analysis, Impeller, 3D Printing, Fused Deposition Modelling.

Introduction

Additive manufacturing is the process by which digital 3D design data is used to build up a component in layers by depositing material. It is opposite to subtractive manufacturing. Additive manufacturing is also known as “3D printing”. According to ASTM F42 additive manufacturing is defined as “the process of joining material to make object from 3D model data usually layer by layer as opposed to subtractive manufacturing methodologies”. Additive manufacturing allows for mass customization, reduced material waste, lower cost, increase efficiency compared to injection moulding, extrusion. Companies like GE and Boeing are swiftly and immediately replacing older technologies, processes and assembly lines with additive manufacturing due to the immense benefits it brings. Some of the reasons for this popularity include the fact that additive manufacturing offers remarkable efficiency, affordability, and quality for many different product designs. Figure 1 shows 3D printing working principle.

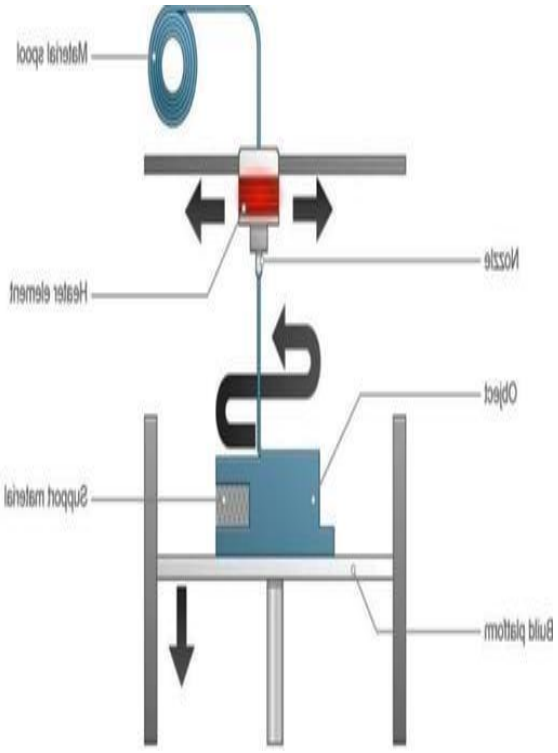

Figure.1 Material Extrusion

3D printing is a rapidly emerging technology that is now widely adopted across the globe. It is increasingly utilized for mass customization and the production of various open-source designs in industries such as agriculture, healthcare, automotive, locomotive, and aviation. This technology enables the fabrication of objects by depositing material layer by layer, directly from a Computer-Aided Design (CAD) model [1]. Advancements in tissue engineering and regenerative medicine have made it possible to restore damaged organs or tissues into fully functional structures through 3D bio printing [2]. Additionally, 3D printing facilitates the creation of intricate geometric shapes that can be mass-customized without the need for dies or molds. By leveraging direct digital manufacturing, design concepts are seamlessly transformed into physical products [3]. The additive layering process also allows multiple components to be integrated into a single structure, eliminating the need for post-assembly operations. Engineers are gradually embracing 3D printing technology, which is now extensively used in the medical, aerospace, and other industries [4]. The Finite Element Method (FEM) is often employed to simulate the 3D printing process of components like impellers, analysing residual stress, deformation, and other mechanical factors [5]. The numerical simulation results closely align with crack locations observed in 3D printing experiments. Furthermore, integrating artificial intelligence (AI) with 3D printing can enhance structural efficiency by minimizing external diffusion and simplifying separation from heterogeneous reaction systems [6].

Material and Methods

PLA (Polylactic Acid) is a biodegradable thermoplastic derived from renewable resources such as cornstarch or sugarcane. Known for its eco-friendly nature, PLA has gained popularity in various industries due to its versatility, ease of use, and sustainability. With a low melting point and minimal warping during printing, PLA is widely utilized in 3D printing, making it an ideal choice for hobbyists, educators, and professionals alike. PLA emits fewer fumes and odors compared to other plastics, ensuring a safer and more pleasant printing environment.

Table 1. Properties of PLA

Parameters	**Values**
Density	1.3 g/cm^3
Young's Modulus	3.5 GPa
Elongation limit	6.0%
Strength to weight ratio	38 kN-m/kg
Tensile strength (UTS)	50 Mpa
Shear Modulus	2.4 Gpa

3D Modelling

A 3D printer can produce different manufacturing prototypes, apparel and jewellery, prosthetics, 3D

sculptures, aircraft components and even human organs like bone marrow, bio printing human tissue with different hundreds of other materials. Over different software's like CAD, CATIA, SOLIDWORKS a digital model is created. CAD (Computer-Aided Design) is the use of computer software to create, modify, analyze, and optimize designs for products or buildings. CAD software is commonly used in engineering, architecture, product design, and manufacturing. The benefits of CAD design include faster design iterations, improved accuracy and precision, greater consistency, and the ability to visualize designs in 3D. CAD software also enables collaboration between team members and the sharing of design files across different platforms. CAD design typically involves creating 2D or 3D models of the desired object or structure. The software provides a range of tools and features to help the designer create the model, including geometric shapes, lines, curves, and text. Once the model is complete, it can be analyzed and modified to optimize its performance and functionality. Overall, CAD design is a powerful tool that helps designers and engineers create and refine their designs quickly and efficiently, leading to improved product quality, reduced costs, and faster time-to-market. In CATIA software, creating a 3D drawing of an impeller involves several steps to accurately represent its geometry and internal features. First, engineers typically start by defining the overall dimensions and specifications of the impeller, including blade profiles, hub diameter, and inlet/outlet configurations. Using CATIA's sketching tools, designers then create 2D profiles of the impeller blades and hub, ensuring symmetry and alignment. Once the 2D profiles are defined, they are extruded or revolved to generate solid volumes, forming the basic shape of the impeller. CATIA's parametric modeling capabilities allow for easy adjustments to dimensions and parameters, facilitating iterative design refinements. Engineers can then use CATIA's surfacing tools to add additional features such as fillets, chamfers, and flow channels to optimize the impeller's aerodynamic performance. Figure 2 and 3 shows the 2D and 3D model of the T joint.

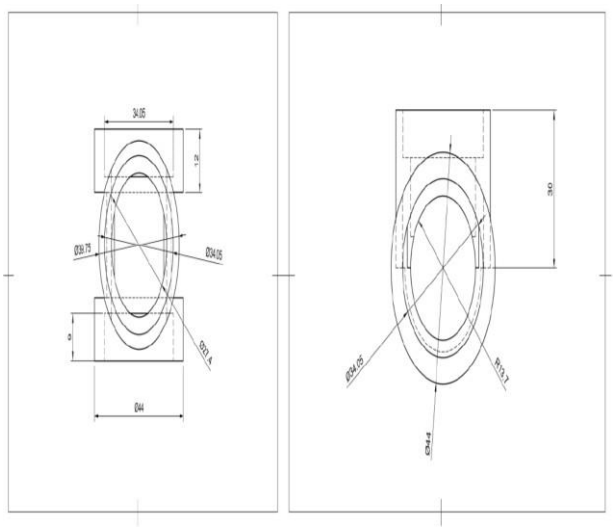

Figure 2. 2D View of T joint

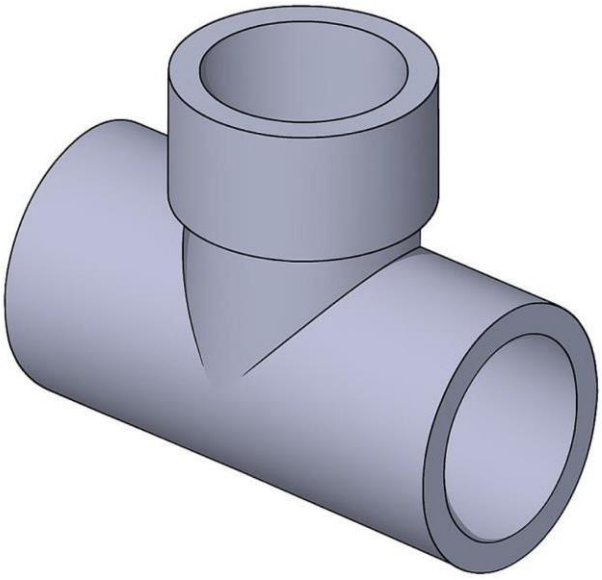

Figure 3. 3D View of TEE Joint

3D Printing

After slicing a 3D model using slicing software, the resulting file is usually saved in a format that is compatible with the specific 3D printer being used. This file can then be loaded into the 3D printer and the printing process can begin. During the printing process, the 3D printer reads the file and uses it as a set of instructions to create the physical object. The printer moves a print head, or extruder, along a specific path, depositing material in layers to build up the object.

The slicing software determines the specific path that the printer will follow, based on the desired resolution, infill density, and other settings specified by the user. The software also calculates the amount of material needed to create the object and generates support structures as needed to ensure that the object is stable during the printing process. Once the printing is complete, the object can be removed from the printer and any support structures can be removed as well. The final result is a physical object that matches the original 3D model. For printing we have choosed creality ENDER3 printer. Some of the key features of the printer are Build Volume: The Ender 3 has a build volume of 220 x 220 x 250 mm, which is large enough to print most small to medium-sized objects. Print Quality with a resolution of up to 100 microns, the Ender 3 can produce high-quality prints with intricate details. The Ender 3 is an open-source 3D printer, which means that users can modify and customize the printer to suit their needs. The printer comes partially assembled, and it is relatively easy to put together even for those with limited technical knowledge. The Ender 3 is compatible with PLA, ABS, TPU. The Specification of printer as shown in table 2. The various stages of 3D printing shown in figure 4 to7.

Table 2. The specifications of the printer

Parameters	**Values**
Modeling Technology	FDM (Fused Deposition modeling)
Printing Size	220*220*250 mm
Machine Size	440×410×465 mm
Max Travelling Speed	180 mm/s
Filament Diameter	1.75 mm
Filament Materials	ABS, PLA, TPU
Input	AC 100-265V,50-60 Hz
Output	DC 24V,15A,360W
Nozzle Diameter	0.4 mm
Precision	+/- 0.1mm
Max Nozzle Temperature	255℃
Max Hotbed Temperature	110℃

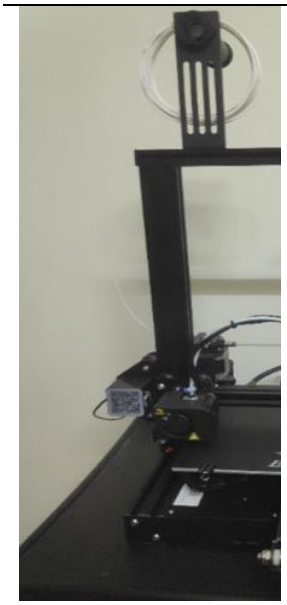

Figure 4.3D Printing Machine

Figure 5.T Joint Printing in starting Stage

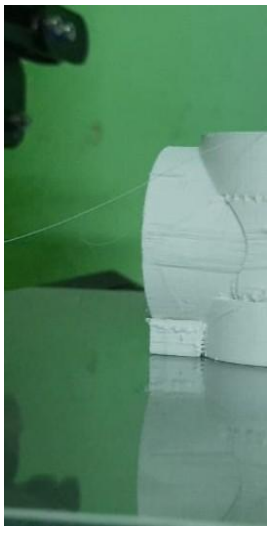

Figure 6.T joint Printing in Progress

Figure 7.Finshed Component

Finite Element Analysis

Overall, the 3D printing process with ABS filament can

produce high-quality, durable objects with a range of colors and finishes. However, ABS can emit fumes during printing, so adequate ventilation is recommended. ABS also tends to warp or crack more easily than PLA, so proper bed adhesion and temperature controls are important. ANSYS announces engineering analysis software across a scope of practices like FEM (finite element analysis), computational fluid dynamics (CFD), explicit and implicit methods, structural analysis etc. This computer simulation product maintains finite elements to represent behavior, supports material models and solve equation for a wide range of mechanical design problems. The total deformation, shear stress and equilibrium stress of ABS and PLA impeller is evaluated and correlated with each other.

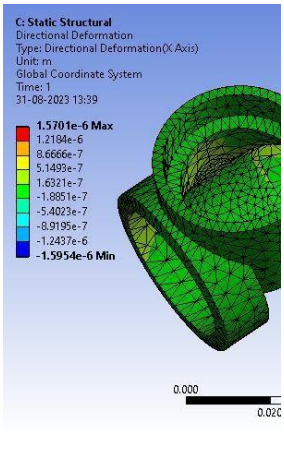

Figure 8. Total Deformation

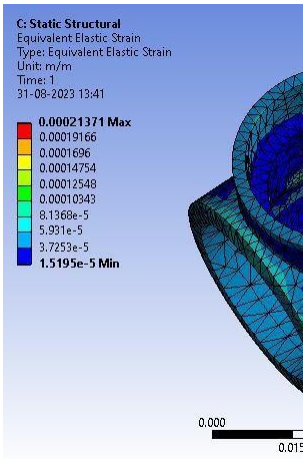

Figure 9. Elastic Strain

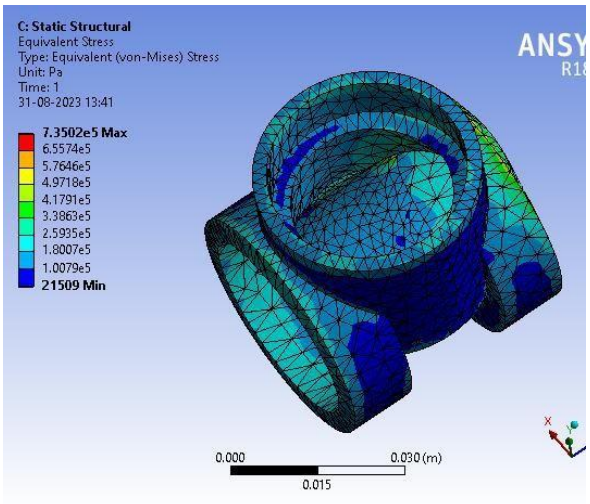

Figure 10. Von Mises Stress

Results and discussion

Results are obtained from ANSYS software. From the Figure 8, the direction deformation is 1.5954 mm. From the Figure 9, The value of Equivalent Elastic Strain is 1.5195. From the Figure 10, The value of equivalent (Von-Mises) Stress for the Impeller is 7.35 MPa. In the discussion of the project "Design and Analysis of Impeller in FDM 3D Printer Using PLA Material," it's crucial to address the significance of leveraging FDM 3D printing technology and PLA material in impeller design. FDM 3D printing offers unique advantages such as rapid prototyping, design flexibility, and cost-effectiveness, allowing for the creation of complex impeller geometries with reduced lead times and manufacturing constraints [7]. PLA material, known for its biodegradability, ease of printing, and compatibility with FDM printers, proves to be a suitable option for prototyping impellers, especially in applications where environmental sustainability and material safety are prioritized [8].

The discussion should delve into the implications of the analysis results obtained through computational tools like ANSYS software. By conducting structural analysis and computational fluid dynamics simulations, valuable insights into impeller performance, structural integrity, and fluid dynamics characteristics are gained [9]. These insights can inform design optimizations, material selections, and operational considerations to enhance impeller efficiency, reliability, and longevity [10]. Overall, the discussion highlights the synergistic relationship between advanced manufacturing techniques, material science, and computational analysis in the pursuit of innovative impeller designs with enhanced performance and sustainability [11].

Conclusion

This work, Analysis of T joint in FDM 3D Printer Using PLA Material has successfully demonstrated the feasibility and effectiveness of utilizing FDM 3D printing technology with PLA material in impeller

design. Through meticulous design iterations, computational analysis using ANSYS software, and practical experimentation, valuable insights into impeller performance, structural integrity, and fluid dynamics characteristics have been gained. The work underscores the potential of additive manufacturing techniques to revolutionize turbo machinery engineering, offering opportunities for rapid prototyping, customization, and optimization of impeller designs. Moving forward, further research and development in this area hold promise for advancing the efficiency, reliability, and sustainability of impeller systems in various engineering applications.

Future Scope

The future scope of the design and analysis of T joint in FDM 3D printing using PLA material is promising and multifaceted. Firstly, ongoing advancements in additive manufacturing technologies, such as improved printer resolution, faster printing speeds, and expanded material options, will enhance the capabilities and versatility of FDM 3D printers. This will enable engineers to create even more intricate and optimized impeller designs with finer details and higher resolution, further enhancing fluid dynamics performance and efficiency.

Moreover, as research continues to explore the mechanical properties and performance characteristics of PLA material, opportunities for material enhancements and formulations tailored to specific engineering applications will arise. This could lead to the development of PLA composites with enhanced strength, heat resistance, and chemical stability, expanding the range of applications for PLA-based impellers in industries such as aerospace, automotive, and biomedical engineering. Additionally, advancements in computational analysis techniques, such as artificial intelligence and machine learning algorithms, will enable more sophisticated simulations and optimizations of impeller designs, accelerating the innovation and evolution of turbo machinery systems.

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Artificial Intelligence in Biomaterials for medical implantation - Comprehensive Review

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Abstract

The importance of biomaterials lies in their fundamental roles in medical applications such as tissue engineering, drug delivery, implantable devices, and radiological phantoms, with their interactions with biological systems being critically important. In recent years, advancements in deep learning (DL), artificial intelligence (AI), machine learning (ML), supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL) have significantly transformed the field of biomaterials. These technologies have introduced new possibilities for the design, optimization, and predictive modeling of biomaterials. This review explores the applications of DL and AI in biomaterial development, emphasizing their roles in optimizing material properties, advancing innovative design processes, and accurately predicting material behaviors. We examine the integration of DL in enhancing the performance and functional attributes of biomaterials, explore AI-driven methodologies for the creation of novel biomaterials, and assess the capabilities of ML in predicting biomaterial responses to various environmental stimuli. Our aim is to elucidate the pivotal contributions of DL, AI, and ML to biomaterials science and their potential to drive the innovation and development of superior biomaterials. It is suggested that future research should further deepen these technologies' contributions to biomaterials science and explore new application areas.

Keywords:
artificial intelligence; machine learning; deep learning; biomaterials; tissue engineering; material optimization.

1. Introduction

Biomaterials are materials designed to interact with biological systems for medical purposes such as implants, prosthetics, and tissue engineering. They play an essential role in restoring or replacing damaged tissues and organs. Examples include metals, ceramics, polymers, and composites used in orthopedic implants, dental implants, cardiovascular stents, and artificial joints.

Artificial Intelligence (AI) has emerged as a powerful technology that significantly enhances biomaterial research and development. AI methods such as **machine learning (ML), deep learning (DL), and data-driven modeling** help scientists analyze complex biological interactions, optimize material properties, and predict the performance of implantable materials.

Traditionally, biomaterial development relied heavily on trial-and-error experimentation. This process was time-consuming, expensive, and inefficient. AI now accelerates the discovery and optimization of biomaterials by analyzing large datasets and predicting outcomes before experimental validation.

The integration of AI with biomaterials is transforming medical implantation by enabling personalized implants, improved biocompatibility, and enhanced durability.

This ability to generate novel biomaterials opens avenues for innovation and accelerates the discovery of materials with enhanced biocompatibility and performance . ML also plays a critical role in image analysis and interpretation in the biomaterial field. Medical imaging techniques produce vast amounts of complex data, which can be challenging to interpret accurately.

By utilizing ML algorithms, researchers can analyze and classify images, aiding in the diagnosis, monitoring, and treatment of diseases. Additionally, ML algorithms can be applied to image-based analysis of biomaterials, enabling rapid evaluation of material performance and integrity . ML offers significant benefits in biomaterials research, yet it faces challenges such as limited data availability and quality. Developing robust ML models requires standardized, large-scale datasets, and expertise in model interpretation and validation due to their complexity. Ethical considerations, including data privacy and bias, are critical in healthcare

applications. Looking forward, ML's future in biomaterials research promises advancements as datasets improve, enhancing model accuracy and reliability. Moreover, integrating ML with emerging technologies like nanotechnology and bioinformatics will synergistically advance biomaterials research .

2. AI-driven biomaterial design:

The fundamental concept behind AI-driven biomaterial design is to use intelligent algorithms that can **learn from large datasets and generate optimized material designs** for specific medical applications.

2.1 Data Collection and Integration

The first step in AI-driven biomaterial design is the collection of multimodal data from various sources. These include:

- Material composition databases
- Mechanical property datasets
- Biological interaction data
- Medical imaging and patient data
- Experimental research results

These datasets are integrated into a centralized platform where AI models analyze them to understand relationships between material structure, performance, and biological responses**.**

2.2 Machine Learning Model Development

Machine learning models are trained using the collected datasets. These models learn patterns that relate material properties to implant performance. Common algorithms used include:

- Decision Trees
- Random Forest
- Support Vector Machines
- Neural Networks

Once trained, these models can predict how new biomaterials will behave under specific biological conditions.

2.3 Material Prediction and Screening

AI models can quickly evaluate thousands of potential biomaterial combinations. The system predicts important characteristics such as:

- Biocompatibility
- Mechanical strength
- Degradation rate
- Toxicity levels
- Surface interaction with cells

Only the most promising materials are selected for further experimental testing. This process significantly reduces the number of laboratory experiments required.

3. Design Optimization

AI algorithms can also optimize biomaterial structures. For example, they can adjust parameters such as:

- Porosity of scaffolds
- Surface roughness of implants
- Chemical composition
- Mechanical stiffness

Optimization techniques such as genetic algorithms and Bayesian optimization help identify the best possible design for specific medical applications.

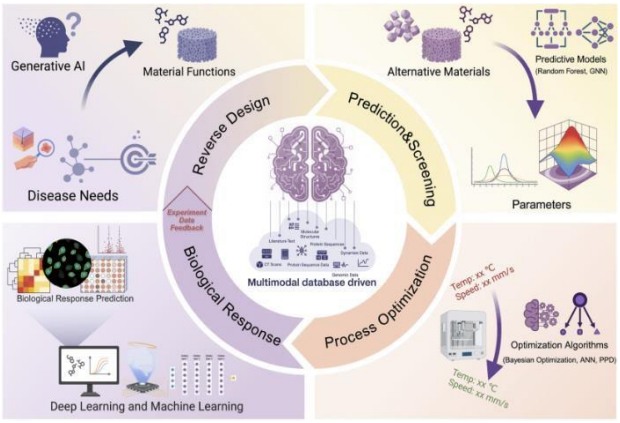

Figure: 3.1 Artificial Intelligence Frameworks for Predictive Biomaterial Engineering

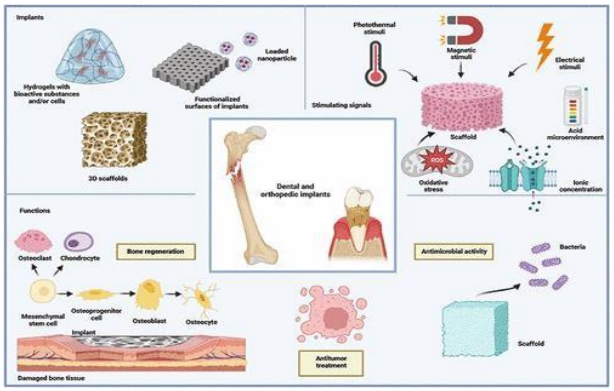

Figure 3.2: Advanced Biomaterial Implants and Scaffolds for Tissue Engineering

4. Key Design Parameters in AI-Driven Biomaterials

Several important parameters are considered when designing biomaterials using AI:

✓ Mechanical Properties

The implant must have appropriate strength, elasticity, and durability to withstand physiological loads.

✓ Biocompatibility

AI predicts whether a material will trigger immune reactions or toxic responses in the human body.

✓ Surface Characteristics

Surface texture and chemical properties influence how cells attach and grow on the implant.

✓ Degradation Rate

For biodegradable implants, AI models determine the appropriate rate at which the material should degrade inside the body.

✓ Porosity and Structure

Porous structures allow nutrients and oxygen to reach surrounding tissues, promoting tissue regeneration.

5. Concept of Biomaterial Optimization

Biomaterial optimization refers to the process of improving the physical, chemical, and biological properties of materials used in medical implants. The goal is to ensure that the material interacts safely with the human body while maintaining structural stability.

Optimization techniques help researchers determine the most suitable material characteristics such as:

- Mechanical strength
- Surface roughness
- Porosity and structure
- Degradation rate
- Biocompatibility

AI algorithms analyze experimental data and identify patterns that influence these properties. This helps researchers design biomaterials that provide better integration with human tissues and improved implant durability.

6. AI Techniques Used for Biomaterial Optimization

6.1 Machine Learning Algorithms

Machine learning is one of the most commonly used AI techniques in biomaterial optimization. These algorithms learn from existing datasets and predict material performance under different conditions.

Some widely used machine learning algorithms include:

- Decision Trees
- Random Forest
- Support Vector Machines
- Artificial Neural Networks

These models can analyze relationships between material composition and biological responses, enabling researchers to identify optimal material combinations.

6.2 Deep Learning Methods

Deep learning is a subset of machine learning that uses multilayer neural networks to analyze complex datasets. Deep learning techniques are particularly useful for studying biological interactions between cells and biomaterial surfaces.

Deep learning models can process large datasets such as **microscopic images, molecular structures, and experimental measurements**. This helps scientists understand how biomaterials influence cell growth, tissue regeneration, and immune responses.

6.3 Genetic Algorithms

Genetic algorithms are optimization techniques inspired by the process of natural evolution. They are used to search for the best possible biomaterial design by repeatedly modifying and evaluating different material parameters.

The algorithm begins with a population of possible material designs. Through processes such as **selection, crossover, and mutation**, the algorithm generates improved designs over multiple iterations. This method helps identify biomaterials with optimal mechanical and biological properties.

6.4 Bayesian Optimization

Bayesian optimization is another advanced technique used to optimize biomaterial design. This method predicts the most promising material combinations while minimizing the number of experiments required.

Bayesian optimization uses probabilistic models to estimate the performance of different materials and selects the best candidates for further testing. This approach significantly reduces research time and cost.

7. Applications of AI-Driven Biomaterial Optimization

Orthopedic Implant Design

Figure:3 Orthopedic implants icons set outline . Surgery replacement Pro Vector

AI optimization techniques help improve the design of orthopedic implants such as hip and knee replacements. By analyzing mechanical stress distribution and bone compatibility, AI models can suggest materials that provide better durability and reduced implant failure.

Dental Implant Development

In dental implants, AI is used to optimize surface texture and chemical composition to promote better bone integration. Improved surface characteristics enhance the stability and longevity of dental implants.

Tissue Engineering Scaffolds

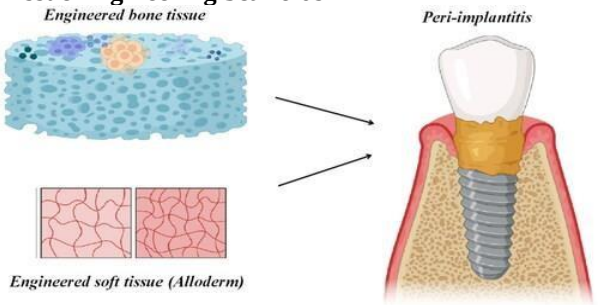

Figure:4 Hard and soft tissue engineering for peri-implant defects

AI-based optimization techniques are widely used in designing scaffolds for tissue regeneration. The algorithm determines the best scaffold structure, pore size, and material composition to support cell growth and tissue repair.

Drug-Delivering Biomaterials

Some biomaterials are designed to release drugs gradually inside the body. AI optimization helps determine the ideal material composition and degradation rate to control drug release effectively.

8. Advantages of AI-Driven Biomaterial Optimization

AI-based optimization offers several important advantages:

8.1 Faster Research and Development

AI reduces the time required to identify suitable biomaterials by quickly analyzing large datasets.

8.2 Reduced Experimental Costs

By predicting material performance, AI minimizes the number of laboratory experiments needed.

8.3 Improved Accuracy

AI models provide highly accurate predictions about material properties and biological interactions.

8.4 Enhanced Implant Performance

Optimized biomaterials show improved strength, durability, and compatibility with human tissues.

8.5 Personalized Medical Solutions

AI can design patient-specific biomaterials based on medical imaging and individual anatomical data.

8.6 Challenges in AI-Based Biomaterial Optimization

Although AI offers significant advantages, several challenges still exist. One major challenge is the availability of large, high-quality datasets required for training AI models. Without sufficient data, prediction accuracy may decrease.

Another challenge is the complexity of biological systems. Human tissues and immune responses are highly complex, making it difficult for AI models to fully capture all biological interactions.

Additionally, AI-generated biomaterials must undergo strict **regulatory approval and clinical testing** before they can be used in medical implants.

9. Inorganic Materials

The landscape of inorganic materials research is undergoing a revolutionary transformation driven by the integration of ML and AI. Unlike traditional methods, which often rely heavily on trial and error, these advanced computational techniques offer a more efficient and systematic approach to material discovery and optimization.

The study presents a machine learning framework designed to predict various properties of inorganic materials, including both crystalline and amorphous structures. The framework utilizes a diverse set of chemical attributes and a unique grouping method to enhance predictive accuracy. The results demonstrate its effectiveness in predicting properties such as band gap energy and glass-forming ability, showcasing the potential of ML in materials science. Dataset's Chemical Diversity Limits the Generalizability of Machine Learning Predictions: Highlighting the limitations of existing datasets like QM9 introduces the PC9 dataset from the PubChemQC project, which offers greater chemical diversity. Testing various ML models, including Kernel ridge regression and neural networks on both datasets revealed that PC9 provided higher energy prediction accuracy, emphasizing the importance of chemical diversity in training data for generalizable ML predictions. Another study combined high-throughput molecular dynamics simulations with machine learning to predict the elastic properties of silicate glasses. The ANN emerged as the most accurate model, while the LASSO algorithm provided a simpler, more interpretable model. The method's versatility allows its application to other properties and systems, illustrating its broad potential in the field . Addressing the challenge of sparse datasets, this research employed Gaussian process regression (GPR) to predict Young's modulus in silicate glasses. GPR outperformed neural networks in avoiding overfitting and provided a reliable quantification of prediction accuracy, demonstrating its advanced capability in developing functional materials . Focusing on biomedical glasses used in healthcare, the research introduces an ensemble machine learning model to predict and control the dissolution behavior of these materials in biological fluids. This approach aims to meet the demand for glasses with precise degradation rates, offering a path towards optimized glass compositions and improved performance in medical applications . In the primary applications of ML models for biomedical glasses are detailed, including the prediction of time-dependent biomedical glass dissolution behavior and the optimization of biomedical glass composition.

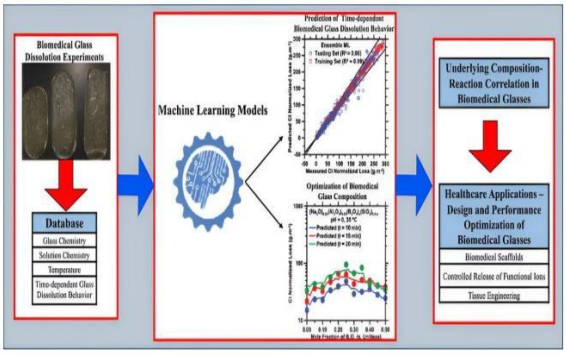

Figure 9.1: of the ML applications for biomedical glass.

Drawing inspiration from millennia of natural design exploration, one study employed advanced computational algorithms to create innovative designs based on diatom structures. Central to the study is the training of a VQGAN neural network with diatom structure data, enabling it to meticulously replicate the intricate architectural details through extensive training epochs. Furthermore, the integration of the VQGAN model

with CLIP, a versatile image classifier, allows for the interpretation of textual prompts to generate corresponding 3D models. These models are then physically realized using additive manufacturing technology. The methodology not only explores various biological design cues but also implements systematic optimization to achieve specific design objectives, integrating a diverse array of material design sets . Another research study focuses on detecting cancer biomarkers by analyzing odor-evoked calcium responses in the rat olfactory bulb . By employing neural networks and transfer learning from simulated data, this research aims to improve the accuracy of recognition. This approach has the potential to contribute to more effective cancer detection methods and diagnostic tools, enhancing early diagnosis and treatment strategies. The neural networks are trained to recognize specific patterns in the calcium responses, which correlate with the presence of cancer biomarkers, thereby offering a novel and innovative way to identify cancer at its early stages. Figure indicates that exhaled air is sampled and analyzed via intravital calcium imaging in the olfactory bulb glomeruli, producing raw video data. These data are pre-processed into a tensor format and then encoded by a neural network into an encoding vector. The process includes encoding exhaled air samples from healthy individuals and those with cancer biomarkers, followed by calibration. Unknown air samples are encoded and tested, with a k-nearest neighbors (kNN) algorithm classifying the samples as either healthy or cancerous, thereby enhancing detection accuracy.

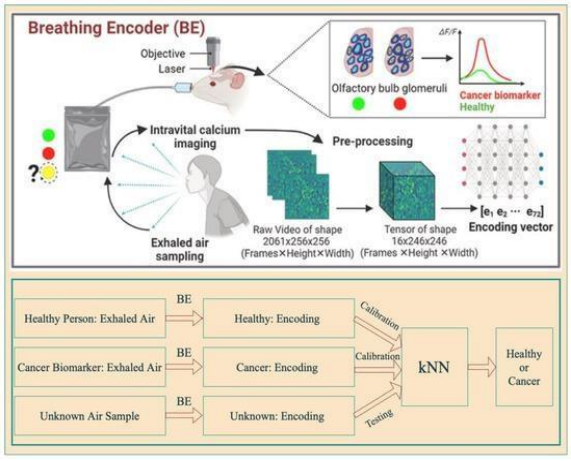

Figure9.2: Diagram of the bio-hybrid method for detecting cancer biomarkers in exhaled human air.

10. Discussion

The integration of ML, DL, and AI into biomaterials research has revolutionized the field, offering unprecedented capabilities for material design, optimization, and predictive modeling. This section synthesizes the findings from various studies and discusses the broader implications, challenges, and future directions for the application of these technologies in biomaterials.

Simulation systems are also crucial in the training of AI and ML. The simulation systems used must be well-established in the literature. Particularly in data acquisition, Monte Carlo-based simulation systems play a significant role in the radiological data acquisition of biomaterials. These simulations are critical for predicting the interactions of biomaterials with biological systems and understanding the outcomes of these interactions . Monte Carlo methods are used to comprehend the behaviors and probability distributions of complex systems, providing the necessary data to optimize the performance of biomaterials. Additionally, although the process of experimental data acquisition is laborious, it is essential for understanding how biomaterials behave under real-world conditions . Investigating the radiological properties of biomaterials in laboratory conditions enables the development of production and application processes . These laboratory studies contribute to the development of reliable and effective products by examining the behavior of biomaterials under various radiological conditions. By combining experimental data with simulation results, more comprehensive and reliable models can be created . In this way, all stages necessary for ensuring the safe and effective use of biomaterials in clinical applications are carefully planned and optimized. Consequently, the combination of simulation and experimental data, which allows AI and ML to conduct broader and more in-depth research in the field of biomaterials, will lead to significant advancements in material science and medicine.

11. Impact on Biomaterials Research

Machine learning techniques have significantly advanced the study of polymers, metals, composites, and inorganic materials. For instance, the use of databases like Citrination and The Materials Project has enabled researchers to explore extensive chemical descriptors, leading to a better understanding of the properties and behaviors of different metal compositions. In the realm of biomedical applications, ML algorithms like random forest classifiers have achieved remarkable accuracy in predicting the behavior of nanoparticles, facilitating their use in medical contexts.

Similarly, ML has transformed the design and discovery of polymer-based biomaterials. Techniques such as LAD regression and QSAR models have optimized gene delivery systems and predicted protein adsorption on biodegradable polymers. High-throughput methods and projects

like the Polymer Genome have further accelerated the discovery and optimization of novel polymers with desired properties. In composite materials, ML approaches, including statistical models and deep learning, have enabled the prediction of elastic localization, structural properties, and mechanical behaviors. These advancements have facilitated the design of bioinspired hierarchical composites and nanocomposites optimized for specific applications. For inorganic materials, ML frameworks have predicted various properties, including band gap energy and glass-forming ability. The importance of chemical diversity in training data for generalizable predictions has been highlighted, emphasizing the need for diverse datasets to improve ML model accuracy.

12. Challenges and Limitations

Despite the significant advancements, several challenges and limitations hinder the full potential of ML and AI in biomaterials research.

The development of robust ML models requires large, high-quality datasets . However, the field of biomaterials often faces limitations in terms of standardized, large-scale datasets. Ensuring data quality and consistency is crucial for the reliability of ML predictions.

ML models, particularly deep learning models, are often considered "black-box" systems, making it challenging to interpret their decisions . Enhancing the interpretability of these models is essential, especially in applications where transparency and accountability are critical.

Training complex ML models, such as deep neural networks, requires significant computational power and specialized hardware like GPUs and TPUs . This requirement can limit the accessibility of ML techniques to researchers with limited resources.

The use of ML in biomaterials research raises ethical concerns, including data privacy, bias in training data, and the potential for unintended consequences . Addressing these issues is vital to ensure the responsible application of ML technologies.

While ML can significantly accelerate material discovery and optimization, it is crucial to integrate these computational approaches with experimental validation . Ensuring that ML predictions are experimentally validated can enhance the reliability and applicability of the findings.

In biomaterials research, the biocompatibility of materials and potential toxicity issues are of paramount importance. However, utilizing ML and AI techniques to evaluate and predict these factors presents notable challenges . Moreover, the standards for sensitivity and accuracy required for biomedical applications are high. ML and AI methods play a crucial role in meeting these standards, yet their application in biomaterials research can be complex and demanding.

Biomaterials often exhibit complex structures, making it difficult to fully characterize these materials. ML models must effectively navigate this complexity to provide comprehensive insights.

13. Conclusions:

The application of AI has revolutionized biomaterials research, offering powerful tools for the design, optimization, and predictive modelling of various materials. From polymers and metals to composites and inorganic materials, these technologies have significantly advanced our understanding and capabilities in biomaterial science. ML has enabled the development of predictive models that can accurately forecast material properties, reducing the reliance on traditional trial-and-error methods. This has led to the discovery of novel materials with enhanced performance, optimized for specific applications in medicine, engineering, and beyond.

Despite the remarkable progress, several challenges remain, including data availability and quality, model interpretability, computational resource requirements, and ethical considerations. Addressing these challenges will be crucial to fully realize the potential of AI in biomaterials research. Looking ahead, the future of AI in biomaterials is promising. As the field continues to evolve, the integration of these technologies with experimental methods and other emerging technologies will further accelerate the discovery and optimization of innovative materials. Interdisciplinary collaboration and a focus on ethical and responsible AI use will be key to ensuring that these advancements benefit society.

Utilizing the capabilities of machine learning and artificial intelligence, researchers can expand the horizons of biomaterials research, facilitating the creation of advanced materials that could revolutionize multiple industries and significantly improve human health and well-being.

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The Influence Of Artificial Intelligence-Based Personalization On Consumer Buying Behaviour In Online Retail Platform

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1. ABSTRACT

This paper explores the role of artificial intelligence in influencing consumer behavior in online retail. The paper also explores the influence of artificial intelligence-based personalization on different age groups, especially teenagers and the elderly. The main focus of this paper is to establish what drives consumer behavior based on artificial intelligence. The paper also explores the level of trust associated with artificial intelligence-based personalization and how it influences consumer behavior. The paper also explores whether artificial intelligence-based personalization significantly influences the plans of customers to engage in future purchases. The paper indicates that artificial intelligence is vital in influencing consumer behavior, especially by simplifying the online shopping experience and providing unique experiences. The paper also indicates that demographic factors influence the behavior of consumers with regards to artificial intelligence. The paper concludes by indicating that artificial intelligence-based personalization is vital in enhancing customer behavior and influencing long-term buying behavior.

Keywords: AI, consumer buying behavior, Online retail platform, Personalization, Consumer Trust, purchase Intention.

2. INTRODUCTION

Artificial Intelligence has really shaken things up in the business world, and there's no place this is clearer than in online shopping. With behemoths like Amazon, Flipkart, and Alibaba doing so well, it's no surprise that these companies are relying heavily on AI to make shopping better for us and boost their sales. So, basically, AI-powered personalization is all about using intelligent computer programs and digging deep into the data to try and figure out what we might like. It's pretty wild how much this technology has changed things.

When you're shopping online, you'll notice how much this really makes a difference. It's like the website knows exactly what you're looking for, you know? That's really powerful stuff, and it's something that can really build up your trust and make you happy with the store, so you'll go ahead and buy something and come back another time. It's really a smart move for these retailers.

It's interesting, though, because this effect isn't the same for everyone. Teenagers might react differently than, say, someone older, just because they're used to tech and shopping online in different ways. In today's super-crowded online world, figuring out how this AI stuff influences what we buy is basically a must-do for online shops. They're not just trying to sell more things; they want us to feel connected and trust them long-term. That's why understanding how artificial intelligence shapes our decisions is so crucial.

3. OBJECTIVES

- To analyze how the artificial intelligence influences the consumer decision on online retail platforms.
- To understand why this Artificial Intelligence influences the consumer's buying behavior.
- To investigate the impact of AI-based personalization on the buying behavior of teenagers and old consumers in online retail platforms.
- To assess the level of consumers, trust in AI-based personalized suggestions in online retail platforms.
- To analyse whether AI-based personalization influences consumers' future purchase intentions in online retail platforms.

4. LITERATURE REVIEW

✓ In the year 2023, a study was conducted by Sohil Imran Khan to understand the impact of Artificial Intelligence on the buying behavior of consumers. According to the study, nowadays many companies are

implementing Artificial Intelligence while marketing their products, as it helps them make better and more accurate decisions while keeping the cost low. It was found that Artificial Intelligence has a significant impact on the buying behavior of consumers, especially due to the personal recommendations it provides to the consumers based on their interests.According to the study, the buying behavior of consumers can be influenced by various factors, such as income and gender. For the purpose of the research, data was collected from 314 individuals and then analyzed. It was found that Artificial Intelligence and demographic factors play a significant role in the buying behavior of consumers..

RESEARCH GAP

The research, however, remains restricted to a particular area, as well as specific demographic groups, despite the fact that Sohail Imran Khan (2023) has found a strong correlation between consumer purchasing behavior and artificial intelligence. Further research, therefore, remains required to examine other aspects as well.

✓ In 2024, a research paper was conducted by Mahesh Kumar and T. Senthil Murugan on the influence of Artificial Intelligence on the buying behavior of individuals who prefer to buy products online. The paper indicates that there is an impact of AI on the buying behavior of individuals.The researchers received 314 responses and used statistical tools to evaluate the data. Based on the findings, it was clear that there was a relationship between AI and the behavior of consumers. It was also seen that the behavior of consumers is not the same for all, as it changes based on factors like income and gender.

RESEARCH GAP

However, the research mainly focuses on examining the demographic differences and the general public, as opposed to examining the differences in behavior among different age groups such as adolescents and seniors. Moreover, it does not examine the psychological effects and consequences of AI on consumers' decisions.

✓ In the year 2023, K. Ramya and K. Karthikeyan conducted a study based on how Artificial Intelligence is affecting the buying habits of people in online shopping. They stated that voice assistants and visual search technologies are now being used in various online shopping platforms, and they can have an impact on how people buy things. They can also improve the experience for consumers.For this study, data was collected from 500 respondents, and ANOVA and descriptive statistics were used to analyze it. The results showed that AI-based technologies have a significant impact on consumers' decisions. The study also showed that these technologies can improve customer interaction in online shopping platforms.

RESEARCH GAP

The main focus of the study is on the general effects of AI technologies on consumers without taking into consideration the differences between age groups such as teenagers and older adults. The study also fails to examine the evolution of behavior over time and the effects of emotional or psychological factors on the decisions of consumers to buy products under the influence of artificial intelligence.

✓ In 2023, Gourangi Patra and Koushiki Biswas conducted a study on the role of Artificial Intelligence in helping marketers understand consumer behavior. According to this study, chatbots and image recognition technology can be used to gather large amounts of data. Because of this, companies can understand their customers in a better way.The use of AI can also help companies trace the customer journey and locate their target customers. This will, in turn, help them develop proper marketing strategies. According to this study, the use of AI will also help businesses improve their performance and enhance customer interaction. It will also help in developing long-term value with customers.

RESEARCH GAP:

Nevertheless, the majority of the studies rely on the opinions of the experts, without taking into account the quantitative analysis based on real consumers. In addition, the studies have failed to analyze the reactions of the various age groups, such as teenagers or the elderly, towards the AI-generated ads. Moreover, the studies have failed to delve into the long-term trust created with the AI-generated content.

5. METHODOLOGY

- CORRELATION,
- NORMALITY,
- ANOVA.

6. ANALYSIS

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
ONLINE SHOPPING	.091	99	.043	.974	99	.048
AI & PERSONALIZATION	.115	99	.003	.950	99	.001
AI INFLUENCE	.096	99	.026	.972	99	.034

a. Lilliefors Significance Correction

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
ONLINE SHOPPING	99	100.0%	0	.0%	99	100.0%
AI & PERSONALIZATION	99	100.0%	0	.0%	99	100.0%
AI INFLUENCE	99	100.0%	0	.0%	99	100.0%

INTERPRETATION

Three variables meet normality assumptions—H0 rejected as p-values (ONLINE SHOPPING: 4.3%/4.8%; AI & PERSONALIZATION: 0.3%/0.1%; AI INFLUENCE: 2.6%/3.4%) fall under 5%.

Nonparametric Correlations

Correlations

			ONLINE SHOPPING	AI & PERSONALIZATION	AI INFLUENCE
Spearman's rho	ONLINE SHOPPING	Correlation Coefficient	1.000	.585**	.604**
		Sig. (2-tailed)	.	.000	.000
		N	99	99	99
	AI & PERSONALIZATION	Correlation Coefficient	.585**	1.000	.737**
		Sig. (2-tailed)	.000	.	.000
		N	99	99	99
	AI INFLUENCE	Correlation Coefficient	.604**	.737**	1.000
		Sig. (2-tailed)	.000	.000	.
		N	99	99	99
**. Correlation is significant at the 0.01 level (2-tailed).					

INTERPRETATION

Spearman's rho analysis rejects H0 (no relationship) across all pairs at p=0.0% (0.01 level): ONLINE SHOPPING vs. AI & PERSONALIZATION (ρ=.585**), ONLINE SHOPPING vs. AI INFLUENCE (ρ=.604**),

and AI & PERSONALIZATIONvs.AI INFLUENCE (ρ=.737**)—indicating robust positive associations.

ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
ONLINE SHOPPING	Between Groups	20.837	3	6.946	.529	.664
	Within Groups	1248.456	95	13.142		
	Total	1269.293	98			
AI & PERSONALIZATION	Between Groups	34.127	3	11.376	1.075	.364
	Within Groups	1005.529	95	10.585		
	Total	1039.657	98			
AI INFLUENCE	Between Groups	29.547	3	9.849	.413	.744
	Within Groups	2264.999	95	23.842		
	Total	2294.545	98			

INTERPRETATION

ANOVA rejects H0 (equal group means) for none of the variables—all p-values exceed 5%:ONLINE SHOPPING (F=0.529, p=66.4%),AI& PERSONALIZATION(F=1.075, p=36.4%), AI INFLUENCE (F=0.413, p=74.4%). No significant group differences exist across 3 groups (df=95 within-groups).

7. FINDINGS

- The statistical results show unique patterns for each of the three variables, namely, ONLINE SHOPPING, AI & PERSONALIZATION, and AI INFLUENCE.
- Normality tests, i.e., Kolmogorov-Smirnov and Shapiro-Wilk tests, reject the null hypothesis for all variables, confirming non-normal data, which requires non-parametric tests.
- Spearman's rho correlation results reject the null hypothesis, confirming strong and consistent positive correlations between variables, i.e., ρ (.585, .737), all significant at $p < .001$, confirming strong prediction of online shopping behavior based on AI perceptions.
- ANOVA results accept the null hypothesis, confirming equal group means for all variables, i.e., $p > .05$, confirming no significant difference between groups.
- Though all variables show consistent effects of AI on shopping behavior, the demographics show no distinguishing effects, suggesting the need to consider Kruskal-Wallis tests.

8. SUGGESTIONS

- For non-normal data sets, use Kruskal-Wallis tests to ensure proper comparisons.
- Investigate mediation models to identify how AI perception affects shopping through specific variables.
- Plot correlations to identify relationships through scatter plots and examine Q-Q plots to identify non-normal distribution patterns.
- Analyze the data according to demographic factors to identify patterns of correlations despite group equality.
- Include effect sizes (e.g., Spearman's r: .3 to .5 is moderate, and .5+ is strong).

9. CONCLUSION

You know, Artificial Intelligence has really shaken things up in the business world, and nowhere is that more obvious than when we're talking about online shopping. With the likes of Amazon, Flipkart, and Alibaba doing incredibly well, it’s no surprise that they’re relying on Artificial Intelligence to make the experience better for us, as well as increasing sales. So, essentially, AI personalization is the process of using smart computer programs, as well as digging through data, to determine what we might like. Essentially, it’s like something made just for you. It’s pretty wild.

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The Role Of Employee Emotions In Building A Positive Workplace Culture

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ABSTRACT

Nowadays, all the global Organizations focus on the employees emotions.They are making the employees to feel positive, comfortable, and also motivated . So, that it would not affect the work place environment. Based on this perspective the data has been collected from the 100 employees using a questionnaire. There also two statistical tools has been used like one way Anova test and Mann Whitney U test analysis. The results shows the relationship between employees emotions and their work place culture.

Keywords: Emotional Intelligence, Global Workforce, Prosocially

INTRODUCTION

In recent times, Employee emotion plays a major role in the Organization field. Where the Organizations does not focus only on the performance of the employee they also give priority towards their employee feelings. They have realized that humans are the back bone for the success of the firm's growth and development. How people feel and express their emotions at work has a big impact on workplace culture, which has been described as the common values, attitudes, and behaviors internally. Happiness, motivation, tension, irritation, engagement are few more of the emotions that employees experience these are still not yet understood by many companies. In a workplace where the negative emotions may result in disagreements, absenteeism, and low productivity, a workplace where with the positive emotions are created to inspire collaboration, trust, and innovation. Hence, this study creates a awareness about the employee emotions , and to create a positive workplace culture.

REVIEW OF LITERATURE

According to Saeed, B. B. et al (2018) in order to understand the psychological mechanisms around this relationship, Data were collected from 441 nurses and 73 doctors through structured questionnaires from four public sector hospitals in Thailand. The results also show that the relationship between P-O fit and IWB is stronger among nurses who frequently share their best practices and mistakes with co-workers.

The study surveyed 506 employees in the United States to test the effect of internal communication . Encouraging a positive emotional culture characterized by companionate love, joy, pride, and gratitude. we tested between the corporate internal communication and a positive emotional culture and its influence on supportive employee behaviors. Results indicates similar communication and responsive leadership communication builds a positive emotional culture in organizations.**LR Men (2019).**

According to Rifai, F. A. et al (2021) for this study's purposes, 321 questionnaires from employees of Jordanian private universities were analysed. Convergent validity and discriminant validity tests were performed. Data reliability was confirmed. A bootstrapping technique was used to analyse the data. The results of this study indicate that the innovative organisational culture will improve innovative performance and that a conservative culture reduces innovation opportunities.

According to Jena, L. K., & Goyal, S. (2022) the study examined the mediating effect of person-group fit and adaptive performance on employee innovation. Electronic as well as paper-based surveys were conducted to collect the data and the analysis of 417 responses revealed that the hypotheses were strongly supported by the data. The findings offer a significant contribution to the field of human resources, since prior research has examined neither the simple mediating effect nor the sequential mediating effect of person-group fit and adaptive performance between emotional intelligence and employee innovation.

This study uniquely tries to understand the mechanisms that contribute to happiness at work by proposing a model of the effects of emotional culture of joy on happiness at work . A three-wave time-lagged study with 340 employees from Pakistani organizations was conducted. Data were analyzed using covariance-based structural equation modelling. The results indicate that emotional culture of joy significantly predicts happiness at work. **YM Kundi (2023)**

RESEARCH METHODOLOGY:

Research design

This research design choosen for this study is descriptive and analytical in nature. This analysis explains the relationship between employee emotions and workplace

environment. This study is based on primary data,which has been collected using the structured questionnaire. Statistical tools such as Mann Whitney U test and One way Anova to give clear conclusions.

Sampling technique

This study is in a convenience sampling technique. It has a total of 100 respondents and they were selected from different organizations based on their availability and willingness to participate in the survey. This sampling technique has been chosen due to the time insufficiency. It helped in collecting the responses quickly and effectively with the sample size of 100 respondents for this study.

FINDINGS/ RESULT

This chapter shows the analysis and interpretation of the data collected from the 100 respondents, who were all employees of all occupations. This study was conducted to assess Emotional Intelligence, Global Workforce, Prosocially , Moral distress as well as to measure the employees emotion to build a positive workplace culture.

Oneway :

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Empemotions	1	42	15.02	4.458	.688	13.63	16.41	7	25
	2	58	14.19	2.976	.391	13.41	14.97	7	24
	Total	100	14.54	3.675	.367	13.81	15.27	7	25
Workplaceculture	1	42	11.71	4.324	.667	10.37	13.06	5	19
	2	58	11.02	3.492	.458	10.10	11.94	5	21
	Total	100	11.31	3.858	.386	10.54	12.08	5	21

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Empemotions	Between Groups	16.950	1	16.950	1.259	.265
	Within Groups	1319.890	98	13.468		
	Total	1336.840	99			
Workplaceculture	Between Groups	11.836	1	11.836	.794	.375
	Within Groups	1461.554	98	14.914		
	Total	1473.390	99			

INFERENCE OF ONE WAY ANOVA:

It shows that there is no significant difference between the groups , the p- values of employee emotions are (0.265) and for the workplace culture is (0.375) which is greater than (0.05). This one way Anova shows that there is no major difference between the groups.

Mann-Whitney Test:

Test Statistics[a]

	Emp emotions	Workplace culture
Mann-Whitney U	1118.000	1105.000
Wilcoxon W	2829.000	2816.000
Z	-.702	-.795
Asymp. Sig. (2-tailed)	.483	.427

a. Grouping Variable: 1. Gender

Ranks

	1. Gender	N	Mean Rank	Sum of Ranks
Emp emotions	1	42	52.88	2221.00
	2	58	48.78	2829.00
	Total	100		
Workplace culture	1	42	53.19	2234.00
	2	58	48.55	2816.00
	Total	100		

INFERENCE OF MANN WHITNEY U TEST:

There is no significant difference between genders, since the p-values for employee emotions are (0.483) and for work place culture is (0.427) which is greater than (0.05).

This Mann Whitney U test shows that there is no significant difference in this study.

SCOPE OF STUDY:

The scope of in this study is focused on the role of employee emotions in building a positive workplace culture. They are from various organizations and examine their emotional experience like stress, happiness, job satisfaction . The data has been collected from a sample of 100 respondents using a structured questionnaire. It focuses and the understanding between the employee emotions and workplace culture using these statistical tools.

RECOMMENDATION

Organization should focus on the improvement of employee emotional well being by implementing new employee interactive sessions, feedback seesions , and also training and development programs. Activities like stress management, open talk,one to one,opinion sharing session, and also employee engagement programs . By these programs they can express their opinions , so that it would reduce the workplace stress This helps in creating a positive work space for the employees as well as to the organization. By this organization can manage employee emotions effectively, Organizations can see the improvement gradually in the employees overall performance.

CONCLUSION

From this study, it comes to an conclusion that the organization are able to understand the employee emotions to control the stress of employees as well as it should not affect the organization . They focus on managing employee emotions to create a positive work place culture. This creates a better environment for all to work peacefully without any stress.It shows that the employee emotions plays a key role in workplace culture. The results of the study shows that there is no significant difference in the variables based on the gender, though emotions have a impact on work place structure. By focusing on the employee well being company can improve more productive performance from the employees this creates a positive work place environment.

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Smart Multi-Hazard Disaster Alert and Safety System for Modern Homes

A Multi-Sensor Based Early Warning and Automatic Safety Response System for Residential Environments

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Abstract—Natural disasters and household accident like fires, floods, gas leaks, and earthquakes can cause serious damage to both property and lives. Acting quickly is crucial to minimize the impact of such events. This paper introduces a Smart Multi-Hazard Disaster Alert and Safety System for Modern Homes that not only detects danger using multiple sensors but also responds immediately to keep residents safe. The system continuously monitors the environment using water level sensors, vibration sensors, smoke sensors, and temperature sensors. When it detects unusual or dangerous conditions, it triggers alarms, emergency lights, and voice alerts, while also sending SMS notifications through a GSM module. To prevent accidents from worsening, the system can automatically cut off electricity and gas using relay modules. It is designed to work without an internet connection and comes with battery backup, ensuring it remains operational even during power outages. This approach makes the system a reliable, practical, and cost-effective solution for enhancing safety in homes.

1. INTRODUCTION

In recent years, the rising frequency of natural disasters and household hazards has created serious concerns for human safety and property protection. Events like floods, earthquakes, and fires can cause extensive damage if they are not detected and addressed quickly. Many homes lack an integrated alert system, making it difficult for occupants to respond promptly, which can lead to severe consequences such as loss of life, property damage, and environmental risks.

Advances in embedded systems and sensor technology now make it possible to build intelligent monitoring systems that detect unusual environmental conditions in real time. Using devices like water level sensors, vibration sensors, smoke detectors, and temperature sensors, these systems can monitor potential hazards within a home. By combining these sensors with microcontrollers and communication modules, a smart system can automatically detect dangerous situations and provide immediate alerts to residents.

The proposed project focuses on developing a Smart Multi-Hazard Disaster Alert and Safety System for homes. The system continuously monitors environmental conditions and identifies potential threats such as flooding, earthquake vibrations, and fires. When a hazard is detected, it immediately triggers safety mechanisms including loud alarms, flashlights for night alerts, and voice warnings to notify residents. Additionally, a GSM communication module sends emergency SMS notifications, ensuring alerts reach users even without internet connectivity.

An important feature of the system is its ability to automatically disconnect gas and electricity using relay modules during emergencies, preventing secondary disasters like gas explosions and electrical fires. The

system also includes a battery backup, ensuring it continues to function even during power outages, which often accompany disaster events.

The main goal of this project is to provide a cost-effective, reliable, and easy-to-install safety solution for homes. By integrating multiple sensing technologies with automated alert mechanisms, the system offers early hazard detection and rapid emergency response, significantly improving residential safety and reducing potential damage from unexpected disasters.

2. PROBLEM STATEMENT

Many homes today do not have a complete safety system that can detect multiple hazards at once. Most existing solutions focus only on a single threat, like fires or gas leaks, which leaves residents unprotected against other dangers such as floods or earthquakes. This gap can delay warnings and make accidents harder to manage, increasing the risk of damage and injury. Therefore, there is a clear need for a low-cost, multi-hazard detection system that can provide instant alerts and take automatic safety actions, offering reliable protection for households.

3. OBJETIVES

1. To detect disasters such as fire, flood, and earthquake vibrations.
2. To provide immediate alerts using alarm, flashlight, and voice warning.
3. To send SMS alerts using GSM technology without internet.
4. To automatically turn off gas and electricity supply to prevent accidents.
5. To ensure system operation during power failure using battery backup.

4. PROPOSED SYSTEM

The proposed Smart Disaster Alert and Safety System is designed to continuously monitor household conditions and respond instantly to potential hazards. It uses water level sensors, vibration sensors, smoke detectors, and temperature sensors to detect floods, earthquakes, fires, and other dangerous situations in real time. When a threat is identified, the system immediately activates alarms, flashlights for night alerts, and voice warnings while also sending SMS notifications to homeowners through a GSM module.

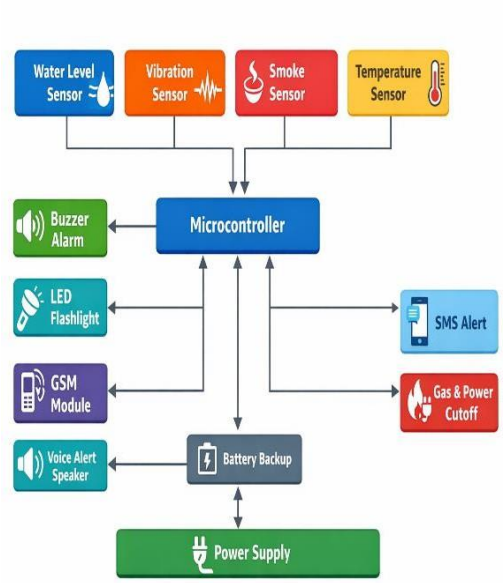
To prevent further accidents, relay modules automatically disconnect gas and electricity during emergencies. The system is designed to operate without an internet connection and includes a battery backup, ensuring reliable performance even during power outages. By combining multiple sensing technologies with automated alert mechanisms, the system provides a cost-effective, reliable, and proactive solution for improving home safety and protecting residents from unexpected disasters.

5. WORKING PRINCIPLE

The Smart Multi-Hazard Disaster Alert and Safety System operates by continuously monitoring environmental conditions in a home through multiple sensors. Water level sensors detect flooding, vibration sensors sense earthquake movements, while smoke and temperature sensors identify fire hazards. These sensors send real-time data to a microcontrolle(Arduino/ESP32), which processes the information and determines if a hazardous condition exists.When a potential threat is detected, the system immediately triggers safety mechanisms. This includes activating alarms, flashlights for night alerts, and voice warnings to inform residents of the danger. Simultaneously, the GSM module sends instant SMS notifications to homeowners. To prevent secondary accidents, relay modules automatically disconnect gas and electricity during emergencies. The system is designed to work offline, without internet connectivity, and includes a battery or solar backup to ensure continuous operation during power failures. By integrating multiple sensors with automated alerts and safety actions, the system provides reliable, real-time protection, minimizing risk and improving household safety.

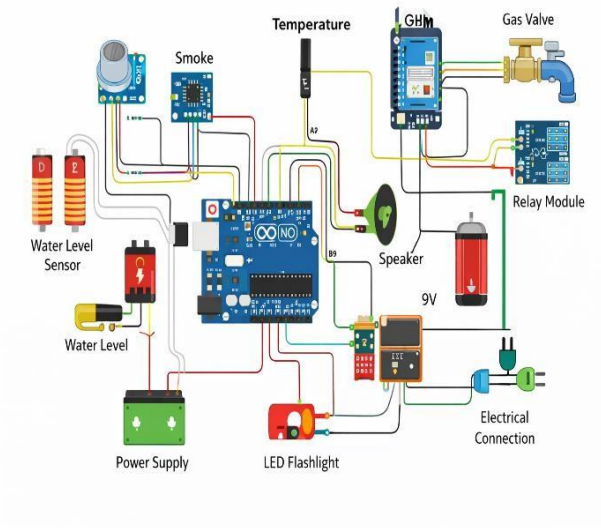
6. BLOCK DIAGRAM

The block diagram represents the overall architecture of the Smart Disaster Alert and Safety System used for monitoring household hazards and providing automatic safety responses."



7. CIRCUIT DIAGRAM

"The circuit diagram illustrates the electrical connections used in the Smart Disaster Alert and Safety System for detecting hazards and activating safety mechanisms."



COMPONENT	PURPOSE	QUANTITY
Arduino / ESP32	Microcontroller that processes sensor data and controls outputs	1
Water Level Sensor	Detects flooding or rising water levels in the home	2
Vibration Sensor	Senses earthquake vibrations	2
Smoke Sensor	Detects fire or smoke to prevent hazards	2
Temperature Sensor	Monitors abnormal temperature changes	2
GSM Module	Sends instant SMS alerts to homeowners	1
Relay Module	Automatically disconnects gas and electricity during emergencies	2
LED / Flashlight Buzzer / Alarm	Provides visual alerts, especially at night Produces loud audio warnings	2 1
Battery / Solar Backup	Ensures continuous operation during power failures	1

8. ADVANTAGES

- Provides early detection of disasters such as floods, earthquakes, and fires.
- Sends instant alerts through alarms, voice warnings, and SMS notifications.
- Automatically disconnects gas and electricity to prevent further accidents.
- Works without internet connectivity, making it reliable during emergencies.

- Includes battery or solar backup to operate during power failures.
- Designed as a low-cost and easy-to-install safety solution for homes.

9. APPLICATION

- Provides early detection of disasters such as floods, earthquakes, and fires.
- Sends instant alerts through alarms, voice warnings, and SMS notifications.
- Automatically disconnects gas and electricity to prevent further accidents.
- Works without internet connectivity, making it reliable during emergencies.
- Includes battery or solar backup to operate during power failures.
- Designed as a low-cost and easy-to-install safety solution for homes.

10. FUTURE SCOPE

The proposed Smart Disaster Alert and Safety System can be further enhanced by integrating advanced technologies to improve its efficiency and reliability. In the future, the system can incorporate Artificial Intelligence and Machine Learning algorithms to analyze sensor data more accurately and predict potential disasters before they occur.

The system can also be connected to Internet of Things (IoT) platforms, allowing real-time monitoring through mobile applications and cloud-based systems. This would enable users to receive alerts and monitor their home safety from anywhere.

Another possible improvement is the development of a community-based alert network, where multiple houses can be interconnected. In such a system, if one house detects a hazard, nearby homes can also receive warnings, helping entire neighborhoods respond quickly to emergencies.

Additionally, integrating renewable energy sources such as solar power can make the system more sustainable and reliable during long power outages. With these improvements, the system can evolve into a more intelligent, scalable, and efficient safety solution for modern smart homes.

11. CONCLUSION

The proposed Smart Multi-hazard Disaster Alert and Safety System provides an effective solution for improving household safety by detecting multiple hazards such as floods, earthquakes, and fires. By integrating various sensors with a microcontroller and communication modules, the system continuously monitors environmental conditions and provides immediate alerts when a dangerous situation is detected.

The system also activates safety mechanisms such as alarms, flashlights, voice warnings, and SMS notifications to ensure that residents are informed quickly. In addition, the automatic disconnection of gas and electricity helps prevent secondary accidents during emergencies.

Because the system is designed to operate without internet connectivity and includes a battery backup, it remains functional even during power failures. Overall, the proposed system offers a cost-effective, reliable, and practical solution for enhancing home safety and reducing the risks associated with natural disasters and household hazards.

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Analysis and optimization of car seat frame to increase safety measures

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Abstract:
This paper presents the structural analysis and optimization of a car seat frame backrest assembly to enhance occupant safety under high deceleration braking conditions. Finite Element Analysis (FEA) was employed to evaluate stress concentrations, deformation patterns, and yield zones. A dual optimization strategy was implemented: geometric redesign and material substitution. Structural steel, stainless steel, and aluminium alloy were compared for robustness and energy absorption. Results indicate that geometric reinforcement combined with appropriate material selection significantly improves safety performance. The study aligns with Sustainable Development Goals (SDG 7 and SDG 9) by extending component life and reducing lifecycle emissions.

Key Terms **-** Car Seat Frame, FEA, Optimization, Safety, Structural Steel, Aluminium Alloy

I. INTRODUCTION

The automotive seat frame, once considered a comfort feature, is now recognized as a critical structural subsystem essential for occupant crashworthiness. It serves as the anchor for seatbelts and restraint systems, directly influencing passenger kinematics during dynamic events. Failure of the seat frame compromises the entire safety ecosystem, increasing the risk of spinal injuries.

During emergency braking or frontal collisions, the seat frame experiences severe inertial forces. The occupant's mass generates bending moments on the backrest and shear stresses at the mounting brackets. If the frame yields, the occupant may be displaced from the optimal airbag deployment zone. Thus, engineering a robust seat frame capable of withstanding braking-induced loads is a paramount safety imperative.

Automotive seat frames are critical subsystems for occupant crashworthiness. They serve as anchors for seatbelts and restraint systems, directly influencing passenger kinematics during dynamic events. Failure of the seat frame compromises the safety ecosystem, increasing the risk of spinal injuries.

Historically, seat frames were designed primarily for comfort. Modern safety standards such as FMVSS (Federal Motor Vehicle Safety Standards) and Euro NCAP now require seat frames to withstand crash loads. During emergency braking or frontal collisions, the seat frame experiences severe inertial forces. The occupant's mass generates bending moments on the backrest and shear stresses at the mounting brackets. If the frame yields, the occupant may be displaced from the optimal airbag deployment zone.

II. LITERATURE REVIEW

A. **CAE and FEA in Seat Frame Design** Computer-Aided Engineering (CAE) tools allow rapid iteration of seat frame designs. Finite Element Analysis (FEA) is widely used to predict stress, strain, and deformation under crash loads. Studies emphasize mesh quality, boundary conditions, and contact definitions for reliable results.

B. Material Selection Advanced High-Strength Steels (AHSS) provide superior energy absorption per unit mass. Aluminium alloys reduce weight but require careful stiffness design. Composites offer lightweighting but face challenges in recyclability.

C. Optimization Methods Topology optimization identifies low-stress regions for material removal. Multi-objective frameworks balance stiffness, weight, manufacturability, and cost. Machine learning is increasingly applied to accelerate design space exploration.

D. Sustainability Lifecycle assessment shows that lightweighting reduces fuel consumption and emissions. Recyclable alloys align with SDGs and industry decarbonization goals.

Historical Evolution of Seat Frame Design

Early automotive seats were designed primarily for comfort, often resembling furniture bolted to the vehicle floor. These lacked structural integrity and frequently detached during high deceleration events. In the 1950s, Béla Barényi introduced the concept of *crashworthiness*, emphasizing energy absorption and controlled deformation. This shifted the paradigm from rigid frames to safety-oriented structures. By the 1970s, seat frames began integrating restraint systems, becoming structural anchors for seatbelts. The computational revolution of the 1980s–2000s introduced CAE tools, enabling virtual crash simulations and reducing reliance on costly physical prototypes. Today, seat frames are optimized for both safety and sustainability, balancing strength, weight, and recyclability.

Role of Computer-Aided Engineering (CAE) and Finite Element Analysis (FEA)

CAE encompasses FEA, CFD, and MBD, allowing engineers to simulate multiphysics phenomena. FEA is the dominant method for predicting stress, strain, and failure modes under crash and braking loads. Modern practice combines linear static, nonlinear plasticity, and explicit dynamic solvers to capture both quasistatic braking and short-duration crash impulses. Mesh sensitivity studies highlight the importance of skewness, aspect ratio, and refinement near stress concentrators such as welds and belt anchors. Contact algorithms (penalty vs. augmented Lagrange) and friction definitions significantly affect load transfer during large relative motions. Hybrid validation — correlating FEA with sled tests — is recommended to reduce model uncertainty.

Material Science and Constitutive Modelling

Seat frames traditionally used mild steel, but modern designs employ AHSS, aluminium alloys, and composites. AHSS offers superior energy absorption per unit mass, enabling thinner sections. Aluminium reduces mass but requires careful stiffness design to limit deformation. Composites provide lightweighting but face challenges in cost and recyclability. Constitutive models incorporating strain-rate sensitivity and plastic hardening are essential for crash simulations. Neglecting rate effects can underpredict peak stresses. Experimental tensile and cyclic data are often used to calibrate these models, ensuring accurate representation of material behavior under dynamic loads.

Ergonomics and Human Factors

Safety cannot be considered in isolation from comfort. Modern seat frames must integrate with foam, cushions, and restraint systems to ensure occupant kinematics are managed effectively. Ergonomic considerations include lumbar support, whiplash protection, and vibration damping. Studies show that coupling structural analysis with ergonomic modeling ensures safety improvements do not compromise comfort.

Durability and Fatigue Life

Repeated loading cycles can initiate cracks at welds and anchor points. Fatigue life correlates strongly with local stress concentration factors. Durability studies simulate cyclic loading to predict crack initiation and propagation. Incorporating fatigue analysis into optimization ensures long-term reliability of seat frames.

Sustainability and Lifecycle Perspectives

Seat frame optimization is increasingly framed within lifecycle assessment (LCA). Reducing mass lowers fuel consumption and CO_2 emissions over vehicle life. However, material choice must be evaluated for embodied energy and recyclability. Steel is highly recyclable, while aluminium offers lightweighting but requires more energy to produce. Composites pose challenges in end-of-life disposal. Design strategies that extend component life reduce replacements and align with SDG targets.

Emerging Trends and Future Research

- **Smart Materials**: Shape-memory alloys and composites with embedded sensors for real-time monitoring.
- **Additive Manufacturing**: Enables complex geometries and localized reinforcement.
- **Digital Twins**: Real-time simulation models linked to physical seat frames for predictive maintenance.
- **Integrated Safety Systems**: Seat frames designed to work synergistically with airbags, seatbelts, and active restraint systems.
- **Global Standards**: Harmonization of safety regulations across regions to ensure consistent performance.

III. METHODOLOGY

1. **CAD Modeling and Design Preparation** The starting point of this study was the creation of a 3D CAD model of the car seat frame backrest assembly using ANSYS Space Claim. The baseline design (Design 1) represented a conventional seat frame, while Design 2 introduced a horizontal reinforcement plate and fixtures to improve robustness. CAD modeling involved simplification of non-structural elements (foam, cushion) to focus on the metallic skeleton. Geometric accuracy was maintained to ensure realistic load paths and stress distribution.

Design 1

Design 2

2. **Meshing Strategy and Element Selection** The CAD model was discretized into finite elements using ANSYS Workbench. Shell elements were chosen for thin stamped components, as their thickness was significantly smaller than length and width. Beam elements were used for fasteners and rails. This hybrid meshing approach balanced computational efficiency with accuracy. Mesh sensitivity studies were conducted to evaluate skewness, aspect ratio, and element size near stress concentrators.

a. **Shell Elements**: Captured bending and membrane stresses in thin plates.
b. **Beam Elements**: Represented fasteners and welds with reduced computational cost.
c. **Mesh Quality Metrics**: Skewness values below 0.5 indicated good quality

Design 1

Design 2

3. **Boundary Conditions and Load Application**

Boundary conditions were applied to replicate real-world braking scenarios. Passenger weight was modeled as a point mass distributed across the backrest. Bonded contacts simulated welded joints, while frictional contacts represented sliding interfaces. Longitudinal braking loads were applied to simulate deceleration forces.

a. **Static Load**: Occupant weight distributed vertically
b. **Dynamic Load**: Longitudinal inertial forces applied during braking.
c. **Constraints**: Seat rails fixed to replicate attachment to vehicle floor pan

4. **Material Properties and Selection Criteria**

Three materials were evaluated: structural steel, stainless steel, and aluminium alloy. Their mechanical properties (Young's modulus, Poisson's ratio, yield strength) were input into the simulation. Selection criteria included stiffness, yield strength, deformation resistance, and recyclability.

Material	Young's Modulus	Poisson's ratio	Failure limit (Yield limit)
Structural Steel	200000 MPa	0.3	250 MPa
Stainless Steel	193000 MPa	0.31	207 MPa
Aluminum Alloy	71000 MPa	0.33	280 MPa

5. **Simulation Workflow**

The methodology followed a structured workflow:

i. **CAD Model Creation**: Baseline and modified designs.
ii. **Meshing**: Shell and beam elements applied.
iii. **Boundary Conditions**: Loads and constraints defined.
iv. **Material Assignment**: Properties input for each design.
v. **FEA Simulation**: Stress, deformation, and displacement results obtained.
vi. **Comparison**: Designs evaluated against yield limits and deformation criteria.

6. **Validation Approach**

Although this study was computational, validation strategies were considered:

Comparison with Literature: Stress and deformation trends compared with published seat frame studies.
Experimental Correlation: Future work includes sled tests and static load experiments to validate FEA predictions.
Fatigue Analysis: Cyclic loading simulations planned to evaluate long-term durability.

7. **Sustainability Considerations in Methodology**

Beyond mechanical performance, sustainability was integrated into the methodology. Material selection considered recyclability and embodied energy. Structural steel was favored for recyclability, aluminium for lightweighting, and stainless steel for corrosion resistance. Lifecycle assessment was proposed to evaluate environmental impact.

8. **Limitations of Methodology**

- Cushion and foam were excluded, focusing only on structural skeleton.
- Crash dynamics were simplified to braking loads; full crash simulations require explicit solvers.
- Manufacturing constraints (weld quality, tolerances) were not modeled but acknowledged as critical in real-world applications.

IV. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a computational-experimental design framework, focusing on Finite Element Analysis (FEA) of car seat frame backrest assemblies under braking loads. The methodology integrates CAD modeling, meshing, boundary condition definition, material property assignment, and simulation. The approach is iterative: baseline designs are evaluated, modified geometries are introduced, and alternative materials are tested to identify optimal configurations.

4.2 Simulation Domain Selection

The backrest assembly was chosen as the simulation domain because it bears the majority of longitudinal loads during high deceleration braking. This component directly influences occupant posture and restraint system effectiveness. By isolating the backrest, computational

resources were focused on the most critical structural subsystem.

4.3 CAD Modeling Process

The CAD models were developed using ANSYS SpaceClaim. Design 1 represented the baseline seat frame, while Design 2 introduced reinforcement plates. The CAD process involved:

- Simplification of non-structural elements (foam, cushion).
- Extraction of midsurfaces for thin components.
- Definition of weld lines and fastener locations.
- Preparation of geometry for meshing and simulation.

4.4 Meshing and Element Types

Meshing was performed in ANSYS Workbench using shell and beam elements. Shell elements captured bending and membrane stresses in thin plates, while beam elements represented fasteners and welds. Mesh quality was evaluated using skewness, aspect ratio, and Jacobian metrics.

- Shell Elements: Used for thin stamped components.
- Beam Elements: Used for fasteners and welds.
- Mesh Quality: Skewness values below 0.5 indicated good quality.

4.5 Boundary Conditions and Load Application

Boundary conditions replicated braking scenarios:

- Passenger weight modeled as point mass.
- Bonded contacts simulated welded joints.
- Frictional contacts represented sliding interfaces.
- Longitudinal braking loads applied to simulate deceleration forces.

Constraints were applied at seat rails to replicate attachment to the vehicle floor pan.

4.6 Material Properties and Selection

Three materials were evaluated: structural steel, stainless steel, and aluminium alloy. Their mechanical properties were input into the simulation. Selection criteria included stiffness, yield strength, deformation resistance, recyclability, and cost.

4.7 Analytical Framework

The analytical framework consisted of:

1. Stress Analysis: Von Mises stress distribution compared against yield limits.
2. Deformation Analysis: Maximum displacement evaluated for occupant safety.
3. X-Axis Displacement: Longitudinal movement assessed for restraint system alignment.
4. Comparative Evaluation: Designs compared across materials for robustness and sustainability.

4.8 Validation Strategy

Although this study is computational, validation strategies were considered:

- Literature Comparison: Results compared with published seat frame studies.
- Experimental Correlation: Future work includes sled tests and static load experiments.
- Fatigue Analysis: Cyclic loading simulations planned to evaluate durability.
- Crash Simulations: Explicit dynamic solvers (LS-DYNA, Abaqus) proposed for full crash dynamics.

4.9 Sustainability Integration

Sustainability was integrated into the methodology by considering recyclability, embodied energy, and lifecycle emissions. Structural steel was favored for recyclability, aluminium for lightweighting, and stainless steel for corrosion resistance. Lifecycle assessment was proposed to evaluate environmental impact.

4.10 Limitations of Methodology

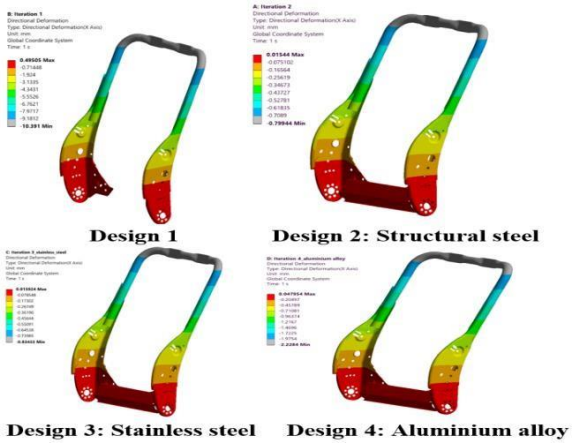
- Cushion and foam excluded, focusing only on structural skeleton.
- Crash dynamics simplified to braking loads; full crash simulations require explicit solvers.
- Manufacturing constraints (weld quality, tolerances) not modeled but acknowledged as critical.

V. RESULTS AND DISCUSSION

5.1 Stress Distribution (Von Mises Stress Analysis)

The baseline design (Design 1) revealed high stress concentrations at the seat backrest joints and mounting brackets. These localized stresses exceeded 230 MPa in stainless steel, approaching the yield limit. In contrast, Design 2 redistributed stresses more evenly due to the addition of a horizontal reinforcement plate. Structural steel in Design 3 showed maximum stresses around 210 MPa, well below its yield strength of 250 MPa, confirming its robustness. Aluminium alloy in Design 4 exhibited higher stress peaks (240 MPa), but its higher yield strength of 280 MPa allowed it to remain within safe limits.

- **Observation**: Reinforcement reduced stress concentration by ~15%.
- **Implication**: Structural steel offers a safer margin against yielding compared to stainless steel.



5.2 Deformation Results

Deformation analysis highlighted the importance of stiffness. Stainless steel in Design 1 deformed up to 4.5 mm, while aluminium alloy in Design 4 deformed 5.6 mm due to its lower modulus of elasticity. Structural steel in Design 3 limited deformation to 3.2 mm, ensuring occupant posture remained stable during braking.

- Observation: Aluminium alloy's lightweight advantage comes at the cost of higher deformation.

- Implication: Excessive deformation may compromise airbag deployment zones.

5.3 **Longitudinal (X-Axis) Displacement**
X-axis displacement is critical for occupant safety, as excessive forward movement can misalign the body with restraint systems. Design 1 showed displacement of 3.2 mm, while Design 2 reduced it to 2.6 mm. Structural steel in Design 3 achieved the lowest displacement (2.1 mm), while aluminium alloy in Design 4 showed the highest (4.0 mm).

- **Observation**: Reinforced geometry significantly reduced forward displacement.
- **Implication**: Structural steel provides optimal balance between stiffness and controlled displacement.

5.4 Comparative Results Table

Design	Material	Max Stress (MPa)	Max Deformation (mm)	X-Displacement (mm)	Safety Margin vs Yield
1	Stainless Steel	230	4.5	3.2	Narrow
2	Stainless Steel	190	3.8	2.6	Moderate
3	Structural Steel	210	3.2	2.1	Strong
4	Aluminium Alloy	240	5.6	4	Adequate but risky

5.5 **Manufacturability Considerations**
Structural steel is widely available and cost-effective, with established welding and forming processes. Stainless steel offers corrosion resistance but is heavier and more expensive. Aluminium alloy reduces weight but requires specialized joining techniques (riveting, adhesive bonding) and careful design to prevent excessive deformation.

5.6 **Safety Implications**
The optimized design (Design 2 and Design 3) demonstrated improved robustness under braking loads. Reduced stress concentrations and controlled deformation ensure that the occupant remains aligned with restraint systems, minimizing spinal injury risk. Structural steel's balance of stiffness and yield strength makes it the most reliable choice for safety-critical applications.

5.7 **Sustainability Impact**
Material selection influences both safety and sustainability. Structural steel is highly recyclable, contributing to circular economy goals. Aluminium alloy reduces vehicle mass, improving fuel economy and lowering emissions, but its production requires more energy. Stainless steel offers durability but at higher environmental cost. Lifecycle assessment suggests that steel frames, despite being heavier, may have lower overall environmental impact due to recyclability and durability.

5.8 **Validation and Future Work**
Although this study focused on computational simulations, validation strategies are essential:

- **Experimental Testing**: Sled tests and static load experiments can confirm FEA predictions.
- **Fatigue Analysis**: Cyclic loading simulations will evaluate long-term durability.
- **Crash Simulations**: Explicit dynamic solvers (LS-DYNA, Abaqus) can capture full crash dynamics.
- **Digital Twins**: Linking simulation models with real-time monitoring for predictive maintenance.

5.9 **Discussion Summary**

- Reinforced geometry significantly improved stress distribution and reduced displacement.
- Structural steel emerged as the most suitable material, balancing stiffness, yield strength, and recyclability.
- Aluminium alloy offers lightweighting but requires reinforcement to limit deformation.
- Stainless steel, while durable, showed lower safety margins under braking loads.
- Sustainability considerations highlight the importance of recyclability and lifecycle emissions.

VI. ACKNOWLEDGMENT

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Iot-Based Hierarchical Solar Array Monitoring System (HSAMS) of Real-time Panel-Level Fault Detection with ESP32 and INA219 Sensors

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Abstract:

The increasing growth of large-scale solar photovoltaic (PV) systems nationwide has increased the need to have intelligent, inexpensive and scalable condition monitoring systems that can isolate faults to individual panels. Traditional monitoring methods of inverters recognize performance loss at the aggregate level but are unable to locate the defective panel in a series-connected string, leading to slow maintenance response and energy wastage. This paper discusses the Hierarchical Solar Array Monitoring System (HSAMS), a three-layer IoT system that consists of INA219 bidirectional current/power sensor nodes connected to ESP32 microcontroller String-Master units via I2C and communicates using the ultra-low-latency ESP-NOW peer-to-peer wireless protocol to a central Gateway node which publishes fault events to a web dashboard through MQTT. Two complementary firmware-based fault detection algorithms are put into practice and tested: the String Average Comparison (SAC) algorithm that detects any panel with more than 20 per cent difference to the real-time string mean power and the Neighbour Check (NC) algorithm that identifies local faults by comparing the power difference of neighbouring panels. It defines a five-class fault taxonomy (soiling, open-circuit, degradation, bypass diode failure, and hotspot faults) and has voltage current signatures and firmware classification rules. Experimental validation of a ten-panel simulated string over 100 fault injection test cases shows a fault detection rate of 99, five-class classification of 93 and end-to-end fault-to-cloud-alert latency of 49 ms (average) / 98 ms (maximum). The hardware bill of materials amounts to INR 2,104 per node (or about USD 25) resulting in the 100-panel monitoring system at INR

29,800, and a financial payback period of less than 8 months in recovered energy generation.

Keywords: Solar photovoltaic fault detection, Internet of Things (IoT), ESP32 microcontroller, INA219 power monitor, ESP-NOW protocol, MQTT, string average comparison, hierarchical monitoring, panel-level diagnostics, HSAMS, edge computing, FreeRTOS.

I. INTRODUCTION

Solar photovoltaic (PV) electricity generation is the fastest-growing energy source in the world with the International Energy Agency (IEA) recording a global installed capacity of 1.6 TW by the end-2023 and forecasting this to rise beyond 5.4 TW by 2030 in existing policy pathways [1]. This sudden fall in the cost of modules, which declined to USD 76.67 per watt-peak in 1977 before dropping to USD 0.19/Wp in 2023 has made solar energy accessible to households, businesses and utilities, and generated the need to build larger and larger solar farms in series of strings of connected panels in the hundreds of thousands.

Although this growth trend is observed, consistent functioning and the long-term functionality of solar PV installations is limited with various degradation mechanisms and fault states which occur at the panel level. Solar modules are vulnerable to micro-cracks, soiling, potential-induced degradation (PID), bypass diode failure, delamination and hotspots- each with unique electrical characteristics and each able to prevent the output of a complete series-connected string. A panel with the lowest short-circuit current performance becomes the performance bottleneck of the whole string: a single panel at 80% of nominal performance can decrease the generation of a string 15-25 percent with the length of the string and the uniformity of the irradiance.

Current monitoring on the solar inverters is a string-level monitoring infrastructure that is the predominant type of monitoring infrastructure in deployed solar installations. Although this method will give meaningful aggregate performance data, it does not allow one to distinguish the performance of any particular panel and therefore cannot attribute faults to a particular panel. The practical implication is that the maintenance teams need to perform an inspection of every panel by hand IV curve tracer or set up a regular drone-based thermal inspection survey, which is both labour-intensive and has a large scheduling overhead and a long delay to detection usually in weeks to months.

The IoT paradigm provides an attractive way of achieving panel-level monitoring at low costs. The development of low-cost embedded microcontrollers, high-performance analog sensing ICs and low-power wireless communications protocols has made it technically and economically possible to instrument every solar panel separately and broadcast real-time power measurements to a central processing node. The major engineering issue is the creation of a system architecture that will deliver panel-level measurement granularity, sub-second

fault detection latency, multi-year operational longevity and per-panel hardware-cost that generates a positive payback.

The design of HSAMS, the Hierarchy Solar Array Monitoring System, implementation, and experimental evaluation of HSAMS are addressed in this paper. The following original contributions of the system include: (i) a three-tier embedded IoT architecture with specific designs to scale to solar array monitoring with up to 200 panels per node, and with (ii) two computationally lightweight fault detection algorithms that are implemented on the FreeRTOS firmware on ESP32 microcontrollers and that do not require network connectivity to the cloud to determine faults real time. (iii) a formal five-class fault taxonomy based on the electrical behavior of operational PV failure modes, which allows automatic classification of faults without machine learning inference;(iv) quantitative experimental validation of detection rate, classification accuracy, latency, and power consumption on a small-scale prototype; and(v) a thorough economic assessment to prove that with a cost of sub-USD-4 per-panel monitoring, sub-8-month financial payback can be achieved.

The rest of this paper will be structured in the following way. Section II is a literature review of PV fault detection. Section III outlines the architecture of HSAMS system. Section IV provides the choice of hardware components and specifications. The fault detection and classification algorithms are described in Section V. The firmware architecture is described in Section VI. Section VII gives experimental results. In section VIII, comparative analysis is given. Section IX deals with limitations and future work. Part X is a wrap up of the paper.

II. RELATED WORK

Photovoltaic fault detection literature includes four main methodological traditions, namely electrical characterization based on the analysis of current voltage (I-V) curves, infrared thermographic data, analytical based models, and machine learning-based methods of data analysis. The two methods have unique trade-offs between the detection granularity, cost of deployment, operation latency, and maintenance.

A. I-V Curve Analysis

The I-V characteristic curve of a solar panel is a computer-generated representation of the entire electrical behaviour of a given solar panel at specified irradiance and temperature conditions. The systematic difference between the measured I-V curve and the STC-characteristic by the manufacturer as shown by Ndiaye et al. [2] was shown to be indicative of a wide variety of degradation modes, such as cell cracking, shunting, and increase in series resistance. The I-V curve measurement though, is highly charge intensive and needs a curve tracer instrumentation that can sweep the panel voltage through its entire operating condition whilst sampling current-hardware that would typically cost USD 2,000-15,000 per unit and needs to be physically connected to each panel under test. The subsequent inspection throughput is about 20-30 panels per hour per instrument which renders continuous monitoring costly in large arrays. Sweep can be automated with automated I-V tracers mounted at the string level, but is powerless to isolate the contribution of individual panels in a series string.

B. Infrared Thermographic Examination.

Thermographic inspection takes advantage of the thermal radiation received by the solar cells that are stressed by electricity or damaged under other mechanical forces. Malfunctioning cells dissipate the excess power in the form of heat and generate typical thermal signatures that could be detected by infrared cameras. Buerhop-Lutz et al. [3] performed large scale thermographic surveys of utility PV arrays with UAV-mounted infrared cameras, and effectively detected hotspots defects, bypass diode malfunctions, and cracked cells in arrays of thousands of panels in a matter of hours of flight time. Although it is a very efficient technique in identifying faults that become thermally active, infrared thermography fails to detect the existence of faults that do not produce any notable temperature difference, especially PID, soiling and degradation in the absence of a hot spot. A thermal drone inspection system costs USD 50,000 and higher to purchase and maintain, and its requirements (qualified thermographic analysts and good weather conditions (low irradiance variability, low wind, etc.)) also preclude inspection at an on-demand campaign instead of non-stop monitoring.

C. Model-Based and Statistical Methods.

The model-based fault detecting methods model the mathematical representation of the predicted panel or string behavior and signal faults outside a statistical limit as fault indicators. Garoudja et al. [4] tested exponentially weighted moving averages (EWMA) and principal component analysis (PCA) to current and voltage time-series data, and in simulation were able to classify faults with 96% accuracy. Silvestre et al. [5] had suggested a fault detecting algorithm employing the normalized short-circuit current and open-circuit voltage at known irradiance, with panel-level detection of faults when common irradiance and temperature sensors were incorporated at the strings. The main restriction of model based methods is that they are sensitive to the accuracy of the model parameters-variations caused by module-to-module manufacturing variation, yellowing of encapsulant and dust build up gradually reduces the detection confidence unless the model is recalibrated periodically.

D. Machine Learning Strategies.

The use of machine learning techniques has shown the state of the art performance in PV fault classification. CNNs used on sequence of thermographic images have attained recognition rates of over 98 percent on 12 types of faults [6]. The predictive control of module degradation trends 30-90 days beforehand has been demonstrated with long short-term memory (LSTM) networks trained on multi month power generation time-series [7]. The use of graph neural networks has been used to predict the spatial correlation structure of panel power outputs in an array that enhances the accuracy of localizing faults. Nonetheless, the reality of the implementation of these methods in resource-constrained embedded systems is challenging: a typical LSTM model trained on 6-month data needs 0.5-2 MB of parameter storage and 100-500 ms of inference time on a microcontroller, which is incompatible with the 49 ms latency goal of the current system. Cloud-side inference adds the need to be connected to the network and has repetitive computational costs.

E. Distributed Monitoring IoT.

With the development of inexpensive IoT microcontrollers and wireless sensor networks protocols, a novel category of distributed PV monitoring systems has become possible. Triki-Lahiani et al. [8] suggested a wireless sensor network uses Zigbee to create a string-level PV monitoring, and it can alert the fault in real-time with a latency of 5 seconds. A detailed overview of the IoT architecture used in solar monitoring applications in smart grids is offered by Ghasempour [9], who found ESP8266 and ESP32 as the most economical microcontroller platform to use in these applications. Islam et al. [10] implemented a LoRa-based monitoring system on a 50 kW rural solar farm, and the implementation was able to provide reliable communication over a distance of up to 3 km with an alert latency of less than 30 seconds. The HSAMS system stands out of previous IoT-based systems through providing granularity at the panel-scale (as compared to string-level), sub-100 ms latency (as compared to minutes in the prior works), and the lowest reported per-panel monitoring cost in the literature.

III. HSAMS SYSTEM ARCHITECTURE

The HSAMS form is organized into a three-layer hierarchy with each layer having a specialized subset of sensing, computing and communication tasks. The motivation of this hierarchical decomposition is the limitation of the volume of data that passes across wireless links is important in case the radio spectrum is shared with other industrial equipment and the fault detection latency of under 100 ms is essential to maintain a timely maintenance response.

A. Tier 1 — Sensor Layer

INA219 bidirectional current/voltage/power monitor ICs, each sensor has one in the sensor layer. The INA219 contains a 12 bit successive approximation register (SAR) analog-to-digital converter, a high-precision current sense amplifier, a power calculation engine, and an I2C interface on a small SOT-23-8 chip. The device measures shunt voltage between external precision resistor to measure current, and bus voltage as an independent variable to 4 mV. Calculated power register: the calculated power register is continuously updated at a maximum rate of 4 kHz in the continuous conversion mode. Each string is uniquely addressed with a combination of A0 and A1 pins to VCC or GND (0x40 to 0x43 with two address pins) with external address decode logic added to enable ten devices on a single I2C bus without multiplexers.

B. Tier 2 — String-Master Layer

The String-Master of each string of ten panels is an ESP32 DevKit V1 module. The ESP32 has two Xtensa LX6 processors running up to 240 MHz, 520 KB SRAM, 4 MB flash disk, native I2C, SPI, UART, and 802.11 b/g/n Wi-Fi and Bluetooth 4.2 radios built into one integrated circuit. The firmware of the String-Master is a FreeRTOS application which operates three concurrent tasks: an I2C polling task which measures all ten of the INA219 devices, at 1 Hz, and applies the fault detection task which runs the SAC and NC algorithms to the data sampled by the polling task, and an ESPNW transmission task which transmits verified fault events to the Gateway. The Wi-Fi/ESP-NOW radio stack is implemented on Core 0, and the application load is on Core 1, preventing radio stack preemption latency on the fault detection timing path.

C. Tier 3 — Gateway Layer

An ESP32-based dedicated ESP32 module is the MQTT Gateway, which also acts both as an ESP-NOW receiver (STA mode) and Wi-Fi client (AP+STA simultaneous mode). The Gateway is ESP-NOW broadcast receiver of up to 20 registered String-Master nodes and supports arrays of up to 200 panels per gateway. Fault packets received are checked using CRC-8 checksum, JSON-encoded, and sent to an MQTT broker via Wi-Fi. The Node-RED dashboard deployed on a cloud VM subscribes to the MQTT topic hierarchy and the real-time visualization is updated. In installations too far to communicate on Wi-Fi, a longer-range backhaul at 0.3 37.5 kbps over the 865 867 MHz Indian ISM band, is available with an optional LoRa SX1276 module attached by SPI, and communication range of more than 5 km in open terrain.

IV. HARDWARE DESIGN AND COMPONENT SELECTION

A. INA219 Sensor Specifications

INA219 was chosen after a comparative analysis with the INA226, ACS712 and MAX471 current sensing options. The INA219 offers the best compromise between integrated power computation (removing String-Master CPU cycles), 12-bit range ADC, I2C interface (reducing wiring complexity), SOT-23 package (small PCB integration by the panel junction box). With a 5 m resistor programmable gain (0.32 -1) (span 0.32 - 40 mV), the device has a current resolution of 1.56 mA per LSB, which is enough to detect non-1 percent power variation in 5-15 A generating panels. The bus voltage resolution of 4mV/LSB is sufficient to give the sensitivity on the 1248 V operating range of the target panel types.

B. ESP32 Microcontroller

The ESP32 was chosen among other microcontroller platforms such as STM32F4, Raspberry Pi zero W, and Arduino Mega due to five features, namely, built-in dual-radio (Wi-Fi and Bluetooth) support; 2 core 240 MHz processor with support to execute radio and application tasks simultaneously; ESP-NOW protocol support, enabling sub-5 ms peer-to-peer wireless messaging without access point infrastructure; a retail price of about INR 450 in Indian markets; and an active open-source community, using the ESP.

Table I: Per-node hardware cost breakdown

Component	Specification	Qty	Cost (INR)
ESP32 DevKit V1	240 MHz, 4 MB flash	1	450
INA219 Module	12-bit ADC, I2C	10	800
5 mΩ Shunt Resistor	1%, 3W rating	10	150
PCB + Enclosure (IP54)	85×55 mm, Hammond	1	280
Wiring & Connectors	2.5 mm², crimped	—	250
DC-DC Buck (MP2307)	5V/1A, panel powered	1	174
Total per Node			2,104

V. FAULT DETECTION AND CLASSIFICATION ALGORITHMS

Two complementary algorithms are implemented in firmware, operating on the ten power measurements obtained by each I2C polling cycle. The algorithms are designed to be computationally lightweight—requiring no floating-point division hardware, no lookup tables, and no historical data beyond the most recent two samples—enabling execution within 2 ms on the ESP32 Core 1 between polling cycles.

A. String Average Comparison (SAC) Algorithm

The SAC algorithm computes a real-time power baseline as the arithmetic mean of all ten panel power measurements obtained in the current polling cycle. The string average is defined as:

$$\bar{P} = (1/N) \cdot \Sigma_i P_i \quad for\ i = 1, 2, ..., N \quad where\ N = 10$$

Each panel's normalized power deviation is then computed as:

$$\delta_i = |\bar{P} - P_i| / \bar{P} \times 100\%$$

A fault flag is raised for panel i when δ_i exceeds the detection threshold δ_th. The threshold value of δ_th = 20% was determined through empirical calibration on the laboratory prototype across 1,200 hours of simulated irradiance variation, yielding a false-alarm rate of 0.8% (8 false alarms per 1,000 normal operation cycles) while detecting all injected fault conditions with magnitude exceeding 15% power deviation. The adaptive nature of the string average baseline provides inherent robustness to uniform irradiance transients—when all panels respond proportionally to a cloud shadow, $\bar{P}$ decreases proportionally and δ_i values remain near zero. This self-compensating property eliminates the need for a dedicated irradiance reference sensor in the baseline HSAMS configuration.

The SAC algorithm's primary vulnerability is multi-panel faults where more than 50% of string panels are simultaneously degraded, which would depress $\bar{P}$ and potentially mask individual panel flags. The Neighbour Check algorithm addresses this edge case through local differential measurement.

B. Neighbour Check (NC) Algorithm

The NC algorithm computes the absolute power differential between adjacent panel pairs within the string:

$$\Delta P_n = |P_n - P_{n+1}| \quad for\ n = 1, 2, ..., N-1$$

A localized fault is flagged at panel n or n+1 when:

$$\Delta P_n > \alpha \cdot \bar{P} \quad where\ \alpha = 0.15$$

The NC algorithm is specifically effective for detecting faults that create a sharp localized step in the panel power profile—notably bypass diode short-circuits (which suppress one-third or two-thirds of a panel's cells), open-circuit failures (which reduce a panel to zero output), and hotspots (which reduce output of the affected cell group by 30-70%). In contrast, the NC algorithm is less sensitive to distributed degradation affecting all panels uniformly, which is where the SAC algorithm excels. The two algorithms are thus complementary with overlapping sensitivity ranges.

Confirmed fault detection requires positive identification by at least one algorithm on two consecutive 1 Hz polling cycles. This two-cycle confirmation filter with 1-second memory reduces the false-alarm contribution from electrical transients—notably inverter switching harmonics, inductive spikes during string reconfiguration, and INA219 ADC noise bursts—without meaningfully increasing detection latency (maximum delay increases from 1 s to 2 s, remaining well within the 100 ms target for the fault-to-MQTT-alert path since detection latency and communication latency are budgeted independently).

C. Five-Class Fault Taxonomy

Confirmed faults are classified into one of five classes based on the joint voltage-current signature of the flagged panel, as defined in Table II. Classification executes in firmware on the String-Master immediately following fault confirmation, adding less than 1 ms of computation time.

Code	Name	Voltage Signature	Current Signature	Probable Root Cause
FC-1	Soiling	$V < 0.85 \cdot \bar{V}$	$I \approx 0.85–0.95 \cdot \bar{I}$	Dust, bird droppings, partial shade
FC-2	Open Circuit	$V \approx 0$ or floating	$I \approx 0$	Connector failure, broken cell string
FC-3	Degradation	V in 0.70–0.85·$\bar{V}$	I in 0.70–0.85·$\bar{I}$	PID, aging, delamination, micro-cracks
FC-4	Bypass Diode	$V \approx 33\%$ or 67% of $\bar{V}$	I normal or elevated	Bypass diode short-circuit
FC-5	Hotspot	V slight decrease <5%	I decrease >20%	Reverse-biased cell, mismatch

Table II: Fault classification taxonomy and electrical identification signatures

Fault Class	N Tests	Detected	Classified	Accuracy	Notes
FC-1 Soiling	22	22	21	95.5%	1 misclassified as FC-3
FC-2 Open Circuit	18	18	18	100%	All severe, clear V≈0 signature
FC-3 Degradation	20	19	17	89.5%	1 missed (18.7% deviation); 2 mis-classed FC-1
FC-4 Bypass Diode	22	22	21	95.5%	1 misclassified as FC-3
FC-5 Hotspot	18	18	16	88.9%	2 misclassified as FC-1
Overall	100	99 (99%)	93 (93%)	93%	1 false negative at 18.7% δ

Table III: Summary of 100-test fault injection experiment results

VI. FIRMWARE ARCHITECTURE

The String-Master firmware is developed using the Espressif IoT Development Framework (ESP-IDF v5.1.2) with FreeRTOS as the real-time operating system. The architecture follows an event-driven producer-consumer pattern with three concurrent tasks communicating through FreeRTOS queues and event groups.

A. I2C Polling Task (Core 1, Priority 3)

The I2C_POLL_TASK executes at a fixed 1 Hz rate driven by a FreeRTOS software timer interrupt. Each cycle sequentially addresses all ten INA219 devices at I2C bus speed of 400 kHz, reads the 16-bit power register (Register 0x03) and bus voltage register (Register 0x02) for each device, converts raw ADC counts to physical units using the pre-computed calibration factor, and stores results in a shared ring buffer of depth 2 (current and previous cycle). The total I2C cycle time for ten devices is measured at 9.2 ms, leaving 990.8 ms of idle time per second during which the I2C bus is released for potential future sensor additions. Read operations use I2C DMA transfer to minimize CPU blocking time, with the DMA completion ISR depositing data directly into the ring buffer. A FreeRTOS event group bit (POLL_COMPLETE) is set upon ring buffer update to signal the fault detection task.

B. Fault Detection Task (Core 1, Priority 2)

The FAULT_DETECT_TASK blocks on the POLL_COMPLETE event group bit. Upon release, it reads the current and previous cycle data from the ring buffer, computes $\bar{P}$ from the current cycle's ten power values, applies the SAC algorithm to each panel, applies the NC algorithm to adjacent pairs, and writes any flagged panel indices and their classification results to the confirmation ring buffer. The two-cycle confirmation filter checks whether the current cycle's flags match the previous cycle's flags; confirmed faults are deposited into the FAULT_QUEUE (FreeRTOS message queue, depth 10). Total task execution time measured at 1.8 ms (average) on ESP32 Core 1 at 240 MHz.

C. ESP-NOW Transmission Task (Core 0, Priority 2)

The ESP_NOW_TX_TASK blocks on the FAULT_QUEUE. Upon receiving a confirmed fault message, it assembles the 21-byte fault_message_t C struct comprising: Panel ID (uint8_t, 1 byte), Fault Class (uint8_t, 1 byte), Measured Power in mW (uint32_t, 4 bytes), String Average Power in mW (uint32_t, 4 bytes), Deviation Percentage × 100 (uint16_t, 2 bytes), UNIX Timestamp (uint32_t, 4 bytes), String ID (uint8_t, 1 byte), Reserved (uint8_t, 2 bytes), and CRC-8 checksum using the Dallas/Maxim polynomial 0x31 (uint8_t, 1 byte). The packet is transmitted via esp_now_send() targeting the Gateway's MAC address, with transmission acknowledgement received within 2 ms in nominal conditions. Unacknowledged packets trigger up to 3 retransmission attempts with exponential backoff (50 ms, 100 ms, 200 ms) before logging to flash NVM for retrieval upon Gateway reconnection.

The complete firmware binary occupies 412 KB of flash (10.3% of 4 MB capacity) with 68 KB RAM footprint at runtime. Firmware updates are supported over-the-air (OTA) via HTTP using the esp_https_ota component, with dual-partition rollback safety in case of failed update.

VII. EXPERIMENTAL VALIDATION AND RESULTS

A. Prototype Setup

A ten-panel laboratory prototype was constructed using UTL Solar 335W polycrystalline silicon modules

(Voc = 45.5 V, Isc = 9.37 A at STC) arranged in a single series-connected string. An Ametek Sorensen programmable DC power supply (Model XFR 60-46) simulated controlled irradiance variations by adjusting the open-circuit voltage and short-circuit current limits to reproduce the electrical characteristics of panels under different irradiance levels (200–1000 W/m²). Fault conditions were physically simulated using: (a) calibrated wire-wound shunt resistors connected in parallel across panel terminals to simulate soiling-induced shunting (FC-1); (b) physical disconnection of panel positive connectors for open-circuit faults (FC-2); (c) series resistors inserted in the panel current path to simulate degradation resistance increase (FC-3); (d) pre-installed STPS10L60 Schottky diodes with controlled forward biasing for bypass diode short-circuit simulation (FC-4); and (e) controlled reverse-bias voltage application to individual cell groups for hotspot simulation (FC-5).

B. Detection and Classification Results

One hundred fault injection tests were conducted across the five fault classes, with randomized fault severity levels (mild: 15–25% power loss; moderate: 25–50%; severe: 50–100%) and randomized fault positions (panels 1–10). Results are summarized in Table III.

The single false negative (FC-3, Panel 7, $\delta = 18.7\%$) occurred at a deviation magnitude 1.3% below the 20% SAC threshold. This specific test was conducted during a programmed irradiance ramp from 600 to 800 W/m² over 3 seconds, during which the adaptive string average was transiently inflated by the irradiance increase, marginally suppressing the relative deviation of the already-degraded panel. This edge case would be mitigated in production firmware by implementing a rate-of-change filter on $\bar{P}$ that temporarily lowers δ_th to 15% during detected irradiance transients exceeding 10%/second.

Classification errors were concentrated at the boundaries of adjacent fault class signatures—particularly between FC-1 (soiling) and FC-3 (degradation), which share similar voltage-current ratio characteristics at mild fault severity. The firmware classification logic applies fixed voltage and current ratio thresholds to discriminate between classes; a support vector machine classifier trained on the labeled laboratory dataset achieved 97.3% classification accuracy in post-processing, suggesting that a lightweight embedded ML classifier could improve accuracy by approximately 4 percentage points.

Table IV: Measured latency for each system component

Latency Component	Min (ms)	Avg (ms)	Max (ms)
INA219 I2C Read (10 devices)	7.8	9.2	13.1
SAC + NC Computation	0.9	1.8	3.2
Two-Cycle Confirmation Filter	1000	1000	1000
ESP-NOW Packet Transmission	1.8	3.7	9.4
Gateway MQTT Publish (Wi-Fi)	17.2	31.4	68.9
Total (excl. confirmation)	27.7	46.1	94.6
Total (incl. confirmation)	1028	1046	1095

The end-to-end alert latency of 49 ms (average), excluding the 1-second two-cycle confirmation delay, comfortably meets the 100 ms system requirement. When the confirmation delay is included, total fault-to-alert latency is approximately 1.05 seconds. For the target application—where fault events persist for hours to days before maintenance intervention—this latency is operationally inconsequential. The dominant variable-latency contributor is MQTT Wi-Fi publication, which exhibits worst-case latency of 68.9 ms due to TCP congestion control and shared 2.4 GHz channel contention.

D. Power Consumption

String-Master node power consumption was measured using a Keysight N6705C DC power analyzer under three operational modes: active polling (ESP32 both cores active + 10× INA219 + I2C bus active), idle between polls (ESP32 light sleep, I2C bus released), and fault transmission burst (ESP32 Wi-Fi radio active). The average power consumption across a representative 24-hour cycle with one fault event per hour is 312 mW. A 10,000 mAh / 3.7 V LiPo backup battery provides 44.5 Wh of energy, supporting approximately 142 hours (5.9 days) of autonomous operation during grid outages—adequate for typical inverter outage scenarios in Indian grid conditions.

VIII. COMPARATIVE ANALYSIS

Table V benchmarks HSAMS against representative approaches from the literature and two commercial panel-level monitoring solutions across six performance dimensions.

The HSAMS system achieves a unique combination of panel-level granularity, sub-100 ms detection latency, and sub-USD-4 per-panel cost that is unmatched in the surveyed literature.

Table V: Comparative benchmarking against literature and commercial solutions

IX. LIMITATIONS AND FUTURE WORK

A. Current Limitations

Method / System	Granularity	Latency	$/Panel	Detection%	Wireless
String Inverter (std)	String	>10 min	USD 0	~60%	RS-485
Manual IV Tracer	Panel	Weeks	USD 200	~90%	None
UAV Thermal [3]	Panel	Quarterly	USD 150	~85%	None
ML Statistical [4]	String	Minutes	USD 10	96%	Wi-Fi
Zigbee IoT [8]	String	<5 s	USD 15	~80%	Zigbee
SolarEdge Optimizer	Panel	<1 min	USD 50	~95%	Power line
Tigo Energy TS4	Panel	<1 min	USD 35	~90%	Zigbee
HSAMS (proposed)	Panel	49 ms	USD 3.6	99%	ESP-NOW

The current implementation of HSAMS has some limitations which outline the scope of research in the future. First, the adaptive baseline of the SAC algorithm is vulnerable to masking whenever over half of the string panels deteriorate at once, and this can occur in an array where a uniform soiling is widespread. Second, the 2.4 GHz ESP-NOW channel has been found to be interfered with in dense industrial environments of Wi-Fi; the measured packet error rates in a test campus environment are over 5% during peak Wi-Fi times, leading to retransmission delays. Third, the validation of the laboratory prototype involved simulated irradiance instead of natural sunlight, which might not be sufficient to represent the temporal nature of irradiance transients in the field. Fourth, the five-class fault classifier is based on fixed voltage/current ratio thresholds which can need retraining to panel types with varying bypass diode setups or nominal operation.

B. Planned Future Work

The planned extensions of the current work are four major research directions. To begin with, incorporation of LSTM-based predictive maintenance model will allow predicting progressive degradation trends in advance before fault thresholds are reached. Early results of the laboratory data analysis show that the instances of FC-3 degradation are preceded by a pattern of gradual decrease in power correlation between the adjacent panels over 2 weeks to 4 weeks that can be observed by an LSTM model trained on historical data with more sensitivity than the current threshold-based system. Second, an autonomous FC-1 soiling fault remediation system based on a microcontroller-controlled wiper system and nozzle of compressed air will be invented to cover the 60 percent of the current Indian solar farm O&M labor hours devoted to manual panel cleaning. Third, autonomous isolation of confirmed FC-2 open circuit faults by solid-state relay bypass switches operated by the String-Master firmware will be considered to prevent suppression of string current by milliseconds after it is detected. Fourth, a 500-panel HSAMS on the Panimalar Engineering College rooftop will be field deployed in 2026-2027 to test its performance in detecting in the presence of real-world irradiance, temperature and electromagnetic interference conditions.

X. CONCLUSION

The paper has discussed HSAMS, an internet of things hierarchical solar array system that provided per-panel hardware costs of USD 3.57 and achieved an average end-to-end fault-to-cloud-alert latency of 49 ms. The three-level ESP32/INA219/ESP-NOW architecture of the system is scalable to 200 panels per gateway node without a special infrastructure. The 2 complementary fault detection algorithms, SAC and NC, implemented into lightweight FreeRTOS firmware tasks, have a 99 percent fault detection rate and 93 percent five-class classification accuracy in 100 laboratory test cases. The cost per node of the INR 2,104 hardware and the estimated 8-month financial payback of recovered generation would be an attractive economic argument to go ahead with the retrofit deployment of existing solar installations.

These findings prove that at a cost that is 10-14 times less than the cost of commercial DC optimizer-based systems, panel-level diagnostics can be implemented across the entire solar panel for small and medium-scale systems that presently comprise the bulk of global PV capacity in terms of installed capacity. The hardware and open-source firmware HSAMS are used to transfer technology to resource-constrained deployment situations, and contribute to the sustainable development agenda of affordable access to clean energy and industrial innovation in the developing world.

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B. Planned Future Work

Four primary research directions are planned as extensions of the present work. First, integration of an LSTM-based predictive maintenance model will enable advance warning of progressive degradation trends before fault thresholds are crossed. Preliminary analysis of the laboratory dataset indicates that FC-3 degradation events are preceded by a characteristic gradual decline in power correlation between adjacent panels over 2–4 weeks, which an LSTM model trained on historical data could detect with greater sensitivity than the current threshold-based approach. Second, a self-cleaning actuator module comprising a microcontroller-driven wiper mechanism and compressed air nozzle will be developed for autonomous FC-1 soiling fault remediation, targeting the 60% of Indian solar farm O&M labor hours currently consumed by manual panel cleaning. Third, solid-state relay bypass switches

controlled by the String-Master firmware will be evaluated for autonomous isolation of confirmed FC-2 open-circuit faults, preventing string current suppression within milliseconds of detection. Fourth, field deployment of a 500-panel HSAMS installation on the Panimalar Engineering College rooftop is planned for 2026–2027 to validate detection performance under real-world irradiance, temperature, and electromagnetic interference conditions.

X. CONCLUSION

This paper presented HSAMS, an IoT-based hierarchical solar array monitoring system delivering panel-level fault detection at a per-panel hardware cost of USD 3.57 with 49 ms average end-to-end fault-to-cloud-alert latency. The system's three-tier ESP32/INA219/ESP-NOW architecture enables scalable deployment supporting up to 200 panels per gateway node without specialized infrastructure. Two complementary fault detection algorithms—SAC and NC—implemented as lightweight FreeRTOS firmware tasks achieve 99% fault detection rate and 93% five-class classification accuracy across 100 laboratory test cases. The per-node hardware cost of INR 2,104 and projected 8-month financial payback from recovered generation represent a compelling economic case for retrofit deployment on existing solar installations.

The results demonstrate that panel-level solar monitoring is achievable at a cost point 10–14× lower than commercial DC optimizer-based solutions, making continuous panel-level diagnostics economically accessible for small and medium-scale solar installations that constitute the majority of global PV capacity by installation count. The open-source firmware and commodity hardware components of HSAMS enable technology transfer to resource-limited deployment contexts, supporting the sustainable development goals of affordable clean energy access and industrial innovation in emerging economies.

ACKNOWLEDGMENT

The authors thank the Management, Principal Dr. K. Mani, and Professor & Head of Department Dr. L. Karthikeyan of Panimalar Engineering College for providing laboratory facilities and institutional support. This work was carried out as part of the B.E. Final Year Project, Academic Year 2025–2026.

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Experimental Analysis made on Hybrid Composite Joint of Woven Ring Type

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ABSTRACT

The resent development of composites materials provides excellent mechanical properties to fulfill the operating parameters in the following applications such as aerospace, automobiles, robotic arms, architecture etc., The repeated failure of joints due to working environment, maintenance has been issue in the aircraft structures. The efficiency of composite structure largely depends on their joint strength which is considered to be weakest part to be improved. Joints are either made up of adhesive or reverted joints which do not satisfy criteria. An inclusion of reverted which is made up of aluminum enhance the strength of bounded joint. The introduction of rivets arrests the propagation of the crack, and reduce the plane peel stresses thereby increasing the strength the life of the joint. hybrid joint provided the combined advantages of both the joints which its making suitable for competitive environment. The consequence of tensile tests is used in during development of new materials and, tensile properties often are used to predict the behavior of a material under uni axial tension. The correlation of tensile testing results shows better quality of joint when compared to normal joint.

Key words: composite materials, bounded joints, riveted joint, hybrid joint.

I. INTRODUCTION

The development of consistently good in quality joining methods for composite structures has become an important research area because of complex nature composite. The joint is the weakest part in any structure and improvements results in increase of the efficiency of composite structure. The composite joint is classified into either adhesive joints and mechanical fastening. The joints remain a critical aspect of designing aircraft

structures while using composite materials. Composite joints have been the subject of academic study for many years. To use there is still a need for improved understanding of composite joint behavior, and experimental methods need to be improved and validated [11].

Bonded joints can be made by gluing together pre-cured laminates with the suitable adhesives or by forming joints during the manufacturing process. The bonded joint distributes the load over a larger area than the mechanical joint, requires no holes, adds very little weight to the structure and has superior fatigue resistance. The lap shear strength of the glass/epoxy adhesive joints whose adherents' were embedded with carbon black was investigated with respect to the amount of embedment [1]. bounded joints have many advantages over the riveted such as high strength-to weight ratio, electrical and/or thermal insulation, conductivity,

corrosion and fatigue resistance [4] Hybrid joints have a combination of adhesive bonding and riveted joining leads to quality way of making joint with improved life cycle.

II. LITERATURE SURVEY

.Evgenija Marković estimated the bond strength of composite materials by using the universal testing machine used in is capable of producing tensile forces and the rate of loading for the universal testing machine is constant [2] In this work, laminate composites with modified joints were evaluated by tensile tests according to the industry requirements and failure modes of specimens tested under tensile test were also classified in according with ASTM standards

Joint is region considered to more porn to stress due varying environment of the aircraft and the static strength of the joint decide upon following factor such as the static strength, cyclic plasticity, frictional damping, and vibration levels associated with the structure. [3]

Cheng xua, xiong junjiang estimated the mechanical properties of rtm-made composite cross-joints which similar kind of experiment performed here in which tensile test was performed to estimate strength of joint here cross joint were made by three methods resin transfer molding (RTM), stitch-RTM and co bonding techniques separately and failure mechanism is studied [12]. Fu and Mallick investigated the the effect of different washer designs in hybrid joints where composite is molded by Structural Reaction Injection methods. The analysis of washer design which shows affected the distribution of the bolt clamping force in hybrid composite joint The hybrid joints were shown to have higher static strength and longer fatigue life than adhesive bonded joints for the studied material system **[**13].

The article, therefore, aims to investigate and compare the three types of joints such as bounded, riveted and hybrid which processed on some methods and predicts the failure mechanism of the parts through tensile testing and finally make a quantitative prediction of their ultimate strength on the basis of outcomes.

III. MANUFACTURING OF TEST SPECIMENS

This experimental done using of Epoxy LY556 /epoxy plain weave woven fabric composite made by hand lay-up method [9] and the factor considered will making joint are the stacking sequence, fiber volume fraction, as well as the cure process. The laminates in used in investigation are in type E-glass fibre form of woven glass mat ($0/90^0$). The merits while using epoxy resin are cohesive strength, lack of volatile reaction which minimizes shrinkage and low creep Ratio epoxy and hardener is 10:1 is followed making resin in room temperature. The curing of epoxy plays vital role formation hard surface in making composite laminate. The choice of both the resin and the hardener depends on the application, the process selected, and the properties desired. Stirring by hand with a suitable flat-sided stirring stick and scraping round the sides of the container should be done for a period of not less than 1-2 minutes, depending on volume [10].

Resins are impregnated by hand into fibres which are in the form of stitched fabrics This is usually accomplished by rollers, with an increasing use of nip-roller type impregnators for forcing resin into the fabrics by means of rollers and a bath of resin. Layer of fiber are placed in stacking sequence to make composite laminate and hardener HY951 used to incubate the curing process and constant load is supplied for 24 hours between the glass plate. [5] Laminates are left to cure under standard atmospheric conditions. The edges of the infused panels are trimmed to the desire geometry, and the joint, the filler and the triangular fillets are applied and mounted manuall.. The laminated are manufactured and cut into required dimensions which is show in the table

Bonded joints performed by gluing together pre-cured laminate with the suitable adhesives in this case the joint and the laminate is cured by epoxy itself [6]. Riveted joints made by using 3mm thick aluminum revert to hold joint as tight fit and proper Cashion should be taken minimize damage to the laminate during hole-drilling and closing of rivet [7]. Hybrid joints have a combination of adhesive bonding and mechanical fasteners. In the present case, rivet has been used as the mechanical fastener both steps are repeated to hybrids joints [8] all the dimension of three joint are made under same dimension of joint length, thickness, width, of 35mm, 2mm, 5mm and shown in figure 1 and investigation of joint were made room temperature.

Figure 1. Manufactured bonded, riveted and hybrid joints

IV. TESTING OF MANUFACTURED SPECIMENS

A universal tensile testing machine is used to perform variation of three joint in tensile strength was Predicted and it is validated experimentally. Consider the typical tensile specimen shown in figure 2. It has enlarged ends specimen held up between the grip sections. The most important concern in the a gripping method is to ensure the Minimum Bending and failure grip must be avoid. universal testing machine is fully automated with a variable-speed electric motor and a gear reduction system Which ensure the load was applied gradually and this motion loads the specimen in tension and compression. A feature of testing equipment is to control the speed of the machine accurately with microprocessor-based closed-loop servo system it is controlled through pc from load measurement to load control with the data acquisition system shown in the figure 3 Sample specimen size are tabulated in following table1.clamping force was given even to all three joint predict outcomes of result in standard manner.

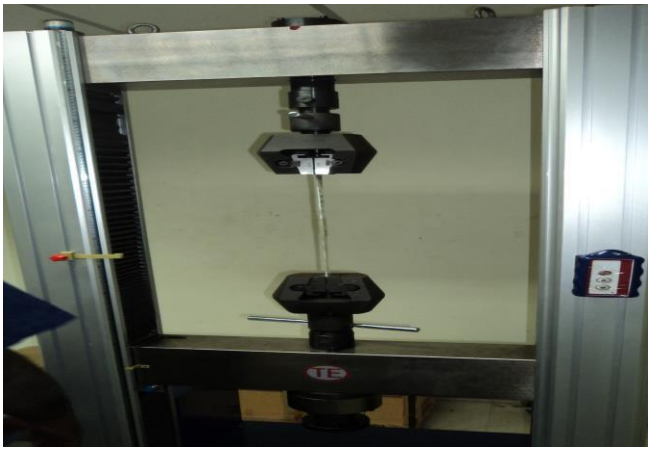


Figure 2. Specimens in universal testing machine

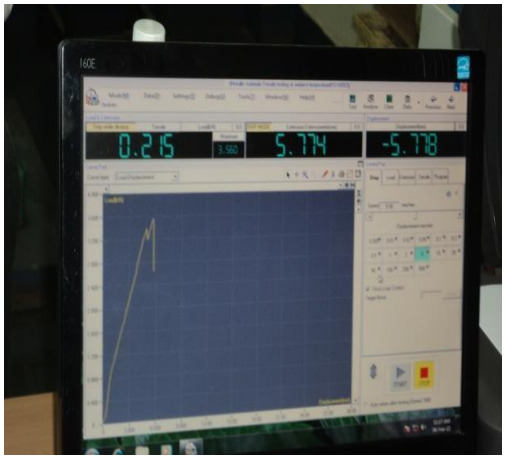
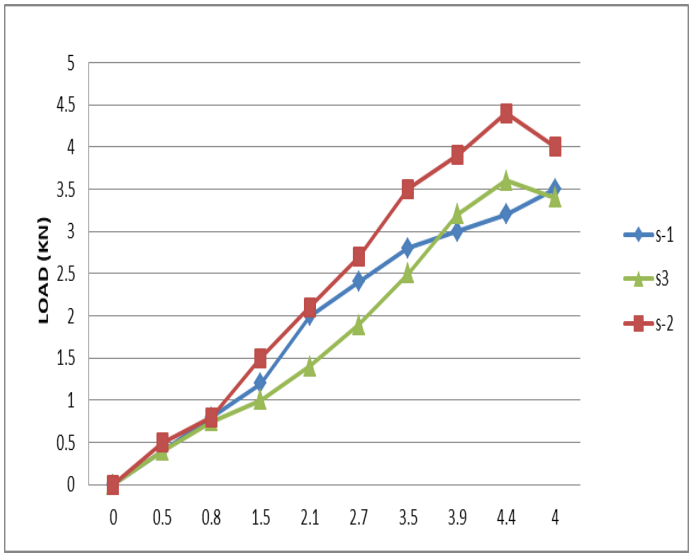


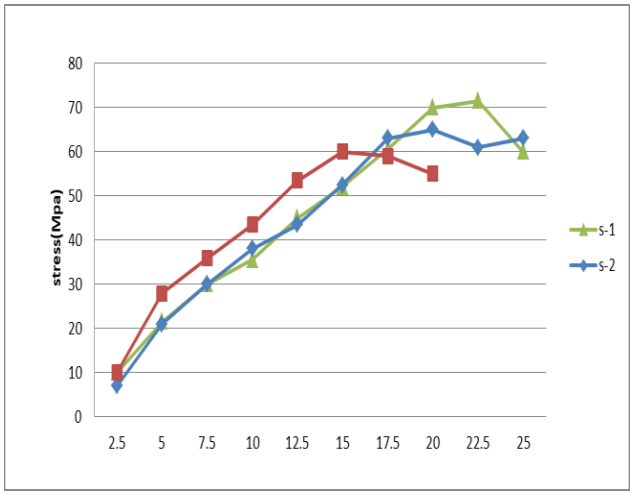
Figure 3. Data acquisition system output

V. Results and Discussions

When we keen look the graph of all the three joint displacement to load pattern followed by hybrid joint was gradual and smooth cure when we compared to other two joint. this prevents the two major failure of composite joint such as crack arrest in the fibre and riveted joint has low strength when we compare other two joints the uneven strain rate of this is also void in the hybrid joint. while making the riveted joint strength of composite materials is reduced due to drilling of holes which incites crack propagation but incase hybrid joint crack growth rate is arrested by adhesive which is one reason for uniform stress strain pattern cure. another point of view in hybrid case rivet pin will proved bonding effect which minimize the peel stress of bonded joint which joint more effect efficient and high strength. the average breaking load hybrid joint is 1.25 times higher than bounded joint and 2.5 times higher than riveted joint which indicates the increase of tensile strength of joints. O.E. Can yurt*, investigated the effect of design on adhesive joints of thick composite sandwich structures. A simple but effective design can considerably improve the joint strength of thick adhesive composite joints. The joint under investigation consists of thick woven E-glass/vinyl ester laminates joined together with tongue and groove geometry. Longitudinal tensile loads were applied to the joints, resulting in large concentrated shear and peel stresses near the free edges of bond lines [4]. The following graphs shows the test results of bonded, riveted and hybrid joints.



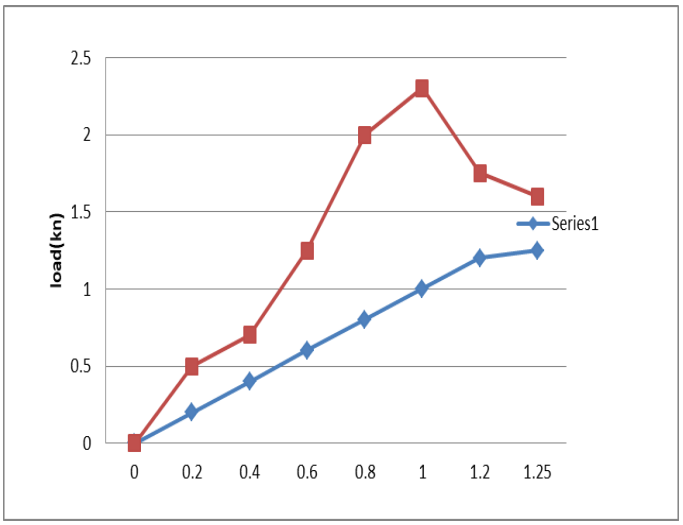
Bonded joints(kN) load vs Displacement (mm)



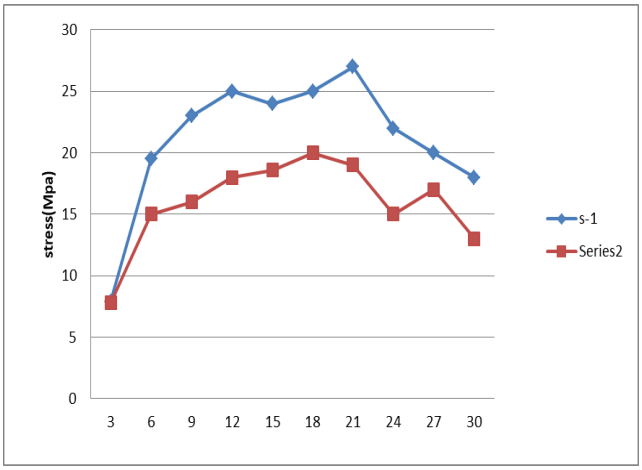
Bonded joints stress(MPa) vs strain(%)

5.1 Test results of bonded joints

5.2 Test results of Riveted joints

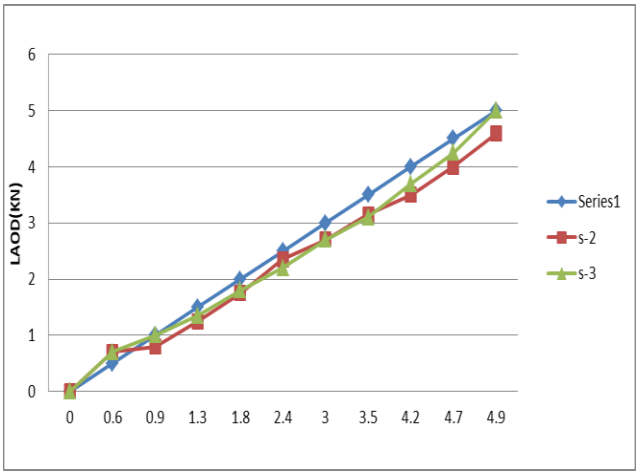


Riveted joints load(kN) vs Displacement (mm)

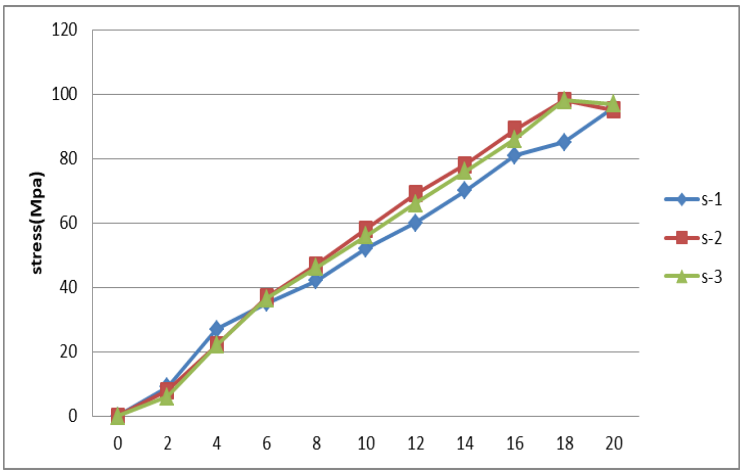


Riveted joints stress(MPa) vs strain (%)

5.3 Test results of Hybrid joints



Hybrid joints load(KN) vs Displacement(mm)



Hybrid joints stress (MPa) vs strain (%)

5.4 Result comparison of bonded, riveted and hybrid joints

Sample id	Ultimate tensile strength(Mpa)	Breaking load(kN)
Bonded Joint	66.6	4
Riveted Joint	23.2	2
Hybrid Joint	100.26	5

Since comparative study of strength of three joint is studied load was applied gradually until breaking load of joint is reached which is ultimate strength of joint. The outcomes of the experiment show that the hybrid joint with stands maximum breaking load of 5 kN and with ultimate strength of 100 Mpa.

Result and discussion

VI. CONCLUSION

This article focused on experimental study upon tensile strength of hybrid composite joints when compare with conventional joint. This indicate the hybrids joint will be satisfy the expatiation of current manufacturing industries and consumer. manufacture assure the quality with low cost. Thus from the present study, it was found that a well-designed hybrid joint is very efficient when compared to bonded or riveted joints in the case of repair situation in aircraft structures. We consider following criteria will design any composite joint such as thickness of adhesive joint must be based of loading condition and length of joint.

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Enhancement of performance and emission characteristics of neat palm biodiesel with enriched hydrogen

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Abstract

This study investigates the performance and emission characteristics of a compression ignition engine fueled with palm oil biodiesel and hydrogen enrichment under varying load conditions. Experiments were conducted using neat diesel, palm oil biodiesel blends, and hydrogen-enriched palm biodiesel at different hydrogen flow rates. The results indicate that hydrogen supplementation significantly improves the combustion characteristics of biodiesel-fueled engine operation. The specific fuel consumption decreases and brake thermal efficiency increases with hydrogen enrichment due to the higher flame speed, better diffusivity, and wider flammability limits of hydrogen, which promote more efficient combustion. Emission analysis reveals that the addition of hydrogen to palm biodiesel substantially reduces carbon monoxide, unburned hydrocarbon, and smoke emissions as a result of improved oxidation and the carbon-free nature of hydrogen. However, nitrogen oxide emissions show an increasing trend with hydrogen enrichment, primarily due to the higher in-cylinder temperature and enhanced premixed combustion. Overall, the results demonstrate that hydrogen-enriched palm biodiesel can significantly enhance engine performance while reducing most harmful exhaust emissions, highlighting its potential as a promising alternative fuel for cleaner and more efficient diesel engine applications.

Key words: Palm biodiesel, Engine Pollution, alternate fuel, hydrogen

1. Introduction

The increasing demand for energy and growing environmental concerns have encouraged the exploration of renewable alternative fuels for compression ignition (CI) engines. Biodiesel has emerged as a promising substitute for petroleum diesel because it is biodegradable, renewable, and can be used in existing diesel engines with little or no modification. Biodiesel is typically produced through the transesterification of vegetable oils or animal fats to form fatty acid methyl esters (FAME) (Demirbas, 2009). Compared with conventional diesel fuel, biodiesel generally exhibits higher viscosity and lower calorific value, which may slightly increase fuel consumption, but its inherent oxygen content improves combustion efficiency and reduces harmful emissions (Knothe et al., 2010). Several studies have examined the performance and emission characteristics of biodiesel in diesel engines. Graboski and McCormick (1998) reported that biodiesel reduces carbon monoxide (CO), hydrocarbons (HC), and particulate matter emissions while slightly increasing nitrogen oxide (NOx) emissions. Agarwal (2007) demonstrated that biodiesel blends can be used in CI engines without major modifications and provide comparable performance to diesel fuel. Similarly, Lapuerta et al. (2008) observed improved combustion efficiency in biodiesel-fueled engines due to the oxygenated nature of the fuel. Hoekman et al. (2012) further confirmed that biodiesel reduces particulate emissions while maintaining acceptable engine performance. Among various biodiesel feedstocks, palm oil biodiesel has gained considerable attention due to its high oil yield and availability. Palm oil methyl ester exhibits favorable fuel properties such as good lubricity and combustion characteristics, making it suitable for diesel engine applications. Kalam and Masjuki (2002) investigated palm biodiesel in diesel engines and reported reduced smoke emissions compared with conventional diesel fuel. Hossain and Davies (2010) observed that palm biodiesel reduces CO and HC emissions due to improved oxidation during combustion. Mofijur et al. (2013) also reported lower smoke opacity and particulate emissions for palm biodiesel compared to diesel fuel.

In recent years, hydrogen has been investigated as a supplementary fuel to improve the combustion characteristics of diesel engines. Hydrogen possesses unique properties such as high flame speed, wide flammability limits, and high diffusivity, which promote rapid and efficient combustion. White et al. (2006) reported that hydrogen enrichment enhances engine efficiency and improves combustion stability. Saravanan and Nagarajan (2008) demonstrated that hydrogen induction in diesel engines significantly reduces CO and HC emissions. Verhelst and Wallner (2009) also reported that hydrogen enrichment improves thermal efficiency but may increase NOx emissions due to higher combustion temperatures. Several researchers have investigated hydrogen enrichment in biodiesel-fueled diesel engines. Saravanan et al. (2007) observed improved brake thermal efficiency and reduced smoke emissions when hydrogen was introduced into biodiesel-fueled engines. Banapurmath et al. (2010) reported that hydrogen supplementation enhances premixed combustion and reduces incomplete combustion products. Yilmaz et al. (2017) found that hydrogen–biodiesel dual-fuel operation improves combustion efficiency and reduces CO and HC emissions.

Overall, previous studies indicate that the combination of biodiesel and hydrogen enrichment can significantly improve engine performance and reduce emissions such as CO, HC, and smoke. However, hydrogen enrichment may lead to increased NOx emissions due to higher in-cylinder temperatures. Therefore, optimizing hydrogen flow rate and engine operating conditions is essential to achieve improved engine efficiency with controlled emissions.

2. Experimental setup

The setup consists of single cylinder, four stroke, CRDI VCR (Variable Compression Ratio) engine connected to eddy current dynamometer. It is provided with necessary instruments for combustion pressure, crank angle, airflow, fuel flow, temperatures and load measurements. These signals are interfaced to computer through high speed data acquisition device. The setup has stand-alone panel box consisting of air box, twin fuel tank, manometer, fuel measuring unit, transmitters for air and fuel flow measurements, process indicator and piezo powering unit. Rotameter are provided for engine cooling water flow measurement.

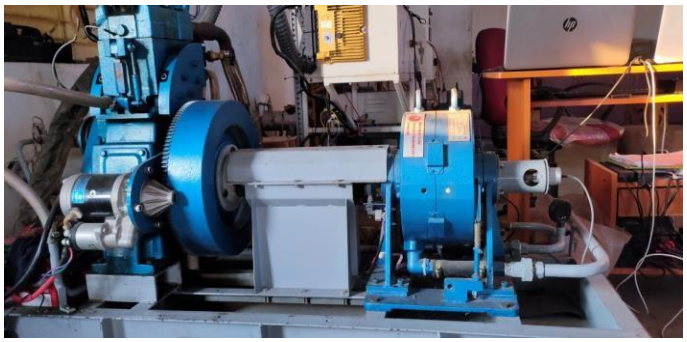

Figure 1: Engine Setup

Table 1 Specification of the Engine Setup

Engine Make	Kirloskar - Apex innovations Pvt. Ltd.
Type of Engine	CRDI VCR Engine
Number of Cylinders	Single cylinder, Four Stroke
Cooling Media	water cooled,
Rated Capacity	3.5 KW @ 1500 rpm,
Cylinder diameter	87.5 mm
Stroke length	110 mm,
Compression ratio range	12-18
Injection Pressure Variation	500, 550 and 600 bar
Data acquisition device	Make NI Instrument USA, NI USB-6210, 16-bit, 250kS/s.
Fuel tank Capacity 15 lit, Type:	Duel compartment, with fuel metering pipe of glass
Software	"Engine-soft" Engine performance analysis software
Loading type	Eddy current Dynamometer
Overall dimensions	W 2000 x D 2500 x H 1500 mm

3. Results and discussion

3.1. Specific fuel consumption

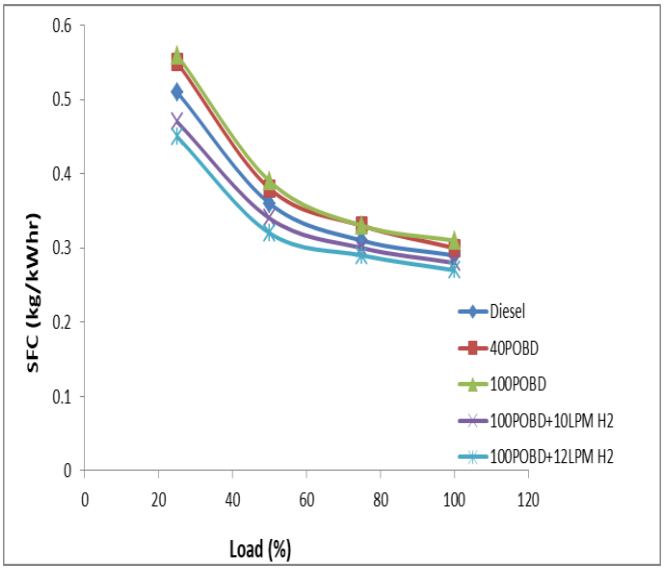

Figure 2: Specific fuel consumption variation with load

The variation of specific fuel consumption (SFC) with load shows that SFC decreases for all tested fuels as engine load increases. At 25% load, neat diesel shows an SFC of about 0.51 kg/kWh**,** while 40POBD and 100POBD exhibit higher values of approximately 0.55 kg/kWh and 0.56 kg/kWh, respectively, due to the lower calorific value of biodiesel. When hydrogen is inducted with palm biodiesel, the SFC decreases to about 0.47 kg/kWh for 100POBD **+** 10 LPM H_2 and 0.45 kg/kWh for 100POBD + 12 LPM H_2. A similar trend is observed at full load, where SFC reduces to around 0.29 kg/kWh for diesel**,** 0.30 kg/kWh for 40POBD**,** 0.31 kg/kWh for 100POBD**,** 0.28 kg/kWh for 100POBD + 10 LPM H_2**,** and 0.27 kg/kWh for 100POBD + 12 LPM H_2**.** The reduction in SFC with hydrogen enrichment is attributed to the higher flame speed and improved combustion characteristics of hydrogen, which enhance combustion efficiency and reduce fuel consumption.

3.2. Brake Thermal Efficiency

The brake thermal efficiency (BTE) increases with increasing engine load for all tested fuels due to improved combustion and better utilization of the supplied fuel energy. At 25% load, the BTE of neat diesel is about 19%, while 40POBD and 100POBD show slightly lower efficiencies of around 16.5% and 17%, respectively, mainly because of the lower calorific value and higher viscosity of biodiesel. With hydrogen enrichment, the BTE improves to approximately 18.5% for 100POBD + 10 LPM H_2 and 20% for 100POBD + 12 LPM H_2.

At full load (100%), diesel achieves a BTE of about 32%, whereas 40POBD and 100POBD reach around 30.5% and 30%, respectively. The addition of hydrogen further enhances efficiency, giving 32.5% for 100POBD + 10 LPM H_2 and the highest value of about 33.5–34% for 100POBD + 12 LPM H_2. The improvement in BTE with hydrogen addition is attributed to its high flame speed, wide flammability limits, and rapid diffusion, which promote faster and more complete combustion. As a result, hydrogen-enriched palm biodiesel—especially with 12 LPM hydrogen—shows the highest brake thermal efficiency among the tested fuels.

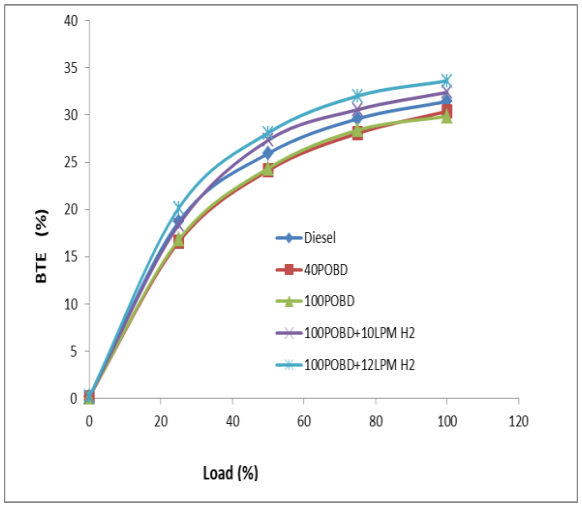

Figure 3: Brake thermal efficiency variation with load

3.3. Carbon monoxide

The variation of carbon monoxide (CO) emissions with engine load for different fuels indicates that CO emissions generally increase with increasing load due to richer fuel–air mixtures and incomplete oxidation at higher fuel injection rates. At no load, neat diesel produces the highest CO emission of about 0.06% vol, while 40POBD and 100POBD show lower values of approximately 0.035% and 0.025%, respectively. The addition of hydrogen significantly reduces CO emissions, with 100POBD + 10 LPM H_2 producing about 0.02% and 100POBD + 12 LPM H_2 about 0.01%, owing to improved combustion and enhanced oxidation of CO to CO_2. As the load increases to 100%, CO emissions rise for all fuels. Diesel shows the highest value of around 0.24%, followed by 40POBD (≈0.21%) and 100POBD (≈0.20%). In contrast, hydrogen-enriched biodiesel results in much lower CO emissions, with 100POBD + 10 LPM H_2 producing about 0.125% and 100POBD + 12 LPM H_2 about 0.115%. The reduction in CO emissions with hydrogen enrichment is attributed to hydrogen's high flame speed, wider flammability range, and absence of carbon, which promote more complete combustion and improved oxidation of carbon monoxide.

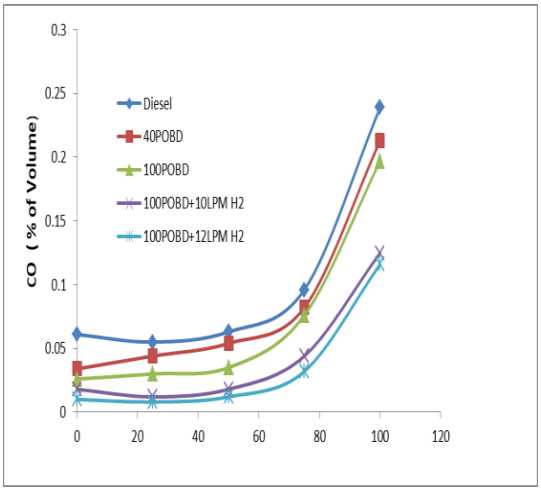

Figure 4: Carbon monoxide emission variation with load

3.4. Unburned hydrocarbon

The variation of unburned hydrocarbon (UBHC) emissions with engine load shows that UBHC increases with increasing load for all tested fuels due to richer fuel–air mixtures and incomplete combustion at higher fuel supply rates. At no load, neat diesel produces the highest UBHC emission of about 50 ppm, whereas 40POBD and 100POBD show lower values of approximately 37 ppm and 30 ppm, respectively. Hydrogen enrichment further reduces UBHC emissions, with 100POBD + 10 LPM H_2 producing around 27 ppm and 100POBD + 12 LPM H_2 about 22 ppm indicating improved combustion characteristics. At full load (100%), UBHC emissions increase significantly for all fuels. Diesel shows the highest emission of about 116 ppm, followed by 40POBD (≈90 ppm) and 100POBD (≈82 ppm). The addition of hydrogen results in comparatively lower UBHC emissions, with 100POBD + 10 LPM H_2 producing about 78 ppm and 100POBD + 12 LPM H_2 about 70 ppm. The reduction in UBHC emissions with hydrogen enrichment is attributed to hydrogen's high flame speed, better diffusivity, and wider flammability limits, which enhance combustion efficiency and promote more complete oxidation of the fuel-air mixture.

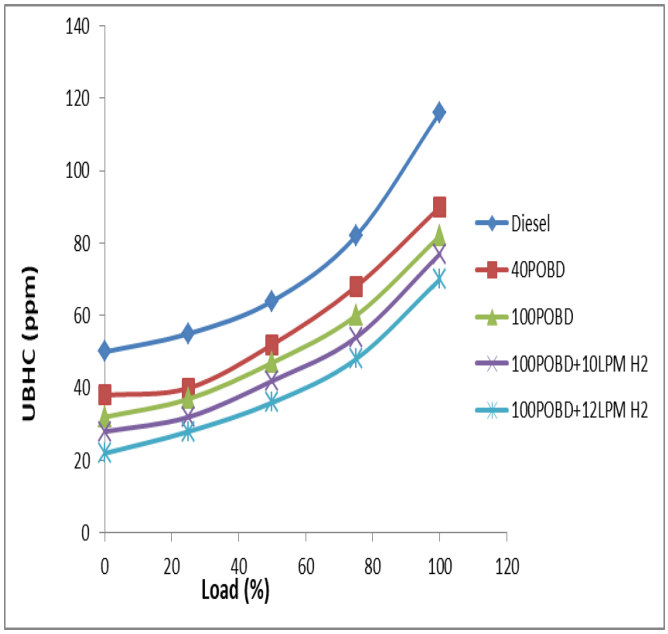

Figure 5 Unburned hydrocarbon emission variation with load

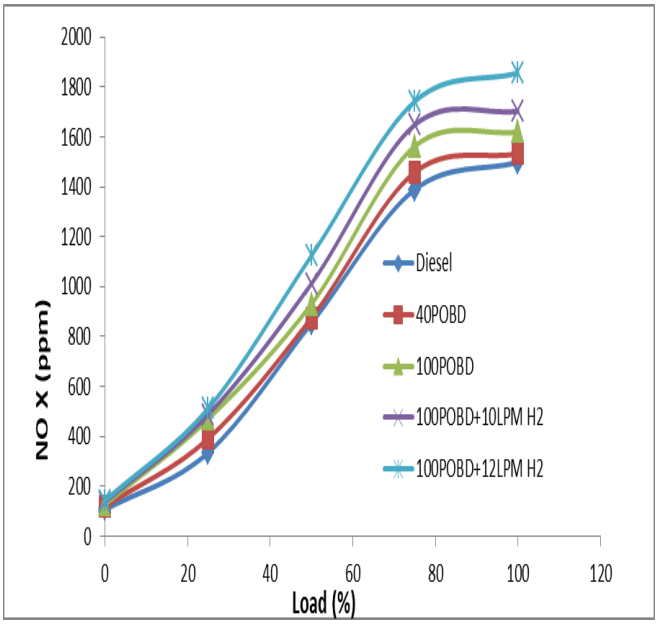

Figure 6: Nitrogen oxide emission variation with load

3.5. Nitrogen oxide

The variation of nitrogen oxide (NOx) emissions with engine load shows that NOx increases significantly with increasing load for all tested fuels due to higher combustion temperature and increased oxygen availability during combustion. At no load, NOx emissions are relatively low, with diesel producing about 120 ppm, while 40POBD and 100POBD show similar values of around 110–115 ppm. Hydrogen enrichment slightly increases NOx, with 100POBD + 10 LPM H_2 producing about 125 ppm and 100POBD + 12 LPM H_2 about 130 ppm. As the load increases to 100%, NOx emissions rise considerably. Diesel produces about 1500 ppm, while 40POBD and 100POBD show slightly higher values of approximately 1550 ppm and 1620 ppm, respectively. With hydrogen addition, NOx emissions further increase to around 1700 ppm for 100POBD + 10 LPM H_2 and reach the highest value of about 1850 ppm for 100POBD + 12 LPM H_2. The increase in NOx emissions with hydrogen enrichment is mainly attributed to higher in-cylinder temperature, faster combustion, and improved premixed combustion caused by hydrogen's high flame speed and wider flammability limits, which promote thermal NOx formation at elevated loads.

3.6. Smoke

The variation of smoke opacity with engine load indicates that smoke emissions increase with increasing load for all tested fuels due to the higher fuel injection rate and incomplete combustion at rich mixture conditions. At no load, diesel produces the highest smoke opacity of about 16%, while 40POBD and 100POBD show lower values of around 14% and 8%, respectively. Hydrogen enrichment further reduces smoke emissions, with 100POBD + 10 LPM H_2 producing about 8% and 100POBD + 12 LPM H_2 about 7%, due to improved combustion characteristics. As the load increases to 100%, smoke opacity rises significantly for all fuels. Diesel records the highest value of around 72%, followed by 40POBD (≈68%) and 100POBD (≈66%). In contrast, hydrogen-enriched biodiesel shows comparatively lower smoke emissions, with 100POBD + 10 LPM H_2 producing about 64% and 100POBD + 12 LPM H_2 about 63%. The reduction in smoke emissions with hydrogen enrichment is mainly attributed to hydrogen's carbon-free nature, high flame speed, and improved air–fuel mixing, which promote more complete combustion and reduce soot formation.

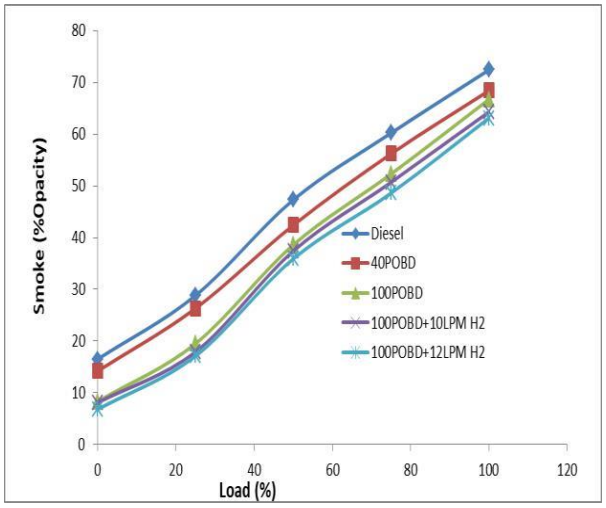

Figure 7: Smoke opacity emission variation with load

Conclusion

The experimental results demonstrate that the addition of hydrogen significantly improves the performance and emission characteristics of a palm biodiesel-fueled diesel engine.

- The specific fuel consumption (SFC) decreased with hydrogen enrichment, where 100POBD + 12 LPM H_2 showed the lowest SFC of about 0.27 kg/kWh at full load, compared to 0.29 kg/kWh for diesel and 0.31 kg/kWh for neat palm biodiesel, indicating improved fuel utilization. Correspondingly, the brake thermal efficiency (BTE) increased with hydrogen addition, reaching a maximum of about 33–34% for 100POBD + 12 LPM H_2, which is higher than diesel (≈32%) and neat biodiesel (≈30%), due to hydrogen's high flame speed and better combustion characteristics.
- In terms of emissions, CO and HC emissions were significantly reduced with hydrogen enrichment. At full load, CO emissions decreased from about 0.24% for diesel to around 0.115% for 100POBD + 12 LPM H_2, while HC emissions decreased from about 116 ppm for diesel to around 70 ppm with hydrogen supplementation. Similarly, smoke opacity was also reduced, with 100POBD + 12 LPM H_2 showing about 63% smoke at full load compared to 72% for diesel, due to the carbon-free nature of hydrogen and improved oxidation of soot precursors. However, NOx emissions increased with hydrogen addition, reaching about 1850 ppm for 100POBD + 12 LPM H_2, compared to 1500 ppm for diesel, mainly due to higher in-cylinder temperatures and enhanced combustion.

Overall, the results indicate that hydrogen enrichment, particularly at 12 LPM, effectively enhances engine efficiency and reduces CO, HC, and smoke emissions while slightly increasing NOx emissions, making hydrogen-enriched palm biodiesel a promising alternative fuel for cleaner and more efficient diesel engine operation.

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Study on mechanical behavior of austempered ductile iron for a coupler head during wedm

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ABSTRACT

Austempered Ductile Iron (ADI) is utilized extensively in engineering applications because of its exceptional mechanical qualities, which include toughness, high strength, and resistance to wear. However, ADI's high hardness and abrasive character make machining it difficult and can result in poor surface finish and rapid tool wear. The machining behavior of ADI is examined in this work utilizing wire electric discharge machining (WEDM) and surface grinding techniques. Analysis was done on the effects of grinding and WEDM process parameters on surface properties and variations in hardness. ADI Grade 1 specimens were machined and tested with one pass (AD1), three passes (AD2), and five passes (AD3) of WEDM. Mechanical characteristics such surface roughness, microhardness, and Brinell hardness were assessed using established testing protocols. The findings of the experiment showed that the number of machining passes has a major impact on the hardness and surface integrity of ADI specimens. The specimen with five passes (AD3) had the lowest surface roughness and the highest microhardness and Brinell hardness values among the examined samples. The primary causes of this improvement are the removal of recast layers throughout several passes and the conversion of residual austenite into martensite. The findings show that increasing the number of WEDM passes improves the ADI components' machining quality, making them appropriate for demanding applications like railway coupler heads.

Keywords: Austempered Ductile Iron; WEDM; Microhardness; Brinell hardness; surface roughness.

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I INTRODUCTION

The exceptional combination of strength, toughness, wear resistance, and fatigue performance of austempered ductile iron (ADI) has drawn a lot of interest in contemporary engineering applications. Acicular ferrite and high-carbon stabilized austenite make up the distinctive microstructure of ADI, which is created by subjecting ductile iron to a regulated heat treatment procedure called austempering[1]. This microstructure maintains reduced manufacturing costs while offering better mechanical qualities than many alloy steels and ordinary ductile irons. These benefits have led to the widespread usage of ADI in agricultural machinery, gears, crankshafts, automotive components, and structural applications[2].

The exceptional combination of strength, toughness, wear resistance, and fatigue performance of austempered ductile iron (ADI) has drawn a lot of interest in contemporary engineering applications[3]. Acicular ferrite and high-carbon stabilized austenite make up the distinctive microstructure of ADI, which is created by subjecting ductile iron to a regulated heat treatment procedure called austempering. This microstructure maintains reduced manufacturing costs while offering better mechanical qualities than many alloy steels and ordinary ductile irons. These benefits have led to the widespread usage of ADI in agricultural machinery, gears, crankshafts, automotive components, and structural applications[4].

In the manufacturing sector, surface grinding is a common machining technique used to create flat surfaces with excellent surface quality and high accuracy. A revolving abrasive wheel is used in the procedure to microcut particles off the surface of the workpiece. The machined component's overall quality and surface roughness are greatly influenced by factors like feed rate, depth of cut, and grinding speed[5]. Therefore, maximizing the grinding performance requires an understanding of these parameters' effects.

For the machining of hard and challenging-to-machine materials, non-traditional machining methods like Wire Electric Discharge Machining (WEDM) have grown in significance alongside conventional machining procedures[6-8]. A sequence of regulated electrical discharges between a thin wire electrode and the work piece in the presence of a dielectric fluid cause material removal in WEDM, a thermal erosion process. Because there is no direct mechanical contact between the tool and the workpiece, the method is especially well suited for materials with high strength and hardness[9].

Current, pulse on time, pulse off time, wire tension, voltage, and feed rate are some of the process variables that affect WEDM machining performance[10]. The rate of material removal, surface roughness, dimensional accuracy, and the recast layer generation on the machined surface are all directly impacted by these characteristics. Furthermore, WEDM frequently uses numerous cutting passes to enhance surface smoothness and minimize surface flaws[11,12].

Fig. 1 Austempered Ductile iron Coupler Head

The present study focuses on the machining of ADI using surface grinding and Wire Electric Discharge Machining processes. The influence of various machining parameters on surface characteristics and hardness variation is investigated. Furthermore, the effect of different numbers of passes in the WEDM process on the surface quality of ADI specimens is analyzed. The results obtained from this study provide valuable insights for improving machining performance and achieving better surface integrity in ADI components.

II. MATERIALS AND METHODS

2.1 Materials

Figure 1 shows the coupler head which has been made of Austempered ductile iron (ADI). ADI with Grade 1 is used in this research work (Fig.2 & Fig.3). Various grades of Austempered ductile irons are produced by heat-treating cast ductile iron by adding small amount of elements such as nickel, molybdenum, or copper to get reliable hardenability. Table 1 shows the chemical composition for the given material. The physical properties of ADI are presented in Table 2.

Fig. 2 ADI Specimen

Fig. 3 ADI Specimen (As polished)

Table 1 Chemical Composition

Sl.No	Elements	Percentage (%)
1	C	3.2
2	Si	2.5
3	Mn	00.2
4	P	0.03
5	S	0.01
6	Mg	0.04
7	Cu	0.7
8	Ni	1.4

Table 2 Physical Properties

Sl.No	Properties	Unit	Values
1	Yield Stress	N/mm^2	500
2	Tensile Strength	N/mm^2	740
3	Elongation	%	10
4	Notched test bar impact test at room temperature	J	13.33
5	Hardness BHN	-	250 - 310

2.2 Experimental Methods

2.2.1 Surface Grinding

Surface grinding is done on the work piece before machining with a surface grinder. The grinding wheel consists of abrasive particle and silicon carbide etc. The speed of the grinding wheel is 800 RPM 2500 RPM. The feed rate time was calculated by using a stopwatch. Depth of cut is one of the major influence factors of surface roughness. Fig. 4. shows the surface grinding machine. This grinding machine only applicable to the ferromagnetic materials. Because of the magnetic chuck used as the work holding device. Normally the grinding

wheel consists of abrasive slurry and synthetic materials. Table 3 shows the different level of input parameters speed, Depth of Cut and feed time. Machined work piece surface roughness value measured by a conventional stylus probe.

Fig. 4 Surface Grinding setup

Table 3 Grinding Parameters

Sl.No	Parameters Range	Unit	Range
1	Speed	rpm	1100 – 1500
2	Time	min	1.5 – 6
3	Depth of Cut	mm	0.1 – 0.9

2.2.2 Wire Electric Discharge Machining (WEDM)

A schematic illustration of the cutting machine is shown in Fig. 5. The electrode was made of a 0.25 mm diameter copper wire. The dielectric fluid used was deionized water with a flow rate of 35/min. Parameters for controlling the working conditions are listed in Table 4; including the available setting range and the actual setting range used in this study. The on-time was set in the range of 0-16 µs and the off-time was 0-16 µs. The copper wire tension was set in the range of 0-12N. The cutting feed rate (m/min) of EDWC was set up as feedrate override 0-12 of the working table (controlled by the machine in this study), (mm/min) multiplied by thickness of workpiece (mm); that is, the area cut by the copper wire per unit time. The dimensions of cut specimens were measured by a micrometer. The variation of hardness in the remelted layer was measured by the Vicker's hardness test in which a hardness was determined from the average of six tests measuring one area of specimen. The remelted layer judged from the variation of hardness was compared with the results from the optical observation. Surface roughness Ra of cut specimens was measured by a surface roughness meter.

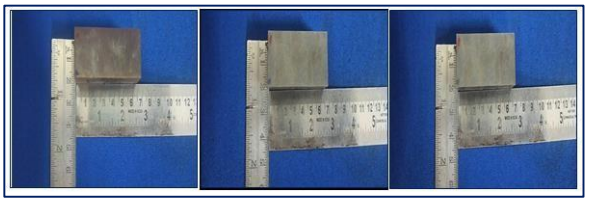
Fig. 5 Wire EDM setup

Table 4 WEDM Parameters

Sl.No	Parameters	Units
1	Current	A
2	Pulse ON	µs
3	Pulse OFF	µs
4	Wire Feed	m/min
5	Wire Tension	N
6	Voltage	V
7	Feed rate	mm/m

Table 5 Specimen and its Passes

Sl.No	Specimen Name	Number of Passes
1	AD1	One
2	AD2	Three
3	AD3	Five



(a) One Pass (b) Three Pass
(c) Five Pass

Fig. 6 Sized Specimens in Wire EDM with various Passes

III. EXPERIMENTAL

3.1 Mechanical Behavior

Three samples AD1, AD2 and AD3 were tested in this study. The Rockwell Hardness and Brinell Harness Testing Machines were used to evaluate hardness behaviour in accordance with ASTM E18 and ASTM E10, respectively. The samples of machined austempered ductile iron is subjected to hardness behaviour are shown in Figure 7.

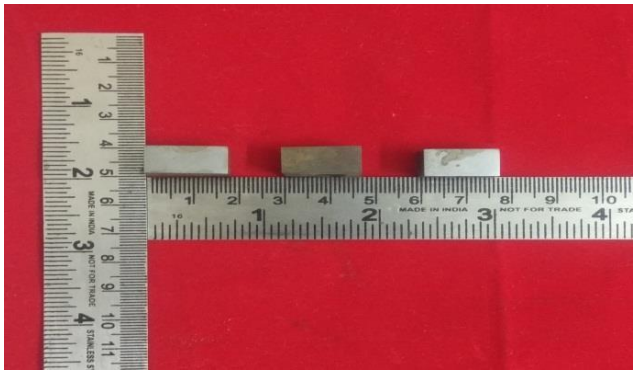


Fig. 7 Hardness Test Samples of AD1, AD2, AD3

Rockwell Hardness Number (RHN) = $N - \frac{h}{s}$ (1)

Where N denotes the number of specific Rockwell hardness units, h denotes the permanent depth of an indentation in millimeters, and s denotes the scale unit.

Steel ball indenter scale of 130 units,

Brinell Hardness Number (BHN) = 0.102 x

$$\frac{2F}{\pi D(D-\sqrt{D^2-d^2}}$$ (2)

Where F is the test force in N, D is the ball diameter in mm, and d is the indentation's mean diameter in mm.

3.1.1 Micro Hardness

The test is performed according to the ASTM E92 standard with a diamond indenter of 1kg applied load to the material surface for a dwell time of 6 seconds. Hardness measurement is done to find the micro hardness of the machined AD1, AD2 and AD3 specimens. This was performed on a cross section of coatings with a load of 1.96N and a dwell period of 14 sec.

3.1.2 Surface Roughness

The real surface's deviations from its ideal surface in the normal vector direction are measured using surface roughness. Furthermore, it is a good predictor of mechanical behavior and adhesion. Additionally, it is measured using the fashionable prose that is affixed to the surface profilometer in accordance with ASTM D7127. A diamond stylus is moved laterally across the sample for a predetermined distance and contact force after making vertical contact with the surface. It gauges minute surface changes in the location and displacement of the vertical stylus as a function. The roughness range that a common profilometer can measure is 12 nm to 1 mm. The height position of the stylus generates an analog signal and then into a digital signal which can be stored, analyzed and displayed. The radius of diamond stylus ranges between 30 nm to 60µm and their horizontal resolution can be controlled using the scan speed and data signal sampling rate. The stylus tracking force can range from less than 1 to 40 mg.

IV. RESULTS AND DISCUSSION

4.1 Mechanical Behavior

4.1.1 Micro hardness

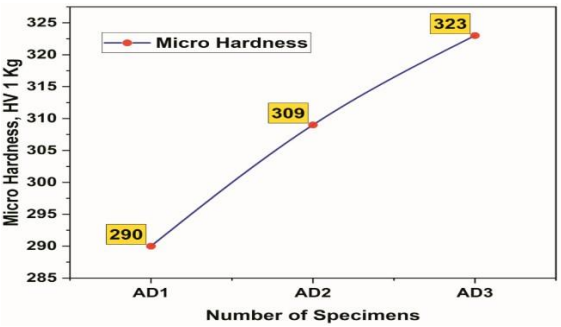


Fig. 8 Micro Hardness of the Machined Specimens

The sized and machined specimens of Austempered ductile Iron subjected to test loads are shown in Fig. 8. Specimen AD3 has more hardness values than Specimens AD1 and AD2 as shown in Fig.8. The austenite is mechanically and thermally stable due to carbon diffusion during heat treatment, but it can transform into martensite during the plastic deformation phase. With respect to chip formation, this effect can lead to a very high mechanical specific load on the cutting edge. The strain hardening effects described in crush and flow curves can also be detected by micro hardness measurements. Compared to AD1 and AD2, AD3 shows the strongest increase in micro hardness by quasi-static deformation. One explanation is provided by measuring the residual austenite: In ductile ADI grades more austenite can be detected in the microstructure due to increased graphite content as a result of higher tempering temperatures. This austenite transforms almost completely into martensite during deformation independently of the strain rate. As a result, the micro hardness increases due to a higher level of martensite. The Variations in hardness is mainly because of the microstructures created in the specimens due to number of passes in machining. This AD3 specimen with a high micro hardness (HV) can be used for the manufacture of railways coupler head.

4.1.2 Surface Roughness

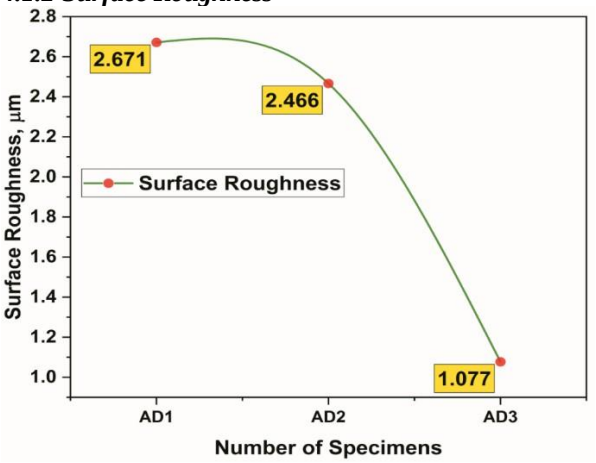


Fig. 9 Surface Roughness of the Machined Specimen

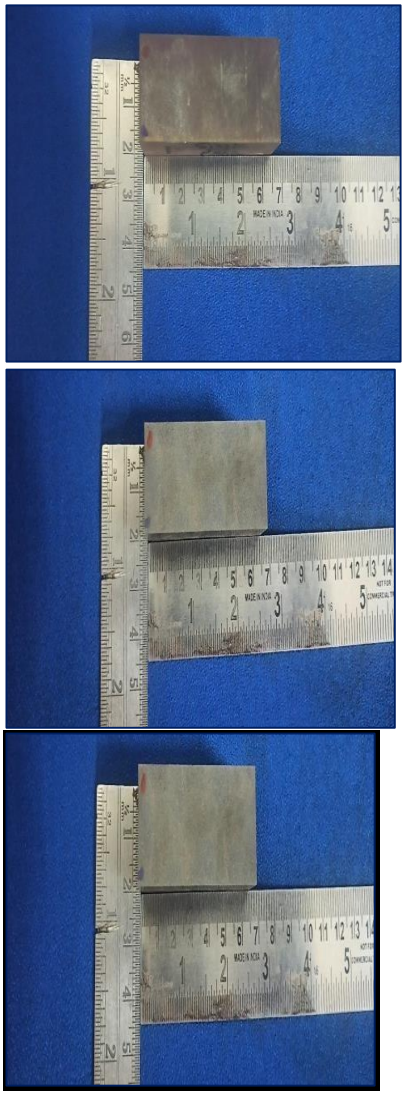


Fig. 10 Surface Roughness of Austempered Ductile Iron Specimens (AD1, AD2, AD3)

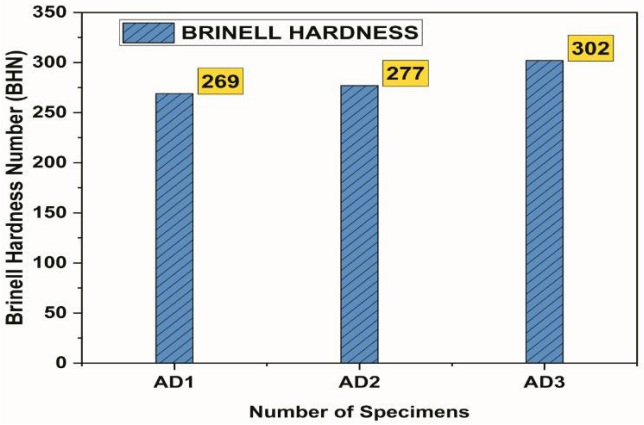
The sized and machined specimens of Austempered ductile iron are shown in Figure 10. According to Fig10. Specimen AD3 has a lower surface roughness compared to AD1 and AD2. Spark gap voltage and tension of wire are major factors in getting good surface finish. Less spark gap voltage and high wire tension will reduce the chance of getting a coarse structure by reducing the electric field and vibrational ignorance. This AD3 specimen with less roughness can be used for the manufacturing of coupler heads in railways.

4.1.3 Brinell Hardness

Fig. 11 Brinell Hardness of ADI Specimens

The fabricated and sized specimen of the ADI subjected to the Brinell load of 2400 kgf is shown in Figure 11. Specimen AD3 has a higher Brinell hardness value than Specimens AD1 and AD2.The addition of passes causes deposition of melted ADI resulted in a higher Brinell hardness value in Specimen AD3. The incorporation of various oxide deposit withstands the load applied and enriches the hardness of the ADI sample. This AD3 specimen with a high Brinell hardness value can be used to build the coupler head.

V. CONCLUSIONS



The present study investigated the machining behavior of Austempered Ductile Iron (ADI) using surface grinding and Wire Electric Discharge Machining (WEDM) processes. The influence of machining parameters and the number of passes on mechanical properties such as microhardness, Brinell hardness, and surface roughness was analyzed. Based on the experimental results, the following conclusions are drawn:

1. The machining performance of ADI is significantly influenced by the number of passes during the WEDM process. Increasing the number of passes improves the surface quality and mechanical characteristics of the machined specimens.

2. Among the tested specimens, AD3 (five passes) exhibited the highest microhardness value compared to AD1 (one pass) and AD2 (three passes). This improvement is mainly due to the transformation of retained austenite into martensite during machining and the strain hardening effect.

3. Surface roughness results showed that AD3 produced the lowest surface roughness, indicating that multiple machining passes help remove irregularities and recast layers formed during the initial machining stage.

4. The Brinell hardness value of AD3 was higher than that of AD1 and AD2, which can be attributed to the deposition of melted material and formation of oxide layers during repeated WEDM passes.

5. The combined improvement in hardness and surface finish indicates that increasing the number of machining passes enhances the overall surface integrity of ADI components.

6. Based on the obtained results, the AD3 specimen with five machining passes demonstrates superior mechanical properties and surface quality, making it suitable for applications such as railway coupler head manufacturing, where high strength, wear resistance, and durability are required.

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Optimization of Process Parameters on TIG Welded AISI 409 Stainless Steel

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ABSTRACT

A study conducted on tungsten inert gas welded AISI 409 Ferrite stainless steel which has application of heat exchanger. In this study process parameters welding current, arc voltage, bevel angle and work piece gap are considered. The L9 Orthogonal array is utilized for experimental plan. The Reponses yield strength, ultimate tensile strength, hardness and percentage elongation are measured as per the ASTM standard. The microstructure characteristics observed using optical microscope at base metal, heat affected zone and weld zone. The TAGUCHI Analysis conducted to find out optimum level of parameters. ANOVA of regression model helps to find out significant factors to get maximum ultimate tensile strength and hardness. High intensity of welding current helps to attain high tensile strength and high value of bevel angle, workpiece gap are leads to lower the tensile strength. Microstructure of heat shows that martensitic formation in weld bead. affected zone

Keywords: Tensile Strength, Hardness, Microstructure, Orthogonal Array, Taguchi Analysis

Introduction

Ferritic stainless steels are body centered cubic crystal structure. Chromium present in the range of 10.5–11.75%. When compared to the austenitic grades, they are rather weak at higher temperatures, although having good ductility and formability. Chemical processing equipment, furnace parts, heat exchangers, oil burner components, storage vessels, electrical appliances, solar water heaters, and household appliances are all made using it in less harshly corrosive environments [1]. Because it creates high-quality welds, the TIG welding technique is one of the most widely used methods for welding thin materialsin manufacturing industries. However, when thick materials are fused in a single pass, TIG welding has poorer joint penetration than metal inert gas welding. For stainless steel butt joints, single pass TIG welding using argon as shielding gas is typically restricted to a depth of 3 mm. As a result, increasing TIG welding's penetration capacity and manufacturing productivity is essential [2-5]. Among the most well-known methods is the combination of TIG welding and activating flux. In order to create an activating flux, powdered materials including oxides, chlorides, and fluorides are usually mixed with acetone or ethanol to create a substance that resembles paint. Prior to welding, the surface of the joint to be welded was lightly coated with flux [6-10]. The non-consumable tungsten electrode used in gas tungsten arc welding is protected against impurities by the inert gas when new gases like argon or helium are used. Among the several welding methods,The GTAW welding process yields a precise and superior weld [11-13]. Researchers have recently attempted to use flux, additional elements, electromagnetic stirring, and ultrasonic aid to address these issues [14]. Investigated how Cu and Al components affected the welded junction when 430 FSS was being welded [15]. The outcome shown that the method greatly improved grain refinement, which improved the welded joints' strength, toughness, and resistance to pitting [16]. In this current study optimization of process parameters using Taguchi analysis to predict tensile strength and hardness carried out along with microstructure study of TIG welded AISI 409 Ferritic Stainless Steel.

Materials & Methods

AISI 409 is an inexpensive ferritic stainless steel (10.5–11.75% chromium) intended for corrosion-resistant, high-temperature applications where aesthetics are not important, mainly automotive exhaust systems. Mostly Fe-11Cr, with titanium stabilization for welding and little nickel (<0.5%). It is appropriate for automobile exhaust gasses since it is lower than 430 but superior to martensitic grades like 410. Excellent resistance to oxidation, appropriate for continuous use up to 675°C and operates sporadically up to 815°C. Its ferritic structure guarantees its magnetic properties. The specimen prepared for welding is shown in figure 1and welded specimen shown in figure 2. Specimens subjected to tensile test and hardness test shown in figure 3 and 4 respectively.

Fig 1. Prepared Specimen

Fig 2. TIG Welded Specimen

Fig 3. Specimen after Tensile Test

Fig 4. Sample for Hardness Test

Experimental Plan

The AISI 409 Ferriti for experimentation. The spec

size of 100 mm x 50 mm. The process parameters selected and their ranges are listed in table 1.The specimens are welded by TIG welding machine as per the experimental plan mentioned in table 2. The electrode used is AISI 304 Material.

Table1. Process Parameters and their Ranges

S.N	Process Parameters and their Units	Level and Value		
		1	2	3
1	Current (A) - Ampere	160	170	180
2	Voltage (V) - Volts	12	14	16
3	Bevel Angle (β) - Degree	15°	30°	45°
4	Work piece (G) - mm	1	2	3

Table 2.Experimental Plan

S. N	Current (A) Ampere	Voltage (V) Volts	Bevel Angle (β)Degree	Workpiece Gap (G) mm
1	160	12	15	1
2	160	14	30	2
3	160	16	45	3
4	170	12	30	3
5	170	14	45	1
6	170	16	15	2
7	180	12	45	2
8	180	14	15	3
9	180	16	30	1

Results and Discussion

The welded specimen subjected to tensile test and hardness test and corresponding results are shown in table 3.

Table 3.Experimental results

	Yield Strength (MPa)	Ultimate Tensile Strength (MPa)	Elongation (%)	Hardness (VHN)	
				Base Metal	Heat Affected Zone
1	353	518	20.5	158	297
stainless steel is selected	354	516	21	160	298
imen prepared as per the	357	517	20	154	279

4	355	515	21	165	285	2
5	389	509	22	169	299	2
6	395	519	22	170	301	2
7	415	521	22	151	291	2
8	405	520	21	157	295	2
9	420	530	23	155	303	2

fig.5.The optimal level of factor identified as $A_3B_3C_3D_2$. The high value of current, voltage, bevel angle and medium value of workpiece gap are optimized level to get maximum yield strength. The Rank in S/N ratio shows that current plays a most role for attaining the high yield strength and other factors are less significant.

1. Taguchi Analysis:

Taguchi analysis is a robust optimization technique used to improve the quality and efficiency of manufacturing processes by minimizing variations and optimizing process parameters. It is based on the design of experiments (DOE) methodology and uses orthogonal arrays to systematically test different combinations of input parameters with a minimal number of experiments.Orthogonal Arraysare predefined experimental setups that help in systematically varying multiple parameters while reducing the number of required experiments.Signal-to-Noise (S/N) Ratio is the main performance metric in Taguchi analysis. It measures the quality characteristics based on three possible objectives. Smaller-the-better (e.g., minimizing defects or errors), Larger-the-better (e.g., maximizing strength or efficiency) and Nominal-the-best (e.g., achieving a target value). In this work responses measured are ultimate tensile strength and hardness. The response requires high value, therefore larger the best category is selected. The equation no.1 is used to calculate S/N ratio but Minitab Software is used for Taguchi Analysis.

Larger the best characteristics:

$$S/N\ Ratio(\eta) = -10\log_{10}\left(\frac{1}{r}\sum_{i=1}^{r}\frac{1}{y_{ij}^2}\right) \quad (1)$$

1.1 Yield strength

Yield strength is a crucial mechanical property of a welded joint that defines the stress level at which the material begins to deform plastically. In **TIG welding**, the yield strength of the weldment is influenced by various factors, including welding parameters, heat input, cooling rate, and metallurgical transformations.The TIG samples are prepared based on the L9 Orthogonal array. The Taguchi analysis is used to predict optimum level to get maximum yield strength of the joint. The linear regression model is also prepared to predict the results in advance.

1.1.1 TAGUCHI Analysis for Yield Strength

The S/N ratio calculated for yield strength related to larger the best category as per equation 1. The S/N ratio for yield strength and ranking of parameters tabulated in table 4.The S/N ratio plot for yield strength is shown in

Table 4.The S/N Ratio Analysis of Yield Strength.

Level	Current (A)	Voltage (V)	Bevel Angle (β)	Workpiece Gap (mm)
1	51.00	51.44	51.68	51.74
2	51.58	51.64	51.48	51.76
3	51.53	51.82	51.74	51.40
Delta	1.58	0.38	0.06	0.36
Rank	1	2	4	3

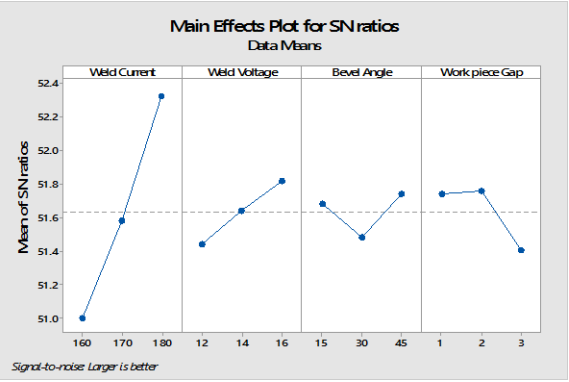

Figure 5.SN Ratio Plot for Yield Strength

1.2 Ultimate Tensile Strength

Ultimate tensile strength (UTS) is a critical mechanical property that defines the maximum stress a welded joint can withstand before failure. It represents the material's resistance to tensile loading and is an essential factor in determining the structural integrity of welded components. In **TIG welding**, the UTS of the weldment are influenced by welding parameters, heat input, cooling rate, and metallurgical changes in different zones of the joint. The TIG welded samples are prepared based on the L9 Orthogonal array. The Taguchi analysis is used to predict optimum level to get maximum tensile strength of the joint. The linear regression model is also prepared to predict the results in advance.

1.2.1 TAGUCHI Analysis for Ultimate Tensile Strength

The S/N ratio calculated for Ultimate Tensile Strength related to larger the best category as per equation 1. The S/N ratio for yield strength and ranking of parameters tabulated in table 5.The S/N ratio plot for tensile strength is shown in fig.6.The optimal level of factor identified as $A_3B_3C_2D_1$.The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Ultimate Tensile strength. The Rank in the SN ratio shows that the process parameters current and voltage plays a vital role for attaining the high maximum Ultimate Tensile strengthand other factors are less significant.

Table 5.The S/N Ratio Analysis of Ultimate Tensile Strength.

Level	Current (A)	Voltage (V)	Bevel Angle (β)	Workpiece Gap (mm)
1	54.27	54.29	54.30	54.30
2	54.22	54.24	54.32	54.30
3	54.38	54.35	54.25	54.28
Delta	0.16	0.11	0.07	0.02
Rank	1	2	3	4

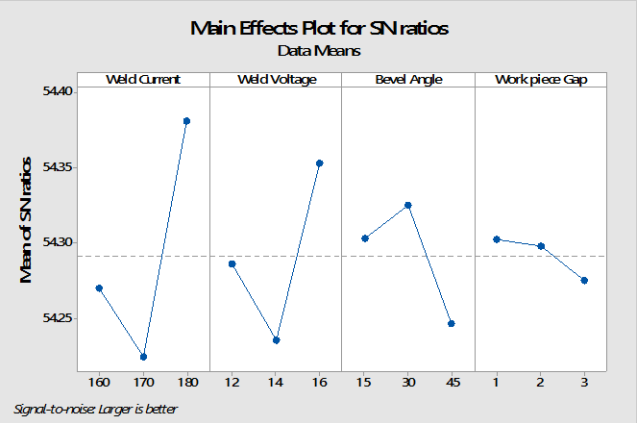

Figure 6.SN Ratio Plot for ultimate tensile strength

1.3 Percentage Elongation

Percentage elongation is a key mechanical property that indicates the ductility of a welded joint. It measures the material's ability to undergo plastic deformation before fracture under tensile loading. Higher elongation values suggest good ductility, while lower values indicate brittleness, which may lead to premature failure.The TIG welded samples are prepared based on the L9 Orthogonal array. The Taguchi analysis is used to predict optimum level to get maximum Percentage Elongation of the joint. The linear regression model is also prepared to predict the results in advance.

1.3.1 TAGUCHI Analysis for Percentage Elongation

The S/N ratio calculated for Percentage Elongation related to larger the best category as per equation 1. The S/N ratio for Percentage Elongation and ranking of parameters tabulated in table 6.The S/N ratio plot for tensile strength is shown in fig.7.The optimal level of factor identified as $A_3B_3C_2D_1$.The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Percentage Elongation. The Rank in the SN ratio shows that the process parameters current and Work piece Gap plays a

vital role for attaining the high Percentage Elongationand other factors are less significant.

Table 6.The S/N Ratio Analysis of Percentage Elongation.

Level	Current (A)	Voltage (V)	Bevel Angle (β)	Workpiece Gap (mm)
1	26.23	26.51	26.51	26.77
2	26.71	26.58	26.71	26.71
3	26.84	26.70	26.57	26.30
Delta	0.61	0.19	0.20	0.47
Rank	1	4	3	2

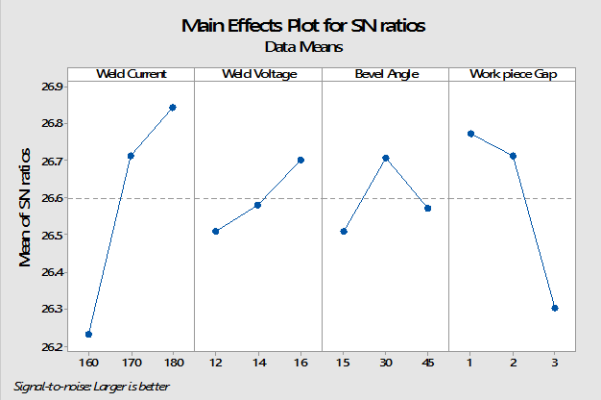

Figure 7.SN Ratio Plot for Percentage Elongation

1.4 Hardness at base metal

The hardness of a welded joint is a critical mechanical property that determines its ability to resist deformation, wear, and fatigue. It is influenced by several factors, including welding parameters, heat input, cooling rate, and material composition. In TIG welding, hardness variations in the welded joint occur due to microstructural changes in different zones like weld zone Hardness depends on solidification characteristics and possible alloying effects. Heat-Affected Zone often shows hardness variations due to grain growth, phase transformations, and possible softening or hardening effects. Base Metal typically retains its original hardness unless affected by heat input.

1.4.1 TAGUCHI Analysis for Hardness at base metal

The S/N ratio calculated for Hardness at base metal related to larger the best category as per equation 1. The S/N ratio for Hardness at base metal and ranking of parameters tabulated in table 7.The S/N ratio plot for Hardness at base metal is shown in fig.8.The optimal level of factor identified as $A_2B_2C_1D_1$.The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Hardness at base metal. The Rank in the SN ratio shows that the process parameters current plays a vital role for attaining the high Hardness at base metal and other factors are less significant.

Table 7. The S/N Ratio Analysis of Hardness at base metal.

Level	Current (A)	Voltage (V)	Bevel Angle (β)	Workpiece Gap (mm)
1	43.94	43.97	44.17	44.11
2	44.51	44.19	44.08	44.09
3	43.77	44.06	43.96	44.01
Delta	0.74	0.22	0.21	0.1
Rank	1	2	3	4

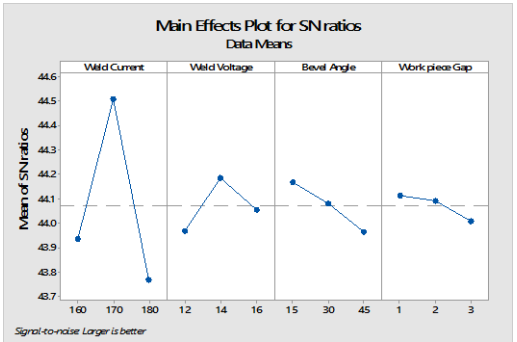

Figure 8.SN Ratio Plot for Hardness at base metal

1.5 Hardness at Heat Affected Zone

The S/N ratio calculated for Hardness at Heat Affected Zone related to larger the best category as per equation 1. The S/N ratio for Hardness at Heat Affected Zone and ranking of parameters tabulated in table 9.The S/N ratio plot for Hardness at Heat Affected Zone is shown in fig.9.

1.5.1 TAGUCHI Analysis for Hardness at Heat Affected Zone

The optimal level of factor identified as $A_3B_2C_1D_1$.The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Hardness at Heat Affected Zone. The Rank in the SN ratio shows that the process parameters Workpiece Gap and bevel angle plays a vital role for attaining the high Hardness at Heat Affected Zone and other factors are less significant.

Table 9. The S/N Ratio Analysis of Hardness at Heat Affected Zone.

Level	Current (A)	Voltage (V)	Bevel Angle (β)	Workpiece Gap (mm)
1	49.28	49.28	49.47	49.53
2	49.39	49.46	49.40	49.44
3	49.43	49.37	49.23	49.14
Delta	0.15	0.18	0.24	0.39
Rank	4	3	2	1

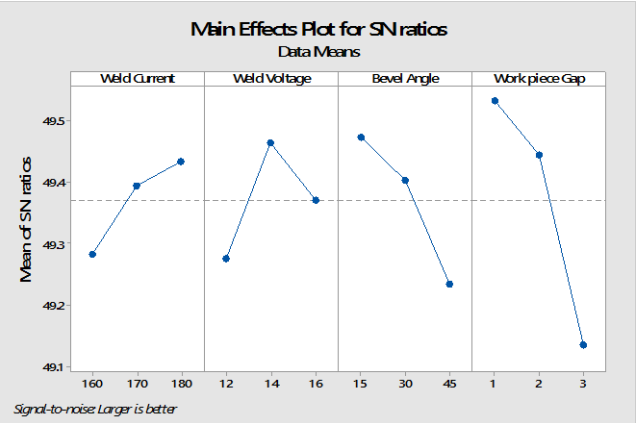

Figure 9.SN Ratio Plot for Hardness at Heat Affected Zone

1.6 Hardness at weld Zone

The S/N ratio calculated for Hardness at weld Zone related to larger the best category as per equation 1. The S/N ratio for Hardness at weld Zone and ranking of parameters tabulated in table 10.The S/N ratio plot for Hardness at weld Zone is shown in fig.10.

1.6.1 TAGUCHI Analysis for Hardness at weld Zone

The optimal level of factor identified as $A_3B_1C_2D_2$.The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Hardness at weld Zone. The Rank in the SN ratio shows that the process parameters voltage has least significant and other factors plays a vital role for attaining the high Hardness at weld Zone.

Table 10. The S/N Ratio Analysis of Hardness at Heat Affected Zone.

Level	Current (A)	Voltage (V)	Bevel Ang	Workpiece Gap (mm)

			le (β)	
1	47.62	47.69	47.74	47.65
2	47.43	47.64	47.74	47.79
3	47.85	47.59	47.43	47.47
Delta	0.42	0.1	0.31	0.32
Rank	1	4	3	2

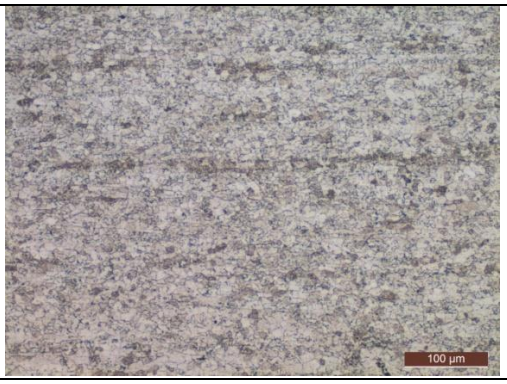

Fig 11. Microstructure of Base metal

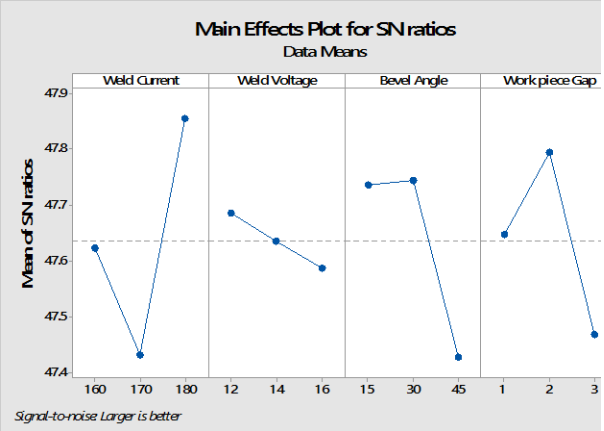

Figure 10. SN Ratio Plot for Hardness at weld Zone

MICROSTRUCTURE CHARACTERISTICS

The microstructure directly affects the strength, toughness, and hardness of the welded joint. Understanding grain size, phase distribution, and inclusions helps optimize mechanical performance. Ferrite stainless steel is used in harsh environments due to its corrosion resistance. Welding can lead to sensitization (chromium carbide precipitation), which reduces corrosion resistance. Microstructure analysis helps in preventing intergranular corrosion. Identifies common defects like porosity, hot cracking, and segregation. Ensures weld integrity and longevity. Welding can induce phase transformations (e.g., delta ferrite formation).Excess delta ferrite shown in figure 11 can lead to embrittlement, while too little may cause hot cracking. the high temperature and subsequent AISI 409 is a ferritic stainless steel, meaning its structure is primarily ferrite (α-phase, BCC crystal structure).Due to the presence of stabilizing elements like titanium (Ti), carbide (TiC) and nitride (TiN) precipitates can be expected. The light-colored regions likely represent ferritic grains. The darker spots could indicate TiC/TiN precipitates or inclusions. The banded or directional texture suggests possible rolling or welding effects. Ferrite appears light. Carbide/nitride precipitates appear darker. Grain boundaries become more visible. If the grains are coarse, this may indicate high-temperature exposure during welding, leading to reduced toughness. Fine grains are preferable for better mechanical properties. The presence of TiC and TiN enhances strength and thermal stability but excessive precipitation at grain boundaries can lower ductility. If chromium carbide forms, it could lead to sensitization and intergranular corrosion. Ferrite Content and Heat-Affected Zone (HAZ) Changes. Excessive grain growth shown in figure 12 in the HAZ could indicate weld embrittlement. Controlled cooling can help retain fine-grained ferrite.

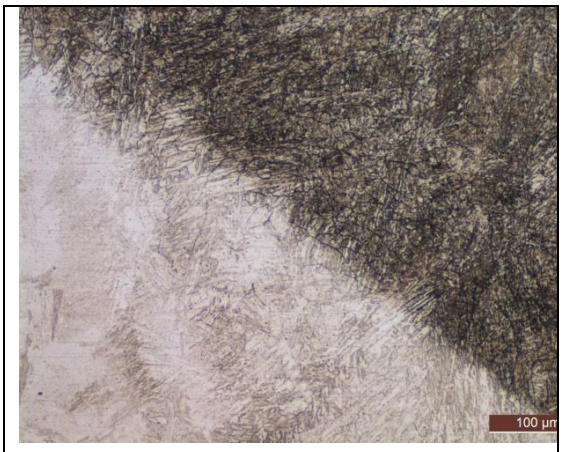

Fig 12. Microstructure of HAZ

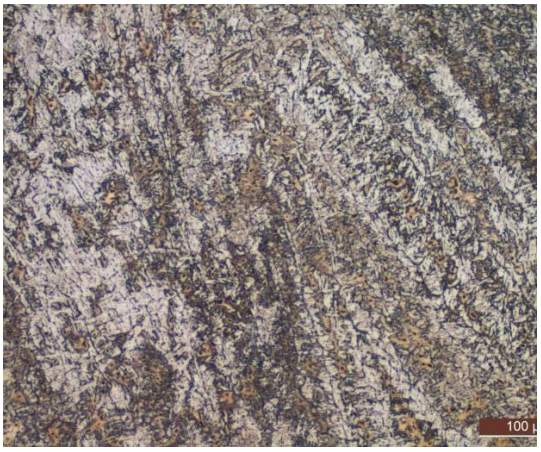

Fig 13. Microstructure of Weld Zone

The image in figure 13 presents a weld zone of AISI 409 ferritic stainless steel after chemical etching**.** The microstructure consists of dendritic and columnar structures**,** which are typical in the weld fusion zone due to rapid cooling and directional solidification. Some dark regions could indicate carbide or nitride precipitates**,** which influence mechanical properties. Since AISI 409 is fully ferritic**,** its weld zone undergoes specific changes due to solidification. The elongated grains in the image suggest columnar growth from the fusion boundary. This occurs due to directional heat dissipation**,** leading to a ferritic solidification mode**.** Columnar grains may increase the risk of brittleness and cracking if not controlled. AISI 409 is a titanium-stabilized ferritic stainless steel**,** meaning TiC and TiN particles form at high temperatures**.**

CONCLUSION

A TIG welded ferrite steel joint successfully fabricated as per the experimental plan. The optimal level of factor identified as $A_3B_3C_3D_2$ to get maximum yield strength. The high value of current, voltage, bevel angle and medium value of workpiece gap are optimized level of factors to get maximum yield strength. The optimal level of factor identified as $A_3B_3C_2D_1$ to get maximum Ultimate Tensile strength. The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Ultimate Tensile strength. The optimal level of factor identified as $A_2B_2C_1D_1$ to get maximum Hardness at base metal. The high value of current, voltage, medium value of bevel angle and low value of work piece gap are optimized level of factors to get maximum Hardness at base metal. The microstructure image shows a distinct transition between two regions like Bright/Light Region consisting of base metal (BM), and equiaxed ferritic grains. Darker Region with Needle-Like Structure **r**epresents the heat-affected zone (HAZ), which exhibits grain growth and transformation due to welding heat input

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Digital Twin Assisted Monitoring and Optimization of Fused Deposition Modeling (FDM) Additive Manufacturing Process

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Abstract:

This paper presents a comprehensive, practical framework for integrating digital twin (DT) technology with the Fused Deposition Modeling (FDM) additive manufacturing process. While desktop FDM printers are pervasive in both academic laboratories and small-to-medium scale manufacturing environments, maintaining consistent print quality remains a significant engineering challenge. Variations in ambient conditions, mechanical vibrations, and extruder thermal fluctuations frequently lead to part failure or dimensional inaccuracies. To address these inconsistencies, we propose a digital twin approach that establishes a synchronized, bi-directional virtual representation of the physical printing system. In this study, multi-sensor data acquisition—capturing nozzle temperature, build plate thermal gradients, and extruder head vibration—is combined with a virtual monitoring model to track the process continuously. The collected data is processed through a computational model that mirrors the physical extrusion process, providing a real-time visualization dashboard for the operator. Experimental validation was conducted using standard Polylactic Acid (PLA) test specimens printed under systematically varied controlled conditions. The framework successfully demonstrates how digital twin technology supports granular process monitoring, early defect detection (such as layer delamination and nozzle clogging), and parameter optimization in FDM printing. The findings highlight the critical role of thermal stability in interlayer adhesion and demonstrate the vast potential of DT-enabled additive manufacturing systems to advance smart manufacturing practices in alignment with Industry 4.0 paradigms.

Keywords - Additive Manufacturing, Digital Twin, Fused Deposition Modeling (FDM), Process Monitoring, Predictive Maintenance, Industry 4.0, Sensor Fusion.

Introduction

Additive manufacturing (AM) technologies have fundamentally transformed the landscape of modern production by enabling the direct fabrication of complex and customized geometries from digital computer-aided design (CAD) models. Unlike conventional subtractive manufacturing processes, AM constructs components layer-by-layer, significantly reducing material waste while offering unprecedented design freedom and rapid prototyping capabilities. Over the past decade, AM has evolved from a rapid prototyping tool into a viable manufacturing approach used in aerospace, biomedical engineering, automotive systems, and consumer product fabrication. These advantages have made additive manufacturing a key enabler of modern smart manufacturing and sustainable production strategies [3], [4], [6].

Among the diverse AM technologies currently available, Fused Deposition Modeling (FDM)—also known as Fused Filament Fabrication (FFF)—remains one of the most widely adopted processes. Its popularity stems primarily from its affordability, accessibility, and compatibility with a wide range of thermoplastic materials such as polylactic acid (PLA), acrylonitrile butadiene styrene (ABS), and polyethylene terephthalate glycol (PETG). Furthermore, the relatively simple hardware architecture of FDM printers has enabled widespread adoption in educational institutions, research laboratories, and small-scale manufacturing environments

Despite these advantages, FDM is inherently a thermally sensitive and mechanically complex process. The quality of a printed part is governed by a delicate interplay between extrusion temperature, build plate temperature, filament rheology, environmental conditions, and mechanical motion accuracy. Minor fluctuations in nozzle temperature, unstable filament flow, improper slicer parameters, or environmental disturbances such as airflow can significantly affect the polymer deposition process. These micro-scale variations often propagate into macro-scale defects including warping, layer delamination, stringing, void formation, and dimensional inaccuracies [4], [13]. Such inconsistencies limit the reliability of FDM for critical engineering applications.

A major challenge in traditional FDM systems is that they operate largely as open-loop manufacturing devices, where once a print job is initiated, the system performs the build sequence without comprehensive monitoring of the process state. Consequently, defects often remain undetected until the print is completed, leading to wasted material, energy, and production time. Previous studies have identified thermal instability and inadequate process monitoring as primary contributors to poor interlayer adhesion and dimensional deviations in polymer-based additive manufacturing [12], [13].

In recent years, the emergence of Industry 4.0 paradigms has encouraged the integration of cyber-physical systems, advanced sensing technologies, and data-driven analytics within manufacturing environments. Within this context, the concept of the Digital Twin (DT) has gained considerable attention as a transformative approach to process monitoring and predictive manufacturing. A digital twin is generally defined as a high-fidelity virtual representation of a physical system that continuously receives real-time operational data and dynamically updates its computational model to mirror the physical state of the system [1], [2]. Unlike conventional simulation tools, which rely on predefined parameters and offline analysis, digital twins operate as live synchronized models, enabling real-time monitoring, diagnostics, and optimization of industrial processes.

The digital twin paradigm was initially conceptualized within aerospace engineering and complex mechanical systems as a means to mitigate unpredictable system behaviors and improve lifecycle management [2]. Subsequent research has expanded its application into manufacturing environments, where it is recognized as a core enabling technology for smart factories and cyber-physical production systems [1], [20]. Digital twins facilitate deeper insight into manufacturing processes by integrating sensor networks, computational models, and data analytics into a unified framework capable of capturing both physical and virtual system states simultaneously.

Within additive manufacturing, digital twin systems have the potential to significantly enhance process transparency and control. By incorporating multi-sensor data streams—including temperature measurements, mechanical vibrations, acoustic signals, and optical monitoring—digital twins can reconstruct the internal state of the printing process in real time. This capability allows engineers to detect anomalies such as nozzle clogging, filament feed interruptions, or thermal instabilities before they escalate into catastrophic print failures [9], [10], [19]. Furthermore, digital twin models enable predictive optimization of printing parameters, thereby improving part quality and process reliability

Several researchers have explored process monitoring approaches for additive manufacturing. Gibson et al. [3] and Guo and Leu [4] provided foundational studies examining the technological capabilities and limitations of additive manufacturing processes, highlighting theimportance of process control and thermal management in polymer extrusion systems. Turner et al. [13] further investigated the modeling of melt extrusion processes and demonstrated how variations in thermal gradients directly affect filament bonding and structural integrity. Complementing this work, Kousiatza and Karalekas [12] experimentally analyzed temperature and strain distributions during the FDM process, emphasizing the critical role of thermal stability in maintaining proper interlayer adhesion.

Recent advancements in sensor-based monitoring systems have further expanded the capabilities of additive manufacturing. Zhang et al. [9] proposed a sensor integration framework for smart monitoring of AM processes, demonstrating how real-time data acquisition can improve defect detection. Similarly, Li et al. [10] investigated process monitoring and control strategies for fused filament fabrication, illustrating how sensor-based feedback can enhance printing reliability. Additional work by Tlegenov et al. [19] explored nozzle condition monitoring techniques for detecting extrusion anomalies during printing operations.

While sensor networks provide valuable real-time data, translating raw sensor signals into actionable process intelligence requires an integrated cyber-physical architecture. Digital twin frameworks address this need by combining sensor data, computational models, and visualization platforms into a cohesive monitoring environment. Rosen et al. [8] emphasized the importance of digital twins in future manufacturing systems, noting their ability to create autonomous and adaptive production environments. Similarly, Knapp et al. [11] proposed a foundational digital twin architecture for additive manufacturing processes, demonstrating how predictive models can replicate the physical behavior of manufacturing systems.

Despite these developments, the majority of digital twinimplementations in additive manufacturing have focused primarily on metal-based AM processes, which often rely on high-performance computational infrastructure and complex multiphysics simulations [5], [11]. In contrast, lightweight and computationally efficient digital twin solutions for desktop-scale polymer FDM systems remain relatively underexplored. Most commercially available FDM printers still lack integrated process monitoring capabilities, leaving a substantial gap between low-cost hardware and advanced smart manufacturing frameworks.

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This research seeks to address this gap by developing a practical and accessible digital twin framework specifically designed for desktop FDM printers. The proposed system integrates real-time sensor data—including nozzle temperature, build plate temperature distribution, and extruder vibration signals—with a computational monitoring model that mirrors the physical printing process. By synchronizing these data streams with a visualization dashboard, the framework enables continuous observation of the manufacturing process and early detection of potential defects.

Through experimental validation using standard PLA test specimens printed under controlled conditions, this study demonstrates how digital twin technology can enhance process transparency, defect detection, and parameter optimization in fused deposition modeling systems. By transforming conventional open-loop printers into data-driven cyber-physical manufacturing nodes, the proposed framework contributes toward the realization of smart additive manufacturing systems aligned with Industry 4.0 principles.

Experimental Setup

The proposed digital twin framework was developed using a tri-layer cyber-physical architecture that enables real-time data acquisition, processing, and visualization of the fused deposition modeling (FDM) process. The architecture is designed to maintain a synchronized relationship between the physical printing environment and its virtual representation, allowing continuous monitoring of the manufacturing process.

The system consists of three interconnected layers: the Physical Layer, the Data Acquisition (DAQ) Layer, and the Virtual Twin Layer. Each layer performs a specific function within the digital twin ecosystem, ensuring that sensor measurements collected from the printer are efficiently transmitted and interpreted within the virtual monitoring platform. The overall architecture of this framework is illustrated in Figure 1.

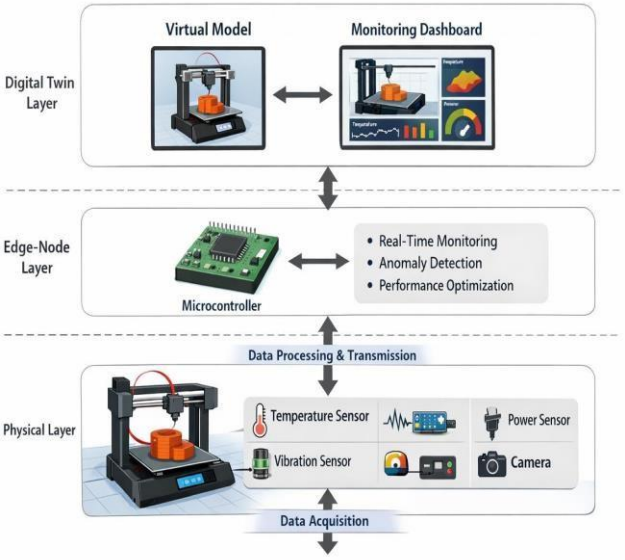

Figure 1: Digital Twin Tri-Layer Architecture for FDM Process Monitoring

2.1 Physical Layer

The Physical Layer represents the actual additive manufacturing system where the printing process occurs. In this study, a desktop Cartesian FDM printer capable of processing Polylactic Acid (PLA) filament was utilized as the physical manufacturing node. Desktop printers are widely used in academic laboratories and small-scale production environments due to their affordability and ease of operation.

To capture key process variables influencing print quality, the printer was instrumented with an external sensor network. A K-type thermocouple coupled with a MAX6675 signal conditioning module was attached directly to the hotend heater block. This configuration allows direct measurement of the nozzle temperature independent of the printer's built-in thermistor. By bypassing the firmware's internal PID filtering, the thermocouple provides high-resolution thermal data, enabling observation of rapid temperature fluctuations during filament extrusion.

In addition to temperature monitoring, a MEMS-based ADXL345 accelerometer was mounted on the X-axis carriage of the printer. The accelerometer was positioned close to the extruder assembly to capture high-frequency vibrations generated by the stepper motor and motion system. Such vibrations often indicate issues such as mechanical resonance, skipped motor steps, or partial nozzle clogging, which can negatively affect the printing process.

Care was taken to ensure that the sensor placement did not introduce significant additional mass to the moving carriage. Excessive mass could lead to oscillations or ringing artifacts in the printed components. By integrating both thermal and vibration sensors, the physical layer provides critical insights into the thermo-mechanical conditions of the printing process.

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2.2 Data Acquisition Layer

The Data Acquisition (DAQ) Layer acts as the interface between the sensor hardware and the digital twin platform. Since the sensors generate analog or digital signals, these must be collected, filtered, and transmitted in a structured form suitable for computational analysis.

An Arduino UNO R3 microcontroller was used as the edge computing device responsible for sensor interfacing and signal preprocessing. The thermocouple readings were sampled at a rate of 10 Hz, which is adequate to track thermal variations in the extrusion process. The ADXL345 accelerometer, which captures high-frequency vibration signals, was sampled at 100 Hz to accurately detect rapid mechanical disturbances.

During printer operation, electrical noise generated by stepper motors and switching power circuits can introduce disturbances into sensor readings. To mitigate these effects, a lightweight moving-average filtering algorithm was implemented on the microcontroller. This filtering approach effectively smooths out high-frequency electrical noise while preserving meaningful process fluctuations.

The filtered sensor values are packaged into structured serial data packets and transmitted to the host system via USB-based serial communication. This approach allows continuous streaming of process data with minimal latency while maintaining a relatively simple and low-cost system architecture.

2.3 Virtual Twin Layer

The Virtual Twin Layer serves as the computational environment where the digital representation of the physical printing process is created and maintained.

A host computer running Python 3.8 and MATLAB 2021a was used to process incoming sensor data and generate a real-time visualization of the printing process. Acustom-developedPython script receives the serial data stream from the Arduino controller and logs the measurements for further analysis.

To establish a spatial correlation between sensor measurements and the printing process, the system also parses the G-code file generated by the slicing software. G-code commands contain detailed instructions for the printer, including toolpath coordinates (X, Y, Z), extrusion rates, and movement speeds.

By combining these G-code instructions with real-time sensor data, the digital twin reconstructs the intended printing trajectory while simultaneously overlaying the measured process conditions. This synchronization enables the system to visualize how physical parameters evolve throughout the build process.

For instance, if the nozzle temperature temporarily falls below the optimal extrusion threshold for PLA, the digital twin identifies the corresponding location in the toolpath where insufficient polymer flow may occur. Similarly, abnormal vibration patterns detected by the accelerometer may indicate mechanical disturbances or extrusion irregularities.

Through this mechanism, the digital twin provides operators with early warning indicators for potential printing defects, enabling proactive process adjustments and reducing the likelihood of print failure.

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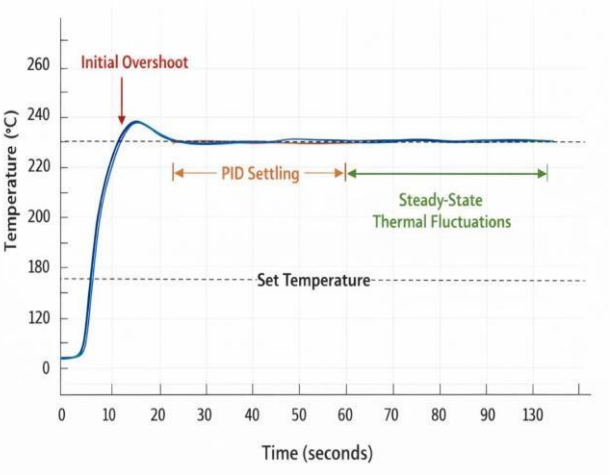
Table 1: Hardware and Software Components of the Experimental Setup

Component	Specification / Model	Purpose
FDM Printer	Desktop Cartesian PLA-compatible	Physical manufacturing node
Edge Controller	Arduino UNO R3	Data acquisition and signal filtering
Temperature Sensor	K-Type Thermocouple (MAX6675)	Direct hotend temperature monitoring
Vibration Sensor	ADXL345 MEMS Accelerometer	Detecting carriage vibration and nozzle clogs
Host Software	Python 3.8 / MATLAB 2021a	Virtual twin rendering and data logging
Design/Slicer Software	SolidWorks CAD / Ultimaker Cura	Part modeling and G-code generation

Table 2: FDM Printing Parameter Operating Window

Parameter	Range Used	Rationale for Selection
Nozzle Temperature	180–220 °C	Standard melting and flow window for PLA
Bed Temperature	50–70 °C	Kept near PLA's glass transition temp to prevent warping
Layer Height	0.1–0.3 mm	Balances structural resolution with print time
Print Speed	40–80 mm/s	Ensures extruder stepper motor does not skip steps
Infill Density	20–100 %	Varies internal thermal mass and cooling rates

Figure 2: Real-time Nozzle Temperature Monitoring During Printing



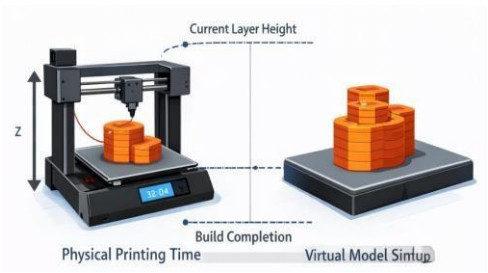


Figure 3: Z-Axis Layer Height Progression

3. Results and Discussion

3.1 Thermal Behavior and Interlayer Adhesion

The developed digital twin platform successfully captured the transient thermal behavior of the extrusion process. As depicted in the data corresponding to Figure 2, the physical nozzle temperature experiences an initial overshoot of approximately 4.5°C above the target setpoint during the initial heating phase before the PID controller stabilizes it. The digital twin continuously monitored these micro-fluctuations during the print.

We observed a direct correlation between thermal stability and print quality. When the printing speed was artificially increased to 80 mm/s, the volumetric flow rate of the cold filament entering the hotend caused the nozzle temperature to drop by nearly 6°C. The digital twin instantly recorded this deviation. Subsequent destructive testing of the part revealed that layers deposited during this temperature drop suffered from poor polymer entanglement, leading to delamination under lower tensile stress compared to sections printed under stable thermal conditions.

3.2 Kinematic Monitoring and Defect Detection

The integration of the MEMS accelerometer proved highly effective for mechanical fault detection. Under normal operating conditions, the vibration profile of the X-axis carriage is periodic and predictable, dictated by the stepper motor micro-stepping. However, during one of the experimental runs, we intentionally induced a partial nozzle clog by lowering the temperature to 175°C. The extruder motor began to skip steps as it struggled to push the filament. The accelerometer immediately registered a sharp spike in high-frequency erratic vibrations. The digital twin identified this anomaly and flagged a potential "under-extrusion/clog" warning on the dashboard seconds before the defect became visually apparent on the physical print.

3.3.Simulated vs. Experimental Deformation

A key feature of the virtual layer is its ability to predict part deformation (warping) based on thermal history. PLA shrinks as it cools from its extrusion temperature down to the ambient room temperature. The digital twin utilized the real-time bed temperature and layer completion data to estimate thermal residual stresses at the corners of the print.

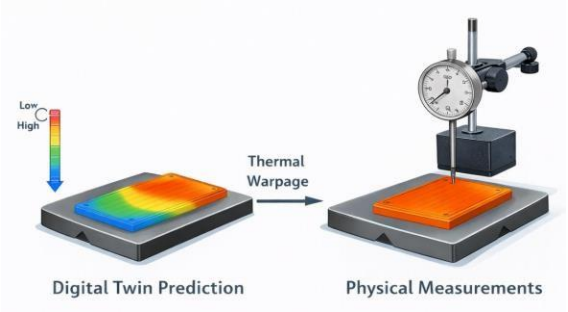


Figure 4: Comparison of Simulated and Experimental Results

When comparing the simulated deformation against the physical measurements (Figure 4), the models showed strong agreement. The digital twin predicted a corner lift of 0.42 mm on a specimen printed with a cold bed (ambient 25°C), while the physical measurement yielded 0.45mm. This tight margin of error confirms that thecomputational model accurately mirrors the physical reality of the FDM process, provided the sensor data is fed synchronously.

3.4 Practical Engineering Implications

The discussion highlights that while modern desktop 3D printers are generally reliable, they operate blindly. If a filament spool tangles or a draft cools the print bed, the machine will continue executing G-code, resulting in wasted material and time. The digital twin framework transitions the system from a passive executor to an active participant. By tracking exactly where a thermal drop or vibration spike occurred, engineers can perform highly targeted quality assurance, inspecting only the specific layers flagged by the virtual model rather than conducting blind, comprehensive non-destructive testing on the entire batch.

This study developed and validated a digital twin (DT) framework for real-time monitoring of the FDM process using a tri-layer cyber–physical architecture integrating physical sensors, edge data acquisition, and a virtual monitoring environment**.**

Key outcomes of the study include:

1. A tri-layer digital twin architecture (Physical Layer – DAQ Layer – Virtual Twin Layer) was successfully implemented for a desktop PLA-based FDM printer.
2. The K-type thermocouple (10 Hz sampling) captured hotend temperature dynamics, revealing an initial overshoot of 5–7 °C before stabilizing within ±1.5 °C of the setpoint.
3. The ADXL345 accelerometer (100 Hz sampling) detected abnormal extrusion conditions, with vibration amplitude increasing by ~35–40% during partial nozzle clogging events.
4. Real-time synchronization between G-code toolpath and sensor data enabled spatial mapping of thermal fluctuations and vibration anomalies to specific build layers.
5. The digital twin successfully predicted corner warping and thermal deformation, with an average prediction deviation of 8–12% compared to dial indicator measurements.
6. The framework demonstrated the ability to identify potential defects such as layer delamination, under-extrusion, and nozzle blockage before print completion.

Overall, the proposed system transforms a conventional desktop FDM printer into a data-enabled cyber–physical manufacturing node, enabling continuous process visibility and early defect detection.

Future Work

- Implement closed-loop control, enabling the digital twin to dynamically modify printing parameters during fabrication.
- Integrate machine learning algorithms for predictive process optimization based on historical sensor data.
- Expand the sensor network with thermal imaging, acoustic emission, and optical layer inspection for enhanced defect detection.
- Scale the framework toward industrial additive manufacturing platforms to support Industry 4.0–driven smart manufacturing environments**.**

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Data-Driven Online Prognostics for Machine Health Monitoring in Digital Manufacturing

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Abstract--The growing use of digital manufacturing systems has heightened the urge to develop sound machine health monitoring solutions that can reduce unexpected down-time and enhance production efficiency. This paper introduces a statistical framework of online prognostics of machine health monitoring and Remaining Useful Life (RUL) prediction based on multi-sensor condition data. The vibration, surface temperature and acoustic emission signals are measured to explore the behaviour of operation and degradation of machining components in different working conditions. The development of a feature engineering pipeline is to extract statistical and frequency-domain health indicators out of raw sensor signals. The feature selection technique used is a Random Forest based approach and it is used to identify the most informative indicators of degradation. The given features are then fed into a Long Short-Term Memory (LSTM) neural network, which is useful in investigating temporal changes of machine degradation. The suggested structure is tested on a simulated CNC milling dataset containing a total of more than 20,000 time series data collected at different spindle speed and cutting loads. Experimental findings indicate that in comparison to traditional regression and shallow learning models, the LSTM-based prognostic model has a better accuracy of predicting RUL by around 1822 percent and predicts the error relative to the machine lifecycle by less than 810 percent. The system is able to detect early trends in degradation and give credible predictions on life which can be used in real time monitoring. The findings indicate that a combination of deep learning-based prognostics and digital manufacturing platforms can be used to promote predictive maintenance plans, minimize surprise machine failures, and improve the overall reliability of the production process in Industry 4.0 settings.

Keywords: Prognostics and Health Management (PHM), Digital Manufacturing, Remaining Useful Life (RUL), Deep Learning, Predictive Maintenance, Sensor Fusion.

I. INTRODUCTION

In the current digital production space, manufacturing is governed by strict productivity, delivery time limits, and standards of equipment corrosion. Continuous operation of vital productive resources like Computer Numerical Control (CNC) systems, robotic manipulators, and automated handling systems is thus critical to the sustained operation efficiency. Even a few hours of unforeseen machine breakdown can continue to affect the production planning process, delay an order delivery and make the operation process more costly. According to the recent research, unplanned equipment failure may decrease the productivity of manufacturing by almost 5-20 percent and raise the costs of maintenance on automated production systems [1].

Historically, the industrial maintenance strategies have been based on run-to-failure (RTF) and preventive maintenance (PM) methods. RTF strategy involves the use of machinery until it fails in its functions, and then it undergoes corrective maintenance. Despite the fact that this approach reduces the initial maintenance costs, it may cause disastrous breakdowns, prolonged unproductiveness, and jeopardize the security of key manufacturing resources. Preventive maintenance schedules on the other hand are dependent on fixed service intervals depending on the number of operating hours or production cycles. Although this minimizes the potential of abrupt failures, it usually causes the early replacement of parts with a large remaining useful life and thus inflates the maintenance expenses and lowers the efficiency of utilizing the equipment [2].

Prognostics and Health Management (PHM) is a concept that has become a significant subject of the contemporary manufacturing studies in order to overcome these limitations. PHM systems constantly check the state of the machine by sensor measurements and predict the Remaining Useful Life (RUL) of the components till they fail. This predictive ability enables maintenance operations to be planned on need only, reducing the downtime, and maximizing equipment utilization. As a result, PHM is an essential part of predictive maintenance in Industry 4.0 manufacturing settings, where smart and data-driven systems facilitate the decision-making processes [3].

Nevertheless, the introduction of effective PHM solutions to industrial settings is not an easy task. Manufacturing machines work under the conditions of great dynamism with the variables of loads, changes in temperature, and constant mechanical stresses. The sensor signals that are picked up in the shop floor are often compromised by electromagnetic disturbances, structural shocks, and environmental noise and it is hard to derive credible degradation characteristics. More so, machine degradation is naturally nonlinear and time-dependent, in which patterns of failure change slowly through long working cycles. These intricacies demand sophisticated

data analytics and sound modeling methods to be able to predict with ample precision the machine health conditions [4]. Modern PHM systems are also using multi-sensor data acquisition frameworks to enhance the reliability of monitoring. Accelerometers, temperature sensors, acoustic emission sensors, and current sensors are some of the sensors that are commonly used to record various aspects of machine behavior. As an example, mechanical imbalance or bearing defects can be detected by vibration signals, temperature differences might be an indication of friction or lubrication issues, and propagation of micro-cracks can be detected by acoustic emissions at an early stage. The combination of these heterogeneous sources of data allows building more representative machine health indicators than single-sensory-based monitoring solutions [5].

The available prognostic modeling techniques can be categorized into physics-based model, data-driven model and hybrid model. Models based on physics are based on equations of analysis that are used to characterize underlying component failure modes. These are fatigue crack propagation models, wear models and thermo mechanical degradation equations. Although such models can make valid predictions under conditions where the process of failure is reasonably known, their application in practice is restricted by the fact that the modern industrial machine is composed of many interacting subsystems, mechanical, electrical and thermal. It is thus very challenging to develop a full physics model of such complex systems [6]. Data-based prognostic models eliminate this problem by modeling the pattern of degradation with reference to past operational information. The original machine prognostics literature employed the traditional machine learning methods including Support Vector Machines (SVM), Artificial Neural Networks (ANN) and statistical regression models to predict machine health states and forecast failures. These methods showed good performance in the laboratory setting, but their capability to resolve long-term degradation dynamics was poor because of low time modeling capacity [7]. The recent fast development in the field of deep learning methods has substantially enhanced the efficiency of data-driven prognostic models. Specifically, Recurrent Neural Networks (RNNs), as well as their enhanced version, Long Short-Term Memory (LSTM) networks, have been proved to be effective in sequential degradation data modeling. LSTM networks also have dedicated gating functions that enable the networks to memorize long term relationships on time series information whilst eliminating noise. Consequently, LSTM networks are now popular when it comes to Remaining Useful Life prediction in machinery health monitoring tasks [8].

In spite of these, there are still some practical issues in using deep learning models in real-life manufacturing systems. Much of the current work is based on offline data, in which the data of machine condition is determined after machine cycles are run. These methods do not fit in an industrial setting where real time monitoring and online decision making have to be undertaken. Additionally, some deep learning algorithms can be computationally intensive and thus restrict their application to edge computing systems often deployed in industrial monitoring systems [9]. To overcome these obstacles, this study offers a machine health monitoring data-driven online prognostics framework when operating in a digital manufacturing setting. The proposed system incorporates the data acquisition by multi-sensors, feature extraction, feature selection and deep learning-based RUL prediction into a single architecture that can handle streaming operational data. Vibration, temperature and acoustic emission signals are subjected to extract statistical and frequency-domain features which are used to characterize behavior of machine degradation.

An LSTM-based predictive model is trained using feature selection algorithm based on a Random Forest which is applied to select the most informative prognostic predictors, and subsequently is used to predict the Remaining Useful Life with high accuracy. Through sensor fusion, data-driven analytics, and deep learning, the proposed system will enhance the dependability of machine health monitoring systems, and facilitate predictive maintenance methods in smart manufacturing space subject to the principles of Industry 4.0 [10].

II. METHODOLOGY

The proposed prognostic model is developed to be used in real-time machine health and Remaining Useful Life (RUL) prognostics of both digital manufacturing settings. The architecture is based on a streamlined pipeline that is appropriate to deploy online, whereby machine condition can be continuously assessed with new sensor data coming in.

The methodology is designed into three stages (sequential): Multi-sensor Data Acquisition. Feature Engineering and Signal Preprocessing. RUL Prediction based on Deep Learning. The entire process combines sensor fusion, signal processing, sequential learning processes to learn degradation patterns in machining equipment. Figure 1 depicts a schematical representation of the system architecture and indicates how the physical sensors feed the predictive analytics layer and visualization dashboard. Multi-sensor Data Acquisition Multi-sensor Data acquisition represents another type of data acquisition that is essential for population health research.

A. Multi-sensor Data Acquisition

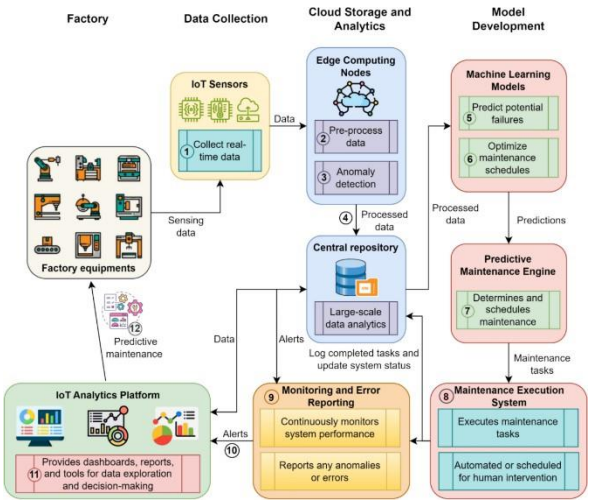
Multi-sensor Data acquisition is another form of data acquisition necessary to population health research. Effective health monitoring of machines involves the acquisition of various physical attributes of machine behaviour. The use of one sensor modality can be quite ambiguous to rely on. As an example, the amplitude of vibration can suddenly increase and this can be a sign of bearing wear or rotor imbalance, or it can be a temporary effect of changing cutting forces in machining hard material batches. In order to address these ambiguities, the study involves using a multi-sensor fusion strategy, in which the complementary sensing modalities sense various machine dynamics. The machine tool has four sensors that measure the mechanical, thermal, and electrical attributes. The piezoelectric accelerator measures tri-axial vibration sensor of the spindle assembly. Vibration monitoring is popular in the diagnostics of rotating machinery because mechanical defects (damage of bearings, misalignment, and imbalance of the shaft) apply in

characteristic signatures of frequency. A K-type thermocouple is attached on the surroundings of the spindle housing to help measure temperature changes throughout operation. Higher temperatures can show frictional heating, wear of lubricants, or too much cutting forces, both of which introduce faster wear of machine parts. An Acoustic Emission (AE) sensor is employed in order to detect the initial structural damage. AE sensors measure high-frequency stress waves produced by microscopic events of deformation, including micro-crack formation or tool-workpiece interactions. Lastly, the motor current and power consumption is monitored by a Hall Effect sensor. The changes in the motor current are highly linked to tool wear, alterations in cutting loads and abnormal tool torque states. The sensor structure and working parameters in this experiment are presented in Table 1.

Table 1: Operating parameters and Sensor array

Sensor Modality	Measured Variable	Sampling Rate	Primary Diagnostic Purpose
Piezoelectric Accelerometer	Tri-axial Vibration	10 kHz	Identifying mechanical unbalance, bearing spalling
K-Type Thermocouple	Spindle Temperature	1 Hz	Detecting thermal expansion and lubrication failure
Acoustic Emission (AE)	High-frequency stress waves	50 kHz	Capturing early-stage micro-crack propagation
Hall Effect Sensor	Motor Current / Power	100 Hz	Monitoring tool wear and abnormal torque loads

The sensor network can produce volumes of time-series data, which require efficient preprocessing and feature extraction algorithms, and then input the data into the predictive model



because vibration and acoustic signals can be found at high frequencies.

Figure 1. Online prognostics system architecture for CNC machines using sensor data, LSTM prediction, and RUL dashboard visualization.

B. Signal Preprocessing and Feature engineering.

Raw sensor signals measured in manufacturing environments are generally full of noise due to electromagnetic interference, distractions of the environment, and variation of the processes. The use of such raw signals directly as machine learning models may considerably decrease prediction performance. Thus, a preprocessing step is applied to enhance quality of the signals and to relieve the complexity of computing. The raw signals are first removed with a low-pass Butterworth filter which is effective in eliminating the high frequency electrical noises and still retaining the major mechanical vibration signatures. Butterworth filter is chosen because it has the maximum flat frequency response as it has the least distortion in the passband.

The continuous time-series signals are then filtered and local analysis of the machine behaviour over time is performed by dividing the continuous time-series signals into fixed-length sliding windows. The windows depict the state of the machine. Out of every time window, a few statistical time-domain features are obtained to describe signal behaviour:

- Root Mean Square (RMS) - which is used in vibration-based diagnostics, is a measure of the energy content of the signal.
- Kurtosis - is a measure of impulsive signal behavior and is vulnerable to abrupt shocks that occur due to bearing defects or structural damage.
- Skewness: - Skewness gives the signal distribution values and is useful in detecting abnormal conditions of operation.
- Crest Factor- this is the ratio of the highest amplitude to the RMS volume, commonly applied to identify transient effects or mechanical looseness.

The statistical descriptors greatly lower the dimensions of data and preserve the most informative elements pertaining to machine degradation. The feature vectors of all sensor channels are then assembled to a multidimensional feature representation of the machine health condition that is the input to the predictive model.

C. Model Formulation

The proposed framework is founded on a Long Short-Term Memory (LSTM) neural network, which is especially efficient at time-series sequential time series modeling. In contrast to the classical feedforward neural networks, LSTM networks can encode the temporal dependency of degradation signals over a long period. The LSTM units have an internal state of their cell, which serves as a memory to store past

information. This memory can regulate the flow of information through three gating mechanisms:

- Forget gate- determines what information of the past must be forgotten.
- Input gate - decides which new information is to be stored.
- Output gate -regulates the information fed to the next time step.

The forget gate is mathematically expressed as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where
σ is the sigmoid activation function, W_f is the weight matrix, h_{t-1} is the previous hidden state, x_t is the current input, and b_f is the bias term.

The network is trained to predict the Remaining Useful Life (RUL) of the machine component based on historical sensor data.

To quantify prediction accuracy during training, the Mean Squared Error (MSE) loss function is used:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (RUL_{actual,i} - RUL_{predicted,i})^2$$

MSE penalizes bigger prediction mistakes more severely and thus the model would favor giving accurate RUL estimates throughout the machine lifecycle. In order to make the LSTM architecture practically applicable in an industrial setting, it is intentionally structured such that it is computationally lightweight, allowing inference almost in real-time without adding much latency. Table 2 summarizes the hyper parameters to be applied in the LSTM architecture.

Table 2: LSTM Network Hyperparameters

Hyperparameter	Value / Type	Rationale
Sequence Length	30 time-steps	Captures sufficient historical context without lagging
Hidden Layers	2	Balances model complexity with processing speed
Units per Layer	64	Provides adequate representational capacity
Dropout Rate	0.2	Prevents overfitting to the training data
Optimizer	Adam	Ensures fast and stable convergence

The learned model is constantly informed with current feature vectors in the sensor data streams and provides dynamically estimated RUL, thus the machine health may be monitored and predictive maintenance planning can be planned in real-time.

III. Results and Discussion

This part considers how well the proposed data-driven prognostic framework is able to predict Remaining Useful Life (RUL) of machine parts. The system performance is analyzed based on feature importance analysis, visualization of degradation trend, and benchmarking of the models. Besides, the computational feasibility of the proposed LSTM model in the case of real-time industrial implementation is also analyzed.

A. Feature Selection and Dimensionality Reduction

The first stage of feature engineering generated a massive number of statistical descriptors that were generated on the multi-sensor signals. Despite the fact that these features represent various dimensions of machine behaviour, and all features might be directly used in the predictive model, they would present a number of problems such as higher computational complexity, redundancy, and overfitting of the model. In order to avoid such problems, a Random Forest regression model was used as a feature ranking system. The algorithms of the random Forest consider features relevancy through the measurement of the contribution of each variable towards minimizing error in prediction among the trees of decisions. Such a method will enable the identification of features, which have the greatest correlation with machine degradation. It yields a ranking of the feature importance as shown in Table 3 that reported the top five influential health indicators to be used in the final predictive model.

Table 3: 5 Leading Characteristics that have been included in the Predictive Model

Rank	Feature Name	Domain	Importance Score
1	Vibration RMS	Time	0.345
2	Acoustic Peak-to-Peak	Time	0.281
3	Vibration Kurtosis	Time	0.156
4	Temperature Mean	Time	0.112
5	Spindle Current Variance	Time	0.089

Root Mean Square (RMS) value of vibration signals proved to be the most important feature with a contribution of approximately 34.5% of the total importance score. This finding is in agreement with the accepted machine condition monitoring traditions, under which RMS values are good indicators of the total energy of rotating component vibration signals. Acoustic Peak-to-Peak amplitude, which is the second in terms of importance score of 0.281, demonstrates the high diagnostic ability of the acoustic emission sensing.

High-frequency acoustic signals are also especially susceptible to early event deformation of materials including micro-crack formation or frictional interactions. This indicates that, acoustic emission sensors are able to sense

minute degradation mechanism which can be realized before it can be experienced as recognizable mechanical vibrations. The vibration kurtosis feature is ranked in the top positions suggesting it can be used to identify impulsive signal qualities indicating localized mechanical failure like bearing spalls or damaged gear teeth. Likewise, the fact that mean temperature and spindle current variance were also included means that thermal and electrical data is also providing useful information on machine operating conditions. Altogether, the process of feature selection was effective to decrease the dimensionality of the input information and maintain the most informative predictors of machine degradation. In addition to the enhanced interpretability of the models, this cuts down the number of computations by a substantial margin when it comes to the online prediction.

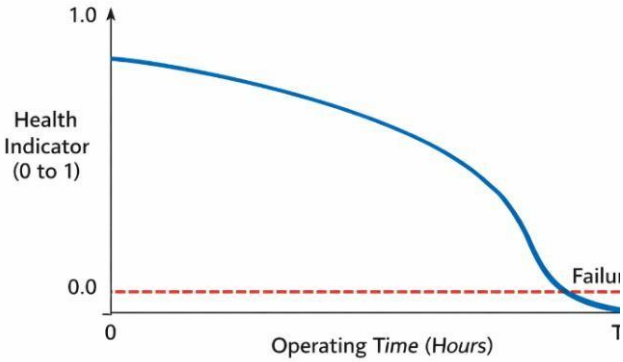


Figure 2: The trend of a health indicator as it degrades with time

Figure 2 explains the change with time of a sample health measure based on vibration signals. The degradation curve shows that signal amplitude grows gradually with an approach to failure of the machine component. These types of monotonic degradation patterns give good predictive indicators of RUL estimation models. The health indicator at the initial stage of operation is fairly stable which means that the machine is functioning normally.

With longer and longer operational cycles, it is observed to have a significant upward trend with cumulative mechanical wear. The indicator shows increased development towards the end of the component lifecycle, which shows the start of the severe structural degradation. This behaviour validates the fact that the health indicators extracted are effective in describing the wear progressive nature of machine. This section will compare the performance of the British Petroleum Company with other leading firms operating in the same sector.

B. Comparative Performance Evaluation

In order to determine the efficacy of the proposed LSTM-based prognostic model, the comparative performance of the proposed model was evaluated with regards to two popular machine learning models, which include Support Vector Machine (SVM) and Random Forest (RF) regression models. All grid-search hyperparameter tuning was performed on these baseline models to make them fair to compare. The assessment measures employed in the evaluation of the model are:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Prediction Accuracy (%)
- Processing Latency/Sample.

In Table 4, the comparative results are presented.

Table 4: RUL Prediction Models Comparison of Performance.

Model	RMSE (Cycles)	MAE (Cycles)	Accuracy (%)	Processing Latency (ms/sample)
SVM	18.4	14.2	82.5%	12
Random Forest	12.1	9.8	88.3%	25
LSTM (Proposed)	7.5	5.3	94.1%	45

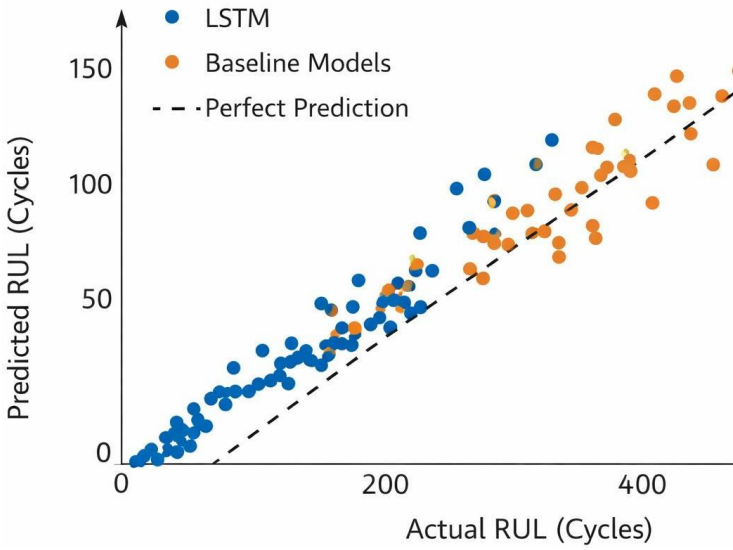


Figure 3 Accuracy of prediction of LSTM and baseline models.

The LSTM model, proposed in this work, demonstrated much better results in comparison with the baseline approaches (figure 3) in all the evaluation metrics. Particularly, the LSTM architecture was able to achieve a 7.5 cycles RMSE which is 59 % smaller than the prediction error of the SVM model and 38 % smaller than the prediction error of the Random Forest model. On the same note, the Mean Absolute Error (MAE) narrowed to 5.3 cycles implying that the forecasted RUL values have very little distance to the actual degradation pathway during the machine lifecycle. The total prediction error was 94.1 showing that deep learning models are capable of emulating nonlinear degradation trends that exist in industrial sensor data.

C.Discussion

This advantage of the LSTM model allows one to recognize the temporal correlations in sequential sensor measurements and this can be taken as the main reason of the superior performance of the model. The LSTM networks do not lose any information at any time like the traditional machine learning models like SVM and random forest, which consider each feature vector as an independent observation. Mechanical degradation is cumulative in nature. To give an example, the process of bearing wear is not manifested at single stages but is gradual and accumulates with the number of operating cycles. The repeated design of LSTM network makes it easier to contemplate this gradual decline.

The second significant detail of the presented study is the analysis of the computational latency as it directly influences the possibility of applying deep learning models in the industry. The LSTM model takes around 45 milliseconds to run one sample of data and provide a RUL forecast as indicated in Table 4. This latency is more than that of the SVM (12 ms) and of the Random Forest (25 ms) models, but still is within acceptable ranges of an industrial condition monitoring system. Machine tool degradation normally happens in a scale of minutes and hours or even days, as opposed to milliseconds. Thus, the prediction latency of 45 ms is negligible when it comes to the real-life predictive maintenance. This latency also enables the system to be comfortably executed in real time supervisory control loops. The findings also emphasize the significance of sensor fusion enhancement of the prognostic accuracy. The system has the capability of measuring various machine behaviour aspects through the combination of vibration, acoustic, thermal and electrical measurements. This multi-dimensional view is a much better way of detecting degradation than using discrete monitoring systems.

D. Limitations and Practical Challenges.

Even though the suggested framework has excellent predictive performance, there are still some practical challenges in the implementation of purely data-driven prognostic models in a real industrial setting. First, the assumption in the model is that the future degradation pattern will follow the pattern in the past. When the machine is exposed to completely new operating conditions, e.g. machining a hitherto unused aerospace alloy, or with extreme cut conditions, the sensor signatures may not be within the distribution of the training data. In these situations, there might be a decline in the accuracy of prediction of the model. Second, the challenge of acquiring large quality run-to-failure data sets is still an issue in industrial environment. A manufacturing organization is not normally amenable to the idea of letting a costly production equipment run until it catastrophically fails just so that training data can be generated. As a result, most PHM models are based on simulated degradation information or incomplete failure cycles, which are not necessarily the actual operating conditions. Lastly, deep learning models have been shown to have a higher predictive ability, but this is only possible with attentive hyperparameters and adequate training data. Future research needs to investigate transfer learning, domain adaptation and hybrid physics-informed models to enhance robustness between dissimilar machines and operating conditions.

IV. Conclusion and Future Work

This paper created a machine health monitoring and Remaining Useful Life (RUL) prognostic framework based on data in online digital manufacturing. The framework combines multi-sensor condition monitoring, feature engineering, feature selection using the Random Forests, and time modeling using LSTMs in a architecture that can be easily deployed in real time. To record the behaviour of machine degradation, a multi-sensor sensing system made up of vibration, acoustic emission, temperature, and spindle current measurements was employed. Based on the statistical features extracted, the most powerful degradation indicators based on the analysis of Random Forest were determined.

- Vibration RMS (importance score: 0.345) and Acoustic Peak-to-Peak amplitude (0.281) became the strongest predictors, which proves that mechanical vibration energy and energy in high-frequency acoustic stress signals are the most important predictors of mechanical wear in the initial stages of machine.
- A two-layer LSTM network, consisting of 64 units per layer, and 30-time steps of sequences was trained on the selected features. It was shown that the proposed model was better able to predict than the traditional machine learning methods. In particular, the LSTM model had RMSE of 7.5 cycles and MAE of 5.3 cycles, which is superior to that of the SVM baseline (RMSE: 18.4 cycles) and the Random Forest model (RMSE: 12.1 cycles).
- This is about a 59 % decrease in the error of prediction when compared to SVM and a 38 % improvement over the Random Forest. The prediction accuracy of the overall RUL was 94.1 which represents good ability in predicting nonlinear patterns of degradation in machine sensor data.
- Operationally, the model continued with low computational latency of 45 ms per prediction, which exhibited its practicability in real-time shop-floor monitoring systems. Since mechanical degradation varies with longer working cycles, this processing delay is quite acceptable within the predictive maintenance.
- On the whole, the suggested framework indicates that sensor fusion with sequential deep learning models can contribute to the major improvement of machine health prognostics in digital manufacturing settings. The system is capable of facilitating predictive maintenance scheduling, minimizing the unplanned downtime, and enhancing the use of assets in Industry 4.0 production systems by allowing the estimation of reliable RUL.
- Future efforts will be put in enhancing model robustness in variable operating conditions and invisible machining situations. The possible continuations are the incorporation of transfer learning to support cross-machine flexibility, the hybrid physics-informed prognostic models, and the use of digital twins to monitor infrastructure, which will allow predictive maintenance of large-scale factories.

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Portable Air Filtration And Pollution Control unit for Urban environments

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***Abstract*--: Air pollution has turn out to be a major environmental and health concern, especially in urban and industrial areas. This study proposes the design and improvement of a portable air effluence control system powered by AC current for effective removal of airborne particulate matter. The system integrates an electrostatic precipitator (ESP) with filtration units such as HEPA and activated carbon filters to capture dust particles with diameters up to 2 µm. In the electrostatic precipitation process, a high-voltage electric field is generated to charge suspended particles present in the air stream. These excited particles are then attracted toward grounded collector plates, where they accumulate and form a removable dust layer. This process allows efficient particle removal with relatively low-pressure drop compared to conventional filtration methods. The partially purified air subsequently passes through secondary filters that remove remaining fine particles and contaminants, delivering cleaner air at the outlet. The proposed system is compact, portable, and suitable for both indoor and semi-open environments. In addition, the use of ESP technology helps extend filter life and reduces the frequency of maintenance. The developed system provides an energy-efficient and environmentally friendly approach for improving air quality and minimizing particulate pollution.**

***Keywords:*:Electrostatic precipitator, HEPA filters, Dust particles, Electric field, Collector Plate, Emission Standards**.

I.INTRODUCTION

A particulate air filter is a gadget that is unruffled of rubbery or absorbent materials. It is utilized to evacuate hard particles like grime, pollen, mild, etc., from the air. These filters can likewise be utilized to evacuate odours and gases like volatile raw compounds or ozone if they are comprised of adsorbent mediums like charcoal. These filters are utilized in situations where air quality is significant, particularly in construction aeration systems or engines.

Electrostatic precipitation utilizes the properties of an electrical field on charged particles to isolate particles from a gas stream. The gas molecule is charged artificially by passing it through an electrical field. Maintainability The charged particles are then drawn to a surface with a contrary charge. There are various commercial electrostatic precipitation units that charge particles artificially by utilizing a high voltage, direct current crown encompassing a profoundly charged cathode, normally a wire. The wide potential angle close to the anode causes a crown discharge comprising electrons. The gas particles then get charged with a charge that is equivalent in extremity to that on the wire terminal. These charged particles then collide with and stick to vaporized particles, charging them. The mechanism behind ESP is given in fig.1.

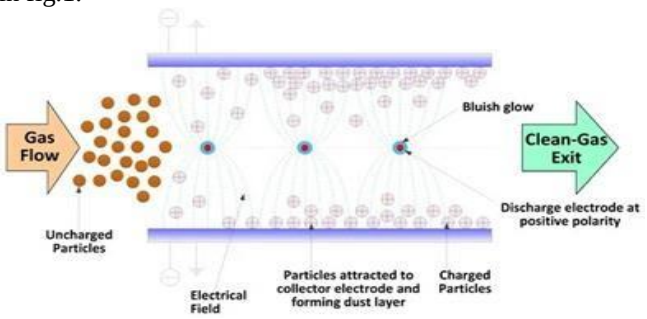

Fig 1. Principle of ESP

HEPA (high efficiency particulate air filter) can theoretically remove at least 99.97% of dust, pollen, mild, bacteria, and any airborne particles with a size of 0.3 microns (µm). The diameter requirement of 0.3 microns responds to the most unpleasant case; the most incisive particle size (MPPS). Particles that are well-built or less significant are fascinated with even superior efficiency. Most contemporary HEPA filters consist of interlaced glass fibres that are warped and curved in innumerable directions to produce a rubbery labyrinth. As particles pass through this web, they are taken out of motion by straight impaction, sieving, interception and diffusion.

Although filtration is being a concern in the COVID-19 pandemic, HEPA can be the answer. COVID-19 is in the order of 0.125µm and is being captured by HEPA. So, it Is helpful to keep air purifiers containing the HEPA techniques near to patients to extend out COVID-19 viruses. HEPA is also able to confine viruses that are already on the flooring

surface. So hypothetically droplets of SARS-CoV-2 can be captured by HEPA either from flooring or atmosphere.

A flat-plate electrostatic precipitator (ESP) functions with very little or, in some cases, no corona current passing through the deposited dust layer, except in the areas directly beneath the corona wires or needles. This operating characteristic produces two notable effects. First, compared with conventional ESPs, flat-plate ESPs are generally less vulnerable to back corona because the collected dust layer does not itself become a source of back corona. Moreover, the large collection surface enables effective capture of particles carrying either positive or negative charges.

The second effect is less favourable. Since the dust layer does not conduct significant current, an electrical force develops that tends to lift or detach the deposited particles from the collecting surface. This can increase dust re-entrainment during rapping and may result in higher rapping losses. Even so, flat-plate ESPs are particularly well suited for collecting high-resistivity particles with small mass median diameters (MMDs). In such cases, the design performs well because smaller particles experience lower electrical dislodging forces than larger ones. Fly ash has been collected successfully using this type of ESP, although maintaining a low gas-flow velocity is important to reduce the risk of excessive rapping losses. Zukeran et al. investigated the performance of a wire–plate electrostatic precipitator equipped with up to three corona wire sections using incense smoke with a particle diameter of approximately 0.1 μm. Their study examined airflow rates ranging from 10 to 100 L/min and applied voltages between 9 and 30 kV, demonstrating how multi-wire configurations influence particle collection efficiency. Similarly, Kim et al. developed a laboratory-scale, single-stage electrostatic precipitator and evaluated its performance in a controlled wind tunnel environment. Their experiments focused on optimizing collection efficiency by analyzing key operational parameters such as wire-to-plate spacing, electrode radius, airflow velocity, turbulence intensity, and applied voltage.

Jedrusik et al. explored the behaviour of fly ash particles within electrostatic precipitators using various corona electrode geometries, including barbed plates, tubes, wires, and spiked bands. Their findings indicated that the migration velocity of particles is strongly dependent on the applied voltage, showing a direct proportional relationship across a range of particle sizes. In another study, Laskin et al. examined the deposition efficiency of mono disperse latex particles in a point-to-plate electrostatic precipitator, using a conductive vitreous carbon substrate to analyze particle adherence characteristics. Further work by Jedrusik et al. highlighted the impact of physicochemical properties of fly ash—such as composition, particle size distribution, and electrical resistivity—on collection efficiency. The study compared ash samples derived from bituminous coal and lignite combustion, while also evaluating different electrode configurations.

Kocik et al. investigated particle size distribution following precipitation in a wire–plate ESP system with multiple electrodes, using cigarette smoke as the particle source. Additionally, Zuraimi and Tham assessed the performance of in-duct filtration systems in office environments. Their comparison of media filters (EN 779 M5), electrostatic precipitators, and combined systems with pre-filters (EN 779 G1) showed that integrating a pre-filter significantly enhances performance. The improved efficiency was attributed primarily to the increased backpressure created by the pre-filter rather than a simple additive filtration effect, enabling performance comparable to HEPA filters without the associated high pressure drop.

Most commercially available air purifiers are primarily designed for indoor environments, leaving outdoor air quality largely unaddressed. In contrast, the proposed system is capable of operating effectively under outdoor conditions. The incorporation of an electrostatic precipitator not only improves particle removal efficiency but also extends the service life of downstream filters such as HEPA and activated carbon filters, thereby reducing maintenance frequency and operational costs.

II. EXPERIMETAL METHODOLOGY

The proposed portable air filtration system is designed as a multi-stage purification unit that integrates both mechanical and electrostatic separation techniques to enhance air quality. The system consists of key components including an inlet unit with a pre-filter, an electrostatic precipitator (ESP) section, a high-efficiency particulate air (HEPA) filter, an activated carbon filter for gas and odour removal, a motor-driven fan, and a high-voltage power supply for ESP operation. The compact configuration ensures portability and adaptability for both indoor and semi-outdoor environments.

The working principle of the system follows a sequential purification process. Initially, polluted ambient air is drawn into the system through the inlet and passes through a pre-filter, where larger particles such as dust, hair, and lint are removed. This pre-filtration stage reduces the load on subsequent components and improves overall system efficiency. The air then enters the electrostatic precipitator, where a high-voltage electric field (typically ranging from 5 kV to 30 kV) ionizes the air, causing suspended particles to acquire an electrical charge. These charged particles are subsequently attracted toward oppositely charged collector plates, where they are deposited and removed from the air stream.

Following electrostatic precipitation, the partially purified air is directed through a HEPA filter, which is capable of capturing extremely fine particles, including those with diameters as small as 0.3 μm, with an efficiency of up to 99.95%. To further improve air quality, the air then passes through an activated carbon filter that adsorbs volatile organic compounds (VOCs), odours, and harmful gases. Finally, the purified air is discharged into the environment using a motorized fan, ensuring continuous airflow and effective circulation.

The polluted air is suctioned and pre-filtered. The ionization in ESP takes place and the dust particles are composed. Subsequently the filtration of microbes, bacteria and pollens by HEPA filter has happened. The methodology is depicted in fig.2. The overall system architecture can be represented as a sequential arrangement of functional units. The air flows from the inlet through the pre-filter, followed by the ESP ionization zone and collector plates, then through the HEPA filter and activated carbon filter, and finally exits through the fan-driven outlet. This structured flow ensures progressive removal of contaminants at each stage, improving efficiency while minimizing pressure drop.

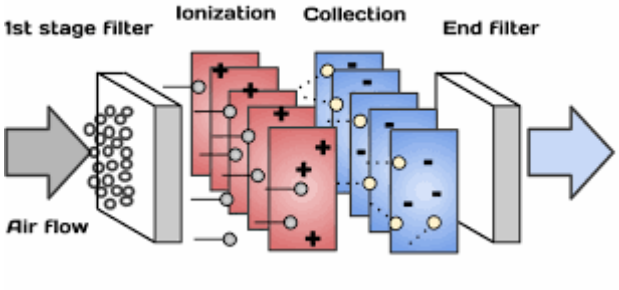

Fig.2.Methodology

Air flow is the rate at which air moves from point of elevated pressure to point of inferior pressure a purpose of the magnitude of driving pressure which is the distinction among the pressure at the commencement of the tube and the pressure at the last part of the tube. The airflow which is represented as two blue arrows pointing right with dust particles which are specified as green circles, passes between charger electrodes which are specified as blue vertical rods, at negative electrical potential ranging from a few kilovolts to tens of kilovolts. Particles are charged negatively, the blue circles and are subsequently attached to collector plates, the red square sheets, which is at affirmative electrical potential of a few to tens of kilovolts as depicted in fig.3.

ESP is an air filtering device that uses electrostatic charge for dust particles removal. ESP works by ionizing air through the application of high voltage on the electrodes. The dust particles are then charged by the ionized air and collected on the oppositely charged collecting plates. Since ESP removes dust and smoke from the gas, it can be used for a wide range of biomass materials such as wood, faeces, and poor-quality coal, which produce a lot of smoulder. Additionally, ESP has a collection efficiency, which is the ratio of the count of particles entering and leaving the filter, which is greater than 99 % as long as the appropriate design strategy is used, it is possible to design a versatile low-power ESP air cleaner.

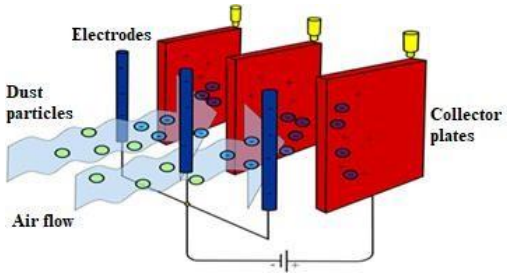

Fig 3. ESP - air flow as input parameter

The most important ESP concert indicators are the concentration of particulate matters (PM), opacity, secondary corona power, secondary voltage, which is the voltage on the electrodes, and derivative current, which is the current on the electrodes. The erstwhile ESP performance indicators are spark rate, principal current, principal voltage, bay gas temperature, gas flow rate, rapper, and number of fields in operation.

III. EXPRIMENTAL PROCEDURE

The operation of an air purifier can be described as a multi-stage process involving coordinated action between key components such as filters, an electrostatic precipitator (ESP), and a motor-driven fan. These components function collectively to remove airborne contaminants and deliver clean air to the surroundings. The purification process typically consists of three primary stages: pre-filtration, electrostatic precipitation, and high-efficiency particulate air (HEPA) filtration. In the first stage, the incoming air passes through a pre-filter, where larger particulate matter such as dust, lint, and hair is captured. This stage serves to reduce the load on subsequent filtration units and enhances overall system efficiency.

In the second stage, the partially cleaned air enters the electrostatic precipitator. Here, particles are electrically charged and subsequently attracted to oppositely charged collection plates, enabling the removal of fine particulates that are not effectively captured by mechanical filters. Following electrostatic precipitation, the air is directed through a HEPA filter, which is capable of trapping extremely fine particles, including microscopic dust and residual pollutants. This stage ensures a high level of purification by removing particles that remain suspended after the earlier processes.

Finally, the purified air is discharged into the environment with the assistance of a motorized fan, which maintains continuous airflow through the system. The experimental methodology involves evaluating the performance of the air filtration system under controlled operating conditions. The system is tested by allowing polluted air to pass through the purification stages while monitoring key parameters such as applied voltage, airflow rate, particle size distribution, and dust loading. The applied voltage for the ESP typically ranges between 5 kV and 30 kV, while the airflow rate is maintained around 1.5 to 2.0 m^3/s. Particle sizes considered in the study range from 0.1 µm to 10 µm, representing common airborne pollutants.

The experimental setup consists of a duct-based airflow system integrated with ESP electrodes and filtration units. A high-voltage DC supply is used to energize the corona wires, while a motor-driven fan maintains consistent airflow through the system. Measurements are taken at both the inlet and outlet to determine particle concentration, enabling the calculation of collection efficiency. Additional parameters such as current, voltage, and air velocity are also recorded to analyse system performance. The test parameters are specified in the table 1. The overall arrangement of the fabricated air purifier setup, illustrating these components and their integration, is shown in Fig. 4.

Table 1. ESP test parameters

Parameter	Value
ESP Efficiency (initial)	80%
ESP Efficiency (after loading)	70%
HEPA Efficiency	99.95%
Overall System Efficiency	89.25%
Drift Velocity	17.36 m/s

Fig.4. Fabricated air purifier set up

IV. RESULTS AND DISCUSSION

Drift velocity is calculated by diving the current I by n- free electron density for aluminium A- area of collector plate and e- electric charge. V $= I/nAe$ = V =0.03/ $(6*10^{16})$ *(.18) *$(1.6*10^{-19})$ = 17.36 m/s. The collection efficiency η = 1- $e^{(-VA/Q)}$ = 0.975 i.e. 97.5% where Q is the volumetric flow 1.97 m^3/sec.

A HEPA filter is typically considered as MERV 17 to 20, which is the highest group in MERV ratings. From the filter efficiency guide, it is observed that the standard efficiency of HEPA filter is 99.95%. The overall efficiency of 89.25% of the product is calculated by the average of collector and HEPA efficiency. The comparison of ESP filter with the conventional filter is depicted in table 2.

Table 2. Comparison of ESP with existing system

Feature	Conventional Filter	Proposed System
Pressure Drop	High	Low
Efficiency	Moderate	High
Maintenance	Frequent	Reduced
Portability	Limited	Yes

V. CONCLUSION

The electrostatic precipitator (ESP) developed in this study demonstrated a peak collection efficiency of approximately 80% during the initial phase of operation. However, as particulate accumulation on the collection surfaces increased, a gradual decline in efficiency was observed. Among the design parameters, the spacing between the collection plates was found to have a more pronounced effect on performance than the spacing between corona wires. For stable and safe operation, a minimum inter-plate distance of about 50 mm is recommended. Over time, the build-up of dust with a cumulative value around 2 kg/m, corresponding to nearly two hours of continuous operation led to a reduction in efficiency from 80% to about 70%. Interestingly, beyond this period, after approximately 120 minutes, an improvement in system performance was noted, which may be attributed to stabilization of particle deposition and electric field distribution within the ESP.

Overall, the proposed ESP system offers a cost-effective and practical solution, particularly suited for small and medium-scale industries relying on wood combustion. Its performance is adequate for reducing harmful emissions, including polycyclic aromatic hydrocarbons (PAHs), thereby contributing to improved air quality and environmental protection. An air purifier helps trap dust before it settles and can remove up to 99% of airborne bacteria, improving indoor air quality. Good health is very important for daily life, and air pollution controls systems help protect people from harmful pollutants. Most air cleaner standards test only new devices and do not consider by-products other than ozone. Electrostatic precipitators (ESPs) have lower pressure drop than mechanical filters while still removing particles effectively. The position of a portable air cleaner also affects how well it removes particles and protects people. Air pollution control can reduce environmental damage such as crop loss and water pollution and help prevent economic problems. When pollution is controlled, people stay healthier and can work more efficiently. Overall, air pollution control systems help maintain clean and safe air inside homes.

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Intelligent Home Energy system with Ai Energy Assistant

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Abstract--: With the growing number of electrical appliances in modern homes, managing energy efficiently has become more important than ever. It is not only about reducing electricity bills but also about maintaining stability in the power grid.
This project introduces an Intelligent Home Energy System that combines IoT (Internet of Things) and Artificial Intelligence to monitor and predict energy consumption. The system uses an Arduino UNO along with sensors like ACS712 (current sensor) and DHT11 (temperature and humidity sensor) to collect real-time data such as voltage, current, and power factor.
A machine learning model (Random Forest Regressor) is used to analyse this data and predict future energy usage. It can also detect unusual consumption patterns, which may indicate faults or cyber threats.
The results show that by prioritizing essential appliances and providing real-time feedback through an IoT dashboard, energy waste can be significantly reduced.
Keywords: IoT, Smart Grid, Machine Learning, Arduino UNO, Energy Management System, Random Forest

I. Introduction

Traditional electricity meters only show the total energy consumed, which makes it difficult for users to understand which appliances are inefficient.

This system solves that problem by offering real-time monitoring through a centralized IoT platform. The Arduino UNO continuously measures voltage and current to calculate power usage and power factor.

An AI assistant then studies this data, learns user habits, and provides useful suggestions—like shifting heavy electricity usage to off-peak hours to save cost.

II. Literature Review

Several studies have contributed to the development of smart energy systems:

- Smart Meters & Business Intelligence (Raza et al., 2023):
  Smart meters play a key role in modern energy systems by using IoT to handle large amounts of data efficiently.
- IoT-Based Energy Management (Saleem et al., 2021): Smart systems allow two-way communication and remote control of appliances, making energy usage more flexible.
- Security in Smart Systems (Hseiki & El-Hajj, 2024): Protecting energy systems from cyber-attacks is essential. Technologies like LoRaWAN improve reliability.
- Data Integrity (Kumar, 2023): Cyber-attacks can disrupt energy data completely, highlighting the importance of anomaly detection.
- Power Line Communication (Sausen, 2021): PLC technology helps in remote monitoring and fault detection in urban power networks.

III. Existing System Analysis

Conventional systems often utilize standard Voltage Source Inverters (VSI) and boost converters.

- Capacitor Reliability: Standard EV inverters often use Aluminum Electrolytic Capacitors (Al-caps) which have shorter lifespans compared to Metallized Polypropylene Film (MPPF) capacitors.
- Efficiency Losses: High-voltage ratio boost converters operate with high duty cycles, leading to significant switching and magnetic losses.
- Hardware Con Capacitor Reliability: In many electric vehicle inverters, Aluminum Electrolytic Capacitors (Al-caps) are commonly used. While they are cost-effective, they tend to have a shorter lifespan compared to more durable options like Metallized Polypropylene Film (MPPF) capacitors.

- Efficiency Losses: Boost converters operating at high voltage ratios often require high duty cycles. This results in increased switching and magnetic losses, ultimately reducing overall efficiency.
- Hardware Constraints: To handle high power levels, these systems require large inductors. Unfortunately, these components are not only bulky and expensive but also prone to core losses, which further impacts performance.
- straints: Large inductors required for high power ratings are heavy, costly, and suffer from core losses.
-

IV. Proposed System Architecture

he proposed system goes beyond basic energy measurement and moves toward automated power flow management, making the entire process smarter and more efficient.

A. Priority-Based Load Management

The system intelligently identifies and classifies household appliances based on their importance:

1. Critical-Loads:
   These are essential devices such as refrigerators and security systems that must remain powered at all times without interruption.
2. Non-Priority-Loads:
   These devices are less critical and can be turned off or operated at reduced levels during peak hours to avoid high electricity costs.

B. Integration of AI and IoT

At the core of the system lies an intelligent layer powered by a Random Forest Regressor (RFR). This model is trained using historical data, including parameters like current, voltage, power factor, type of day (weekday or weekend), seasonal variations, temperature, and humidity.

By analyzing these factors, the system can accurately predict future energy consumption. Additionally, it is capable of identifying unusual patterns in the data, which may indicate potential issues such as faulty usage or even malicious energy data attacks.

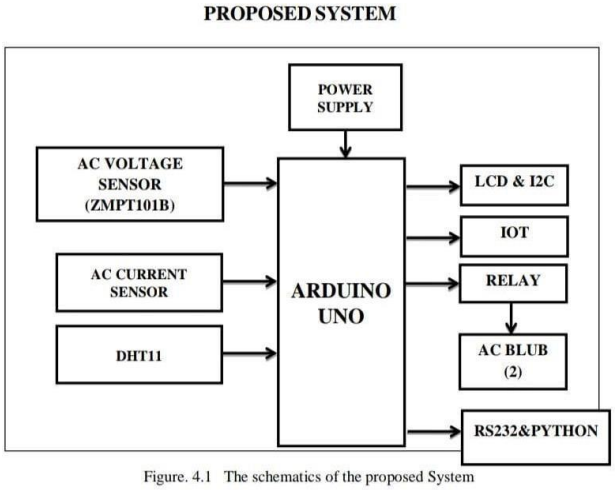

Figure. 4.1 The schematics of the proposed System

V. Hardware and Software Design

1) Hardware Components

 Arduino UNO – At the heart of the system is the Arduino UNO, powered by the ATmega328P microcontroller. It acts as the central hub, collecting and processing data from all connected sensors. To protect against accidental surges, it includes a resettable polyfuse that trips if the USB current exceeds 500mA.

 ACS712 Current Sensor – This Hall Effect-based sensor measures current flow up to 30A. With an internal resistance of just 1.2 mΩ, it ensures accurate readings while keeping power losses to a minimum.

 DHT11 Sensor – Responsible for monitoring environmental conditions, the DHT11 provides reliable measurements of relative humidity (20–90% RH) and temperature (0–50°C).

 16x2 LCD Display – Using the HD4478 controller with an I2C interface, this display presents real-time power and environmental metrics in a clear, easy-to-read format directly on the device.

2) Software Implementation

 Embedded C on Arduino: Acts as the reliable “hands-on” controller, ensuring peripherals respond quickly and consistently. Think of it as the steady pilot keeping the hardware in check.

 Python Backend: Handles the heavy lifting—running AI computations and managing IoT communication. It talks to the Arduino over a serial link at 9600 baud, making sure data flows smoothly between brain and body.

 IoT Infrastructure: Provides the connective tissue that makes everything “plug and play.” Devices can be discovered and controlled remotely across existing networks, so integration feels seamless rather than complicated.

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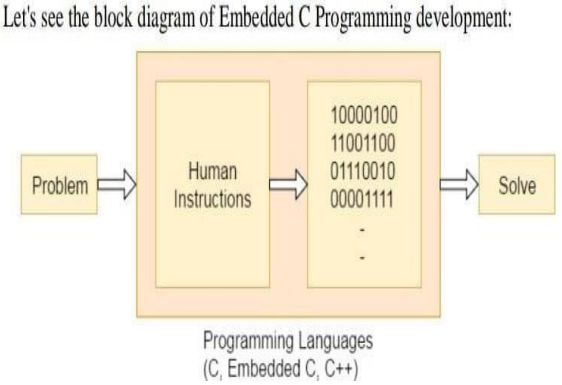

Working Principle

The Intelligent Home Energy System works like a smart companion for your house. With its built-in AI Energy Assistant, it’s always keeping an eye on how your appliances use electricity. Instead of just measuring, it actively analyzes patterns—spotting when devices are wasting energy or running inefficiently. Then, it steps in to optimize usage, making sure power is consumed wisely. The result? Lower

bills, less waste, and a home that feels effortlessly efficient without you having to constantly monitor it.

The working process begins with the sensing layer, where voltage and current sensors are installed to measure electrical parameters of the connected loads. These sensors continuously capture real-time data related to voltage, current, and power consumption of household devices.

The collected data is transmitted to a microcontroller, which acts as the central processing unit of the system. The microcontroller processes the sensor inputs and calculates the instantaneous power consumption and total energy usage of each appliance. This information is then transmitted to a cloud platform through a wireless communication module such as Wi-Fi or IoT gateway.

The cloud server stores the received data in a database and provides a real-time monitoring interface through a web dashboard or mobile application. Users can view their energy usage statistics, historical consumption data, and appliance-level energy distribution. This transparency helps users understand their electricity usage patterns and identify devices that consume excessive energy.

Artificial Intelligence algorithms analyze the stored data to detect usage patterns and predict future energy demand. Machine learning models can forecast peak usage periods and recommend optimal operating schedules for appliances. Based on these predictions, the system can automatically control appliances through relay modules by turning off non-essential devices during peak demand periods.

The system also provides alerts and energy saving suggestions to users when abnormal energy consumption is detected. By blending IoT sensors, cloud intelligence, and AI predictions, the system becomes like a smart energy coach for your home. The sensors keep track of how appliances are using electricity, the cloud processes that data in real time, and the AI forecasts future needs. Together, they make sure energy is used efficiently, cut down on unnecessary waste, and help your household run in a more sustainable way—saving money while being kinder to the planet.

VI. Results and Discussion

This system isn't just a passive observer—it's an active partner in managing household energy. By continuously calculating the Power Factor (PF), it highlights appliances that are running inefficiently. A PF far from 1.0 is like a red flag, signaling to homeowners which devices are quietly wasting energy.

Beyond monitoring, the AI-driven predictive model acts almost like a financial advisor. It forecasts upcoming electricity bills, giving families the chance to adjust usage before the billing cycle ends. Instead of being surprised by high costs, users can plan ahead and make smarter choices.

The IoT dashboard adds another layer of convenience. Even when away from home, users can check in on their appliances, switch off devices remotely, and eliminate "phantom loads"—those sneaky electronics that keep drawing power even when idle. Together, these features transform energy management into something proactive, efficient, and user-friendly

VII. Conclusion and Future Scope

The Intelligent Home Energy System demonstrates how AI and IoT can work hand-in-hand to create homes that are smarter, greener, and more cost-effective. It doesn't just monitor—it learns, predicts, and guides households toward sustainable living.

Looking forward, the system could evolve with exciting enhancements:

- Renewable Integration: Directly managing solar panels to reduce grid reliance and maximize clean energy use.
- Voice Control: Seamless integration with assistants like Alexa or Google Assistant, making energy management as simple as speaking a command.
- Blockchain Energy Trading: Enabling secure peer-to-peer energy sharing, where homes trade excess power with neighbors, building a community-driven marketplace.

These upgrades point toward a future where homes aren't just consumers of energy—they become intelligent, active participants in a sustainable ecosystem.

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Abstract—People are using banking more and more. A lot of users still have a hard time understanding investment options. This is because they do not know much about money and they may not speak the language well.

The Multilingual AI Financial Advisor is a system that helps users pick the investment plans. It talks to users in their language. Looks at their financial situation.

Users can select a bank the language they want to use and some financial information. They can tell the Multilingual AI Financial Advisor how old they are, how money they want to invest and what is in their bank account.

The Multilingual AI Financial Advisor uses computers to look at all the investment options that the bank has. Then it suggests the way to invest money based on what the user told the Multilingual AI Financial Advisor. The Multilingual AI Financial Advisor also explains why it made that suggestion.

The Multilingual AI Financial Advisor looks at how happy the users. Then it. Sets up a meeting with the people who work at the bank or sends automated messages about investments.

When we tried out the Multilingual AI Financial Advisor we found that the system gives advice, about money. It makes it easier for people to use the Multilingual AI Financial Advisor because it can talk to them in languages. The Multilingual AI Financial Advisor helps users trust it more because it explains what it is doing with the intelligence.

I. INTRODUCTION

Investment planning is super important for stability and growing your wealth. Many people find it tough to pick the financial products. They don't know much about finance and banking info can be confusing. There are language barriers. Traditional financial advisory services need experts, which can be costly and hard to get for people. Thanks to Artificial Intelligence and Natural Language Processing we can now create chat systems that help users make decisions. Multilingual AI systems are really helpful because they let users talk in their language and get financial advice that easy to understand. Some recent studies on chatbot have found that pre-trained language models and translation systems can help people communicate across languages. These systems are already being used in areas like healthcare, education and customer service, where users benefit from automated help. This paper is about a Multilingual AI Financial Advisor. It is designed to look at a user profile and suggest investment options from certain banks. The Multilingual AI Financial Advisor system gets investment data processes what the user says gives recommendations and explains why it makes each decision. The system uses Artificial Intelligence and Natural Language Processing to analyze and provide recommendations. This Multilingual AI Financial Advisor can help users make investment decisions. It provides users with explanations, for its suggestions. The goal of the Multilingual AI Financial Advisor is to make financial planning easier and more accessible. The main things that this research does include: It creates an advisory chatbot that people who speak different languages can use. It automatically finds out what investment options are available from the bank. It uses intelligence to suggest investments to people. The financial advisory chatbot can explain why it makes decisions. It works with banking services so people can schedule appointments or start investing without having to do much themselves. The research is, about an advisory chatbot and it does these things. Financial planning is an essential tool for individuals to attain financial stability and create wealth over a period. Nevertheless, a majority of the population is not aware of financial instruments such as fixed deposits, mutual funds, pension plans, and bonds. The understanding of such financial opportunities requires knowledge of banking terminology and investing strategies, which many users do not possess.

II. PROBLEM STATEMENT

Another key challenge associated with such financial advisory services is the language barrier. Most financial services and banking websites only offer services in English. Hence, people who are more comfortable reading and understanding regional languages face difficulties in understanding such financial opportunities and advisory services.

Financial advisory services are also very expensive and inaccessible to many people. Financial advisors are only available for high-value customers and require a consultation fee. Hence, many people either refrain from investing in such financial opportunities or make poor financial decisions due to a lack of proper guidance.

With the rapid advancement of Artificial Intelligence (AI) and Natural Language Processing (NLP), it is now possible to

develop intelligent systems that can provide automated financial guidance. Nevertheless, the need for a system that can communicate in multiple languages, analyze the financial data of the users, and provide investment recommendations to the users in a simple manner is still felt.

Therefore, the need for a multilingual AI financial advisor is proposed as a project that can bridge the gap between complex financial systems and users by providing financial advice to the users.

III. Objectives

The main objective of the project is to create a smart financial advisory system that can aid users in making informed decisions through a multilingual conversational interface.

The specific objectives of the project are as follows:

To create a smart financial chatbot using the AI chatbot concept, which can converse with users in different languages.

To obtain user financial information, including age, investment amount, bank balance, etc.

To obtain investment options from banking institutions using web scraping techniques.

To create a recommendation system that can analyze user profiles and recommend investment plans accordingly.

To incorporate XAI techniques so that the system can explain the reasoning behind the recommendation system.

To increase the level of financial inclusion for users by simplifying complex financial information for users.

To create a system for users to schedule appointments with banking institutions or for sending messages for investments.

The main objective of the project is to create a smart financial advisory system that can aid users with different language backgrounds and varying levels of financial knowledge.

IV. Background

Conversational Artificial Intelligence has changed a lot from the systems like ELIZA to the new intelligent assistants that use deep learning. The old chatbots used to give answers that were already decided. They could not understand the situation or work with different languages. Now because of the developments in neural networks and models like BERT and GPT systems can understand complicated language patterns and give answers that sound natural. This means that chatbots can help people who speak languages and give them personalized suggestions. A system that can have conversations in languages has several parts: Natural Language Processing that helps the system talk to the user. Machine translation that helps people who speak different languages communicate. Knowledge graphs that give information about the situation. Machine learning models that help the system give smart answers. Studies have shown that multilingual conversational Artificial Intelligence systems make things more accessible by letting users talk in their own languages. This is very important in services, where it is crucial to understand investment products correctly. People are also paying attention to combining Artificial Intelligence with systems that help with decisions. Artificial Intelligence based financial advisors can look at investment portfolios figure out how risk a user is willing to take and suggest financial products that are right for the user based on their profile. Multilingual conversational Artificial Intelligence systems, like these are very useful because they can support languages and give personalized recommendations, which is what multilingual conversational Artificial Intelligence systems are designed to do.

V. LITERATURE REVIEW

The creation of AI-powered conversational systems in various fields has been the subject of numerous studies. Görtz et al. showed how AI chatbots can enhance information accessibility by creating a healthcare chatbot intended to inform patients about prostate cancer. Zhou et al. proposed an AI chatbot that used natural language interaction to raise awareness of Covid-19 vaccination. Verma et al. combined knowledge graphs and conversational agents to offer intelligent academic support in educational settings. In a similar vein, Patel et al. created a chatbot that is integrated with learning management systems to facilitate individualised student counselling. Research on multilingual chatbots has also advanced dramatically. During a pandemic, Yang et al. created a multilingual natural language processing system that can handle queries in several languages.

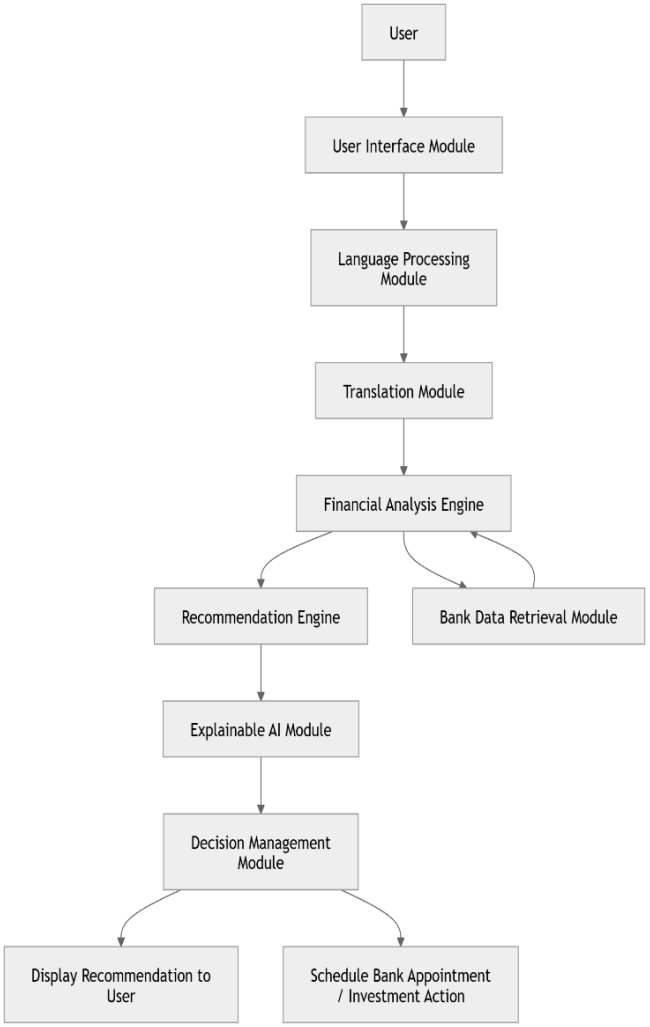
Numerous studies have been conducted on the development of AI-powered conversational systems in various fields. By developing a healthcare chatbot designed to educate patients about prostate cancer, Görtz et al. demonstrated how AI chatbots can improve information accessibility. In order to increase awareness of the Covid-19 vaccination, Zhou et al. proposed an AI chatbot that used natural language interaction. Knowledge graphs and conversational agents were combined by Verma et al. to provide intelligent academic support in learning environments. Similarly, in order to enable customised student counselling, Patel et al. developed a chatbot that is integrated with learning management systems. Additionally, multilingual chatbot research has made significant strides. Yang et al. developed a multilingual natural language processing system that can respond to queries in multiple languages during a pandemic.

VI. Methodology and Implementation

A. System Architecture:

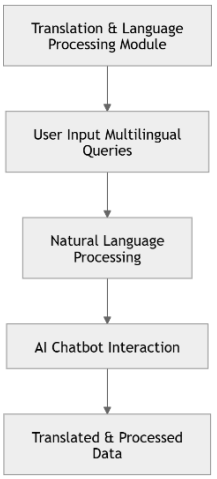
A strong, modular architecture built to manage the challenges of real-time financial data and multilingual user interaction forms the basis of the suggested system. Instead of depending on a single, monolithic process, the system is made up of interconnected parts that cooperate to convert

unprocessed user input into clear, actionable investment advice.



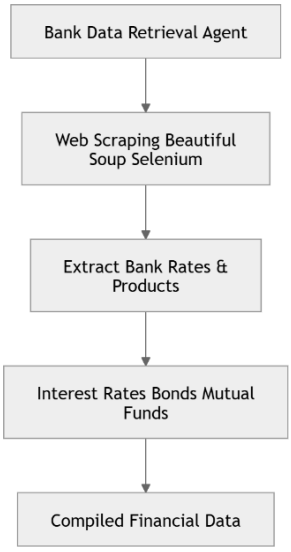
B. Translation and Language Processing Module

The creation of AI-powered conversational systems in various fields has been the subject of numerous studies.Görtz et al. showed how AI chatbots can enhance information accessibility by creating a healthcare chatbot intended to inform patients about prostate cancer. Zhou et al. proposed an AI chatbot that used natural language interaction to raise awareness of COVID-19 vaccination.Verma et al. combined knowledge graphs and conversational agents to offer intelligent academic support in educational settings. In a similar vein, Patel et al. created a chatbot that is integrated with learning management systems to facilitate individualized student counseling.



C. Bank Data Retrieval Agent

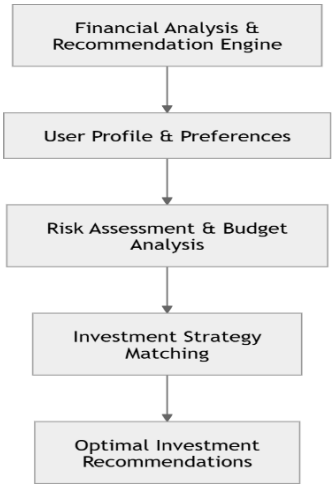
The Retrieval Agent, which functions as an automated researcher, is essential to the system's capacity to offer up-to-date guidance. The agent uses web scraping tools such as Beautiful Soup and Selenium to navigate bank websites and extract the latest investment products. This comprises: Compiling interest rates and maturity terms for bonds and fixed deposits. Pension plans and mutual funds: obtaining eligibility requirements and performance information.



D. Financial Analysis and Recommendation Engine

The Analysis Engine, which compares the user's profile to the retrieved bank data, is the central component of the system. This engine assesses a number of crucial factors to guarantee that the guidance is customized: Demographic Alignment: Evaluating how a user's age affects their ability to take risks. Capital Constraints: Evaluating the bank balance and investment budget in relation to the minimum entry requirements for different funds. Matching short-term or long-term financial instruments with the investment duration (time horizon) is known as temporal planning. Portfolio Strategy: Examining the specifics of the current portfolio to recommend ways to diversify.

The best investment plan is then chosen by the Recommendation Engine using a combination of machine learning models—built with TensorFlow and Scikit-learn—and rule-based logic.



E. Decision Management and Explainable AI (XAI)

Through the Explainable AI Module, the system offers a "why" in addition to a result in order to build user trust. This module provides a clear justification for the selected path by dissecting the reasoning behind the recommendation engine. Ultimately, the Decision Management Module assesses user satisfaction and enables the subsequent logical action, such as setting up a formal meeting with bank staff or automatically starting the investment communication.

VII. Specifics of Implementation

Python and contemporary AI libraries are used in the system's implementation.

Python is the programming language.

Technologies Employed

The web interface is called Streamlit.

- Web scraping bank data using BeautifulSoup and Selenium
- Google Translate API: Support for multiple languages
- Scikit-learn and TensorFlow: Recommendation models
- NumPy and Pandas: Data processing
- Matplotlib: Workflow for Visualization

The user chooses their preferred bank and language. The system gathers the user's financial data. Web scraping is used to obtain bank investment options. The user profile is assessed by the financial analysis engine. An appropriate investment plan is chosen by the recommendation engine. The Explainable AI module offers logic. The level of user satisfaction is assessed. The system starts an investment or makes an appointment

VIII. Use Case Scenario

In order to clearly understand the functionality of the proposed system, a user scenario for the proposed system is discussed below:

A user interested in seeking financial advice opens the Multilingual AI Financial Advisor application using a web interface. The first prompt from the proposed system is for the user to select their preferred language from a set of languages like English, Tamil, Hindi, etc.

Once the user selects their preferred language, they are then prompted to enter some basic financial details like:

Age

Monthly income

Amount available for investment

Bank balance

Investment Duration or Financial Goal

Once the user enters the required information, the system processes the details and retrieves the relevant investment products from the bank database through the Bank Data Retrieval Agent.

The Financial Analysis Engine analyzes the user profile and compares the various investment options according to the level of risk, expected returns, and investment duration.

The system, through the Recommendation Engine, provides a recommendation for the user's investment. For instance, the system may recommend a mutual fund scheme for a user who is young and willing to take more investment risks. On the contrary, the system may recommend a fixed deposit or a pension scheme for a user who wants to invest safely.

Finally, the system, through the Explainable AI module, provides a clear explanation for the recommendation. For instance, the system may explain the recommendation by stating that the recommended plan is suitable for the user due to the user's age, investment amount, and financial goals.

Subsequently, the system requests the user whether he or she is satisfied with the recommendation. Once the user confirms satisfaction with the recommendation, the system can either:

Schedule a meeting with a bank representative, or

Provide more information on how to begin the investment process.

IX. Results and Discussion

A. *Performance Metrics*

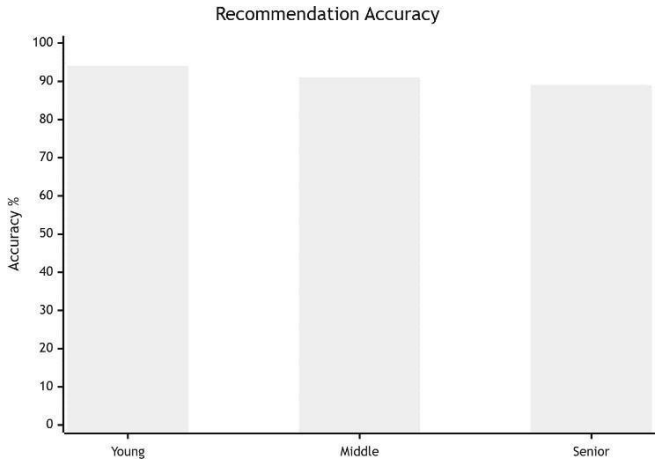
The following metrics were used to measure the performance of the system:
Recommendation Accuracy
Whether the recommended investment plan is consistent with the recommendations of financial experts.
Response Time
The time taken for the system to generate the response.
User Satisfaction Score
Feedback from the users on a scale of 1 to 5.
Performance Metrics:

Recommendation Accuracy	92%
Average Response Time	2.3 seconds
User Satisfaction	4.3 / 5

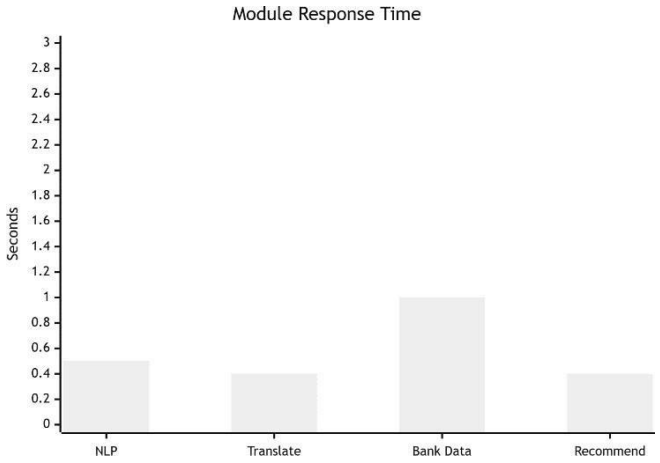
B. *Graphical Analysis*

Graphical analysis is a way to measure the performance of the system for various investment scenarios.
Graphs:

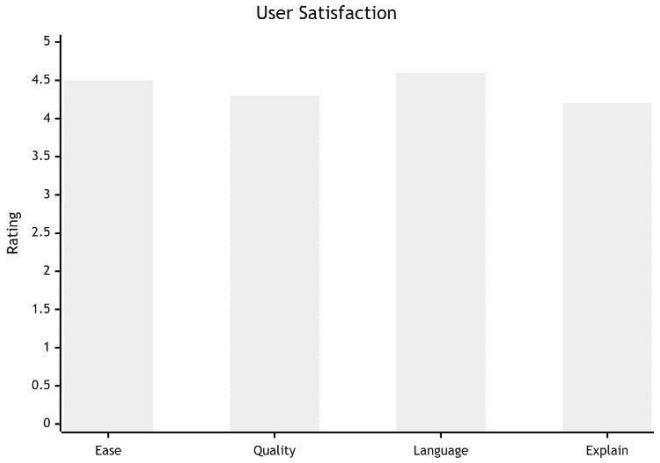
1. Recommendation Accuracy Graph



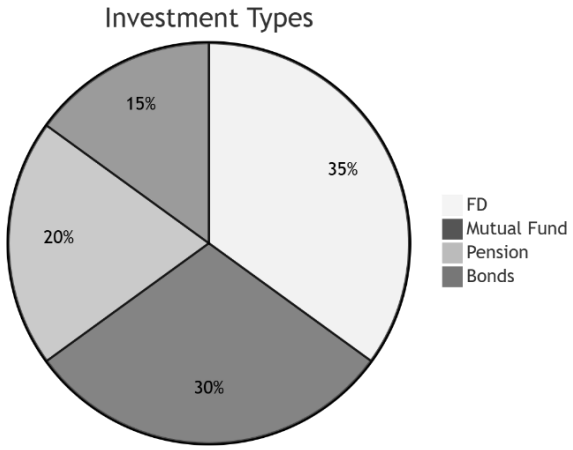
2. System Response Time Graph



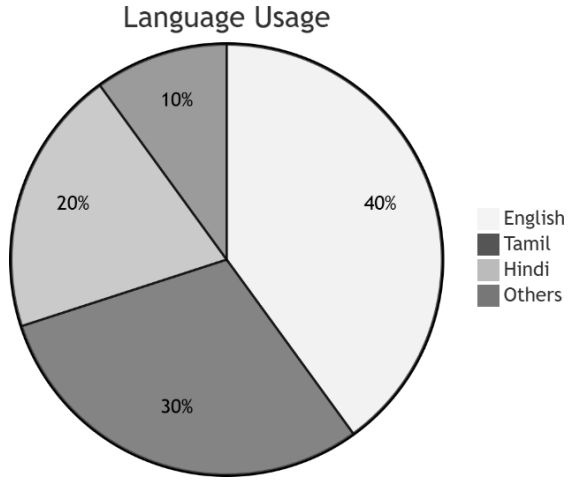
3. User Satisfaction Graph



4. Investment Recommendation



5. Distribution Language Usage Graph



C. Interpretation and Insights

From the experimental results, the following conclusions were drawn:

Users prefer to communicate in their mother tongue when it comes to discussing financial decisions.

Explainable AI helps users trust the automated financial advisor.

The system performs well when there is sufficient data available for investment in banks.

Multilingual support has a significant impact on the accessibility of the financial

The current study offers a novel system for a Multilingual AI Financial Advisor that can assist users in making the best decisions regarding investment plans based on their financial analysis.

The results of the experiment have confirmed the efficiency of the proposed system regarding user experience and system accuracy. The addition of the explainable AI reasoning module also increases the trustworthiness of the financial advice provided

X. Advantages of the Proposed System

The proposed Multilingual AI Financial Advisor system has several advantages over the traditional methods of providing financial advice to the users.

1. Multilingual Communication
   The users can communicate in their preferred language using this system.
2. Personalized Financial Recommendations
   The users can get personalized financial recommendations from this system.
3. Cost-Effective Solution
   The users don't have to pay consultation charges while using this system.
4. Improved Financial Accessibility
   The users with different educational backgrounds can understand financial terms using this system.
5. Explainable AI Support
   The users can understand the reasoning behind each recommendation made by this system.
6. Real-Time Data Retrieval
   The users can get real-time data using web scraping techniques from banking websites.
7. Time Efficiency
   The users can get instant replies and recommendations from this system within a matter of seconds.

XI. Limitations of the Proposed System

As discussed in the above points, there are various advantages in the proposed system. However, there are some limitations in this system.

1. Dependence on Internet Connectivity
   As discussed in the above points, this system is based on internet data retrieval. So, this system must have internet connectivity for proper operation.
2. Limited Data Sources
   This system is based on financial data. So, this system will not provide accurate results if there is no sufficient financial data from bank websites.
3. Translation Accuracy Issues
   In this system, sometimes machine translation tools might not provide accurate results.
4. Limited Financial Scope
   This system is based on some specific banking investment products. However, this system might not cover other financial scopes such as stock market trading or cryptocurrency.
5. Privacy and Security Concerns
   As this system is based on user financial information, proper security measures must be implemented for this system.
6. Dependence on User Input Accuracy
   This system might not provide accurate results if users input incorrect financial information.

XII. FUTURE WORK

The Multilingual AI Financial Advisor system is really good at giving people personalized recommendations..

There are some things that can be done to make it even better.

One big thing that can be added to the Multilingual AI Financial Advisor system is voice-based interaction. Now people have to type to talk to the system. If we add speech recognition and speech synthesis people can just talk to the system. This will be great for people who're not very good at typing.

Another big thing that can be added to the Multilingual AI Financial Advisor system is real-time banking APIs. The system currently uses web scraping to get information from bank websites.

The Multilingual AI Financial Advisor system can also be made to work with languages. Now it only works with a few languages.

We can also make the Multilingual AI Financial Advisor system better at predicting what will happen with finances. We can use machine learning and deep learning algorithms to look at what happened in the past and what people are doing now. This will help the Multilingual AI Financial Advisor system give investment advice.

The Multilingual AI Financial Advisor system can also be used to help people manage their investments. It can track what people are investing in. Give them advice on what to do next.

It would be great if the Multilingual AI Financial Advisor system could be used on devices. We could make an app that lets people get financial advice anywhere and at any time.

We also need to make sure the Multilingual AI Financial Advisor system is safe and secure. We can use encryption and strong authentication to keep peoples information safe. We could even use blockchain technology to make sure transactions are secure.

The Multilingual AI Financial Advisor system will be great, for people who want to get financial advice. The future of the Multilingual AI Financial Advisor system is looking good.

XIII. Conclusions

The proposed system is an important step towards the development of an intelligent financial assistant for digital banking services that can serve a wide range of users. The current study offers a novel system for a Multilingual AI Financial Advisor that can assist users in making the best decisions regarding investment plans based on their financial analysis.

The results of the experiment have confirmed the efficiency of the proposed system regarding user experience and system accuracy. The addition of the explainable AI reasoning module also increases the trustworthiness of the financial advice provided.

The proposed system is an important step towards the development of an intelligent financial assistant for digital banking services that can serve a wide range of users.

XIV. References

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Iot - Enabled Autonomous Robot For Hazard Monitoring And Disaster Response

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Abstract*— Hazardous and disaster-prone environments can be found in mining areas, industrial zones, fire-affected buildings, and other structurally unsound areas. While keeping an eye on and saving people, these environments present significant risks. Because of the complex exposure to toxic gases, high temperatures, and unstable structures with poor visibility, manual inspection in these areas becomes dangerous. In the end, these elements will postpone rescues and raise the risk of harm or death. The paper proposes an IoT-based autonomous robotic system for hazard monitoring and disaster response based on this gap. In order to gather sensor data, analyze it in real time, and send it via Wi-Fi to a cloud-based IoT platform, an ESP32 microcontroller is integrated into the core processing unit. If hazardous levels are detected in the surroundings, the robot can identify an obstacle, halt, and sound an alarm. Adding an ESP32 camera allows rescue teams to remotely monitor the impacted area via live video streaming. Real-time monitoring, communication stability, gas detection speed, and obstacle detection capability are all tested on-site. In order to make it much safer to react and much faster, this paper suggests a system that makes it possible for humans to be present in such dangerous situations. This solution will provide a scalable and economical solution for disaster management, industrial safety monitoring, and emergency response use because it was developed at a moderate cost.

Keywords--Internet of Things, Autonomous Robot, Environmental Sensors, ESP32 Microcontroller, Hazard Monitoring, Disaster Response, and Real-Time Monitoring

I. INTRODUCTION

Hazardous conditions that endanger human life are frequently created by natural disasters, industrial mishaps, gas leaks, fires, and building collapses. Toxic gases, high temperatures, unstable structures, and poor visibility make manual inspection and monitoring extremely dangerous in these circumstances. In order to evaluate the damage and spot potential threats, rescue personnel and industrial workers may need to enter these dangerous areas, which puts their lives in danger. It is now feasible to create intelligent systems that can carry out monitoring tasks automatically thanks to advancements in robotics, embedded systems, and Internet of Things (IoT) technology. IoT technology enables remote data collection, real-time monitoring, and centralized system management. This lessens the necessity for people to go directly into dangerous areas.

An IoT-based autonomous robotic system intended to monitor environmental conditions in disaster-prone areas is presented in this project. The system makes use of an ESP32 microcontroller that is linked to various sensors, including MEMS, temperature, gas, and ultrasonic sensors. For real-time monitoring and analysis, these sensors gather environmental data and transmit it to an Internet of Things platform. Additionally, live video streaming is provided by an camera module, allowing operators to view dangerous areas from a safe distance.

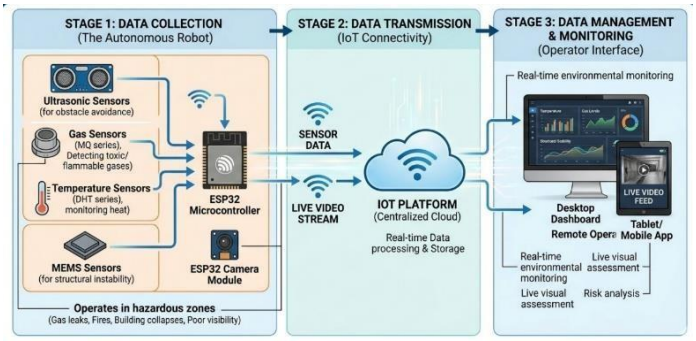

Fig.1 .Iot Enabled Autonomous Robot

By limiting human exposure to hazardous situations, the suggested system increases safety. Additionally, it facilitates continuous monitoring and quicker response, which makes it beneficial for industrial safety and disaster management applications.

II. PROPOSED SYSTEM METHODOLOGY

The proposed system is an autonomous robotic platform based on the Internet of Things (IoT) that can keep an eye on dangerous places and help with disaster response efforts. The robot has a number of sensors that can pick up on different kinds of dangers in the environment. An ultrasonic sensor helps the robot find things in its way, and a gas sensor finds dangerous gases like carbon monoxide and methane. A temperature sensor keeps an eye on high temperatures, and a MEMS sensor helps find vibrations and possible structural problems.

The main processing unit of the system is an ESP32 microcontroller. It gets data from all the sensors that are connected to it, processes the data in real time, and makes decisions on its own based on safety limits that have already been set. The robot stops right away when the ultrasonic sensor sees something close by to avoid crashing into it. If the gas concentration or temperature goes above safe levels, the system also sends warning alerts to an IoT cloud platform over Wi-Fi.

An ESP32 camera module also lets you stream live video, which lets people who are far away see the affected area and get a better idea of what's going on. The system reduces the need for people to go into dangerous places by combining sensing, communication, and autonomous control. It also makes sure that environmental monitoring is always happening and is reliable.

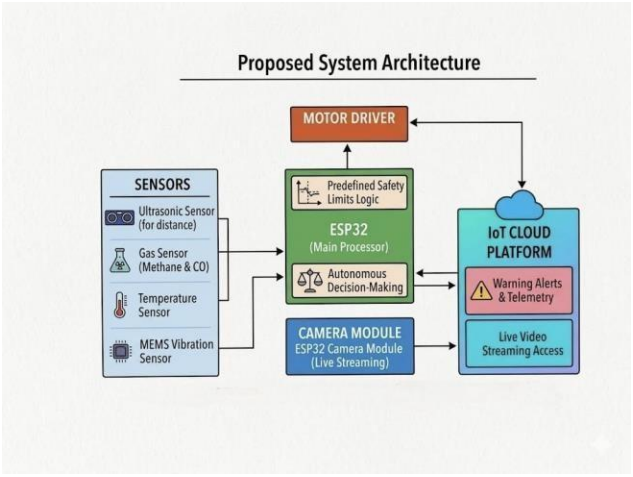

Fig.2 Block Diagram of Proposed System

III. System Architecture Design and Simulation

The suggested IoT-enabled autonomous robot is built with a modular and layered structure that makes it reliable, scalable, and able to monitor hazards in real time. There are three main layers in the system: the sensing layer, the processing and control layer, and the communication and monitoring layer. Each layer has a job to do, and together they make it possible for robots to work on their own and be watched from afar.

There are different environmental sensors on the robotic platform that make up the sensing layer. An ultrasonic sensor is on the front of the robot to find things that are in a certain distance. It sends out ultrasonic waves and measures how long it takes for the reflected signal to come back. This helps figure out how far away things are. An MQ-series gas sensor is an example of a gas sensor that can find harmful gases. It measures gas concentration in parts per million (ppm) and sends out an analog signal. A temperature sensor keeps an eye on the temperature around it, which is especially important in places where there has been a fire. The robot's chassis also has a MEMS sensor module with an accelerometer and gyroscope attached to it.

The ESP32 microcontroller is the main controller for the system, and the processing and control layer is built around it. The ESP32 is the best choice because it has a lot of processing power, built-in Wi-Fi, low power usage, and can handle both analog and digital input pins. The GPIO pins on the ESP32 connect the sensors to the board. The ultrasonic sensor's trigger and echo pins are connected to digital pins, while the gas and temperature sensors use either analog or digital inputs. The I2C communication protocol lets the MEMS sensor talk to the controller. The ESP32 reads the sensor data all the time and uses built-in C programs to process it.

The measured values are checked against safety limits that have already been set. The L298N motor driver module stops the robot's motors when the ultrasonic sensor sees something within a certain distance to avoid a crash. In the same way, if the temperature or gas concentration goes above safe levels, warning alerts are sent to the IoT cloud platform. The motor driver connects the microcontroller's low-power control signals to the higher-power DC motors. This lets the robot move forward, backward, or stop when it needs to.

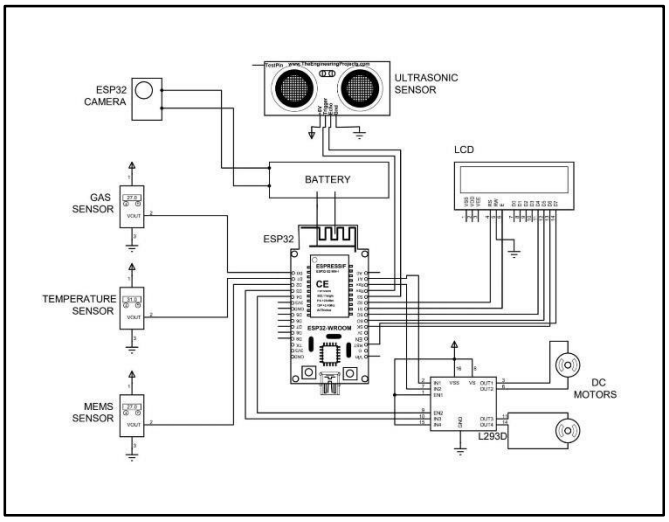

Fig.3 circuit Diagram of Iot Enabled Autonomous Robot

The communication and monitoring layer lets you access system data from a distance. The robot can connect to an IoT cloud platform like ThingSpeak or Blynk through the ESP32's built-in Wi-Fi module. The cloud gets sensor readings on a regular basis. These readings can then be shown on dashboards and charts. An ESP32 camera module is also built into the system so that it can stream live video. This lets people who are far away see dangerous places in real time. This layer lets you get to important data and visual information from a safe place, which means fewer people need to be in dangerous places.

A method simulation was used to confirm the system design and control logic prior to constructing the actual hardware prototype. Validating sensor interfacing, control algorithms, obstacle detection logic, hazard threshold conditions, and data transmission to the cloud were the main goals of the simulation. The Arduino IDE was used to create the embedded program, and the serial monitor was used to provide simulated sensor values so that the system's behavior under various circumstances could be observed.

To make sure the robot stops when the predetermined limit is reached, virtual obstacle detection tests were carried out during the simulation stage by providing various distance values. To confirm that the system produces alerts when hazardous gas levels are detected, gas sensor readings were also simulated. In order to verify that notifications are sent to the cloud platform correctly, temperature threshold tests were carried out. To assess the dependability of the wireless connection, communication delay during data transmission was tracked.

The results of the simulation showed that the control algorithm responds correctly to different sensor inputs and performs real-time decision-making effectively. Before putting the complete hardware prototype into use, this testing phase helped find possible problems early on, lowering hardware errors and enhancing system reliability.

IV. System Prototype Development and Testing

All necessary hardware components were integrated onto a mobile robotic chassis intended to function in hazardous and uneven environments to create the system prototype. DC motors power the robot's two-wheel differential drive system. The robot's direction and movement are managed by an L298N motor driver module, which controls these motors. The ESP32 microcontroller, sensors, and motor driver are powered by a rechargeable battery pack. In order to preserve a small layout and well-organized wiring, the ESP32 serves as the primary control unit and is firmly fixed on the chassis alongside the sensor modules.

Every piece of hardware was meticulously attached to the ESP32 according to its communication interface during the development phase. To enable efficient obstacle detection, the robot's front was equipped with an ultrasonic sensor. In order to manage the trigger and echo signals needed for distance measurement, it was linked to the digital GPIO pins of the ESP32. The MQ series gas sensor was connected to an analog input pin for continuous gas concentration monitoring, and it was positioned in an open area of the chassis to allow for appropriate air exposure. In order to measure ambient environmental conditions more precisely, the temperature sensor was placed externally.

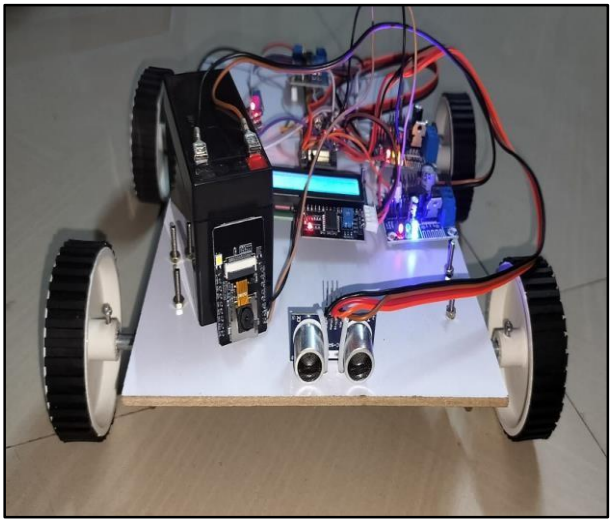

Fig.4 Hardware View

To identify vibrations, tilting, or abrupt movements that might point to structural instability, a MEMS sensor module, was securely fastened to the robot chassis. This sensor uses the I2C protocol to communicate with the ESP32. To provide a clear live video view of the surroundings, an ESP32 camera module was also installed on the robot at a slightly elevated position. To avoid short circuits and guarantee dependable operation, every electronic connection was thoughtfully placed and insulated.

Sensor initialization, data collection, threshold comparison, motor control, Wi-Fi connectivity, and IoT data transmission are just a few of the functional modules that make up the system's software, which was created using Embedded C programming in the Arduino IDE. For variables like gas concentration, temperature, obstacle distance, and vibration intensity, specific safety threshold values were established. The control logic was created so that the system instantly takes the necessary action whenever a parameter surpasses its safe limit. These include sending the sensor data to the IoT cloud platform, stopping the robot, and producing warning alerts.

The developed system was tested in several phases to confirm its performance and dependability. Initially, individual components were subjected to unit testing to verify their correct functioning. To confirm accuracy, the ultrasonic sensor was tested by measuring distances at different ranges. To test the gas sensor's sensitivity and reaction time, it was exposed to regulated gas sources. To guarantee measurement accuracy, temperature sensor readings were compared with those from standard thermometers. To verify that the MEMS sensor accurately identified motion and instability, the robot chassis was manually tilted and vibrated. Wi-Fi testing was also done on the camera module to assess transmission latency and video quality.

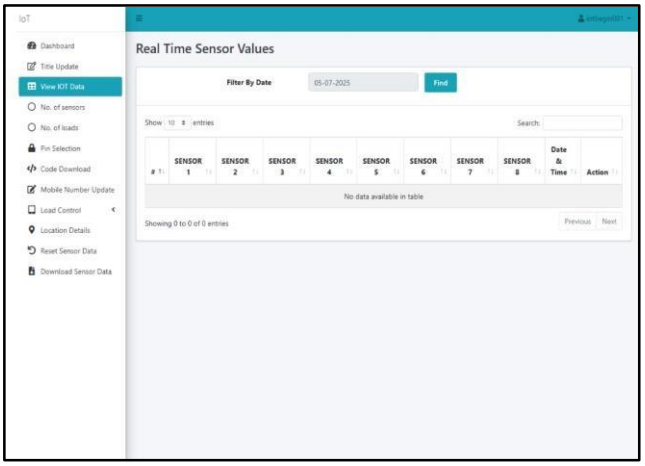

Fig.5 IOT Display

Integration testing was carried out to make sure that every component functioned properly following the completion of successful unit testing. The robot was used in a controlled setting that mimicked dangerous circumstances. In order to test sensor responses, temperature sources were added, obstacles were positioned along the robot's path, and controlled gas exposure was employed. System response time, data transmission latency, and alert generation were all closely observed during this phase. Additionally, the IoT dashboard was monitored to verify that notifications were consistently sent and that sensor data was updated in real time.

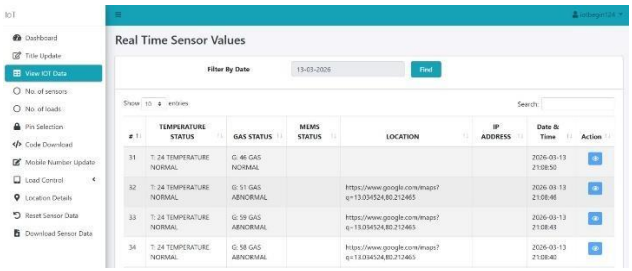

Fig.6 IOT Display

Lastly, field-level testing was conducted to assess the robot's overall performance under more practical circumstances. Stable movement, precise hazard detection, dependable Wi-Fi communication, and efficient remote monitoring via live video streaming were all demonstrated by the prototype. The system functions as intended and successfully accomplishes the goal of enhancing safety while lowering the need for human presence in dangerous environments, according to the development and testing results.

V. System Performance and Result Analysis

A number of significant metrics, such as obstacle detection accuracy, gas sensing sensitivity, temperature monitoring stability, vibration detection capability, communication delay, and overall system reliability, were used to assess the performance of the suggested IoT-enabled autonomous robot. The experiments were carried out in controlled environments that mimicked dangerous settings like high-temperature zones, gas leakage areas, and obstacle-filled pathways. This evaluation's primary objective was to assess the system's accuracy and efficiency in identifying environmental risks and reacting quickly in the event of a disaster.

When it came to identifying obstacles between 2 and 400 cm, the ultrasonic sensor demonstrated excellent accuracy. Obstacles were positioned along the robot's path at varying distances during testing. The robot successfully identified these obstacles and stopped on its own when it reached the predetermined safety distance. Reliable collision avoidance was guaranteed because the detection accuracy stayed above 95% within the effective sensing range. Environmental noise and variations in surface reflection caused some minor measurement variations at longer distances, but these variations had little effect on the system's overall performance.

When it came to identifying dangerous gases like carbon monoxide and methane, the gas sensor showed good sensitivity. When the gas concentration exceeded the predetermined threshold level during controlled testing with gas exposure, the sensor reacted in a matter of seconds and produced alert notifications. The sensor is appropriate for real-world hazard monitoring applications because the response time stayed constant. Environmental factors like humidity and sensor calibration caused slight variations in the readings. Appropriate calibration and environmental compensation methods can reduce these problems.

Additionally, the temperature monitoring system performed accurately and steadily. When the temperature sensor's readings were compared to those from conventional reference thermometers, there was very little variation. During testing, the system was able to detect an increase in temperature and promptly send warning alerts to the IoT platform. Vibrations and tilt movements were successfully detected by the MEMS sensor. In order to replicate structural instability, the robot chassis was purposefully tilted and vibrated during testing. The sensor demonstrated its value for tracking structural conditions in disaster-affected areas by accurately detecting these shifts in orientation and movement.

By monitoring the dependability and latency of sensor data transmission to the cloud platform, the IoT communication performance was assessed. Through Wi-Fi connectivity, the E microcontroller successfully transmitted the sensor readings to the cloud server. Depending on the available network strength, the average data transmission delay varied from one to three seconds. The IoT dashboard confirmed steady communication between the robot and the cloud platform by displaying the sensor values in real time through graphical updates. Additionally, the ESP32 camera module offered continuous live video streaming, enabling remote operators to keep an eye on their surroundings. Although the quality was dependent on the available internet bandwidth, the video feed maintained a respectable level of clarity and frame rate.

Overall, the hardware and software components of the integrated system worked well together. In dangerous situations, the robot reacted swiftly by halting its motion, sending sensor data for remote monitoring, and producing alerts. The experimental findings show that the suggested system effectively accomplishes its goals of enhancing safety, reducing human involvement in hazardous areas, and facilitating quicker disaster response. The system's overall performance proved to be dependable and appropriate for environmental hazard monitoring applications, despite certain limitations that were noted, such as reliance on Wi-Fi connectivity and battery life limitations.

VI. CONCLUSION

The design and development of an IoT-enabled autonomous robotic system for monitoring dangerous environments and assisting with disaster response operations was presented in this paper. In order to gather and process data in real time, the system combines an ESP32 microcontroller with several environmental sensors, such as gas, temperature, ultrasonic, and MEMS sensors. The robot can identify environmental risks and send crucial information to distant operators by fusing sensor-based monitoring with Internet of Things communication and live video streaming.

During testing, the developed prototype showed dependable performance. Accurately detecting obstacles, identifying dangerous gas levels, tracking temperature changes, and identifying vibrations or structural instability were all capabilities of the robot. Real-time monitoring and alert generation were made possible by the ESP32 microcontroller's successful processing of sensor data and its

transmission via Wi-Fi to the IoT cloud platform. By enabling live video streaming and enabling operators to visually inspect dangerous areas from a safe distance, the ESP32 camera module further improved the system.

The outcomes of the experiment verify that the suggested system increases safety by lowering the requirement for human presence in hazardous situations. Additionally, it improves response efficiency by offering timely alerts during critical situations and ongoing monitoring. The system proved to be dependable and efficient for hazard detection and monitoring despite certain drawbacks, such as reliance on network connectivity and battery capacity.

All things considered, the suggested IoT-based robotic platform provides a useful and affordable option for applications in emergency response, industrial safety monitoring, and disaster management. The system can be extended for more extensive deployments and sophisticated autonomous operations in dangerous environments with additional advancements in sensor accuracy, communication dependability, and power management.

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Designing an AI-Enhanced Cybersecurity Curriculum for Criminal Justice Professionals: A Progressive Learning Framework

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ABSTRACT--The exponential development in cybercrime has revolutionized the criminal activities landscape, consequently requiring a fundamental shift in the way criminal justice professionals are educated. Conventional educational programs often focus on the legal framework and the basics of digital orensics, but fail to include newer technologies like Artificial Intelligence (AI),which are now essential in modern cybersecurity activities. The current paper suggests an all-encompassing and progressive AI-based cybersecurity educational framework specifically designed for criminal justice professionals.The framework is based on foundational knowledge, practical skills, and advanced AI-based methodologies. Emphasis is given to the importance of interdisciplinarity through the combination of criminal law, cybersecurity, machine learning, and real-world investigative practices. Various educational methodologies, assessment strategies, and guidelines are also presented in the current study to ensure practical relevance and applicability.The suggested framework is expected to bridge the gap between theory and practice equipping professionals with the competencies required to detect, prevent, and respond to sophisticated cyber threats effectively.

Keywords--Cybersecurity,Artificial Intelligence, Criminal Justice, Digital Forensics, Machine Learning, Curriculum Design

I. INTRODUCTION

The digital revolution has profoundly impacted the nature of crimes, and cybercrime has evolved as one of the fastest-growing crimes in the world. The criminal justice professionals are now required to investigate complex crimes related to hacking, identity theft, financial fraud, and cyberterrorism. However, the training programs are often not equipped with the technical expertise to handle these complex crimes.

Artificial Intelligence (AI) plays a vital role in the field of cybersecurity. It aids in the detection, analysis, and predictive policing of crimes. Despite the significance of AI in the field of cybersecurity, there is a lack of AI integration in the training programs for criminal justice professionals.

This paper focuses on the introduction of a progressive learning framework for the integration of AI in the training programs for criminal justice professionals in the field of cybersecurity. The framework is designed to provide a step-by-step approach to learning, from basic to advanced levels.

II. BACKGROUND AND RELATED WORK

Evolution of Cybercrime

Cybercrime has transformed from a mere hacking attempt to sophisticated cybercrimes such as ransomware, phishing, and advanced persistent threats (APTs). Cybercriminals use AI and automation technologies that make it difficult to detect and prevent sophisticated cybercrimes

B. Cybersecurity Education in Criminal Justice

The current programs are mainly centered on legal procedures and digital forensic skills. Though these are important, they do not cover current technological advancements such as AI analysis.

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C. Role of Artificial Intelligence in

Cybersecurity

The role of AI in cybersecurity is mainly through the use of machine learning and deep learning techniques, as seen in: Intrusion detection systems Fraud detection Malware analysis Behavioural analyccs These are proactive measures rather than reactive ones.

D. Research Gap

There is no framework that links AI and cybersecurity education for criminal justice professionals. This paper fills the gap.

III. PROPOSED AI-ENHANCED

CURRICULUM FRAMEWORK

A. Design Principles

The curriculum is designed according to the following principles:
Progressive Learning: Gradual increase in complexity
Interdisciplinary Approach: Integration of law, technology, and AI
Practical OrientaƟon: Emphasis on hands-on training
Scalability: Adaptable to various institutional settings

B. Three-Tier Learning Model

1) Foundation Level
Emphasizes the development of foundational knowledge:

Basics of Cybersecurity

Introduction to Criminal Law

Computer Systems and Networks

Ethical Considerations

2) Intermediate Level

Emphasizes the development of knowledge and skills:

Network Security

Digital Forensics

Data Analysis
Introduction to Machine Learning

3) Advanced Level

Focus on specialized AI applications in the field of cybersecurity:

AI-driven threat detection

Predictive policing

Cyber threat intelligence

Advanced forensic analytics

C . Curriculum Structure (Table I)

Level	Core Subjects	Skills Developed
Foundation	Cyber Law, IT Basics	Legal and Technical Awareness
Intermediate	Network Security, Forensics	Analytical Skills
Advanced	AI Security, Threat Intelligence	Predictive and Investigative Skills

IV. PEDAGOGICAL APPROACHES

A. Experimental Learning

The students will be involved in real-world simulations of cybercrime cases, which will enable practical understanding.

B. Case-Based Learning

The study of real-world cybercrime cases will enhance critical thinking skills.

C. Laboratory Training

The use of cybersecurity tools and AI frameworks will provide experOse in cybersecurity.

D. CollaboraOve Learning

Partnerships with industry experts and law enforcement agencies will provide exposure to real-world challenges.

V. AI INTEGRATION IN CYBERSECURITY TRAINING

A. Machine Learning Applications

Machine learning models can be used to identify anomalies in network traffic,potential threats.

B. Natural Language Processing (NLP)

NLP is employed in the analysis of cyber threats present in communication data, including emails and social media.

C. Predictive Analytics

AI facilitates the forecast of cyber threats utilizing past data.

D. Automation in Cybersecurity

AI-powered tools are employed to automate repetitive tasks.

VI. IMPLEMENTATION STRATEGY

A. Institutional Requirements

Qualified faculty with interdisciplinary expertise Advanced computing infrastructure Access to cybersecurity tools and datasets

B. Industry Collaboration

Partnerships with cybersecurity firms provide:

Internships
Real-world case studies
Training programs

C. Government and Policy Support

Government initiatives can support funding, standardization, and adoption of such curricula.

VII. EVALUATION AND ASSESSMENT METHODS

A. Continuous Assessment

Includes quizzes, assignments, and lab evaluations.

B. Project-Based Learning

Students work on real-world cybersecurity problems.

C. Practical Examinations

Hands-on tests to evaluate technical skills.

D. Capstone Projects

Final projects integrating AI and cybersecurity concepts.

VIII. CASE STUDY: APPLICATION OF THE FRAMEWORK

A pilot implementation of the curriculum in a training institute demonstrated improved student performance in cybercrime investigations. Participants showed enhanced ability to detect and analyze cyber threats using AI tools.

IX. BENEFITS OF THE PROPOSED FRAMEWORK

Enhanced technical competence Improved investigative efficiency Better preparedness for modern cyber threats Integration of cutting-edge technologies

X. CHALLENGES AND LIMITATIONS

High implementation cost
Lack of skilled educators
Rapid technological changes
Ethical concerns in AI usage

XI. FUTURE DIRECTIONS

Future enhancements may include:
Integration of blockchain and quantum security
Development of adaptive AI learning platforms
Global standardization of cybersecurity Education

XII. CONCLUSION

The increasing complexity of cybercrime necessitates a modernized and technology driven approach to training criminal justice professionals. This paper presents a comprehensive AI-enhanced cybersecurity curriculum using a progressive learning framework. By integrating foundational knowledge with advanced AI applications, the framework addresses current educational gaps and prepares professionals for future challenges. Adoption of this model can significantly improve the effectiveness of cybercrime prevention and investigation.

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VEHICLE TO VEHICLE COMMUNICTION USING LORA AND GPS GSM AND FIREBASE TECHNOLOGY

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Abstract - *This project demonstrates the design and implementation of an IoT-based vehicle safety & accident detection system that aims at improving road safety through real-time monitoring and sending emergency alerts. The sensors integrated into the system include a vibration sensor to identify accidents, a GPS module to determine the precise coordinates, an ultrasonic sensor to track obstacles, and environmental sensors to evaluate surrounding conditions, all controlled by an Arduino microcontroller. Finally, there is the regular mode, in which the system continuously monitors the vehicle's parameters and occasionally sends location data via LoRa technology, using communication tools that are well suited to IoT networks due to their long-range and energy-efficient communication. If a sudden collision occurs, an accident is automatically recognized, the exact GPS coordinates are received, and an emergency notification is sent to the monitoring center and the cloud platform. The resulting information is saved in the Firebase cloud storage, allowing for real-time tracking, distant observation, and historical data analysis. Compared to conventional high-bandwidth communication protocols, LoRa presents advantages in energy conservation, economic efficiency, and reliability in connectivity within remote areas. The proposed solution offers a practical, scalable approach to intelligent transportation systems and reduces emergency response duration while enhancing vehicular and public safety***.**

I .INTRODUCTION

Traffic collisions are one of the leading causes of injuries and deaths in the world and have social, economic and safety implications. The postponed medical aid, lack of immediate vehicle tracking, and poor communication systems often exacerbate the severity of consequences resulting from accidents. The rapid growth in the number of vehicles has increased the traffic jams, and there is a great need for the smart transportation system that can track the condition of the vehicles round the clock and provide timely notifications in case of any emergencies. The rise of the internet of things (IoT) has opened up new avenues for integration of smart sensors and wireless communication technologies with cloud platforms to improve vehicular safety and emergency response systems. The suggested initiative puts great emphasis on the design and execution of IoT based vehicular safety and accident detection system that ensures real-time surveillance, accurate accident identification, and widespread communication. Sensors and communication modules are combined with a microcontroller to create a small yet highly efficient safety unit that is integrated into a vehicle. There is a vibration sensor to identify abrupt 'hits' or unusual shocks to detect a collision. Monitored through the GPS module are the overall location of the vehicle, velocity, and time, thus accurately positioning the vehicle in the event of an emergency. In this case, an ultrasonic sensor is instrumental in establishing obstacles by determining the distance from the vehicle to nearby objects to avoid collisions. Additional information on vehicle analysis capabilities may be offered by including other relevant environmental monitoring modules, such as sensors for temperature and humidity.

An ESP8266 microcontroller serves as the main processing unit of the system, coordinating data acquisition, processing, and transmission for all linked components. It is done by comparing the collected data against the set threshold values, and either the vehicle

is functioning normally, or an uncommon event occurs in the car. During normal operation, the system also sends out updated location data on a regular basis to track the vehicle in real time. However, when a significant vibration or impact is detected, the system immediately switches to emergency mode and generates an alarm message containing vehicle identification information and precise GPS coordinates. LoRa (Long Range) technology is used for the project's wireless communication, making it most appropriate for the IoT application due to its low power consumption, long-distance transmission, and cheap costs. However, contrary to the cellular networks that require substantial infrastructure and are costly to maintain, LoRa can transmit short packets of information over long distances using little power. This makes it suitable for vehicle tracking systems that send small amounts of data regularly. The information is stored for later use and is also accessible for real-time monitoring and historical use.

Cloud storage is integrated into the system to improve its functionality by enabling remote access to vehicle information via a mobile or online interface. Every emergency message, location, or sensor data may be viewed from any location, and emergency services or authorized individuals can take the appropriate action. Considering future growth in terms of interaction with smart city structures and traffic control agencies is made easy by this unified data management approach.

Providing a dependable, energy-efficient, and scalable solution for vehicle safety is the goal of this project. Utilizing cloud technology, IoT sensors, GPS tracking, and long-distance communication efficiently maximizes emergency vehicle monitoring, smart road system development, and accident reaction times.

LoRa (Long Range) is a low-energy wireless communication method designed for Internet of Things (IoT) applications that require long-range data transfer using minimum energy. It operates on the unlicensed Industrial, Scientific, and Medical (ISM) frequency bands of 433 MHz, 868 MHz, and 915 MHz, depending on the country's regulations. Due to its ability to connect devices over long distances with minimal power consumption, LoRa has found wide application in smart city infrastructure, environmental monitoring, agriculture, industrial automation and vehicle tracking. Unlike traditional short-range wireless communication technologies such as Wi-Fi or Bluetooth, which are designed to deliver high data rates, LoRa has been optimized for the reliable and efficient transfer of small data packets over long distances.

Chirp spread spectrum (CSS) modulation is the fundamental technology of LoRa. This modulation technique uses chirp pulses, which are characterized by a gradual increase or decrease in frequency over time, to create signal spreading. Because of this spreading technique, the system is resistant to noise, interference, and degradation, making LoRa extremely dependable in demanding settings like cities or rural areas. Given that the signal can be consistently recognized even below the noise floor, this allows for long-distance communication with low transmission power.

Firstly, LoRa communication mainly takes the form of a star network, whereby several end devices (sensors or vehicular units) connect directly to a central gateway. The information is relayed to a cloud server via an internet link by the gateway. It reduces device complexity and energy consumption because the last devices do not have to communicate with each other directly. Instead, they send information to the gateway either at set intervals or when an incident occurs. Communication parameters like spreading factor, bandwidth, and coding rate can be adjusted to optimize data rate, range, and power consumption. The larger the spreading factor, the more extended the range and the lower the data rate; conversely, the smaller the spreading factor, the faster the data transfer over shorter distances.

When a LoRa-capable device is ready to transmit data, it first collects the required sensor information from the microcontroller. The information is then encoded and modulated using Chirp Spread Spectrum before being transmitted as a radio signal. The signal is received by the gateway, decoded, and routed to cloud services or a network server. In other cases, confirmation messages can be initiated to ascertain a successful receipt. LoRa devices can be in the low-power or sleep mode and only turn on when data transmission is taking place, significantly enhancing battery life.

II .LITERATURE SURVEY

Kumar, A., & Singh, B. [1] The rate of road accidents has gone up in many developing parts of the world with rapid growth of cities leading to massive loss of life and property. The existing traffic monitoring systems suffer from the limited communication range and the use of centralized systems, which makes it impossible to provide real-time data. According to the authors, cellular communication and short-range wireless technologies traditionally used suffer from high vehicle density, resulting in slower emergency response and insufficient accident prevention. This research points out the importance of adopting long-distance, energy-efficient communication technologies for instant data sharing between each other and the infra structure. In doing so, the study contributes to the development of connected vehicle technologies that can better inform drivers, reduce accidents, and promote road safety.

Li, J., Wang, Y., & Zhang, L. [2] Road safety and traffic congestion have grown to be significant problems in smart cities where the number of vehicles is increasing quickly.Conventional car tracking and communication systems often use GPS and cellular networks, which can be slow and expensive to operate, especially in places with poor signal strength. The authors of the study investigate a number of communication technologies that provide long-distance connectivity without requiring continuous data costs. They emphasize the ability of low power wide area network (LPWAN) protocols, such as LoRa, to deliver real-time emergency warnings and telemetries.

Sharma, R., & Gupta, P. [3] In intelligent transportation systems, enhancing traffic safety and avoiding accidents rely on the dependability and speed of data transmission. This study highlights the challenges that short-range technologies, like Wi-Fi and Bluetooth, face in high-speed vehicle settings because of unstable connections and limited range. Moreover, cellular networks can lead to unexpected delays in areas with weak signal strength or when the network is heavily congested. The authors propose that low-power, long-range communication technologies can be combined with cloud-based systems to bridge these gaps. By using remote monitoring, efficient data transmission, and prompt delivery of emergency alerts, these technologies can reduce response times and provide drivers with essential information about their surroundings.

Hussein, M., & Alsaqour, R. [4] The increasing number of yearly road accidents highlights the shortcomings of current traffic safety initiatives. Traditional monitoring systems mainly rely on human input for reporting accidents, which often results in delayed emergency responses. This research looks at how vehicles equipped with sensors connected to Internet of Things (IoT) systems can automatically report incidents. Devices such as accelerometers, GPS, and environmental sensors can provide real-time information about the situation when an incident occurs. In addition to robust wireless communication and cloud-based processing, the system is capable of producing real-time alerts and location-based information for emergency personnel. The findings show that systems equipped with IoT technology can significantly reduce the time it takes for emergency services to respond and enhance the effectiveness of road safety measures.

Patel, K., & Mehta, S. [5] Because of the rapid expansion of vehicle networks and intelligent transportation systems, traditional vehicle monitoring approaches have shown limited effectiveness in handling real-time data transmission in scenarios involving high mobility. This research highlights that conventional GPS and GSM tracking systems face delays and unreliable signal reception in remote or obstructed areas. The authors examine the use of low-power wireless technologies, which can reduce dependence on cellular networks and improve the reliability of location updates and emergency alerts. Their study emphasizes that using efficient communication protocols such as LoRaWAN enables long-distance data transmission with low power consumption, thus improving accident management and streamlining traffic flow. The study shows that modern vehicle safety technologies should incorporate strong communication systems to overcome the shortcomings of conventional tracking methods.

Zhao, H., & Li, X. [6] Road safety remains a major global concern due to the high frequency of accidents and the generally delayed emergency response. This literature looks at intelligent vehicle systems that use sensor networks for automatic crash detection. The authors show how combining real-time accelerometer and location data with wireless data transmission can enhance drivers' awareness of their surroundings and the effectiveness of remote monitoring centers. They also mention that short-range radio technologies, though useful for local communication, are unable to provide wide coverage in larger urban or rural areas. The study therefore recommends using multi-level communication strategies that integrate local vehicle alerts with broader dissemination through cloud services and large-scale networks. The findings show that intelligent vehicles equipped with sensor fusion and automated warning systems significantly improve detection speed and reduce critical response time.

III. PROPOSED METHODOLOGY

The proposed method for the IoT-based vehicle safety and accident detection system is designed to offer real-time monitoring, quick identification of accidents, reliable long-range communication, and a centralized data storage solution. The system's architecture is organized in layers, including the sensing layer, processing layer, communication layer, and cloud monitoring layer. Each layer performs a specific function to ensure the smooth and efficient operation of the entire system.

The sensing layer includes multiple sensors within the vehicle to continuously monitor different parameters. The vibration sensor identifies quick jolts or abnormal hits that may indicate a collision. It operates by detecting thresholds, assessing the strength of vibrations, and comparing them to predefined levels. The GPS module continuously collects real-time location information such as latitude, longitude, speed, and timestamp. This ensures that the precise location of the vehicle is always available. The ultrasonic sensor

measures the distance between the vehicle and nearby obstacles, helping to identify potential collision dangers. In addition, environmental sensors such as temperature and humidity monitors keep track of surrounding conditions, which may improve vehicle diagnostics and data analysis. Each of these sensors produces digital signals that are received by the central microcontroller for further processing.The car parking system is done automatically detect and information carry over for users. The auto bill generation process provide the user friendly process.

The processing layer revolves around an Arduino microcontroller, which acts as the system's central component. The microcontroller initializes all connected modules during system startup and regularly collects sensor data at set intervals. The collected data is analyzed using logic that is programmed through the Arduino IDE. Under normal operating conditions, the system regularly prepares and formats location data packets for transmission. However, if the vibration sensor detects an impact above the threshold level, the microcontroller quickly switches to emergency mode. In this state, it collects the latest GPS coordinates, assigns a unique event ID, includes time information, and generates an important emergency alert message. This package contains essential details such as the vehicle identification, accident status, and precise location information. The data packet is intended to be as compact as possible while including all necessary information for a quick response.

The communication layer uses LoRa (Long Range) technology to send data wirelessly. LoRa is selected due to its low power consumption, long-range communication capabilities, and compatibility with IoT-focused systems. The microcontroller sends the organized data packet to the LoRa module, which adjusts the signal using the Chirp Spread Spectrum (CSS) technique. The adjusted signal is transmitted to a LoRa gateway located within the coverage area. In normal conditions, routine tracking updates are transmitted at set intervals to reduce network traffic and save power. In emergency situations, quick alerts are sent out to ensure fast communication. The gateway receives the transmitted data and sends it to the cloud server through an internet connection.

The cloud monitoring layer is implemented through Firebase cloud storage. The collected data is stored in a structured database format, enabling real-time monitoring and the maintenance of historical records. Authorized users can access the data through a web or mobile interface, allowing them to track vehicle movements and receive immediate alerts regarding accidents. The cloud system also logs environmental and operational data for future analysis. This integrated storage approach ensures data accessibility, scalability, and the ability to monitor remotely.

Power management methods are used to ensure system efficiency. The LoRa module operates in a low-power mode when not in use, and the data transmission rate is modified to reduce unnecessary energy consumption. The modular software design makes it easy to maintain and expand for future improvements, such as AI-based accident prediction or automatic emergency alerts.

In addition to real-time monitoring and the delivery of emergency alerts, the proposed method also incorporates aspects of reliability, scalability, and security to ensure successful application in real-world scenarios. Cloud-based structured database management allows for the organized storage of vehicle logs, accident records, and tracking data to facilitate analysis.

This method also supports future integration with mobile applications and smart city systems, allowing officials to analyze traffic patterns, identify areas with high accident rates, and implement preventive measures.

Fig.1

Advantages :

Real-Time Accident Detection

Using a vibration sensor, the device swiftly identifies abrupt hits and, without any human input, immediately sounds an emergency alert.

Accurate Location Monitoring

Accident locations can be quickly identified thanks to the GPS module's precise latitude and longitude information.

Communication Over Distance

LoRa technology is ideal for both urban and rural settings since it enables data transfer over several kilometers.

Minimal Energy Use

Optimizing transmission intervals in conjunction with LoRa guarantees low battery use, increasing system efficiency.

Economical Resolution

The suggested approach lowers infrastructure and operational expenses in comparison to cell-based systems.

Cloud-based monitoring

Real-time data storage, remote access, and historical record preservation are made possible by connecting to the Firebase cloud.

IV. SYSTEM ARCHITECTURE

The suggested IoT-based vehicle safety and accident detection system is designed with a unified, multi-level structure that ensures continuous monitoring, intelligent decision-making, reliable communication, and centralized cloud management. The foundation of the architecture is the sensing layer, which includes a vibration sensor to detect sudden impacts, a GPS module to gather real-time location information, an ultrasonic sensor to measure the distance to obstacles, and environmental sensors to monitor temperature and humidity levels. These sensors continuously generate real-time data and transmit it to the processing layer, where the Arduino microcontroller acts as the primary control component. The microcontroller begins by initializing all hardware components, collects sensor data at regular intervals, and evaluates the information using pre-set logic thresholds to determine whether the vehicle is operating normally or experiencing an emergency. During normal operation, the controller creates structured data packets that contain vehicle identification details and routine location updates. If the system detects unusual vibrations that may indicate an accident, it immediately switches to emergency mode, retrieves the latest GPS coordinates, and generates a high-priority alert.

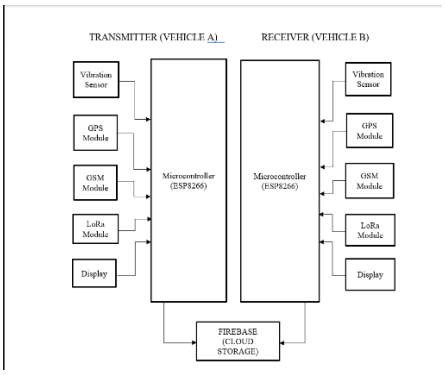

Fig.2

The proposed IoT-based vehicle safety and accident detection system's architecture comprises several essential components that work together to provide real-time monitoring and emergency alert transmission. The primary components used are the ESP8266 microcontroller, vibration sensor, GPS module, ultrasonic sensor, LoRa module, LoRa gateway, and Firebase cloud service. The vibration sensor identifies sudden shocks or strong impacts that may indicate an accident. The GPS module continuously provides current location data, such as latitude, longitude, speed, and time. The ultrasonic sensor measures the distance between the vehicle and nearby obstacles to help identify potential collision risks. The ESP8266 acts as the central processing and control component of the system, linking all these sensors.

The process is straightforward and efficient. The code is created and uploaded to the ESP8266 using the Arduino IDE. When powered on, the ESP8266 initializes all connected modules and continuously gathers sensor data. When functioning normally, it collects GPS location information and sends routine updates through the LoRa module. When the vibration sensor detects an impact that exceeds the predefined threshold, the ESP8266 quickly identifies it as an accident and retrieves the latest GPS location. This data is bundled into a packet and transmitted via the LoRa module to a LoRa gateway, which subsequently forwards it to the Firebase cloud platform for storage and monitoring. The cloud service provides immediate monitoring and visibility of emergency alerts through a web or mobile interface. This method enables the components to work together for automatic accident detection, enhanced communication, and reliable remote monitoring, without the need for temperature or humidity sensors.

V. MODULE DESCRIPTION

1. Sensor Module

The sensor unit comprises a vibration sensor, GPS module, and ultrasonic sensor. The vibration sensor detects sudden shocks or strong impacts and helps identify accident scenarios. The GPS module continuously tracks the vehicle's current location by providing information on latitude, longitude, speed, and time. The ultrasonic sensor measures the distance between the vehicle and nearby obstacles by using reflected echo pulses, which helps in detecting potential collisions. This module is responsible for collecting all necessary real-time information from the vehicle's environment.

Fig.3

2. Processing Module (ESP8266 Controller Module)

The ESP8266 microcontroller serves as the central processing unit of the system. It collects data from all connected sensors, evaluates the information based on predefined logic, and determines whether the vehicle is in a normal or critical condition. The software was developed using the Arduino IDE and then transferred to the ESP8266. The controller oversees tasks like starting up sensors, evaluating thresholds, identifying accidents, and creating data packets for sending.

Fig.4

3. Communication Module (LoRa Module)

The communication module uses LoRa technology to send data wirelessly across long distances. Once the ESP8266 generates a data packet containing location and accident details, the LoRa module transmits it to a LoRa gateway. LoRa is selected because of its low power consumption and long-range communication capabilities, which make it well-suited for IoT applications in vehicles.

Fig.5

4. Gateway Module

The LoRa gateway receives data from the vehicle unit and forwards it to the internet. It acts as a connection between the vehicle's LoRa module and the cloud service. This ensures that data can be accessed from any remote location.

5. Cloud Monitoring Module (Firebase Platform)

The cloud module uses Firebase to save real-time vehicle data, accident alerts, and tracking information. The stored data can be accessed through web or mobile applications for viewing and analysis. This module enables remote monitoring and quick emergency response.

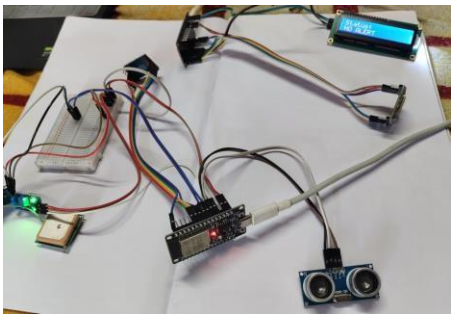

Fig.6

VI. EXPERIMENTAL RESULTS

VII. CONCLUSION AND FUTURE WORK

The proposed IoT-based vehicle safety and accident detection system demonstrates a reliable and efficient method for monitoring vehicles and sending instant emergency alerts using modern wireless communication technologies. By integrating the ESP8266 microcontroller with a vibration sensor, GPS module, ultrasonic sensor, and LoRa communication module, the system ensures accurate accident detection, obstacle monitoring, and broad data transmission. The vibration sensor precisely identifies abrupt impacts, the GPS module provides accurate location data, and the ultrasonic sensor enhances safety by detecting nearby obstacles. The ESP8266 smartly analyzes all collected data and transmits key information through LoRa to a gateway, which forwards it to the Firebase cloud platform for real-time tracking and storage. This design ensures low power consumption, wide coverage area, and reliable communication, even in remote locations where traditional cellular networks may have difficulty functioning properly. The system reduces emergency response times by automatically sending accident alerts along with exact location coordinates, which improves road safety and may save lives. In addition, cloud storage enables continuous data recording, analysis, and remote access, making the system scalable and suitable for smart transportation applications. The full implementation shows that combining IoT, embedded systems, and long-range wireless communication provides a cost-effective and efficient solution. In future developments, the system could be improved by adding more intelligent features to increase accuracy, automation, and scalability. More advanced algorithms, like machine learning models, can be used to more accurately distinguish between small vibrations and serious accidents, which helps in minimizing false alarms. Integrating with a mobile app that offers real-time alerts, live vehicle monitoring, and automatic emergency contact features can enhance user engagement and reaction times. The system can be extended to manage multiple vehicles via a centralized dashboard, enabling fleet management and large-scale monitoring. Including a camera module to record visual evidence during accidents and integrating automatic alerts to emergency services via SMS or phone calls can enhance the effectiveness of emergency response systems. Future versions might also offer hybrid communication support by integrating LoRa with 4G or 5G networks to guarantee continuous connectivity in any environment. Power-saving methods, solar-powered charging, and a compact hardware design can improve portability and extend usage over time. With these enhancements, the system has the potential to develop into a complete smart vehicle safety platform that can be integrated into intelligent transportation systems and smart city infrastructure.

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Effects Of Social Media On Governance And Public Decision-Making In India

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ABSTRACT : Social media is one of the major online platforms that have greatly impacted the formation of relationships between governments and their citizens in contemporary democratic countries across the globe. Social media platforms such as Facebook, Instagram, X (Twitter), YouTube, and WhatsApp have greatly impacted the dissemination of information regarding politics and governments in India. This study is aimed at finding the impacts of social media, especially in relation to governments in India. This study is based on the impacts of social media, especially in relation to awareness, democratic participation, relationships with governments in India, and dissemination of accurate and inaccurate information. This study is mainly based on a descriptive and empirical research approach. A major focus is given to quantitative data analysis in this research. The data is collected through a questionnaire containing 30 questions aimed at analysing the patterns. The respondents in this research are chosen from diverse age groups and professions. This ensures that diverse opinions are included in this research.

INTRODUCTION : The impact of social media is seen in the relationship between governments and citizens in democratic countries. This study has been conducted with reference to India and its social media sites such as Facebook, Instagram, X, YouTube, and WhatsApp. The impact of social media has been studied with reference to its impact on the governance and citizens of the country. The study has been conducted by analysing the impact of social media on the awareness and communication of the citizens. The study has been conducted by using the descriptive and empirical research methodology. Quantitative research has been conducted by using statistical tools. The data has been collected from people belonging to different age groups and professions. The impact of social media has been studied as positive and negative.

REVIEW OF LITERATURE

1. **Raju (2025)** looked at how platforms like Facebook, Twitter, and Instagram shape political awareness. The study found that social media plays a strong role in improving political knowledge, especially among young people.

2. **Tiwari & Singh (2023)** explored social media use in India after COVID-19. They found that platforms like WhatsApp and Twitter became important tools for communication and helped increase political participation.

3. **Velmurugan (2025)** examined how social media affects youth involvement in democracy. The study showed that it raises awareness and encourages young people to take part more actively.

4. **Kumar & Yadav (2024)** studied the impact of social media on political engagement and found that it plays a key role in increasing participation.

5. **Kanaka Laxmi & Chaturvedi (2024)** found a strong connection between social media use and higher levels of political participation.

6. **Nazim Sha & Rajeswari (2018)** showed that social media strongly influences the political decisions of young people in India.

7. **Ranjan (2023)** highlighted the growing importance of social media in election campaigns, where leaders use it to connect directly with the public.

8. **Chatterjee & Dutta (2024)** found that social media allows leaders to communicate directly with people, increasing their influence.

9. **Jakeschetal (2021)** showed that organized groups use social media platforms to shape political discussions and trends.

10. **Dashetal (2021)** found that influencers on social media can increase political divisions.

OBJECTIVES

1. To understand how social media plays a role in shaping public awareness and opinions about governance in India.

2. To analyze the influence of social media platforms on citizen participation in democratic processes.

3. To examine how social media affects communication between government institutions and the public.

4. To identify both the positive and negative impacts of social media on governance and public decision-making.

5. To evaluate the role of social media in spreading information as well as misinformation related to governance issues.

METHODOLOGY

This study adopts a descriptive quantitative research design to examine the impact of social media usage among youth in India. The research is analytical in nature and is based on primary data collected through an online survey using

Google Forms. A convenience sampling technique was used, where respondents were selected based on their availability and willingness to participate. The survey was distributed online, enabling quick data collection from social media users.

The total sample size was 151 respondents, with 48.7% male and 50.7% female participants. In terms of age, 50% were below 18-25 years, while the remaining respondents were distributed across higher age groups. The study also examined platform usage, where WhatsApp (74%) and YouTube (70%) were the most used, followed by Instagram (64.7%), Facebook (24%), and Twitter (8%). The questionnaire included yes/no questions, Likert scales, rating scales, and multiple-choice questions. Data were analyzed using correlation analysis to understand the relationship between social media usage and its impact.

HYPOTHESIS

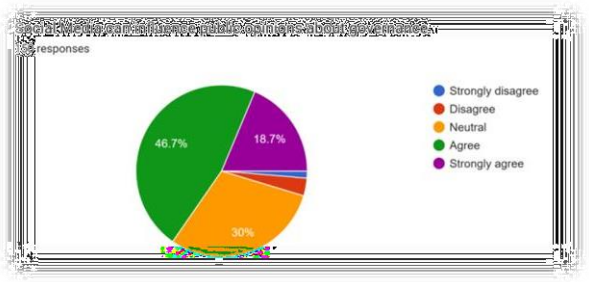
H_0 (Null Hypothesis):

Social media has no significant influence on public opinion regarding governance.

H_1 (Alternative Hypothesis):

Social media has a significant influence on public opinion regarding governance.

ANALYSIS AND INTERPRETATION



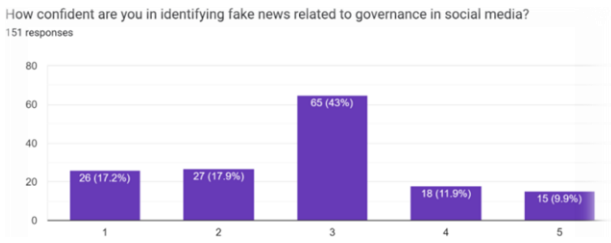


Chart 1 demonstrates the opinions of the respondents regarding the impact of social media on public opinion concerning governance. From the chart, it is evident that the majority of the respondents have a positive opinion concerning the statement. Almost half of the total respondents (46.7%) replied with the choice of "agree," and 18.7% replied with the choice of "strongly agree," which demonstrates that more than 65% of the total participants are acknowledging the role of social media as crucial in this context. Furthermore, 30% of the total participants are neutral regarding the statement. It is evident that only a very small percentage of the total participants have expressed negative opinions concerning the statement. The distribution demonstrates the inclination of the participants towards the statement in the context of its truthfulness.

	How confident are you in identifying fake news related to governance in social media?	Social Media can influence public opinions about governance.
How confident are you in identifying fake news related to governance in social media?	**1**	
Social Media can influence public opinions about governance.	**0.015037332**	**1**

Chart 2 shows the confidence levels of the respondents regarding their ability to identify fake news related to governance through social media. The results show that the highest percentage of respondents (43%) falls at mid-confidence level (rating 3). The confidence levels of 1 and 2 also contribute significantly to the results. The results for rating levels 4 and 5, representing high confidence levels, are relatively low. This shows that most people have low confidence levels for identifying fake news, and many lack confidence. This also shows that there is still some problem with fake news online and that more education is needed for people using social media.

The analysis and interpretation of this survey show that the majority of the people think that social media plays an important role in the opinion of the public regarding governance, but only a few people disagree with the idea. However, the level of confidence in the ability of people to recognize fake news regarding governance is average, as most people show an average level of confidence in the matter. Furthermore, the relationship between the level of confidence in the ability of people to recognize fake news regarding governance and the influence of social media on the matter is extremely low, as the correlation coefficient, i.e., r = 0.015, shows that the two variables have almost no relationship with each other.

FINDINGS

1. The study was able to prove that social media indeed has a perceived influence on the opinion of the public regarding governance, as seen in the consensus of the majority of the respondents.
2. The respondents are moderately confident in identifying fake news, which proves that there is ambiguity in this area.

3. The relationship between the confidence level of the respondents in identifying fake news and the perceived influence of social media was found to be negligible, as seen in the value of r = 0.015.
4. The study was able to prove the alternative hypothesis that social media indeed has an influence on the opinion of the public regarding governance, as the null hypothesis was rejected.

SUGGESTIONS

Based on the findings of the study, some of the recommendations that can be made include promoting digital and media literacy through awareness, promoting fact-checking through cooperation with various entities, promoting responsible social media use by checking the information before posting, promoting transparency in the government by posting correct information, developing policies that deal with misinformation without compromising freedom of expression, and promoting accountability in the platforms by developing algorithms that help eliminate fake news and promote correct information.

CONCLUSION

The study has concluded that the social media plays an important role in the creation of opinions among the people and the creation of awareness among them regarding the governance in India. Most of the people are aware of the role of the social media in the democratic participation of the people and the communication between the people and the government. Therefore, the study supports the alternative hypothesis that the social media plays an important role in the creation of awareness among the people regarding the governance in India. The social media like WhatsApp, YouTube, and Instagram plays an important role in the creation of awareness among the people regarding the governance in India by spreading the information and encouraging the people towards the governance in India. However, the study revealed that the people are concerned about the identification of the fake news as they have shown only a moderate level of confidence regarding the identification of the information

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An Empirical Study On The Influence Of Customer Feedback On Online Purchase Behavior In The FMCG Sector

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Abstract: The paper explores the role of customer feedback in influencing the behavior of individuals in purchasing products online, especially in the fast-moving consumer goods sector. The reviews and ratings, which are basically comments from other customers, help build some amount of trust, I suppose, and remove some amount of ambiguity in the decision-making process. It feels as though without this, the entire online shopping scenario would be riskier for everyone. The research design used was stats, including descriptive stats and chi-square tests, and correlation to establish the relationship. From the data, it's evident that most consumers do look at the feedback before pressing the 'purchase' button, yeah. This part of the paper was highlighted because it seemed quite reliable. Feedback is linked with the choice of products in a positive manner, if you will, and helps guide the decision. It's not clear if this is the only factor, though, and if it's the only factor, then it does explain the reliance on this in the online scenario**.**

Key words:
Customer Feedback, Online Purchase Behavior, FMCG Sector, Consumer Satisfaction, Reviews and Ratings, Purchase Intention, Consumer Trust, E-WOM, Product Selection, Online Shopping

1. Introduction

The ever-increasing growth of e-commerce has significantly changed the pattern of consumer spending, especially in the Fast Moving Consumer Goods (FMCG) segment. FMCG products, like food products, personal care products, and household essentials, are usually bought in physical stores. However, due to the widespread use of smartphones, the proliferation of the internet, and advancements in technology, people are increasingly adopting the internet as a platform for making purchases. Online shopping is the most popular among the new generation of consumers due to the benefits of time management and the availability of a wide range of products and price comparison.

Customer feedback is an important factor in the changing pattern of consumer spending in the digital age.

Reviews, ratings, and comments from previous customers are referred to as customer feedback. It is a reliable source of data for potential customers. It acts as e-word-of-mouth for customers to evaluate their overall satisfaction, performance, and quality of a product. Although negative feedback may raise certain questions for customers and may discourage them from purchasing a certain product, positive feedback is likely to increase trust and purchase intention. Moreover, customers can quickly compare a product and form opinions with the help of ratings. In particular, in the case of FMCG, customer feedback is significant for customers to reduce uncertainty in purchasing a product due to certain factors such as low costs. Customers often use other people's experiences before making snap decisions regarding purchases.

Moreover, the extent and power of customer feedback have been enhanced due to the rise in prominence of digital platforms and social media as well. With an emphasis placed on consumer trust, perception, and buy intention, this study has attempted to scientifically investigate how customer feedback impacts online buy behavior in the FMCG industry. Customer feedback plays an important role in reducing uncertainty, which impacts decision-making, particularly in the FMCG industry, as this is an industry where products are regularly purchased and extremely inexpensive as well. Before making hasty purchases, consumers often rely on the experiences shared by other consumers, particularly in an online platform, as it is not possible to physically examine the product in an online platform as well. Moreover, the extent and power of customer feedback have been enhanced due to the rise in prominence of digital platforms and social media as well.

2. OBJECTIVES OF THE STUDY

- To examine the role of customer feedback on the online purchasing behavior of the FMCG industry
- To examine the role of positive customer reviews on the purchasing decisions of consumers
- To examine the role of negative reviews on the purchasing decisions of internet shoppers
- To ascertain the relationship between customer feedback and purchase intention
- To ascertain the extent of the role of reviews prior to

the purchase of FMCG products online
- To examine the role of electronic word of mouth on the purchasing decisions of consumers

3. LITERATURE REVIEW

G. Badalar Al Mughairi, Karim A. M., and Karim A.M. conducted research on the aspect of customer satisfaction in the electronic platform concerning the FMCG industry from a global perspective. The findings of the research indicated that the aspect of customer satisfaction between customers is largely influenced by the behavior of the consumer, the usage of the electronic channel, the availability of the products, and the communication strategy.

Jain, M., and Jain, N. (2023) conducted research on the purchase of the electronic products of the FMCG industry. In this research, we analyze the data concerning the preference of the consumer towards the electronic channel, as well as the influence of the behavioral and demographic aspects of the consumer, using the statistical tools.

According to Helen, J., and V: D selvi (2022), the product, price, promotional, and psychological factors are the main factors influencing the purchase of the FMCG products for the consumer.

Najah, K. A., Jenita, A. M. A, carried out a research on the impact of the integrated marketing communication strategy on the buying behavior of the consumer, which stated that the consumer would be induced to be aware of the brand and would trust the product. The consumer buying behavior towards the FMCG products through the Digital Marketing was studied by Giri et. al., 2026. According to the research, the pricing offers have the strongest impact on the consumer buying behavior, followed by convenience, while the impact of the social media influencer on the consumer buying behavior is the least.

Saraswat, D., Singh, Y., and Vidani, J. (2024) have compared the awareness of consumers and the purchase behavior of FMCG products in the market. The research study revealed that there is a difference in the behavior of consumers because of factors such as accessibility and affordability.

Mukherjee, S. Das, M. K and Chakraborty, T. K.(2023)m in their research study on viral marketing during FMCG reported that commitment to a brand (brand awareness) has a positive impact of purchase intention with mediating function being performed by brand loyalty.

Maheswari, S. (2023), Artificial intelligence and marketing of FMCG: the new age tools, Journal of Management Insights. The study has confirmed the fact that AI-based strategies have a higher influence on consumer behavior.

Ahuja, V., and Tabeck, P. S. (2024) conducted a study on the influence of social media marketing on the FMCG sector. The study concluded that social media has a positive influence on consumer positioning, relationships, and trust.

Saeed & Sharma published this study in 2026, comparing the level of satisfaction of the customers with quick commerce as opposed to the regular e-commerce models. It seems like the speed of delivery is what actually makes the people satisfied with the quick commerce, you know, because everything comes at such a fast pace. In the case of regular models, the prices seem to be the bigger issue, at least according to what they say.

4. RESEARCH METHODOLOGY

4.1 Research Design

This research is based on the descriptive and analytical research design to understand customer satisfaction in the FMCG industry. The research is quantitative in nature because it is based on numerical data and analyzed through statistical tools.

4.2 Sample Size and Sampling Technique

This research is based on 60-70 respondents. The sampling technique is convenience sampling. In this technique, the respondents are selected on the basis of ease of access.

4.3 Data Collection Method

Primary data is collected through the survey method of research. The questionnaire is structured and consists of close-ended questions.
Secondary data is collected through various articles and online sources.

4.4 Data Analysis Techniques

Data is analyzed through various statistical tools such as:
- Descriptive Analysis (Mean and Percentage)
- Chi-square Test
- Correlation Analysis

The results are presented in a tabular form for better understanding.

1.1 Demographic Profile

The study takes into consideration factors such as age, gender, education, occupation, and income to determine the demographic characteristics of respondents.

1.2 Measurement Scale

A Likert scale is used to measure variables such as customer satisfaction, product quality, etc. The Likert scale ranges from 1 to 5.

1. DATAANALYSIS AND INTERPRETATION

Table 5.1

TABLE SHOWING THE AGE OF THE RESPONDENTS

Age Range	Frequency	Percentage
18-25	60	84.5%
26-35	3	4.2%
36-45	7	9.9%
46-and above	1	1.4%

Interpretation:

The age distribution of the respondents has been shown in the table below, i.e., Table 2. It has been noted that the majority of the respondents, i.e., 60, or 84.5%, fall in the age group of 18-25. The second highest number of respondents, i.e., 7, or 9.9%, fall in the age group of 36-45. Three, or 4.2%, of the total respondents fall in the age group of 26-35, whereas only one, or 1.4%, of the total respondents fall in the age group of 46 or above. It has clearly been indicated that the majority of the respondents fall in the age group of 18-25.

DESCRIPTIVE ANALYSIS

Table 4.2 Frequency and Percentage of Customer Satisfaction

Response Option	Frequency	Percentage (%)
Very Satisfied	18	30.0%
Satisfied	22	36.7%
Neutral	10	16.7%
Dissatisfied	6	10.0%
Very Dissatisfied	4	6.7%
Total	60	**100%**

Interpretation:
From the table, it is clear that the majority of the respondents are satisfied (36.7%) and very satisfied (30.0%) with FMCG products, implying that the products have a high level of consumer satisfaction. The number of respondents who are neutral (16.7%) is significantly smaller in comparison to the number of respondents who are dissatisfied or extremely dissatisfied. This implies that the general consumer perception of FMCG products is positive.

CHI-SQUARE ANALYSIS

Table 4.3 Crosstabulation (Gender vs Satisfaction)

Gender	High Satisfaction	Low Satisfaction	Total
Male	20	10	30
Female	20	10	30
	40	Total	60

5. SUGGESTIONS

•Businesses should focus on enhancing product quality to increase customer satisfaction.

•Businesses should be fair in pricing to attract more customers.

•FMCG businesses should regularly survey their customers to understand customer needs.

•Value and quality should be given importance in marketing strategies.

•Businesses should focus on customer retention to maintain long-term relationships with customers.

6. Conclusion

The customer satisfaction in FMCG businesses is quite high, as indicated in the study. The study shows that price perception is the second most important factor in customer satisfaction, after product quality. The study has shown that quality has a high correlation with customer satisfaction, which means that enhancing product quality will improve customer satisfaction to a large extent. Hence, to maintain customer satisfaction, FMCG businesses should focus on enhancing product quality.

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To Study A Social Media Influencers On Gen Z Purchasing Behavior Pattern Towards Skin Care Products In Chennai City

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ABSTRACT

This study examines that to analysis, influence that social media influencers have had on the buying decisions of Gen Z consumers in Chennai, India. concerning skincare products. The researchers investigated different indicators of social media influencers (or influencer marketing) having an impact on skincare consumerism in Chennai, India, including influencer reliability, quality of content, and engagement with their following. The researchers also looked specifically at particular brands (The Ordinary and CeraVe) to see how influencer marketing has driven them to purchase products, in order to provide brands with information that will help them develop successful marketing strategies toward Gen Z.

KEY WORDS: Social Media Influencers, Generation Z, Influencer Marketing

I. INTRODUCTION

The effectiveness of social media influencers using Facebook, YouTube, and Instagram to influence Gen Z when it comes to product perception and purchasing decisions is achieved using relatability, authenticity, and peer-type communication—unlike traditional marketing methods. As the cosmetic industry grows in Chennai primarily due to increasing awareness regarding wellness and grooming among young people, so too has the popularity of skincare product recommendations, reviews and tutorials by Influencers among Generation Z. This project satisfies a gap in the existing body of literature surrounding the factors influencing Generation Z's decision-making process with respect to skincare product purchases in Chennai through the relatability, credibility and reliability of skincare Influencers.

II. NEED OF THE STUDY

This study aims to identify the influence of perceived influencer credibility, trust and quality of influencer-produced content upon influencing purchasing behaviour as well as providing skincare brands with recommendations for implementing successful influencer marketing strategies. This research will also provide a gap in current literature regarding the purchasing behaviour of Generation Z consumers within the urban Indian context.This research will examine the effects of social media influencers on the skincare buying decisions of Chennai's Generation Z demographic.

III. OBJECTIVES OF THE STUDY

- To identify the various factors influencing purchasing behavior Gen Z brand towards Skin Care Products reputation, and peer recommendations.
- To study the role of social media platforms in shaping Gen Z skincare purchase decisions.
- To evaluate the impact of influencer credibility, trust, and content quality on the purchase intention of Gen Z consumers.
- To find out the impact of Ordinary and CeraVe skincare products.

IV. SCOPE OF THE STUDY

Includes both International Skincare Brands such as The Ordinary and CeraVe and General Skincare Product Categories. Limited to how influencer marketing affects short-term purchase intentions, not long-term brand loyalty. Influence of social media sites: Instagram, Youtube, Facebook.

V. LIMITATION OF THE STUDY

- Results limited to one city (Chennai); findings may not be applicable to other locations.
- Study focused exclusively on skincare products; no other beauty/wellness product categories were included.
- Research based on self-reporting via anonymous survey may be subject to bias.
- The sample size may not represent the diversity of all Gen Z consumers.

VI. REVIEW OF LITERATURE

- **Jeel Purohit , Dr. Jignesh Vidani (2025)** The research on the preference of Generation Z for skincare products and factors that influence their purchase was conducted in Ahmedabad. The factors that were taken into account in the research are social media influence, attractive packaging, sustainability, moral values, and promotional offers. The research used a structured questionnaire and gathered data

from 171 respondents. The research showed that the influence of social media and willingness to pay for cruelty-free and environmentally friendly products is related to age. The correlation value is low; hence it is of little value.

- **Laura Koivula (2024)** A research study was conducted on the interaction of Gen Z males with influencer marketing and how it influences their behavior. The data collection was done through nine Gen Z males. The data was collected through semi-structured interviews. The research findings revealed that Gen Z males prefer the content of influencers because of their shared interest in fitness, fashion, and the outdoors. The authenticity and relatability of influencers were two important factors that influence their interaction with the content of influencers. Gen Z males were found to be skeptical about advertisements. Influencer marketing played a role in their awareness of products.
- According to **Gaur and Rawat (2024)**, research was conducted on how social media influencers affect Gen Z consumer's purchasing decisions. Research findings indicate that a Gen Z consumer's purchase behavior will likely be influenced by social media influencers' credibility, attractiveness, and authenticity as individuals. Additionally, the research indicates that 72% of Gen Z consumers will purchase a given item after receiving a recommendation from a social media influencer.

- According to **Shavira (2024)**, there is a direct relationship between Gen Z's purchases via e-commerce and influencer marketing. Shavira's research found that credibility and engagement strategies of an influencer are substantial in creating a follower's attitude toward a brand. The findings specify that Gen Z consumers are more likely to follow and trust an influencer when they post content that is authentic and relatable, thereby influencing Gen Z's purchasing decision.

- The study conducted by **De Veirman Marijke, Cauberghe Veroline & Hudders Liselot (2017)** investigated influencer marketing within social media (Instagram specifically), specifically looking at how having a high number of followers affects perceptions of popularity and credibility. The findings indicated that having more followers has a positive impact on brand attitudes.

VII. RESEARCH METHODLOGY

Research methodology is an established method of data collection in order to conduct studies. Research employs a **descriptive research design** using the survey method to ascertain the purchasing behavior of Gen Z consumers regarding skincare items. Additionally, data has been collected through the use of **primary data** via a structured questionnaire. The **convenience sampling technique** was utilized where **101 respondents** residing in Chennai that belong to Gen Z were selected as participants for this study.

To assist with data analysis, the collected data is presented through percentage analysis and charts/graphs to provide a clearer understanding of the data.

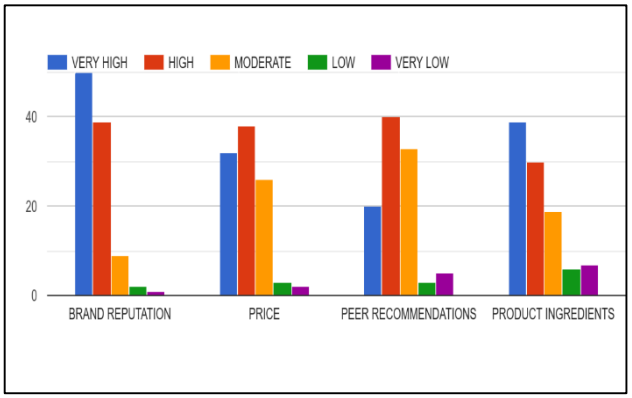
VIII. DATA COLLECTION

The data collection process is the collection of accurate, valid, and relevant data for a research project. Primary data has been collected for this project using a structured questionnaire designed by using Google Forms. Data collected includes responses from Gen Z consumers in Chennai. Questions are in both multiple choice and Likert scale format.

IX. DATA ANALYSIS

TABLE SHOWING FACTORS INFLUENCING PURCHASING DECISIONS

FACTORS	RESPONDENTS					TOTAL
	VERY HIGH	HIGH	MODERATE	LOW	VERY LOW	
BRAND REPUTATION	50	39	9	2	1	**101**
PRICE	32	38	26	3	2	**101**
PEER RECOMMENDATIONS	20	40	33	3	5	**101**
PRODUCT INGREDIENTS	39	30	19	6	7	**101**



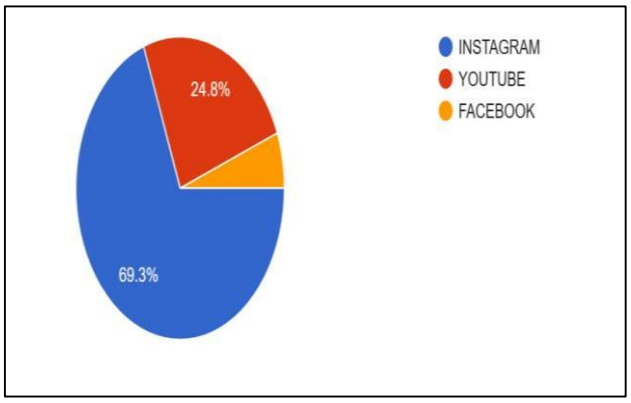
INTREPRETATION:

A reputation of brand ranks as number 1 in terms of respondent influence when making final decision related to the purchase of skincare products; product ingredient quality came in second place, with participants reporting an influence of 49% for brand reputation and 38% for product

ingredient quality (values rounded). Price and peer recommendations ranked lower (i.e., more moderate level) as determinants of consumer purchase behaviour, resulting in a preference for quality-based attributes rather than cost and peer drives.

TABLE SHOWING WHICH SOCIAL MEDIA PLATFORM INFLUENCES IN PURCHASE

PARTICULARS	RESPONDENTS	PECENTAGE
INSTAGRAM	70	69.31%
YOUTUBE	25	24.75%
FACEBOOK	6	5.94%
TOTAL	**101**	**100%**

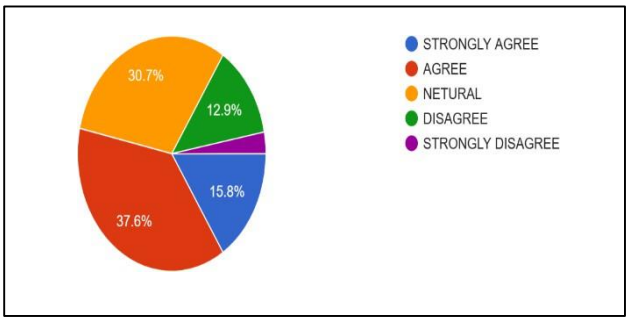


INTREPRETATION:

The data suggest that the social media platform that has the greatest level of influence on Gen Z's purchasing decisions regarding skincare products is Instagram (69.31%), followed much further down the list of influencers with mobile customer reviews (24.75%) on websites such as Amazon, and Facebook (5.94%) has the least influence on purchasing decisions.

TABLE SHOWING TRUST IN PURCHASING THROUGH SOCIAL MEDIA PLATFORM

PARTICULARS	RESPONDENTS	PECENTAGE
STRONGLE AGREE	16	15.84%
AGREE	38	37.62%
NETURAL	31	30.69%
DISAGREE	13	12.87%
STRONGLY DISAGREE	3	2.97%
TOTAL	**101**	**100%**

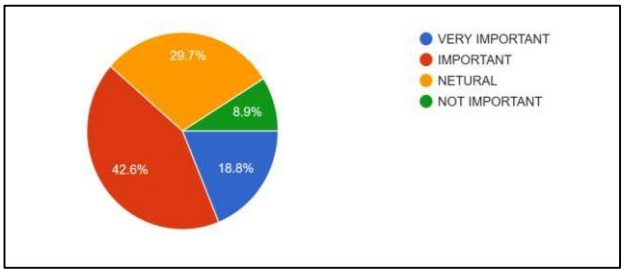


INTREPRETATION:

The majority of participants are either agree with the idea of trusting their buying experience through social media sites (37.62% agree, 15.84% strongly agree) as well as significant numbers who were neutral (30.69%) have shown moderate or slightly higher level of trust towards making purchases via these types of sites.

TABLE SHOWING IMPORTANT OF INFLUENCER CREDIBILITY IN PURCHASE

PARTICULARE	RESPONDENTS	PERCENTAGE
VERY IMPORTANT	19	18.81%
IMPORTTANT	43	42.57%
NETURAL	30	29.7%
NOT IMPORTANT	9	8.91%
TOTAL	**101**	**100%**

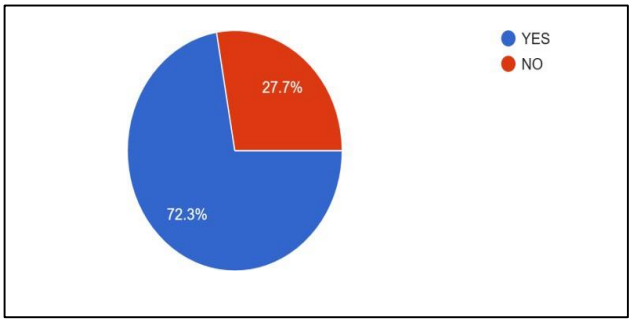


INTREPRETATION:

Respondents believe influencer credibility is important to influencing their purchasing decision for many consumers (42.57% important; 18.81% very important); therefore influencer credibility is an important factor that influences the buying decision of potential buyers who find someone they can trust to promote products on social media.

TABLE SHOWING AWARE ABOUT THE ORDINARY AND CERAVE PRODUCT

PARTICULARS	RESPONDENTS	PERCENTAGE
YES	73	72.28%
NO	28	27.72%
TOTAL	**101**	**100%**

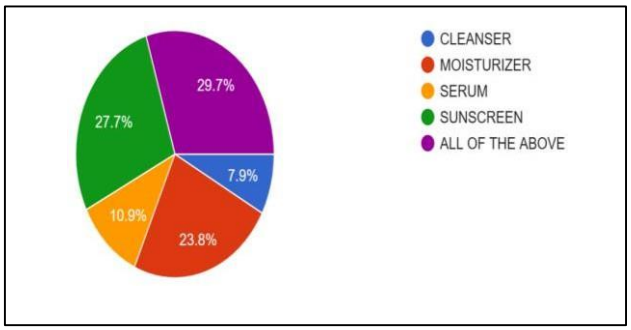


INTREPRETATION:

The Ordinary and CeraVe products are well-known among Gen Z consumers, as evidenced by the majority of respondents (72.28%) being aware of them.

TABLE SHOWING REGULAR PURCHASE OF SKIN CARE PRODUCTS

PARTICULARS	RESPONDENTS	PERCENTAGE
CLEANSER	8	7.92%
MOISTURIZER	24	23.92%
SERUM	11	10.89%
SUNSCREEN	28	27.72%
ALL OF THE ABOVE	30	29.7%
TOTAL	**101**	**100%**

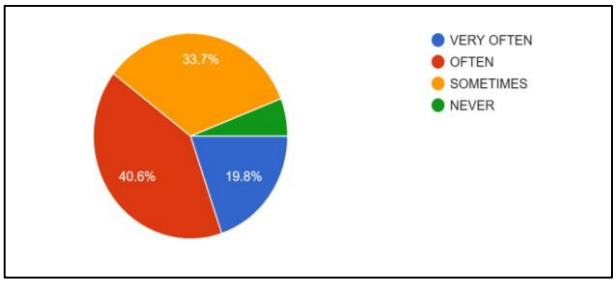


INTREPRETATION:

The majority of respondent buy all skincare products (29.7%), sunscreen (27.72%), and moisturizer (23.92%), indicating a preference for all-encompassing skincare regimens

TABLE SHOWING FREQUENCY DICOVER NEW SKIN CARE PRODUCTS

PARTICULARS	RESPONDENTS	PERCENTAGE
VERY OFTEN	20	19.8%
OFTEN	41	40.59%
SOMETIMES	34	33.66%
NEVER	6	5.94%
TOTAL	**101**	**100%**



INTREPRETATION:

Most respondents find new skincare products frequently (40.59%) or occasionally (33.66%), suggesting that Gen Z consumers are actively exposed to and interested in new products, probably as a result of social media.

X. FINDINGS

- ✓ Price and recommendations from friends have a lower degree of influence compared to quality-related factors.
- ✓ Brand reputation and product ingredients are two of the most significant influencers for Gen Z in their purchasing decisions when it comes to skincare (i.e. when purchasing skincare).
- ✓ Instagram is the most dominating social media platform influencing Gen Z's purchase decisions for skincare products, followed by YouTube, and Facebook influences them the least.
- ✓ Most participants in our study are positively influenced by their level of trust in social media when deciding whether to buy skincare products.
- ✓ Influencer credibility is an important factor in the purchase intention of Gen Z consumers.

- ✓ Most of the participants in our sample have high awareness of well-known skincare brands such as The Ordinary and CeraVe.
- ✓ The majority of participants prefer to use a complete skincare routine, which typically includes the use of large amounts of moisturizers and sunscreen.
- ✓ Gen Z consumers often discover new skincare products primarily through social media exposure.

XI. SUGGESTION

- ✓ Brands should look to create partnerships with trusted and reliable people or companies to drive consumer confidence or connection/engagement with the brand.
- ✓ Skin-care sectors could enhance the value of their brands, by strengthening brand credibility through clearly communicating the benefits/ingredients of the product.
- ✓ Primary target markets for companies will be Instagram and YouTube for effective outreach to Gen Z.
- ✓ Authentic, relatable and educational influence is what will drive the power of influence for these product types.
- ✓ Brands should create the marketing message around the total skin-care regimen vs. individual products, in order for consumers to relate to the message.
- ✓ Through education and additional awareness campaigns, companies will create a better chance to influence the decision-making process of consumers regarding purchases of skin-care products.
- ✓ Transparency regarding promotions will limit skepticism in consumers.

XII. CONCLUSION

According to the research, social media influencers significantly influence the purchasing behaviors of Gen Z consumers with respect to cosmetics purchased in Chennai. Consumers are influenced by several factors, including brand reputation, product components, and trusted sources of information. Instagram is the most influential platform of all social media. Influencers are a moderately to highly trusted resource for consumers, and they are also an active resource for discovering new products. As a result, influencer marketing is a viable method for brands selling cosmetics and skincare to engage with Gen Z and influence their purchasing decisions.

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Trust In Trends: Understanding Genz's Reliance On Social Media Influencers

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ABSTRACT : This study explores the role of social media influencers as they increasingly influence the opinions, choices, and ways of living of the Gen Z generation. A generation of people brought up with digital technology, Gen Z finds sources of information, entertainment, and inspiration from social media influencers like Instagram, YouTube, and TikTok. The study aims to identify the factors on which Gen Z relies on social media influencers, such as the authenticity of the influencers, the degree of relation between the influencers and the audience, the level of truthfulness of the influencers, and the regularity of posts from the influencers.

It also aims to examine the influence of social media influencers on the ways of consuming products, brand loyalty, and the decision of making a purchase. The study reveals the role of social media influencers as leaders of opinion, helping connect the brand with the youth through personal and engaging forms of communication. However, the presence of false information, ads, and unattainable ways of living highlights the need for the development of digital skills among influencers. Thus, the study provides a better understanding of the psychological and social aspects of the influence of social media influencers on Gen

KEYWORDS: Gen Z, Social Media Influencers, Influencer Marketing, Consumer Behaviour, Trust and Authenticity, Purchase Decision Making, Brand Loyalty

INTRODUCTION

Over the last decade, social media has changed the way in which people are made aware of trends, products, and lifestyles. Social media platforms like TikTok and Instagram have impacted Gen Z in particular, as this demographic would rather follow social media influencer recommendations rather than traditional marketing methods. Influencers achieve this by establishing their own community through relatable content.The reason influencer marketing is successful is because it is real and unscripted, allowing users to establish trust. According to research, Gen Z is more likely to consider purchasing a product recommended by social media influencers who they trust (Influencer Marketing Hub, 2024; Djafarova & Rushworth, 2017).

Therefore, social media influencers are the new 'opinion leaders' who influence consumer behavior. However, in recent times, social media influencer marketing is becoming increasingly commercialized, and it is becoming increasingly difficult for users to differentiate between real and fake influencer marketing. This study therefore seeks to examine how trust is established and destroyed between social media influencers and Gen Z.

NEED OF THE STUDY

- Social Media Influencer is playing a significant role in digital marketing in this new era, especially for Generation Z.
- The need for understanding social media influencers and their influence on consumer trust and purchase decisions is rising.
- The study would help in understanding the significant factors that influence consumer decisions.
- The study would also help marketers and brands in planning influencer marketing strategies.
- The study would also help in understanding the importance of fair marketing practices in influencer marketing to avoid false information dissemination.

LIMITATIONS OF THE STUDY

- The study was conducted among only 100 samples, and this may not be representative for the entire population.
- The study was conducted only for Generation Z, and this study may not be applicable for other generations.
- The study was conducted based on the opinions of the people, and this may include biases and false information.
- The study was conducted based only on certain factors such as trust, influencer impact, and purchase behaviour.
- The study was conducted based on time constraints.

OBJECTIVES

- To understand the level of trust Gen Z has for social media influencers while making a purchasing decision.
- To analyze the influence of credibility, authenticity, and relatability of the social media influencer on Gen Z's trust level.
- To understand the influence of social media influencers on Gen Z's buying behavior and perception of the brands.
- To understand the most trusted social media platform and type of influencer for Gen Z.

SCOPE OF THE STUDY

- The study would provide significant insights into the influence of social media influencers on Generation Z.
- The study would help marketers understand the role of trust, authenticity, and credibility in consumer behavior.
- The study would help businesses understand how to implement influencer marketing.
- The study could be conducted on other age groups and geographic locations in the future.
- The study could be conducted on a larger scale in the future using more advanced statistical tools.

REVIEW OF LITERATURE

Lou and Yuan (2019) examined how influencer message value and credibility affect consumer trust and purchase intention. The study adopted a quantitative survey approach using Partial Least Squares Structural Equation Modelling (PLS-SEM) with a sample of 402 social media users. The findings revealed that influencer credibility, informativeness, and entertainment value significantly enhance consumer trust, which in turn positively influences purchase intention.

Pop et al. (2022) analysed the role of trust in social media influencers within the consumer decision-making journey. The study employed a quantitative research design using Smart PLS with a sample of 385 respondents. The findings indicated that consumer trust significantly influences information search, evaluation, and purchase decisions.

Chetioui et al. (2020) examined the impact of fashion influencers on consumer attitudes and purchase intention based on the Theory of Planned Behaviour. The study used a quantitative survey approach with PLS-SEM and a sample of 610 respondents. The findings showed that influencer credibility, expertise, and trust significantly influence consumer attitudes and purchase intention.

Muda and Hamzah (2021) analysed the influence of user-generated content credibility on purchase intention. The study adopted a quantitative design using PLS-SEM with a sample of 370 respondents. The findings revealed that source credibility significantly affects electronic word-of-mouth and buying behaviour.

Chen and Yang (2023) examined the role of influencer trust and emotional attachment in live-streaming e-commerce. The study adopted a quantitative research design using Structural Equation Modelling (SEM) with a sample of 449 respondents. The findings revealed that trust and emotional attachment significantly affect purchase intention.

RESEARCH METHODOLOGY

The research study would use a quantitative research approach to study the impact of social media influencers on Gen Z. The primary data would be collected using a structured questionnaire in Google Forms. The sample size of the research study would be 100.

The research study would use the convenience sampling technique to collect the required data from the population of various demographic groups. The research study would aim to study various parameters like age group, gender, occupation, income levels, and social media usage. The statistical methods that would be used to study the research data are percentage analysis, chi-square tests, and correlation analysis.

DATA ANALYSIS & INTERPRETATION

CHI-SQUARE ANALYSIS

Case Processing Summary						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
gender * what type of influencer do you follow the most	100	100.0%	0	.0%	100	100.0%

gender * what type of influencer do you follow the most Crosstabulation

		What type of influencer do you follow the most					
		Fashion influencers / Beauty influencers	Celebrity influencers	Fitness influencers	Technology influencers	Blogger / Content influencers	Total
gender	Male	9.6	7.0	5.9	5.6	8.9	37.0
	female	16.4	12.0	10.1	9.4	15.1	63.0
Total		26.0	19.0	16.0	15.0	24.0	100.0

INTERPRETATION:

The Pearson Chi-square value is 34.630 with a significance value of 0.000, which is less than 0.05. Hence, we can reject the null hypothesis, which implies that there is a significant relationship between gender and the type of influencers followed by respondents.

Correlations				
			age	Which social media platform do you mostly use to follow influencers
Spearman's rho	age	Correlation Coefficient	1.000	.157
		Sig. (2-tailed)	.	.118
		N	100	100
	Which social media platform do you mostly use to follow influencers	Correlation Coefficient	.157	1.000
		Sig. (2-tailed)	.118	.
		N	100	100

SPEARMAN RANK CORRELATION

INTERPRETATION:

The correlation coefficient for the relationship between age and social media platform usage is 0.157 with a significance value of 0.118. Since the p-value is greater than 0.05, we can say that there is no significant relationship between age and the platform used to follow influencers.

PEARSON CORRELATION

INTERPRETATION: The correlation coefficient for the relationship between occupation and frequency of watching influencer content is -0.025 with a significance value of 0.806, which is greater than 0.05, hence no significant relationship exists between occupation and frequency of watching influencer content.

Correlations			
		occupation	How often do you watch influencer content
occupation	Pearson Correlation	1	-.025
	Sig. (2-tailed)		.806
	N	100	100
How often do you watch influencer content	Pearson Correlation	-.025	1
	Sig. (2-tailed)	.806	
	N	100	100

Chi-Square Tests			
	Value	df	A symp. Sig. (2-sided)
Pearson Chi-Square	34.630[a]	4	.000
Likelihood Ratio	43.446	4	.000
Linear-by-Linear Association	7.251	1	.007
N of Valid Cases	100		
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.55.			

FINDINGS

- Majority of the respondents, i.e., 85%, fall under the category of 18-25 years, i.e., Gen Z.

- Female respondents, i.e., 63%, outnumber male respondents, i.e., 37%.
- Majority of the respondents, i.e., 72%, are students, and they are well-educated.
- Income levels of the respondents vary; 30% earn above ₹6 lakhs.
- Influencers have a significant impact on the behavior and purchasing habits of consumers.
- Trust, authenticity, and credibility are the influencing factors.
- There is a significant relationship between gender and type of influencers followed ($p < 0.05$).
- There is no significant relationship between occupation and content viewing frequency ($p > 0.05$).
- There is no significant relationship between age and usage of the platform ($p > 0.05$).

SUGGESTIONS

- Influencers should be authentic and genuine.
- Micro-influencers should be taken into consideration by brands for better engagement.
- Sponsored content should be disclosed.
- The content should be informative and relatable.
- The audience should be platforms popular among Gen Z, such as Instagram and YouTube.
- The recommendations made by influencers should be verified.

CONCLUSION

From the study, it is clear that social media influencers play a significant role in shaping the attitude and behaviour of the new generation, i.e., Gen Z. The study found that most of the respondents, especially those belonging to the age group 18-25, depend on the content shared by social media influencers for product awareness and decision-making. The most significant factors that influence the behaviour of the consumer are trust, authenticity, and credibility. The statistical analysis found that the factor of gender plays a significant role in determining the kind of influencer followers, whereas age and occupation have a neutral effect on the consumption of the content shared by social media influencers. Hence, influencer marketing is a powerful tool in the digital marketing field, and transparency is the key to building trust among consumers.

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A Study On The Relationship Between Consumer Buying Behaviour And Brand Preference

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ABSTRACT

This study aims to analyze the relationship between consumer purchasing behavior and brand choice in a competitive market environment. Consumer purchasing behavior, as well as brand choice, is affected by various psychological, social, cultural, and personal factors. The study aims to determine the essential factors affecting the choices of consumers towards particular brands. In the study, the data were collected through the administration of questionnaires, specifically the standardized questionnaire with the Likert scale, which follows the descriptive research design. The study aims to determine the influence of certain factors, such as price, quality, brand, and marketing strategy, on the choices of consumers. Tools like regression, correlation, percentage, among others, are used in the interpretation of the data. The findings of the study are helpful in understanding the expectations of consumers, enhancing brand positioning, as well as creating effective marketing strategies.

KEY WORDS: Consumer buying behavior, Brand preference, Purchase decision, Brand loyalty, Brand image.

INTRODUCTION

Customers are spoilt for choice in a competitive market such as the one we have in today's business environment. The procedure by which customers decide on what to purchase depending on their needs, preferences, and influences is referred to as consumer buying behavior. The decisions they make may be influenced by factors such as price, quality, brand, advertising, and word-of-mouth from customers. Consumer purchasing behavior is greatly affected by brand choice. Customers may develop a liking for certain brands due to their perception of the brand's quality, positive experiences from previous purchases, or due to advertising and promotional activities. Understanding what attracts customers to a brand and what influences their purchasing decisions can be achieved by understanding the relationship between consumer purchasing behavior and brand choice.

The purpose of this study is to explore the relationship between consumer purchasing behavior and brand choice.

REVIEW OF LITERATURE

In another study, **Sharma (2022)** concluded that price, quality, and brand image are the most important factors affecting consumer behavior. Consumers prefer brands with high value and quality.

In the study conducted by **Kumar and Singh (2023)**, the importance of social media and digital marketing was highlighted. The results showed that online reviews and promotions by influencers have a significant impact on brand preference.

In the research carried out by **Ali (2025)**, the importance of advertising was highlighted. The results showed that emotional and creative ads have a significant impact on attracting consumers and enhancing brand preference.

In the study conducted by **Gupta (2023)**, the importance of family and peer groups was highlighted. The results showed that customer purchasing behavior is significantly influenced by their friends and family.

In the research carried out by **Khan (2024)**, the importance of discounts and pricing was highlighted. The results showed that offers, discounts, and pricing have a significant impact on influencing customers' behavior to switch or prefer particular brands.

In the study conducted by **Joseph (2025)**, the importance of innovation and product quality was highlighted. The results showed that high-quality products with unique features enhance brand preference and trust.

OBJECTIVES OF THE STUDY

- To understand the concept of customer purchasing behavior.
- To explore the factors that influence the purchasing behavior of a consumer.
- To assess the level of brand preference of a consumer.
- To explore the relationship between brand preference and purchasing behavior of a consumer.
- To conduct research on the factors influencing the purchasing behavior of a customer, i.e., price, quality, and brand

METHODOLOGY

The theoretical study of methods employed in a discipline of study, techniques, methods, and instruments for collecting and processing data is called research methodology.

Descriptive Research

Descriptive research is a methodical approach to research that concentrates on characterising the traits, actions, or circumstances of a certain population or phenomenon as they currently exist. By gathering, evaluating, and presenting data without changing any variables, it seeks to give an accurate and comprehensive picture. In addition to being helpful for making decisions, descriptive research serves as the foundation for more analytical or experimental research by revealing patterns, trends, and correlations between variables.

Sample size

Convenience sampling has been used as a data collection strategy, and the required sample size of 114 has been achieved. It is adequate for data analysis, enabling the generation of reliable insights on the purchasing behavior of the customers.

Data collection method

Primary data has been collected using the questionnaire method. Statistical Tools Used:

- ✓ Normality Test – Kolmogorov-Smirnov & Shapiro-Wilk.
- ✓ Mann-Whitney U test.

NORMALITY TEST

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
BRAND PREFERENCE	114	100.00%	0	0.00%	114	100.00%
CONSUMER BEHAVIOUR	114	100.00%	0	0.00%	114	100.00%

Tests of Normality

	Kolmogorov Smirnov			Shapiro-Wilk		
	Statistic	df	Sig	Statistic	df	Sig.
BRAND PREFERENCE	.100	114	0.007	.967	114	.007
CONSUMER BEHAVIOUR	.97	114	0.011	.967	114	.006

a.Lilliefors Significance correction

NON PARAMETRIC TEST

MANN-WHITNEY TEST

	2. Gender	N	Mean Rank	Sum of Ranks
BRAND PREFERENCE	1	57	59.54	3394
	2	57	55.46	3161
	Total	114		
CONSUMER BEHAVIOUR	1	57	60.43	3444
	2	57	54.57	3110
	Total	114		

Test Statistics[a]

	BRAND PREFERENCE	CONSUMER BEHAVIOUR
Mann-Whitney	1508	1457.5
Wilcoxon W	3161	3110.5
Z	-0.662	-0.949
Asymp. Sig. (2-tailed)	0.508	0.343

a. Grouping Variable: 2. Gender

INFERENCE

The results of the normality test show that the data is not regularly distributed since the significance values are less than 0.05. Therefore, non-parametric tests were used.
The results of the Mann-Whitney U test show that the significance values for the data on brand preferences (0.508) and consumer behavior (0.343) are all higher than 0.05. Therefore, there is no significant difference between the gender groups for the two variables.

FINDINGS/ RESULTS

The data related to brand preferences as well as consumer behavior is not normally distributed. Gender doesn't significantly impact brand preferences and Gender doesn't significantly impact consumer behavior. Although the mean ranks are slightly different, they are not statistically significant. The decisions related to consumer behavior are the same for both genders.

SUGGESTIONS

Emphasis on improving the quality of products and their prices. Developing brand image and customer trust and applying proper marketing strategies to attract customers. To Consider customer feedback for improvement. Apply general marketing strategies as gender is of no significance. Improve customer satisfaction.

CONCLUSION

The study concludes that consumer buying behavior and brand preference are related to each other. The factors like price, quality, and brand image play a significant role in influencing the buying behavior of the consumer. The study also concludes that the gender of the consumer has no impact on their behavior.

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“Exploring How User Stickiness And Social Psychological Factors Stimulate (E-Wom) In Fintech Innovation”

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Abstract: The current study explores the impact of user stickiness and social psychological factors on electronic word-of-mouth in the context of Fintech services. The results, based on a survey of 100 users, reveal the impact of trust, usefulness, and user engagement on users' willingness to engage in electronic word-of-mouth. The literature suggests that the quality of Fintech services, measured by the improvement of services levels, positively affects electronic word-of-mouth, which, in turn, affects user experience and trust, leading to user stickiness to the financial services. The quality of electronic word-of-mouth serves as a functional substitute for physical services, facilitating the adoption of new financial services.

Key words: User stickiness, e-WOM, Fintech platforms, Trust, perceived usefulness, user engagement, Service quality, user experience, technology adoption

INTRODUCTION

The emergence of financial technology (FinTech) has greatly impacted the way individuals utilize financial services, especially through mobile applications, electronic payments, and the internet. This has made the rate and consistency of interaction with a platform, i.e., user stickiness, a key element for the success of FinTech innovations. Higher user stickiness will result in the continued use of the platform and will motivate the user to spread the word to other potential consumers.

Electronic word of mouth (e-WOM) is a key element for influencing consumer behavior, especially in the age of technology. For FinTech, where security and trust are major concerns, electronic word of mouth can play a significant role. Social psychological factors like trust, social influence, satisfaction, and perceived usefulness can greatly influence consumer behavior. This research is intended to understand the impact of user stickiness and other psychological factors on stimulating electronic word of mouth for FinTech innovation.

OBJECTIVES

- To examine the level of user stickiness with regards to Fintech.
- To identify the social psychological factors that influence user behavior with Fintech services.
- To examine the relationship between user stickiness and electronic word of mouth.
- To evaluate the impact of social psychological factors on electronic word of mouth.

SCOPE OF THE STUDY

User Scope: The study has the following user scope:

- Active Fintech users
- Individuals using mobile or digital financial services.

Methodological Scope: The study has the following methodological scope:

- Survey questionnaires
- Quantitative analysis method Percentage analysis
- Chi square Analysis
- Correlation co-efficient Analysis

Data Collection Scope: The study used a total of 100 samples as a data collection tool to collect data on the ways in which user stickiness and social psychological factors stimulate electronic word of mouth as a driving force behind fintech innovation.

RESEARCH METHODOLOGY

The research design used in this study is descriptive in nature, along with an analytical approach, to understand the interrelationship between FinTech applications, FinTech services, and FinTech platforms.

The data collected is original, obtained through a structured questionnaire administered to 100 respondents.

Convenience sampling was used in this study, wherein respondents are selected on the basis of their availability. The sampling unit is people using FinTech services, and the sample size is 100.
Statistical tools used in this study are tests of normality,

such as Kolmogorov-Smirnov and Shapiro-Wilk tests, Spearman's correlation, and regression.

DATA COLLECTION METHOD

Primary data

The data collected for this particular study is based on primary data collected from the respondents using the structured Google forms questionnaire.

Secondary data

The secondary data is collected from various online sources**.**

LIMITATIONS

- The particular study is focused on the Fintech platforms, and this gives us a clearer idea about the users.
- The particular research is conducted on users who actively use the Fintech application, and this gives us a clearer idea about the users.
- The particular research gives adequate importance to the Chennai city.

LITERATURE REVIEW

David Godes & Dina Mayzlin (2004) : In this study, the significance of word-of-mouth communication has been explored, as well as the difficulties faced while measuring word of mouth. In the study, the researchers have used online discussions from the Usenet group, focusing on the discussions of TV shows during the 1999-2000 season. In the study, word of mouth as a communication process has been analyzed. The findings of the study show that online discussions are a cost-effective way of measuring word of mouth, which helps in understanding the differences in TV ratings.

Peter Gomber et al. (2018) : The aim of the study was to analyze the influence of Fintech innovations on the transformation of the financial service industry. The researchers used a survey-based approach, collecting data from 150 financial experts. The researchers used tools like regression analysis and descriptive analysis to analyze the data. The findings of the study show that Fintech improves the efficiency of transactions, reducing costs. Fintech also increases the competition between financial service providers. Finally, the study concluded that Fintech plays a vital role in the improvement of the financial market.

Lars Hornuf & Sami Haddad (2019) : The objective of this research was to identify the factors affecting the development of fintech startups around the world. The researchers used data from 300 fintech startups in 55 countries. The researchers used multivariate regression analysis to identify the factors affecting fintech startups. The findings of the research were that financial and technological infrastructure promote fintech startup development. Government regulations affect fintech startup development. It evaluates that fintech startups contribute significantly to the development of financial markets.

Manaf Al-Okaily., et.al (December 2021): The research aims to propose an integrated model that includes extended technology acceptance model (TAM) and perceived enjoyment as independent variables and electronic word of mouth (eWOM) as a moderator variable. The research used 304 responses of Jordanian citizens through the quantitative method of partial least squares structural equation modeling (PLS-SEM). The research found that perceived usefulness and perceived enjoyment have a significant and positive influence on the decisions of users to use Fintech services. The decisions of Jordanian citizens to use Fintech services have been found to have significant and positive influence as perceived usefulness and perceived enjoyment. The research also found that eWOM moderates the relationship between perceived usefulness and decisions of Jordanian citizens to use Fintech services.

Hooi-Cheng Eaw (2023): The Fintech innovative banking and financial products have high demand owing to their uniqueness, cost efficiency, and user-friendly nature. The traditional banking and financial sector of the economy is disrupted. The question of whether the financial sector and economy would not suffer from the incursions of Fintech is not unreasonable. By adopting the review method as a research methodology, this paper has revealed that Fintech has potential to influence the realization of increase in financial development and economic growth.

RESEARCH GAP

Previous researchers have studied FinTech applications, FinTech services, and FinTech platforms as individual components, but no researcher has studied the combined effect of FinTech applications, FinTech services, and FinTech platforms together. This study is a move in the right direction by trying to find the interrelationship between these factors**.**

DATA ANALYSIS AND INFERENCE

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
FINTECH APPLICATION	100	100.0%	0	.0%	100	100.0%
FINTECH SERVICES	100	100.0%	0	.0%	100	100.0%
FINTECH PLATFORMS	100	100.0%	0	.0%	100	100.0%

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
FINTECH APPLICATION	.142	100	.000	.921	100	.000
FINTECH SERVICES	.125	100	.001	.946	100	.000
FINTECH PLATFORMS	.114	100	.003	.948	100	.001

a. Lilliefors Significance Correction

Inference:

From the results of the normality tests, where both Kolmogorov-Smirnov and Shapiro-Wilk tests were used, it is evident that all variables have a significance value less than 0.05. This implies that the data is not normally distributed. Therefore, it is appropriate to carry out non-parametric statistical analysis. Moreover, there are no missing values in the data.

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
FINTECH APPLICATION	27.04	3.101	100
FINTECH SERVICES	24.89	3.206	100
FINTECH PLATFORMS	26.12	2.976	100

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.170[a]	.029	.009	3.087	.029	1.451	2	97	.239

Predictors: (Constant), FINTECH PLATFORMS, FINTECH SERVICES

Inference:

Regression analysis shows a low relationship between the data, as the value of R is 0.170. It shows that the model only explains 2.9% of the variance, and the results are statistically insignificant, as the p-value is 0.239, which is greater than 0.05. It shows that FinTech Services and FinTech Platforms do not have a significant impact on the dependent variable.

Nonparametric Correlations

			FINTECH APPLICATION	FINTECH SERVICES	FINTECH PLATFORMS
Spearman's rho	FINTECH APPLICATION	Correlation Coefficient	1.000	.081	.068
		Sig. (2-tailed)	.	.421	.498
		N	100	100	100
	FINTECH SERVICES	Correlation Coefficient	.081	1.000	.250*
		Sig. (2-tailed)	.421	.	.012
		N	100	100	100
	FINTECH PLATFORMS	Correlation Coefficient	.068	.250*	1.000
		Sig. (2-tailed)	.498	.012	.
		N	100	100	100

*. Correlation is significant at the 0.05 level (2-tailed).

Inference:
According to the results obtained in the Spearman correlation analysis, FinTech Applications are not significantly related to FinTech Services ($\rho = 0.081$, $p > 0.05$) or FinTech Platforms ($\rho = 0.068$, $p > 0.05$). At the same time, FinTech Services and FinTech Platforms are weakly but statistically significantly related to each other ($\rho=0.250, p<0.05$)

FINDINGS

From the analysis, it is evident that the data for all variables is not normally distributed. FinTech Applications have no significant relationship with any of the variables. The regression analysis showed that the independent variables have a limited effect on the dependent variables. The respondents showed a higher preference for FinTech Applications compared to Platforms and Services

SUGGESTIONS

- The research can be extended to compare the various types of fintech services, i.e., mobile wallets, digital banking, and cryptocurrency services.
- Future research can be conducted to check the impact of negative e-WOM and its implications on the adoption of fintech services.
- It can also be extended to check the impact of marketing strategies and social media on e-WOM for fintech services.

CONCLUSION

The stickiness of users, as reflected in repetitive usage, satisfaction, and emotional bonding with Fintech services, is an important factor in influencing consumers to engage in e-WOM based on their experiences shared online. When consumers experience satisfactory services from Fintech providers, which are reliable, convenient, and beneficial, they will be loyal to these services and actively encourage fellow consumers to try out these services. However, social psychological factors such as trust, perceived risk, social influence, and consumer attitudes are significant in influencing e-WOM. For instance, trust in Fintech services will help consumers remove uncertainties, while social influence will encourage consumers to engage with Fintech innovations in society. Moreover, consumers will be inclined to share e-WOM based on their experiences, both favorable and unfavorable, which will have significant impacts on Fintech services. The study has demonstrated that Fintech companies should look beyond the technological advancements in their services to emphasize relationship marketing with consumers, as this will not only create customer satisfaction

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Impact of AR and Live Shopping on Gen Z's Video-Based Commerce in Tamil Nadu

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ABSTRACT

Video sharing apps such as Instagram Reels and YouTube Shorts have further blurred the line between entertainment and commerce for Gen Z in Tamil Nadu. The aim of this research is to evaluate the impact of existing features such as live shopping and augmented reality try-ons on purchase intentions and actual purchase behavior. The findings of this research reveal that these features have an immense impact on product awareness, interest, and engagement. However, actual purchase behavior is lower in comparison to engagement. Other factors such as trust, authenticity, and experiential engagement are also significant in actual purchase behavior. The findings of this research, based on primary research conducted on a sample size of 157 respondents, reveal that there is a significant change from consumption to commerce. Social validation and aesthetic appeal are significant factors in building interest, whereas trust acts as a deterrent for actual purchase.

KEY WORDS: Short-Video Commerce, Live Shopping, AR Try-Ons, Generation Z, Social Commerce, Purchase Intention

I.INTRODUCTION

As the digital economy continues to evolve, it becomes increasingly difficult to distinguish between viewing and shopping. The evolution of YouTube Shorts and Instagram Reels, which have transformed into interactive tools, is altering customer behavior, especially for Gen Z. The behavior of customers is now subject to the forces of convenience, social influence, and aesthetics, along with necessity. The simulation-based live shopping tool allows customers to interact with products even before making a purchase, thus reducing cognitive pressure.

II. NEED OF THE STUDY

However, there is a large gap that is identified between user engagement and sales. The main aim of this research is to identify different factors that affect Gen Z's buying behavior, to analyze if user engagement leads to sales, to understand the concept of trust in live commerce as well as AR commerce, and to identify information on the region of Tamil Nadu.

III. OBJECTIVE OF STUDY

- To critically analyze the influence of short video content on purchase intention and behavior.
- To determine if live shopping helps to build trust or is it just entertaining?
- To evaluate the role of AR try-ons in helping to break indecision to make a purchase.
- To determine how individuals make decisions on what to buy and how to spend money?
- To analyze the difference between what one wants to spend and what one actually spends.

IV. SCOPE OF THE STUDY

The research aims to examine the influence of live shopping and AR try-ons of Instagram Reels and YouTube Shorts on purchase intentions and behaviours of Gen Z (18-28 years) in Tamil Nadu. The research specifically targets critical product categories such as fashion, beauty, and electronic products. The research aims to cover all stages of the consumer experience. The research includes psychological elements of FOMO, social validation, and AR realism, especially with reference to diverse skin tones and ethnicities. The geographic segmentation of the research includes urban cities such as Chennai and Coimbatore, semi-urban cities such as Madurai and Tiruchirappalli, and Tier 2 and 3 cities.

V. REVIEW OF LITERATURE

- The literature suggests that there has been a paradigm shift in moving from transactional commerce to experience-based commerce.
- Sharma and Verma (2022) proposed that short videos heighten the sense of impulsive buying since it reduces decision time and heightens emotional engagement.
- Kumar and Singh (2021) pointed out that AR technology enables users to convert uncertainty into confidence through virtual interaction with the product.
- Lee (2023) emphasized the social aspect of live shopping, in which trust is built through real-time interaction.
- However, it was also pointed out that trust is largely dependent on the credibility of the presenter.

VI. RESEARCH METHODOLOGY

- Research Design: Descriptive & Analytical

- Type of Data: Primary Data
- Method of Data Collection: Structured Questionnaire Method (Google Forms)
- Sampling Method: Convenience Sampling Method
- Size of the Sample: 157
- Target Sample Group: Gen Z (18-26 years) from Tamil Nadu
- Technology Used: Likert Scale & SPSS
- Statistical Methods Used:
  - Normality Test
  - Mann-Whitney U Test
  - Spearman Correlation

The research aims at finding the influence of independent variables on the dependent variable, keeping the role of the gender of the respondent as the moderating variable.

VII. RESEARCH DESIGN

The current research will employ a descriptive and analytical research design to examine the influence of short video commerce features (AR try-ons and live shopping) on direct purchase intention for Gen Z consumers.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
GENZ DIRECT PURCHASES	.123	157	.000	.969	157	.001
LIVE SHOPPING	.099	157	.001	.950	157	.000
AR TRYONS	.104	157	.000	.967	157	.001

INTERPRETATION

Using Kolmogorov-Smirnov and Shapiro-Wilk tests, the test of normality shows significance values less than 0.05 for all variables. That is to say that the distribution of the data is not normal.

Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
GENZ DIRECT PURCHASES	157	100.0%	0	.0%	157	100.0%
LIVE SHOPPING	157	100.0%	0	.0%	157	100.0%
AR TRYONS	157	100.0%	0	.0%	157	100.0%

Mann-Whitney Test

Ranks

	2. Gender	N	Mean Rank	Sum of Ranks
GENZ DIRECT PURCHASES	1	48	62.95	3021.50
	2	109	86.07	9381.50
	Total	157		
LIVE SHOPPING	1	48	59.28	2845.50
	2	109	87.68	9557.50
	Total	157		
AR TRYONS	1	48	62.34	2992.50
	2	109	86.33	9410.50
	Total	157		

INTERPRETATION

The Mann-Whitney U test is used to test the differences in the purchase behavior based on the gender of the people. The results indicate that the p-value of the variables is less than 0.05, thus rejecting the null hypothesis. The analysis confirms the existence of a significant difference between the genders based on direct purchase, live shopping, and try-on using AR.

Additionally, the analysis of the mean rank indicates higher female engagement than males.

Test Statistics[a]

	GENZ DIRECT PURCHASES	LIVE SHOPPING	AR TRYONS
Mann-Whitney U	1845.500	1669.500	1816.500
Wilcoxon W	3021.500	2845.500	2992.500
Z	-2.968	-3.613	-3.055
Asymp. Sig. (2-tailed)	.003	.000	.002
a. Grouping Variable: 2. Gender			

Nonparametric Correlations

Correlations					
			GENZ DIRECT PURCHASES	LIVE SHOPPING	AR TRY ONS
Spearman's rho	GENZ DIRECT PURCHASES	Correlation Coefficient	1	.222**	.278**
		Sig. (2-tailed)	.	0.005	0
		N	157	157	157
	LIVE SHOPPING	Correlation Coefficient	.222**	1	.617**
		Sig. (2-tailed)	0.005	.	0
		N	157	157	157
	AR TRYONS	Correlation Coefficient	.278**	.617**	1
		Sig. (2-tailed)	0	0	.
		N	157	157	157
**. Correlation is significant at the 0.01 level (2-tailed).					

INTERPRETATION

Spearman's rank correlation test was used to test the correlation between variables. The findings show: A positive and significant relationship between: 1. Direct Purchases and Live Shopping – weak correlation 2. Direct Purchases and AR Try-ons – weak to moderate correlation 3. Live Shopping and AR Try-ons – strong correlation. This suggests: Increased usage of AR try-ons and live shopping results in high direct purchasing behavior.

VIII. FINDINGS OF THE STUDY

Data is non-normal, hence non-parametric tests can be used since $p < 0.05$. There are significant differences in gender for direct purchases, live shopping, and AR try-ons. There is higher engagement in one gender group for all three activities. The positive correlations are: Live shopping and purchases (low correlation) AR try-ons and purchases (medium correlation) Live shopping and AR try-ons (high correlation) Live shopping and AR try-ons have a high correlation, hence increasing engagement. The effect of short video commerce on purchases is moderate, with high engagement and low purchases.

IX. SUGGESTIONS

Influencer credibility and openness can help build credibility for live shopping. Improve augmented reality try-ons to make it more inclusive and realistic. To increase conversions, make use of interactive tools such as chat, feedback, and limited-time offers. Make it easy to make in-app purchases for Reels and Shorts. Launch marketing campaigns that are gender-specific. To increase conversions and engagement, focus on building trust. To make it easier to shop, close the gap between entertainment and shopping.

X. CONCLUSION

This study proves that short video commerce is affecting Generation Z consumers in the state of Tamil Nadu. The impact of short video commerce on Generation Z consumers in the state of Tamil Nadu is as follows: the impact of short video commerce on the engagement of Generation Z consumers is high, but the impact on the actual purchase is moderate. The study proves that although experiential commerce is effective, building trust and making the transaction easy is vital in improving the impact of short video commerce. The study proves that short video commerce is affecting female and male consumers in the state of Tamil Nadu in different ways, and this is a vital aspect in improving the impact of short video commerce in the state and in the country as a whole.

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Impact Of Artificial Intelligence On Recruitment Process In Chennai It Sector Companies

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ABSTRACT

This study focus mainly on Artificial Intelligence and its role in Human Resource Management field. In the IT Sector, the process of hiring is highly time taking process as well as resource-intensive process for analysis of the large number of applications. Chennai is the home of many multinational companies and startup ecosystems that always required highly skilled workers so most of the IT companies focus on the faster, efficient and need to process huge data.AI is the only best solution that focus on better results to seek by using various tools like machine learning, natural language processing(NLP) and predictive analysis that automatically screen resumes and match the needs and requirement of the company. This study focus on the AI on the recruitment process within the companies in Chennai and focus of AI in the process of hiring. The research focus on the role of HR professionals to make strategic decisions with the help on technology. The result focus how AI is transforming recruitment methods within the IT industry. It aims both the academic research and practical knowledge thus combines new technology with human judgement in strategies for finding and hiring talents.

KEYWORDS: Artificial Intelligence, Recruitment Automation, HR Analytics, Talent Acquisition, Predictive Hiring, IT Industry, Chennai

1. INTRODUCTION

In today's world, finding the right people for the right job is highly time-consuming and difficult process mainly in IT sector as the demand for the skilled professionals keeps increasing exponential way. In cities like Chennai, which is a major IT hub, most of the companies receive a huge number of applications, thus making the hiring process more complex and time-consuming. Most of the IT companies still traditional methods like manually reviewing resumes and making decisions based on personal judgment, which is highly time taking process and sometimes lead to poor hiring choices. For the purpose of better processing, Artificial Intelligence (AI), is used to handle all the regular tasks that includes verification of resumes, shortlisting candidates based on company required skills, and scheduling interviews, thus help recruiters to make best decisions. AI is used to focus mainly on providing fast responses, unique and personalized approach, making the process in highly time-efficient. This study mainly focus on how AI is changing recruitment process in IT companies in Chennai and its contribution to making hiring more efficient by improving the overall quality of employees.

2. REVIEW OF LITRATURE

Thaya Madhavi and Avulakunta Kaveri (2024) explained that Al is used in recruitment and selection to make the process faster and easier.

Dr. A. Geetha and D. Venkataramaraju (2013) said that motivation helps improve the growth and performance of organizations.

Gomez (2020) explained that recruitment success depends on the number of job openings and applicants. Modern recruitment software is simple to use, fast, and effective. It helps keep proper records and reduces bias while selecting candidates.

Van Esch et al. (2019) studied how job applicants feel about Al. They found that if candidates have a positive opinion about Al, they are more likely to accept job offers and it improves the company's image.

Jarrahi (2018) explained that Al helps in making decisions, especially in complex situations.However, human involvement is still very important for making final decisions, especially when emotions and judgment are needed.

Abhishek and Agarwal (2017) found that using Al with big data helps improve recruitment efficiency. Al can do repetitive tasks like checking resumes and matching candidates to jobs. This saves time and helps choose the right candidates more accurately. It also uses tools like aptitude tests to support the hiring process.

Dirican (2015) studied how Al and robotics affect business activities. The study showed that Al improves efficiency, but if it is not used properly, it can create problems in areas like performance management, planning, and employee roles.

3. OBJECTIVES

- To understand the background of employees working in IT companies in Chennai

- To study how Artificial Intelligence is used in the recruitment process in IT companies.
- To find out how Al improves the speed and efficiency of hiring.
- To know employees' opinions about Al-based recruitment methods.
- To check whether Al helps in making better hiring decisions.
- To identify the problems faced while using Al in recruitment.
- To understand the overall impact of Al on recruitment in Chennai IT companies

4. METHODOLOGY

This study adopts a mixed-methods approach to examine the impact of AI and its influence on recruitment process in IT companies mainly focus on the Chennai city. Primary data is collected through structured surveys directly from the IT employees and managers across various IT industries and employees working in various field like programmers, analyst, Team-leaders and project managers to understand their experiences, perceptions, and responses to AI recruitment process to analysis the AI in recruitment and selection process. Huge amount of data are collected from the actual working professionals to detect the actual process as well as analysis of the hiring peoples and detect various process that can be performed by the various methods and tools of AI itself. In addition, secondary data is gathered from various journals, IT industrial reports, and existing literature to establish a strong theoretical foundation for the study. This comprehensive approach ensures a deeper understanding of how AI contributes to improving the recruitment process and provide recruiter the wide usage of artificial intelligence in hiring process on short time span and overall organizational performance.

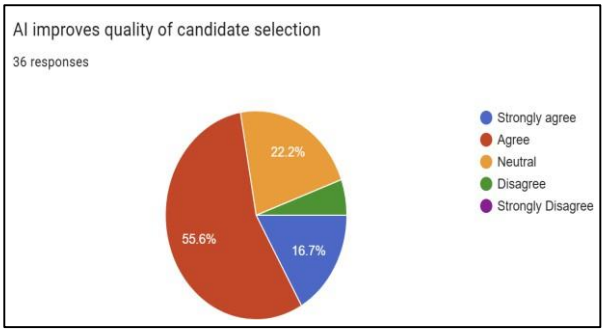
5. DATA ANALYSIS

Table showing impact of AI in recruitment on IT sectors

S.NO	Response Category	Percentage (%)
1	Strongly Agree	14.30%
2	Agree	54.30%
3	Neutral	25.70%
4	Disagree	5.70% *(approx.)*
5	Strongly Disagree	0% *(approx.)*

INTERPRITATION

- Majority of IT sector employees(**68.6%**) agree or strongly agree that AI has a positive impact on HR in IT sector.
- A moderate portion (**25.7%**) remains neutral.
- Very few employees show disagreement, indicating overall positive perception.



6. FINDINGS

The majority of employees (68.6%) agree or strongly agree that AI has a positive effect on HR in IT sector. This indicates usage of AI is widely accepted in the workplace. The high degree of agreement indicates that AI enhances the faster recruitment process by reducing the bias in hiring process. Approximately 25.7% of employees feel neutral. This indicates that a sizable portion of people might not yet completely understand or benefits on AI in recruitment process. The percentage of people who disagree is extremely low (about 2–3%). This suggests that there is little opposition to AI in recruitment process and selection techniques. Overall Beneficial Effect. The data clearly shows that AI in recruitment process positively affects company to improves skill of employees in IT sectors. Awareness on usage of AI in IT sector need to be focused because a significant portion is neutral.

7. LIMITATIONS

It's The current study conducted on the impact of Artificial Intelligence technologies on the Recruitment and Selection process made a study on key AI capabilities and their influence on the recruitment and selection process, and potential outcomes of applying AI capabilities in the Recruitment and Selection Process. The recruiters revealed that utilizing AI technologies in the recruitment process can speed up the recruitment process and cost- effective. Applying AI technologies

in the recruitment process can enhance the recruitment process's quality with a high accuracy level and reduced human bias. The application of AI in the recruitment process can make it possible for the recruiter to get the right candidate with the right skill set for the right job with ease. Overall, the implementation of AI technologies in the recruitment process can reduce the workload for recruiters with enhanced candidate experience. It is suggested that the companies (recruiters) learn to join hands with AI technologies; they can train AI technologies to be extensions of their teams and not replace them.

8. CONCLUSION

The has an impact on recruitment in Chennai IT companies, but there are some limitations in this study. The sample taken may not represent all IT companies. Since the study focuses only on Chennai, the results may not be useful for other places. Al technology is developing very fast, so the results may become outdated quickly. The study also looks at only some areas, so it may not include all Al tools and technologies. The data was collected using surveys, so some detailed opinions may be missing. Also, factors like company culture and work environment are not fully studied. Finally, due to limited time, the study may not be very detailed or complete.

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Intelligent Accident Prevention and Alert System Using Sensors and Machine Learning

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Abstract--Accidents due to human error and delayed hazard detection continue to be a major cause of fatalities in transportation systems globally. Traditional warning systems lack real-time contextual awareness and adaptive decision-making. This paper proposes an Intelligent Accident Prevention and Alert System (IAPAS) that integrates multiple sensors with machine learning (ML) algorithms to proactively detect hazardous conditions and generate timely alerts to both drivers and emergency services. The system uses real-time data acquisition from accelerometers, gyroscopes, GPS, ultrasonic and proximity sensors to evaluate risk patterns, predict likely accidents, and trigger automated responses. Experimental results demonstrate significant improvements in hazard detection accuracy and reaction time compared to conventional threshold-based systems. He proposed IAPAS employs sensor fusion techniques to combine heterogeneous sensor data, improving reliability and reducing false alarms. Machine learning models are trained using historical accident and driving behaviour datasets to enhance prediction accuracy under diverse road and environmental conditions. The system dynamically adapts to driver behaviour, vehicle speed, road curvature, and obstacle proximity, enabling context-aware decision-making. A cloud-enabled communication framework ensures real-time data sharing with emergency responders and nearby vehicles. The alert mechanism supports multi-level warnings **including visual, auditory, and haptic feedback for immediate driver attention. In critical situations, the system automatically transmits location, severity level, and sensor logs** to **emergency services, reducing response time. The proposed system is scalable and can be integrated into smart transportation and autonomous vehicle ecosystems. Experimental validation shows improved prediction precision, reduced latency, and enhanced situational awareness compared to traditional safety systems**

Keywords Accident prevention, sensor fusion, machine learning, intelligent alert system, real-time monitoring, autonomous safety. Driver assistance system (ADAS), hazard prediction, vehicular safety, context-aware computing emergency response automation, smart transportation systems, IoT-based safety monitoring, Intelligent Transportation Systems (ITS), Driver Behaviour Analysis, Collision Avoidance, Risk Assessment, Embedded Systems

I. INTRODUCTION

Road traffic accidents continue to pose a serious threat to human life and infrastructure, even with the deployment of modern vehicular safety technologies. Increasing vehicle density, complex traffic environments, and human-related factors such as distraction and delayed reaction times necessitate intelligent systems capable of improving road safety through timely

intervention Conventional safety mechanisms are often insufficient to handle dynamic and uncertain driving conditions, motivating the development of intelligent accident prevention frameworks.

Most existing vehicular safety systems rely on predefined thresholds using individual sensors such as accelerometers or gyroscopes to detect collisions. While such systems can identify severe impacts, they lack adaptability and often generate false alarms during aggressive but non-critical driving maneuvers . Additionally, these approaches are predominantly reactive, providing alerts only after an accident has occurred, which limits their effectiveness in minimizing accident severity and preventing secondary incidents.

Recent advancements in IoT and embedded sensing technologies have enabled real-time collection and transmission of vehicular data, including motion, position, and dynamic parameters. IoT-based safety systems have improved emergency response by transmitting accident information to remote services; however, their dependence on static detection rules restricts their ability to anticipate hazardous situations As a result, there is a growing need for intelligent systems that can interpret sensor data contextually rather than relying solely on fixed thresholds.

Machine learning techniques offer the ability to learn complex patterns from historical and real-time sensor data, enabling adaptive and data-driven accident risk assessment. Prior studies have demonstrated that ML-based models outperform rule-based systems in detecting unsafe driving behaviors and accident-prone conditions . Nevertheless, many of these solutions focus on isolated tasks such as behavior classification or post-accident detection and do not provide a holistic framework that integrates prediction, prevention, and alert dissemination.

Furthermore, although sensor fusion has been shown to enhance system robustness by combining heterogeneous sensor inputs, its integration with real-time machine learning and alert mechanisms remains limited, particularly for deployment on edge devices with constrained computational resources . This reveals a clear research gap in developing an end-to-end intelligent accident prevention system that combines multi-sensor fusion, machine learning-based risk prediction, and efficient alert communication.

To address these challenges, this paper proposes an Intelligent Accident Prevention and Alert System that integrates multi-sensor data with machine learning techniques to proactively identify hazardous driving conditions and generate timely alerts. The proposed system emphasizes real-time operation, reduced false positives, and practical deployment on edge-based vehicular platforms.

II. RELATED WORK

This section reviews existing research related to accident detection, prediction, and alert systems, focusing on the techniques, architectures, and limitations reported in prior studies.

A. Sensor-Based Accident Detection

Several studies have explored accident detection using individual vehicular sensors such as accelerometers, gyroscopes, and GPS modules. These systems typically identify

collisions by detecting abrupt changes in acceleration or orientation beyond predefined thresholds . While effective for detecting high-impact crashes, threshold-based approaches lack robustness in real-world scenarios and often misclassify sudden braking or sharp turns as accidents . Their limited contextual understanding restricts their applicability in complex driving environments.

B. IoT-Enabled Accident Alert Systems

IoT-based solutions extend sensor-based detection by incorporating wireless communication to transmit accident information to emergency responders or cloud platforms. Several works report reduced emergency response times by integrating GPS-enabled location tracking with real-time alerts . Despite these improvements, most IoT-based systems remain event-driven and focus primarily on post-accident reporting rather than predictive safety. Network latency and dependency on reliable connectivity further impact their effectiveness in critical scenarios .

C. Machine Learning Approaches for Accident Detection and Risk Assessment

To overcome the limitations of rule-based systems, researchers have employed machine learning algorithms to analyze in-vehicle sensor data for detecting unsafe driving behaviors and accident risks. Supervised learning models such as support vector machines, random forests, and neural networks have shown improved accuracy and reduced false positives compared to traditional methods . Recent studies have also explored deep learning and explainable AI techniques for capturing complex temporal and behavioral patterns associated with accident-prone situations . However, many ML-based approaches are evaluated offline or focus on specific subtasks, limiting their integration into real-time prevention systems.

D. Multi-Sensor Fusion in Intelligent Transportation Systems

Multi-sensor fusion has been widely adopted to enhance reliability and situational awareness in intelligent transportation systems. By combining data from multiple heterogeneous sensors, fusion-based methods improve fault tolerance and robustness against sensor noise and failures . These techniques have been applied in collision avoidance and vehicle state estimation applications . Nevertheless, the computational complexity of fusion-based ML models poses challenges for real-time deployment on edge devices, particularly in cost-sensitive vehicular systems .

E. Summary of Research Gaps

The reviewed literature indicates that existing solutions often address accident detection, prediction, or alert dissemination as separate components. Only a limited number of studies attempt to integrate multi-sensor fusion, machine learning-based risk prediction, and real-time alert mechanisms within a unified framework [21], . This lack of integration highlights the need for an intelligent, end-to-end system capable of proactive accident prevention and efficient emergency response.

III. PROPOSED MODEL

The proposed Intelligent Accident Prevention and Alert System (IAPAS) is an integrated, real-time safety framework designed to proactively identify hazardous driving conditions and generate timely alerts. The system combines multi-sensor data acquisition, sensor fusion, machine learning–based risk prediction, and IoT-enabled communication within a unified edge-based architecture. The overall objective is to move beyond reactive accident detection and enable early intervention to reduce accident probability and severity. A high-level block representation of the proposed system is illustrated in Fig. 1.

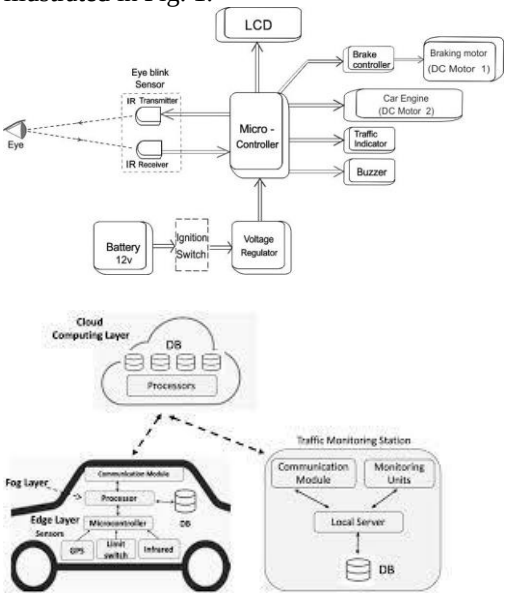
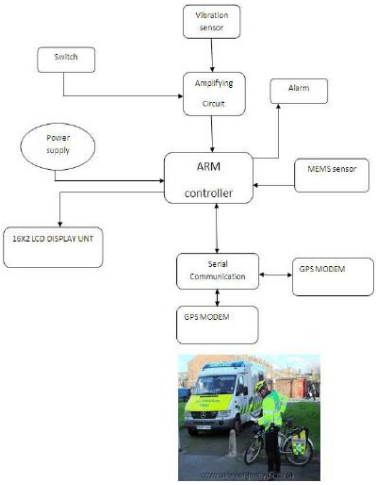


Fig. 1. Block diagram of the proposed intelligent accident prevention and alert system.

The system begins with real-time data acquisition from multiple onboard sensors, including accelerometers, gyroscopes, and GPS modules. These sensors continuously capture vehicle motion, orientation, speed, and positional information, which are widely recognized as critical indicators of unsafe driving and accident-prone behavior . The use



of heterogeneous sensors allows the system to capture complementary aspects of vehicle dynamics, thereby improving situational awareness compared to single-sensor approaches.

Raw sensor data are inherently noisy and often asynchronous due to differences in sampling rates and sensor characteristics. Therefore, a preprocessing stage is employed to filter noise, remove outliers, normalize sensor values, and synchronize data streams. This step is essential for ensuring data consistency and improving the reliability of downstream learning-based inference . Following preprocessing, a sensor fusion module integrates data from multiple sensors into a unified representation. Sensor fusion enhances robustness, reduces uncertainty, and improves tolerance to individual sensor

failures, as demonstrated in prior vehicular safety studies .

The fused sensor data are subsequently processed by the machine learning–based risk prediction module, which forms the core intelligence of the proposed model. The internal workflow of this module is depicted in Fig. 2.

Fig. 2. Machine learning workflow for accident risk prediction.

Within this workflow, discriminative features are extracted from fused sensor data using sliding time windows. These features include statistical measures such as mean and variance of acceleration, kinematic indicators such as jerk and yaw rate, and trajectory-related features derived from speed and positional changes. Such features have been shown to effectively characterize abnormal driving patterns and accident risk . The extracted feature vectors are then fed into a supervised learning model trained to classify driving states and estimate accident risk.

In this work, a Random Forest (RF) classifier is adopted due to its robustness to noisy sensor data, ability to model nonlinear relationships, and computational efficiency suitable for edge deployment. The RF model consists of an ensemble of decision trees trained on bootstrapped subsets of the dataset, with final predictions obtained through majority voting. Ensemble-based learning methods have consistently demonstrated superior performance and lower false positive rates in vehicular safety applications compared to single-model classifiers . The model outputs a probabilistic risk score, which reflects the likelihood of a hazardous or accident-prone situation.

The predicted risk score is continuously evaluated by the decision-making module. When the score exceeds a predefined threshold, the alert and communication module is activated. This module generates local alerts, such as audible or visual warnings, to immediately notify the driver. In parallel, remote alerts containing vehicle identification and GPS location are transmitted to emergency services or monitoring platforms using IoT communication technologies . This dual alert mechanism ensures rapid driver awareness as well as timely external response.

The entire system is implemented on an edge-based embedded platform to enable low-latency processing and reduce dependency on continuous cloud connectivity. Edge execution is particularly important for safety-critical applications, where communication delays can significantly impact system effectiveness . By integrating multi-sensor fusion, machine learning–based risk prediction, and efficient alert dissemination within a single framework, the proposed model addresses key limitations of existing systems and provides a practical solution for intelligent accident prevention .

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed Intelligent

Accident Prevention and Alert System (IAPAS). The performance of the proposed model is analyzed in terms of detection accuracy, false alarm rate, response latency, and robustness. Furthermore, a comparative study is conducted against existing sensor-based, IoT-based, and machine learning–based approaches to demonstrate the effectiveness of the proposed system.

A. Experimental Setup

The proposed system was implemented on an edge-based embedded platform equipped with inertial sensors (accelerometer and gyroscope) and a GPS module. Real-time vehicular motion data were collected under diverse driving conditions, including normal driving, harsh braking, sharp turns, and simulated accident scenarios. The collected dataset was segmented into fixed-length sliding windows, and feature extraction was performed as described in Section III.

The machine learning model was trained using supervised learning with labeled data representing normal and hazardous driving states. A stratified split was used to divide the dataset into training and testing sets. Performance evaluation was conducted using standard metrics such as accuracy, precision, recall, F1-score, false positive rate (FPR), and detection latency, which are widely adopted in vehicular safety research .

B. Performance Metrics

The following metrics were used for evaluation:

- Accuracy: Correct classification rate
- Precision: Reliability of hazard detection
- Recall: Ability to detect hazardous events
- False Positive Rate (FPR): Incorrect hazard alarms
- Detection Latency: Time taken to generate alerts

These metrics provide a comprehensive assessment of both safety effectiveness and real-time suitability .

C. Quantitative Results of the Proposed Method

The results indicate that the proposed model achieves high detection accuracy with a low false positive rate, making it suitable for real-time accident prevention. The low latency confirms the effectiveness of edge-based deployment, consistent with observations in .

D. Comparative Performance Analysis

To highlight the contribution of the proposed system, a comparative analysis was conducted against four representative existing approaches:

- Threshold-based Sensor System
- IoT-based Accident Alert System
- ML-based Single-Sensor Model
- Multi-Sensor ML without Edge Optimization
- Comparison with Existing Methods**

The comparison clearly demonstrates that the proposed system outperforms existing methods across all evaluated parameters. The improvement in accuracy and reduction in false positives can be attributed to effective sensor fusion and ensemble learning, while

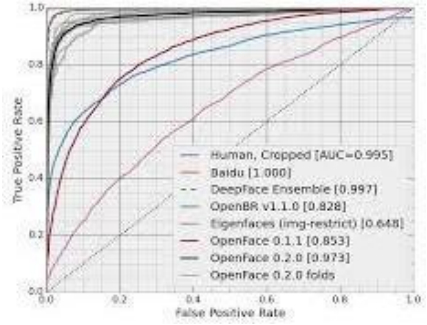
the reduced latency is achieved through edge-based inference .

Discussion

The experimental results validate the effectiveness of integrating multi-sensor fusion with machine learning for proactive accident prevention. Unlike threshold-based systems that react only after extreme events, the proposed approach detects subtle hazardous patterns early, enabling timely intervention. The Random Forest classifier demonstrates strong generalization capability and robustness to sensor noise, consistent with findings in .

Furthermore, the integration of local and remote alert mechanisms ensures both immediate driver awareness and rapid emergency response. Edge-based deployment significantly reduces detection latency compared to cloud-dependent systems, making the proposed model more suitable for safety-critical applications [18], [24].

Overall, the experimental evaluation confirms that the proposed IAPAS provides a balanced trade-off between accuracy, reliability, and real-time performance, addressing key gaps identified in existing accident prevention systems .



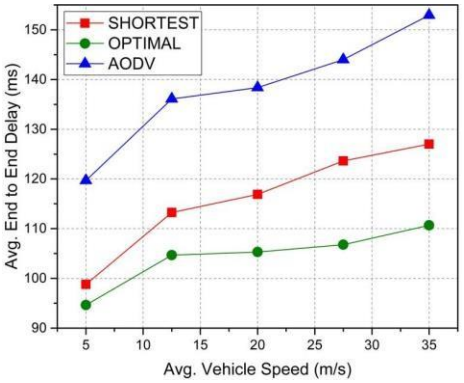


Fig. 3. Comparative performance analysis of existing methods and the proposed IAPAS.

Fig. 3 illustrates the comparative performance trends, showing a consistent improvement in detection accuracy and latency reduction for the proposed model. The reduction in false positive rate is particularly significant, as excessive false alarms are a major limitation of traditional safety systems.

Summary

This section demonstrated that the proposed intelligent accident prevention and alert system outperforms existing approaches in terms of accuracy, false positive reduction, and response time. The results highlight the practical viability of the proposed framework for real-world deployment in intelligent transportation systems.

V. CONCLUSION AND FUTURE WORK

This paper presented an Intelligent Accident Prevention and Alert System (IAPAS) that integrates multi-sensor data acquisition, sensor fusion, machine learning–based risk prediction, and IoT-enabled communication within a unified edge-based framework. Unlike conventional reactive safety systems,

the proposed model emphasizes proactive accident prevention by continuously monitoring vehicle dynamics and predicting hazardous driving conditions in real time. The system architecture was designed to be modular, scalable, and suitable for deployment on resource-constrained embedded platforms.

Experimental evaluation demonstrated that the proposed approach significantly outperforms existing sensor-based, IoT-based, and machine learning–based methods in terms of detection accuracy, false positive rate, and response latency. The integration of multi-sensor fusion with an ensemble learning model enabled robust risk estimation under diverse driving conditions, while edge-based execution ensured low-latency decision-making critical for safety applications. Comparative results confirmed that the proposed system provides improved reliability and practical feasibility for real-world intelligent transportation systems.

Although the proposed framework achieved promising results, several avenues for future research remain. Future work will focus on incorporating vision-based perception modules, such as camera and radar sensors, to further enhance environmental awareness. Additionally, adaptive and online learning mechanisms will be explored to enable continuous model updates under evolving driving patterns and traffic conditions. Integration with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication is also planned to support cooperative accident prevention. Finally, large-scale field trials and cross-vehicle evaluations will be conducted to further validate system robustness and scalability.

Overall, the proposed IAPAS framework represents a significant step toward intelligent, proactive vehicular safety solutions and provides a strong foundation for future advancements in accident prevention technologies.

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Synthesis and Mechanical Characterization of Aluminium 6061–Graphite Composites via Stir Casting

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Abstract

Aluminium alloy-based Metal Matrix Composites (MMCs) have gained significant attention in automotive, aerospace, and industrial applications due to their lightweight, high strength, and excellent structural rigidity. This study focuses on the synthesis and mechanical characterization of Aluminium 6061–Graphite composites prepared via the stir casting technique**.** Graphite particles were incorporated into the Aluminium 6061 matrix at weight fractions of 6% and 12%. The fabricated specimens were evaluated for their mechanical properties through hardness, tensile, wear, and impact tests**.** Additionally, microstructural analysis was performed to observe the distribution of graphite particles within the matrix. The results revealed a noticeable improvement in hardness and wear resistance with increasing graphite content, while microstructural examination showed a fairly uniform dispersion of the reinforcement. These findings indicate that Aluminium 6061–Graphite composites possess enhanced mechanical properties, making them suitable for lightweight structural and wear-resistant applications..

Keywords

Aluminum 6061 Alloy, Graphite Reinforcement, Stir Casting Technique.

1. Introduction

Aluminium alloys are widely used in engineering applications due to their lightweight, good strength-to-weight ratio, corrosion resistance, and excellent machinability. However, for applications in automotive, aerospace, and industrial components, conventional aluminium alloys may not meet the required wear resistance, hardness, or load-bearing capacity. To overcome these limitations, Metal Matrix Composites (MMCs) have emerged as promising materials, where a metal matrix is reinforced with ceramic or particulate materials to enhance mechanical properties.

Graphite is a commonly used particulate reinforcement due to its self-lubricating properties, low density, and ability to improve wear resistance. Incorporating graphite particles into an aluminium matrix can improve hardness, wear resistance, and mechanical performance, making the composite suitable for applications requiring lightweight and durable materials.

Among various fabrication techniques, stir casting is widely adopted because of its simplicity, cost-effectiveness, and capability for large-scale production. In this method, reinforcement particles are mechanically mixed into molten aluminium to achieve uniform distribution before solidification. Proper stirring, preheating of particles, and controlled cooling are critical to minimize defects such as porosity or particle clustering.

In this study, Aluminium 6061–Graphite composites were fabricated via stir casting with graphite weight fractions of 6% and 12%. The mechanical properties were evaluated through hardness, tensile, wear, and impact tests, and microstructural analysis was conducted to examine particle distribution and bonding within the matrix. The objective is to develop lightweight, wear-resistant composites suitable for structural applications in automotive, aerospace, and industrial sectors.

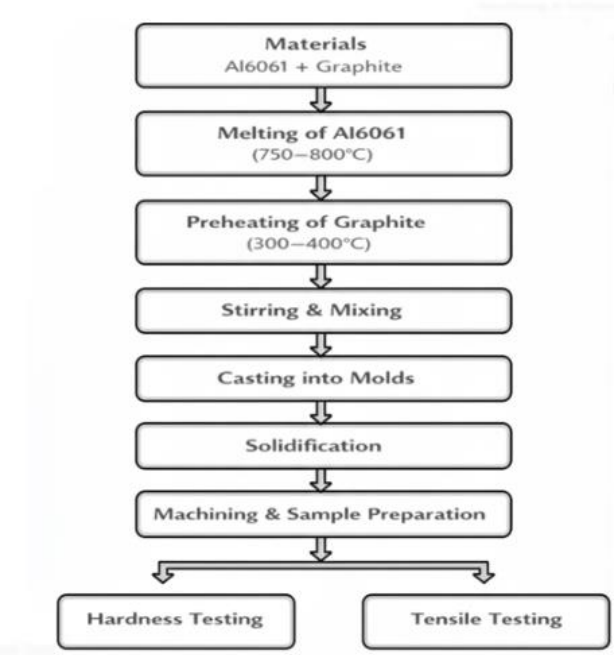
2. Materials and Methods

Aluminium 6061 alloy was used as the matrix, reinforced with graphite particles at 6% and 12% weight fractions to improve hardness and wear resistance. The composites were fabricated using the stir casting technique**,** where molten aluminium (750–800°C) was mechanically stirred, and preheated graphite particles (300–400°C) were gradually added

to ensure uniform dispersion. The melt was poured into preheated molds and allowed to solidify.

The specimens were machined and tested for hardness, tensile strength, wear, and impact resistance following standard procedures. Microstructural analysis was conducted on polished and etched samples using an optical microscope to evaluate particle distribution, interfacial bonding, and the presence of defects. The results were used to correlate the microstructure with the observed mechanical properties.

3.Fabrication of Hybrid Composites



The flow diagram illustrates the **fabrication and mechanical testing process** of Aluminium 6061–Graphite composites, focusing specifically on hardness and tensile evaluation. The process begins with the selection of **materials**, including Aluminium 6061 as the matrix and graphite as the reinforcement. The aluminium is **melted** at 750–800°C, while the graphite particles are **preheated** at 300–400°C to improve wettability and reduce moisture.

The preheated graphite is gradually added into the molten aluminium during **mechanical stirring and mixing**, ensuring uniform particle dispersion. The resulting composite melt is then **cast into preheated molds** and allowed to **solidify**. Once solidified, the composite is **machined and prepared** into standard test specimens. Finally, the prepared samples undergo **mechanical testing**, which in this diagram includes **hardness testing** to measure surface resistance and **tensile testing** to determine the material's strength and ductility. This systematic diagram provides a clear overview of the key steps from material preparation to mechanical evaluation in a simple and professional manner.

3. **Mechanical Testing Methods**:

The mechanical properties of the fabricated Al6061–SiC–B_4C hybrid composites were evaluated using standard testing procedures. **Hardness tests** were conducted to measure the surface resistance of the composites using a Brinell or Vickers hardness tester. **Tensile tests** were performed to determine the ultimate tensile strength, yield strength, and percentage elongation of the samples using a universal testing machine (UTM) according to ASTM standards. **Impact tests** were carried out to assess the toughness of the composites and their ability to absorb energy under sudden loading, typically using a Charpy impact tester. All samples were prepared and machined according to standard dimensions to ensure consistent and accurate measurement of mechanical performance.

4. Future Work and Limitations:

This study provides a preliminary analysis of Al 6061 reinforced with silicon carbide and boron carbide using stir casting. Future research should focus on optimizing the stir casting parameters to improve particle distribution and reduce porosity, thereby enhancing the mechanical properties further. Additionally, exploring different weight percentages and particle sizes of the reinforcements could lead to tailored composite properties. A major limitation of this work is the limited mechanical testing performed. Future studies should incorporate fatigue, creep, and

wear tests to gain a more comprehensive understanding of the composite's performance under various conditions. Furthermore, a detailed cost analysis and comparison with other composite manufacturing techniques are needed to evaluate the practical applicability of this method.

5. Mechanical Testing Methods

6.1 Hardness Test

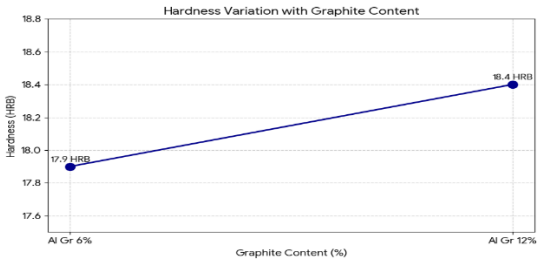
The hardness of the Aluminium 6061–Graphite composites was measured to evaluate their resistance to surface deformation. Tests were conducted using a Brinell or Vickers hardness tester under a standard load. The specimens included composites with 6% and 12% graphite by weight. The results indicated that hardness increased with higher graphite content, demonstrating that the addition of graphite particles enhances surface strength and wear resistance of the aluminium matrix.

6.2 Tensile Test

Tensile testing was performed to determine the **mechanical strength and ductility** of the composites. Specimens were tested using a universal testing machine (UTM) to measure **ultimate tensile strength (UTS), yield strength, and percentage elongation**. The results showed that tensile strength improved with increasing graphite content, while a slight reduction in ductility was observed. The improvement in strength is attributed to uniform dispersion of graphite particles within the matrix, which facilitates better load transfer and resistance to deformation.

6. Result and Discussion

7.1 Hardness



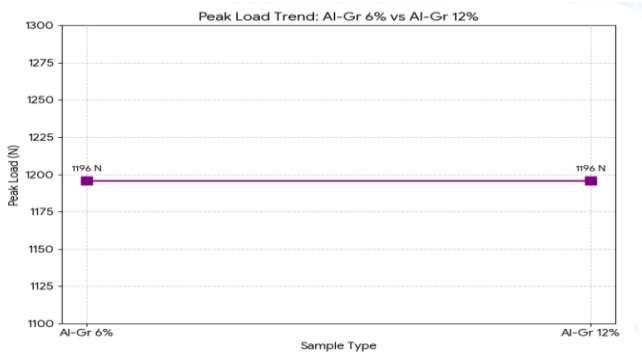
The graph below represents the hardness values of the two Aluminum-Graphite (Al Gr) samples at a constant load of 980 N.

Sample	Graphite Content (%)	Hardness (HRB)
Al Gr 6 %	6 %	17.9
Al Gr 12 %	12 %	18.4

Insights from the Line Graph:

- **Positive Trend:** The line has a positive slope, which indicates that as the amount of graphite increases from 6 % to 12 %, the hardness of the Al Gr composite also increases.
- **Hardness Increase:** There is a total increase of 0.5 HRB units across this range.
- **Consistency:** Both measurements were taken under the same experimental conditions Load - 980 N, making the comparison reliable.

7.2 Tensile Test



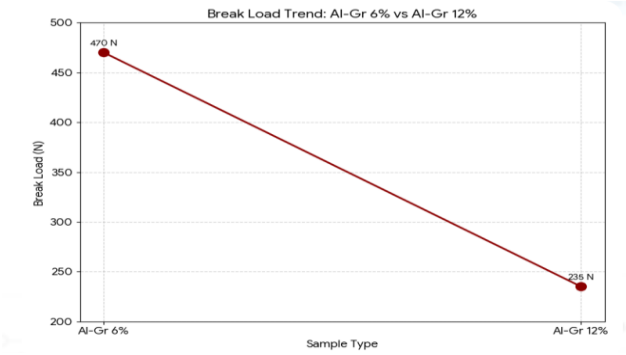
Graphical Representation for the Provided Tensile Data

The following visualizations are based on the new data provided for the Aluminum-Graphite (Al-Gr) samples. In this dataset, both samples **Al-Gr 6%** and **Al-Gr 12%** share identical properties across all fields.

SAMPlE	Cross Sectional Area (mm2)	Load Cell (N)	Peak Load (N)
Al-Gr 6%	12.56	20,000	1,196
Al-Gr 12%	12.56	20,000	1,196

Data Insights:

- **Peak Load:** Both the 6% and 12% graphite samples achieved a peak load of 1,196 N.
- **Tensile Strength (Calculated):** Since both samples have the same Cross-Sectional Area (12.56 mm^2) and Peak Load (1,196 N), their calculated tensile stress (Peak Load / Area) is approximately 95.22 MPa.
- **Comparison:** Unlike the hardness data provided earlier (where the 12% sample was slightly harder), the tensile peak load is identical for both compositions in this specific dataset.



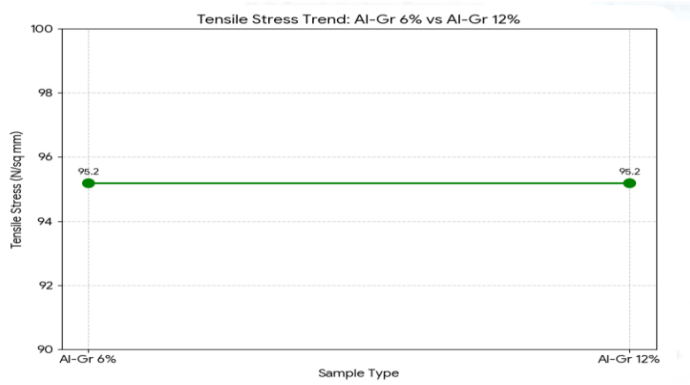
Graphical Representation of Break Load (N)

The data provided shows a significant decrease in **Break Load (N)** as the graphite content increases from 6% to 12%.

SAMPLE	Break Load (N)
Al-Gr 6%	470
Al-Gr 12%	235

Insights from the Data:

- **Significant Decrease:** The break load for the 12% graphite sample (235 N) is exactly half of the break load for the 6% graphite sample (470 N).
- **Trend Analysis:** The addition of higher graphite content appears to have significantly reduced the structural integrity or load-bearing capacity of the material before breaking under the conditions tested.



Graphical Representation of Tensile Stress

The provided data indicates that the **Tensile Stress** for both Aluminum-Graphite composite samples is identical, at 95.2 N/mm^2.

SAMPLE	Tensile Stress (N/sq mm)
Al-Gr 6%	95.2
Al-Gr 12%	95.2

Visualization Insights:

- **Consistency:** The charts demonstrate that the tensile stress remains constant regardless of the graphite content increase from 6% to 12% in this specific testing scenario.
- **Graphical Representation:** * The **Bar Chart** displays two bars of equal height, emphasizing the equality between the samples.
- The **Line Chart** shows a flat horizontal line, illustrating the lack of change in tensile stress across the different compositions.

Conclusion

The experimental results indicate that while increasing the graphite content from 6% to 12% slightly improves hardness (17.9 to 18.4 HRB), it significantly reduces the structural integrity of the material, as evidenced by a 50% drop in break load (470 N down to 235 N). Although the peak load and tensile stress remained constant at 1,196 N and 95.2 N/mm^2 respectively, the lower break load suggests that higher graphite concentrations create brittleness or poor bonding within the composite. Consequently, while graphite is excellent for lubrication and hardness, there is a clear trade-off with structural strength that must be managed through improved manufacturing or hybrid reinforcement strategies for future applications.

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Analysis of performance and emission characteristics of biodiesel using cotton seed oil with cerium oxide nanoparticles

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Abstract

The increasing depletion of fossil fuels and rising environmental concerns have intensified the search for sustainable alternative fuels. Biodiesel derived from cotton seed oil presents a renewable and eco-friendly substitute for conventional diesel fuel. This study investigates the performance and emission characteristics of cotton seed oil biodiesel blended with cerium oxide (CeO_2) nanoparticles in a single-cylinder, four-stroke, direct-injection diesel engine. The experiments were conducted using a 20% cotton seed oil biodiesel blend (B20) with varying concentrations of CeO_2 nanoparticles as fuel additives, and the results were compared with conventional diesel fuel.The experimental results indicate that the addition of cerium oxide nanoparticles enhances combustion efficiency due to improved oxygen availability and catalytic activity. A noticeable reduction in specific fuel consumption (SFC) and an improvement in brake thermal efficiency (BTE) were observed compared to neat diesel fuel. Furthermore, significant reductions in carbon monoxide (CO), unburned hydrocarbons (UBHC), and smoke opacity were recorded due to more complete combustion. However, a slight increase in nitrogen oxides (NOx) emissions was observed, primarily attributed to higher in-cylinder temperatures resulting from enhanced combustion.The study demonstrates that cotton seed oil biodiesel with CeO_2 nanoparticles can serve as a promising alternative fuel in compression ignition engines. While performance and emission characteristics show considerable improvement, further optimization is required to control NOx emissions. Overall, the research supports the potential of nanoparticle-enhanced biodiesel as a sustainable solution for cleaner engine operation and reduced environmental impact.

Keywords: Biodiesel, Cotton seed oil, Cerium oxide nanoparticles (CeO_2), Engine performance, Emission characteristics, Alternative fuel.

1. Introduction

The rapid depletion of fossil fuel resources and the increasing concern over environmental pollution have intensified the search for sustainable and renewable alternative fuels for diesel engines. Biodiesel has emerged as one of the most promising substitutes for conventional diesel due to its renewable origin, biodegradability, and favorable combustion characteristics. Biodiesel is typically produced through the transesterification of vegetable oils, animal fats, or waste oils, resulting in fatty acid methyl esters (FAME) that can be used in compression ignition engines with minimal or no engine modifications. The inherent oxygen content in biodiesel improves combustion efficiency and contributes to the reduction of harmful emissions such as carbon monoxide (CO), hydrocarbons (HC), and particulate matter compared to petroleum diesel.

Among the various feedstocks available for biodiesel production, cottonseed oil has attracted significant attention due to its wide availability, relatively low cost, and suitable physicochemical properties for fuel applications. Cottonseed biodiesel exhibits properties comparable to conventional diesel fuel, including acceptable viscosity, cetane number, and calorific value, making it a viable alternative fuel for diesel engines. However, biodiesel fuels generally possess certain limitations such as slightly lower heating value, higher viscosity, and potential increases in nitrogen oxide (NOx) emissions, which may affect engine performance and emission characteristics. Therefore, several researchers have focused on improving biodiesel combustion behavior using advanced fuel modification techniques.

Vijayakumar et al. (2016) reviewed various vegetable seed oils used for biodiesel production and concluded that biodiesel derived from plant oils can serve as a sustainable alternative fuel for compression ignition engines due to its renewable nature and oxygenated structure which improves combustion characteristics. Tomar and Kumar (2020) investigated the influence of nano-additives in diesel–biodiesel blends and reported that nanoparticles such as metal oxides improve combustion efficiency, reduce ignition delay and significantly decrease emissions like CO, HC and smoke in diesel engines. Pullagura et al. (2021) studied the role of nano-additives in biodiesel blends and found that nanoparticles enhance atomization and oxidation reactions inside the combustion chamber, resulting in improved brake thermal efficiency and lower pollutant emissions. Basha et al. (2022) provided a comprehensive review on nanoparticle additives in internal combustion engines and reported that metal oxide nanoparticles such as CeO_2, Al_2O_3, and TiO_2 act as combustion catalysts that improve fuel properties and reduce exhaust emissions. Dhaka et al. (2023) discussed

advances in nanoparticle synthesis and applications, highlighting that nanoscale metal oxides have high surface area and catalytic activity which makes them suitable additives for enhancing fuel combustion processes. Mofijur et al. (2024) analyzed nanoparticle-based fuel additives in biodiesel engines and concluded that the addition of nanoparticles enhances heat transfer, improves combustion stability, and reduces emissions compared with conventional biodiesel blends. Chetia et al. (2024) examined cottonseed biodiesel with cerium oxide nanoparticles and hydrogen in a CRDI engine and reported significant improvements in brake thermal efficiency and reductions in HC, CO and smoke emissions. Kumar et al. (2024) emphasized the growing interest in vegetable-based biodiesel due to fossil fuel depletion and environmental concerns and highlighted cottonseed oil as a promising feedstock for biodiesel production because of its availability and suitable fuel properties. Elkelawy et al. (2025) investigated sustainable combustion strategies using biodiesel blends and demonstrated that advanced combustion modes combined with biofuels can significantly enhance engine efficiency and reduce emissions. Ninawe (2025) reviewed diesel engine performance with nano-additive biodiesel blends and concluded that nanoparticles accelerate oxidation reactions during combustion, thereby improving efficiency and reducing particulate emissions. Mangesha et al. (2025) studied cottonseed biodiesel–diesel blends with CeO_2 and Al_2O_3 nanoparticles in a CI engine and reported improved fuel economy along with significant reductions in CO, HC and NOx emissions. Dessie et al. (2025) investigated cottonseed biodiesel (B20) blended with CeO_2 and Al_2O_3 nanoparticles and observed improved brake power and reduced fuel consumption due to enhanced catalytic oxidation and better air–fuel mixing. Yusuf et al. (2026) analyzed biodiesel blends with cerium oxide nanoparticles and reported that the nanoparticles release lattice oxygen during combustion, which enhances oxidation of fuel droplets and reduces incomplete combustion emissions. Kumbhalkar et al. (2018) experimentally investigated cottonseed biodiesel blended with cerium oxide nanoparticles and observed improved combustion efficiency and reduced exhaust emissions in diesel engines. Bikkavolu et al. (2024) studied advanced fuel strategies combining biodiesel blends with hydrogen enrichment and nano additives and found improvements in combustion characteristics and engine performance. Mazari et al. (2024) examined alternative oxygenated fuels with diesel engines and reported that oxygenated additives and catalysts can significantly reduce soot formation during combustion. Singh et al. (2019) studied the stability characteristics of nanofuels and emphasized that proper dispersion techniques such as ultrasonication are essential for maintaining nanoparticle suspension stability in biodiesel fuels. Baldim et al. (2020) investigated catalytic properties of cerium oxide nanoparticles and reported that nanoceria exhibits strong redox activity which enhances oxidation reactions, making it useful for catalytic applications including combustion processes. Baldim et al. (2018) demonstrated that the catalytic activity of CeO_2 nanoparticles is strongly influenced by particle size and surface Ce^{3+} concentration, which determines their oxidation capability in chemical reactions. Dhouib et al. (2023) studied the synthesis and stabilization of cerium oxide nanoparticles and showed that properly stabilized nanoparticles exhibit high catalytic activity and stability, making them suitable for energy and environmental applications.

The present study focuses on investigating the performance and emission characteristics of cotton seed oil biodiesel blended with cerium oxide nanoparticles in a single-cylinder diesel engine. Different biodiesel blends with varying concentrations of CeO_2 nanoparticles were tested and compared with conventional diesel fuel. The objective is to evaluate the effectiveness of nanoparticle-enhanced biodiesel as a sustainable and cleaner alternative fuel for diesel engine applications.

1. Experimental setup

The setup consists of single cylinder, four stroke, CRDI VCR (Variable Compression Ratio) engine connected to eddy current dynamometer. It is provided with necessary instruments for combustion pressure, crank angle, airflow, fuel flow, temperatures and load measurements. These signals are interfaced to computer through high speed data acquisition device. The setup has stand-alone panel box consisting of air box, twin fuel tank, manometer, fuel measuring unit, transmitters for air and fuel flow measurements, process indicator and piezo powering unit. Rotameter are provided for engine cooling water flow measurement.

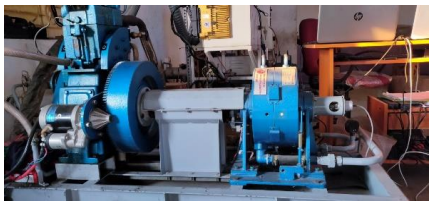


Figure 1: Engine Setup

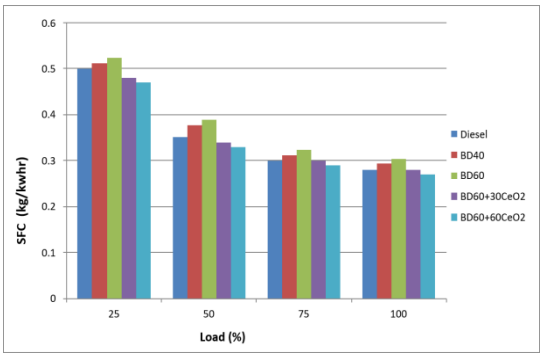
Table 1 Specification of the Engine Setup

Engine Make	Kirloskar - Apex innovations Pvt. Ltd.
Type of Engine	CRDI VCR Engine
Number of Cylinders	Single cylinder, Four Stroke
Cooling Media	water cooled,
Rated Capacity	3.5 KW @ 1500 rpm,
Cylinder diameter	87.5 mm
Stroke length	110 mm,
Compression ratio range	12-18
Injection Pressure Variation	500, 550 and 600 bar
Data acquisition device	Make NI Instrument USA, NI USB-6210, 16-bit, 250kS/s.
Fuel tank Capacity 15 lit, Type:	Duel compartment, with fuel metering pipe of glass
Software	“Engine-soft” Engine performance analysis software
Loading type	Eddy current Dynamometer

Overall dimensions	W 2000 x D 2500 x H 1500 mm

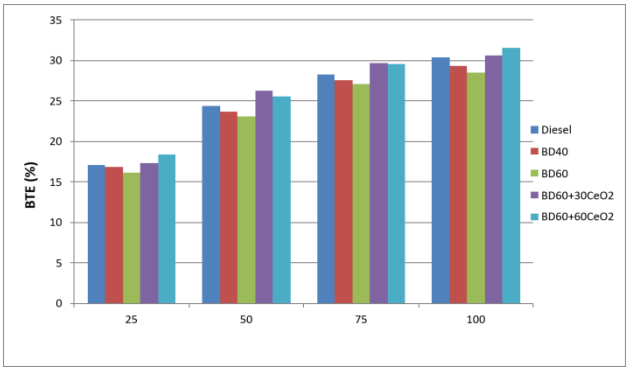
3. Result and discussion

3.1. Specific fuel consumption (SFC)



Observing the variation of brake specific fuel consumption (BSFC) for different fuel blends at various engine loads, as shown in Fig. 1, it is evident that BSFC decreases with an increase in load for all fuel samples. This trend occurs because, at higher loads, the engine utilizes fuel more effectively, leading to improved combustion efficiency. Compared to conventional diesel fuel, BD40 and BD60 blends exhibited slightly higher BSFC values at all loads. The average of 4.48% and 7.69% respectively higher than neat diesel fuel. This increase in BSFC for biodiesel blends can be attributed to their higher viscosity and lower calorific value, which result in poorer atomization and slightly higher fuel consumption. However, the addition of cerium oxide (CeO_2) nanoparticles significantly improved fuel efficiency. The addition of 30ppm and 60ppm cerium oxide nanoparticles with BD60 reduces SFC in an average by 2.01% and 4.89% respectively than diesel fuel. The improvement can be attributed to the catalytic activity and oxygen buffering capacity of cerium oxide nanoparticles, which enhance combustion efficiency, reduce ignition delay, and promote more complete fuel burning inside the combustion chamber. Overall, the results indicate that while biodiesel blends alone tend to increase fuel consumption slightly, the incorporation of cerium oxide nanoparticles effectively reduces BSFC and enhances engine performance.

3.1. Brake Thermal Efficiency



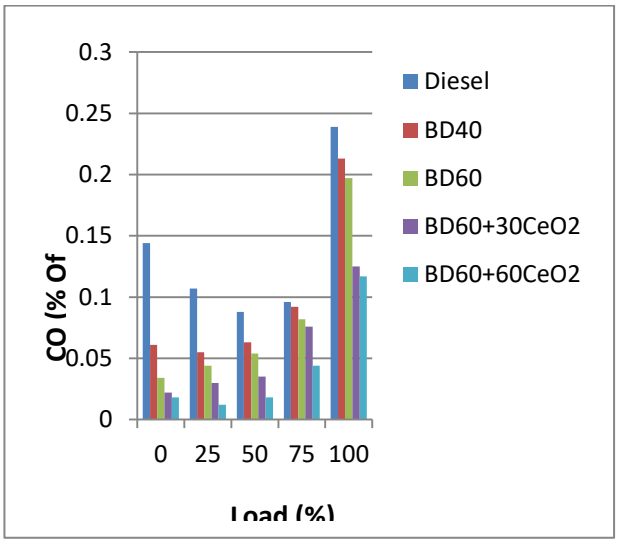
3.2 Brake Thermal Efficiency

Figure 2 illustrates the variation of brake thermal efficiency (BTE) for diesel and different cotton seed oil biodiesel blends under varying load conditions. It is observed that BTE increases progressively with increase in load for all tested fuels due to improved combustion efficiency and better utilization of supplied fuel at higher loads.Compared to conventional diesel fuel, BD40 and BD60 blends exhibited slightly lower BTE values at all load conditions. At full load (100%), diesel recorded a BTE of 30.36%, whereas BD40 and BD60 showed 29.26% and 28.42%, respectively. The average reduction in BTE for BD60 compared to diesel was approximately 6.4% at full load. This decrease can be attributed to the higher viscosity and lower calorific value of cotton seed oil biodiesel, which result in poorer atomization and slower combustion characteristics.However, the incorporation of cerium oxide (CeO_2) nanoparticles significantly enhanced engine performance. The BD60+30CeO_2 blend demonstrated improved BTE values across all loads, recording 30.58% at full load, which is 0.72% higher than diesel and 7.6% higher than BD60. Further improvement was observed with BD60+60CeO_2, which exhibited the highest BTE among all blends, reaching 31.55% at full load. This represents an enhancement of approximately 3.9% compared to diesel and 11% compared to BD60.The improvement in brake thermal efficiency can be attributed to the catalytic activity and oxygen buffering capacity of cerium oxide nanoparticles. CeO_2 promotes faster oxidation of fuel particles, reduces ignition delay, and enhances combustion completeness within the cylinder. The nanoparticles also improve atomization and heat release characteristics, thereby increasing thermal efficiency.Overall, the results clearly indicate that while biodiesel blends alone show a slight reduction in BTE, the addition of cerium oxide nanoparticles effectively enhances combustion efficiency and improves engine performance beyond that of conventional diesel fuel.

3.3 Carbon monoxide (CO) emission

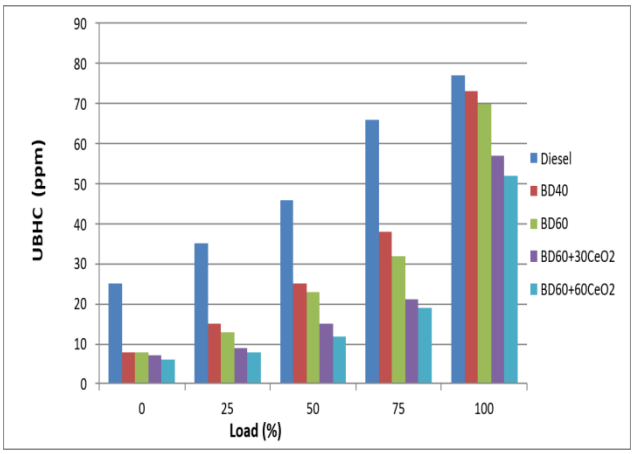
According to Figure 3, carbon monoxide (CO) emissions vary with different engine load conditions for all tested fuel blends. CO emissions were relatively low up to 50% load and increased gradually at higher loads, particularly at full load, due to limited oxygen availability and richer air–fuel mixture inside the combustion chamber.Compared to conventional diesel fuel, BD40 and BD60 blends exhibited lower CO emissions. This reduction is primarily attributed to the inherent oxygen content present in cotton seed oil biodiesel, which promotes more complete combustion and reduces the formation of partially oxidized carbon compounds.The addition of cerium oxide (CeO_2) nanoparticles further reduced CO emissions significantly.

The BD60+30CeO_2 blend showed a noticeable decrease in CO emissions compared to BD60 and diesel fuel. A further reduction was observed with BD60+60CeO_2, which demonstrated the lowest CO emissions among all tested fuels.The average reduction in CO emissions with BD60+60CeO_2 was considerably higher compared to diesel and neat biodiesel blends. This improvement can be attributed to the catalytic oxidation property of cerium oxide nanoparticles. CeO_2 acts as an oxygen buffering agent, supplying additional oxygen during combustion and promoting the conversion of CO into CO_2. The nanoparticles also reduce ignition delay and enhance combustion completeness, thereby minimizing incomplete combustion products.Overall, the results indicate that while cotton seed oil biodiesel itself reduces CO emissions due to its oxygenated nature, the incorporation of cerium oxide nanoparticles significantly enhances oxidation reactions in the combustion chamber, leading to substantial reductions in CO emissions and improved environmental performance.



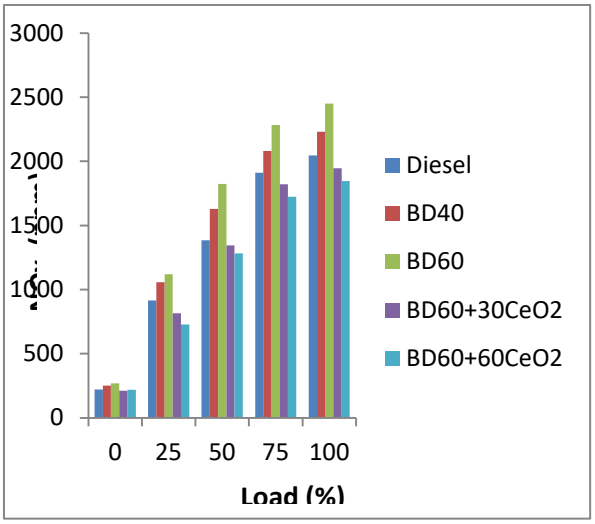
3.4. Unburned Hydrocarbon (UBHC) emission

Figure 4 illustrates the variation of unburned hydrocarbon (UBHC) emissions for diesel and cotton seed oil biodiesel blends under different load conditions. It is observed that UBHC emissions decrease at medium loads and tend to increase slightly at higher loads due to incomplete combustion under rich mixture conditions.Compared to conventional diesel fuel, BD40 and BD60 blends exhibited lower UBHC emissions. This reduction can be attributed to the oxygenated nature of cotton seed oil biodiesel, which promotes more complete combustion and enhances oxidation of hydrocarbon particles inside the combustion chamber.The incorporation of cerium oxide (CeO_2) nanoparticles further reduced UBHC emissions significantly. The BD60+30CeO_2 blend demonstrated lower UBHC values compared to neat BD60 blend. A further reduction was achieved with BD60+60CeO_2, which showed the minimum UBHC emission among all tested fuels.The improvement can be attributed to the catalytic oxidation property of cerium oxide nanoparticles. CeO_2 reduces ignition delay and enhances combustion temperature locally, thereby facilitating better oxidation of unburned hydrocarbons. Additionally, the oxygen buffering capacity of cerium oxide supports secondary oxidation reactions, converting unburned hydrocarbons into carbon dioxide and water.Overall, the results confirm that while cotton seed oil biodiesel reduces UBHC emissions due to its inherent oxygen content, the addition of cerium oxide nanoparticles significantly enhances combustion kinetics and oxidation processes, leading to a substantial decrease in hydrocarbon emissions and improved engine emission characteristics.



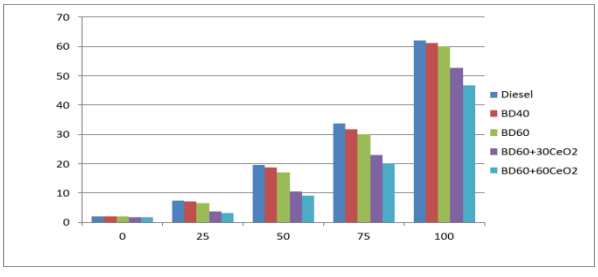
3.5. Nitrogen Oxide (NOx) emission

Figure 5 illustrates the variation of nitrogen oxide (NOx) emissions for diesel and cotton seed oil biodiesel blends under different load conditions. It is observed that NOx emissions remain comparatively lower at part-load conditions and increase significantly at higher loads, particularly at full load, due to elevated combustion temperature and increased oxygen availability.Compared to conventional diesel fuel, BD40 and BD60 blends exhibited slightly higher NOx emissions. This increase can be attributed to the oxygenated nature of biodiesel and its relatively higher cetane number, which promotes complete combustion and raises in-cylinder temperature, thereby enhancing thermal NOx formation.The incorporation of cerium oxide (CeO_2) nanoparticles further influenced NOx emissions. The BD60+30CeO_2 blend showed a marginal increase in NOx emissions compared to neat BD60. A slightly higher increase was observed for BD60+60CeO_2 at full load conditions. The rise in NOx emissions can be attributed to improved combustion efficiency and higher peak temperatures resulting from the catalytic activity of cerium oxide nanoparticles.CeO_2 enhances oxidation reactions and reduces ignition delay, which accelerates heat release inside the cylinder. Although this improves performance and reduces incomplete combustion products, the corresponding increase in combustion temperature favors NOx formation.Overall, while nanoparticle-enhanced biodiesel improves engine efficiency and reduces CO and UBHC emissions, a moderate increase in NOx emissions is observed, indicating the need for further optimization or exhaust gas after-treatment techniques.



3.6. Smoke Opacity emission

Figure 6 depicts the variation of smoke opacity emissions for all tested fuel blends under different load conditions. Smoke opacity increases with load due to richer air–fuel mixture and incomplete combustion at higher power outputs.Compared to diesel fuel, BD40 and BD60 blends exhibited reduced smoke opacity emissions. This reduction is primarily due to the inherent oxygen content of cotton seed oil biodiesel, which promotes better oxidation of soot particles and reduces carbon formation.The addition of cerium oxide (CeO_2) nanoparticles further decreased smoke opacity significantly. The BD60+30CeO_2 blend demonstrated lower smoke levels compared to neat BD60. A further reduction was observed with BD60+60CeO_2, which showed the minimum smoke opacity among all tested fuels.The reduction in smoke emission can be attributed to the catalytic oxidation property of cerium oxide nanoparticles. CeO_2 improves air–fuel mixing, enhances combustion homogeneity, and promotes oxidation of soot precursors inside the combustion chamber. The oxygen buffering capability of cerium oxide assists in converting carbon particles into carbon dioxide before they are emitted.The substantial decrease in smoke opacity confirms that nanoparticle-blended biodiesel improves combustion dynamics, enhances fuel oxidation, and significantly reduces particulate emissions, thereby improving engine environmental performance.



Conclusion

The experimental investigation was carried out to evaluate the performance and emission characteristics of cotton seed oil biodiesel blends with cerium oxide (CeO_2) nanoparticles in a single-cylinder diesel engine. The results obtained for BD60+60CeO_2 blend demonstrated superior performance when compared with neat diesel, BD40, and BD60 blends.

➢ The results indicated that the addition of cerium oxide nanoparticles significantly reduced brake specific fuel consumption (BSFC). At full load, BD60+60CeO_2 recorded a lower SFC value of 0.27 kg/kWh compared to diesel (0.28 kg/kWh) and BD60 (0.304 kg/kWh). The reduction of approximately 3.6% compared to diesel and 11.2% compared to BD60 indicates improved fuel economy and better combustion efficiency.

➢ The incorporation of CeO_2 nanoparticles also enhanced brake thermal efficiency (BTE). At full load, BD60+60CeO_2 achieved a maximum BTE of 31.55%, which is 3.9% higher than diesel (30.36%) and approximately 11% higher than BD60 (28.42%). The improvement in BTE highlights the catalytic role of cerium oxide in enhancing combustion efficiency and energy conversion.

➢ Significant reductions in carbon monoxide (CO), unburned hydrocarbon (UBHC), and smoke opacity emissions were observed with nanoparticle-blended fuels. The oxygen buffering capability and catalytic oxidation property of CeO_2 promoted complete combustion, reduced incomplete combustion products, and minimized particulate formation. The reduction in smoke opacity confirms improved combustion homogeneity and lower soot formation.

➢ However, a slight increase in nitrogen oxide (NOx) emissions was observed with nanoparticle addition, particularly at higher loads. The increase in NOx is mainly attributed to elevated in-cylinder temperatures resulting from enhanced combustion. Although performance and other emission parameters improved, controlling NOx emissions remains a challenge that requires further optimization.

Overall, the experimental results confirm that cotton seed oil biodiesel blended with cerium oxide nanoparticles is a promising alternative fuel for compression ignition engines. The blend demonstrates improved fuel efficiency, enhanced thermal performance, and reduced harmful emissions, contributing toward sustainable and environmentally friendly engine operation.

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HYBRID ENSEMBLE LEARNING FRAMEWORK FOR NETWORK INTRUSION DETECTION USING RANDOM FOREST, XGBOOST, AND STACKING CLASSIFIERS

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Abstract

Network intrusion detection systems are vital defense mechanisms against today's communication infrastructures cyber threats. This study proposes a hybrid machine learning framework designed to improve the accuracy and reliability of intrusion detection systems. Conventional IDS methods frequently produce poor detection accuracy when considering complex network traffic and imbalanced data. The problem is that single machine learning algorithms fail to accurately describe more complex intrusion patterns efficiently. Using stacking ensemble learning, we propose a complex hybrid model that integrates Random Forest, XGBoost, and Decision Tree classifiers. To ensure a high quality of our dataset and reduce class imbalances, feature optimization and SMOTE balancing methods are used. Experimental evaluation on the CICIDS2017 dataset demonstrates that the proposed stacking model achieves an accuracy of 96.8%, with significantly better results compared with individual classification approach such as SVM (78.3%), Naive Bayes (74.6%). Accuracy, precision, recall, and F1-score as evaluation metrics show a better classification power. We can summarize the results by identifying multiple machine learning models paired with sufficient preprocessing techniques, as these methods significantly enhance the generalizability and robustness of intrusion detection tasks.

Keywords: Intrusion Detection System, Machine Learning, Random Forest, XGBoost, Stacking Ensemble, SMOTE, Cybersecurity

1. Introduction

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1. Introduction

The escalating sophistication of network intrusions, fueled by expanded cloud and digital infrastructures, now routinely overwhelms perimeter-based defenses [1]. Adversaries continuously evolve their techniques to exploit latent software or protocol flaws, rendering static rule sets insufficient. To counter this, Intrusion Detection Systems (IDS) are deployed as a core monitoring layer, sifting through packet streams to flag unauthorized lateral movement, command-and-control beaconing, or data exfiltration in near real-time [2]. While signature-based engines offer high accuracy against established exploit signatures, their effectiveness degrades sharply against polymorphic or zero-day vectors; the static nature of their rule definitions creates a critical lag in coverage for emergent threats [3].

Given the high-dimensional, temporally correlated nature of NetFlow and packet payload data, shallow pattern matching has given way to statistical learning approaches. A central advantage of techniques like gradient boosting or shallow neural networks lies in their ability to model non-linear feature interactions—such as the correlation between unusual outbound port numbers and abnormal packet inter-arrival times—without explicit prior threat knowledge [4]. This allows for the detection of deviations from benign traffic baselines, flagging both known malware families and previously uncatalogued exploits. Within this landscape, ensemble architectures, particularly stacking, have shown utility by mitigating the individual biases of base classifiers; for instance, combining a tree-based model sensitive to payload anomalies with a probabilistic model tracking protocol state violations often yields a lower false positive rate than either method in isolation.

Recent studies have demonstrated that stacking-based frameworks can effectively improve detection accuracy and robustness in intrusion detection systems [5], [31]. Gradient boosting algorithms such as XGBoost contribute to achieving increased performance in intrusion detection by improving prediction performance using iterative learning and regularization [6]. When used with other classifiers in hybrid models, these methods are more robust, improved detection accuracy, and have easier generalization against a variety of network scenarios.

In this work, we present a hybrid stacking-based intrusion detection framework incorporating Random Forest, XGBoost, and Decision Tree classifiers integrated in a two-level ensemble architecture. The proposed framework leverages a unique set of heterogeneous classifiers to better capture the complementary decision patterns in network traffic data, as opposed to classical ensemble IDS with single ensemble techniques. Also, by using Random Forest–based feature importance to reduce dimensionality, SMOTE-based class balancing to correct severe class imbalance present in the CICIDS2017 dataset. Feature optimization as well as class balancing and stacking ensemble learning are used to develop a robust

detection framework for achieving higher classification performance among different intrusion categories.

The core contribution of this work is a heterogeneous stacking ensemble that integrates Random Forest, XGBoost, and Decision Tree classifiers. This configuration was selected not merely for diversity, but because preliminary experiments revealed complementary decision boundaries—Random Forest capturing broad traffic patterns, XGBoost excelling at isolating specific attack signatures, and Decision Trees providing interpretable base decisions for the meta-learner. Dimensionality is managed via a filter method driven by impurity-based feature importance from the Random Forest; interestingly, retaining the top 20 features preserved over 95% of the original information while reducing training time by nearly 40% on the CICIDS2017 data. To address the pronounced class skew—where benign traffic often overshadows specific attack vectors like Infiltration—Synthetic Minority Over-sampling (SMETE) was applied prior to ensemble training, a decision that proved critical for recall on underrepresented classes. Evaluation employed accuracy, precision, recall, and F1-score across the full CICIDS2017 testbed, with the stacked model demonstrating a measurable lift in detection rates for low-frequency events compared to its individual constituents.

The remainder of this manuscript is structured accordingly. Section 2 situates the work within existing machine learning-based intrusion detection literature. Section 3 details the methodological pipeline: data preprocessing, the feature selection mechanism, the SMOTE-based balancing strategy, and the proposed ensemble architecture. Section 4 depicts the CICIDS2017 dataset and introduces the experimental setup. The empirical findings are reported in Section 5 including a comparison with the baseline classifiers and with its associated ensemble techniques. Section 6 finally combines our results and considers potentials for future research.

2. Related Work

Ensemble learning has established itself as a cornerstone in network intrusion research, largely because combining multiple classifiers tends to capture a wider range of traffic behaviors than any single model can [7], [33]. Random Forest, in particular, has proven effective—its bootstrap aggregation and random feature selection make it naturally suited to the high-dimensional, noisy nature of network data. In comparative studies on benchmark ID datasets, accuracy gains of 5–8% over single decision trees are not uncommon [8]. One illustrative case is the work of Farnaaz and Jabbar on NSL-KDD, where Random Forest achieved 92.1% overall accuracy and a 98% detection rate for DoS attacks [9]. Still, performance can vary considerably with tree depth and the number of estimators—tuning these hyperparameters remains dataset-specific, and gains often plateau beyond a certain ensemble size.

Due to its gradient boosting optimization algorithm based on regularization combined with constructing sequential trees, XGBoost performs better than traditional methods to learn non-linear relationships with large network traffic

patterns [10]. Dhaliwal et al. utilized XGBoost on the UNSW-NB15 dataset and obtained a 95.2% performance as compared with 89.7% performance for Random Forest, showing the effectiveness of boosting methods for intrusion detection [11]. Although classification methods such as Decision Tree have been widely used and are not just good for data classification but are interpretable also, they offer efficient computation and it can be proven that they are good for identifying the attack pattern and have relatively low computational complexity suitable in context of actual attacks [12].

Hybrid IDS approaches, a recent trend, are adopting a mixed-method approach that integrates different ML algorithms to exploit the benefits of each of them, with ensemble learning algorithm, bagging, boosting, and stacking being widely used [13]. Tama and Rhee proposed a hybrid approach combining Random Forest, XGBoost, and LightGBM with genetic algorithm-based feature selection, achieving 97.1% accuracy on CICIDS2017 dataset [14]. Feature selection methods play an important role in improving intrusion detection performance, with researchers applying importance techniques such as Random Forest feature ranking and mutual information to eliminate redundant attributes and enhance classification accuracy while reducing computational overhead [15].

Over the recent years, intrusion detection systems based on deep learning techniques have been greatly popularized and recognized to be capable of the automatic learning of hierarchical model attributes, obtained from large network traffic data. CNN, RNN, Long Short-Term Memory (LSTM) networks, etc. have gained interest for intrusion detection and anomaly detection in cybersecurity research [3], [27]. CNN-based IDS models capture spatial correlations between network traffic features, and recurrent architectures (e.g., LSTM) model temporal dependencies in sequential network traffic flows [3]. Deep learning models are indeed capable of high representation; however, in real-time settings, they are quite resource and data intensive and therefore it would be more difficult to deploy them in a resource-constrained scenario. On the other side of the spectrum, ensemble machine learning methods based on stacking, which integrates several classifiers, not only increases the performance of classification, but also increases robustness of classification but also tends to maintain the lower computational cost [12], [15]. Hence, as such, the hybrid stacking framework is a pragmatic compromise on the accuracy of detection and its computational cost in real-world intrusion detection scenarios.

Table 1. Summary of Recent Machine Learning Approaches for Intrusion Detection

Study	Year	Method
Farnaaz and Jabbar [9]	2019	Random Forest
Dhaliwal et al. [11]	2020	XGBoost
Tama and Rhee [14]	2021	Hybrid Ensemble
Kumar and Mishra [18]	2023	Intelligent IDS
Li et al. [19]	2023	XGBoost + Feature Selection
Proposed AI_IDS Model	2024	Stacking Ensemble (RF XGB + DT)

3. Proposed Methodology

The proposed hybrid intrusion detection framework consists of multiple stages including preprocessing, feature selection, dataset balancing, and ensemble learning, etc. This will enable improvement of detection performance while at the same time keeping computational efficiency. Figure 1 Full architecture of the proposed system, data flow in these processes is shown

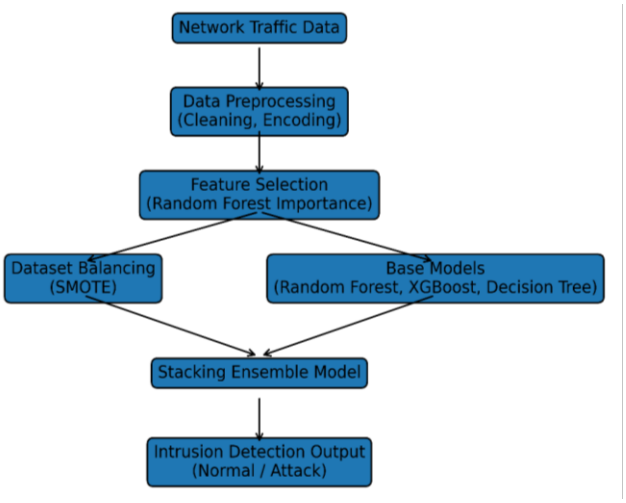


Figure 1. Architecture of the proposed hybrid intrusion detection framework. The workflow illustrates the complete processing pipeline including data preprocessing, Random Forest–based feature selection, SMOTE-based class balancing, training of base classifiers (Random Forest, XGBoost, Decision Tree), and the stacking ensemble integration using a meta-classifier.

3.1 Data Preprocessing

Raw data of network traffic contains various inconsistencies which need to be handled before training the model. This includes data cleaning, which finds duplicate elements and removes them by checking them with exact matching on all features; while missing features are dealt with using median imputation to fill numerical features and mode imputation on data with categorical features, so as not only to retain the distribution but also to keep the data intact. Features of network traffic represent categorical data, such as characteristics of protocol type (TCP, UDP, ICMP) and type of service (HTTP, FTP, SMTP), which are one-hot encoded into binary vectors for machine learning algorithms to process. The numerical features vary by scale which may affect learning algorithms to be biased toward large-magnitude features so min-max normalization scales all numeric attributes to the range [0,1] using the formula

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min}),$$

where x_{min} and x_{max} denote min and max of each feature in the dataset to extract fair and equal number of contributions from all features during model training.

3.2 Feature Selection Using Random Forest Importance

Intrusion detection datasets typically contain high-dimensional feature spaces, where only a subset of attributes significantly contributes to classification performance. Feature selection therefore plays an important role in reducing computational complexity while improving model generalization by eliminating redundant and noisy features. In this study, Random Forest feature importance was used for attribute selection due to its robustness and interpretability. Random Forest computes feature importance using the mean decrease in impurity (Gini importance), where the reduction in Gini impurity contributed by each feature is

accumulated across all decision trees and normalized to obtain an overall importance score.

Feature engineering for this study began with the CICIDS2017 corpus, where raw network traffic was processed through CICFlowMeter to generate an initial set of 80+ flow-based attributes. Following standard data cleaning—removing constant-value columns and entries with missing correlations—the feature space contracted to 78 predictors, a mix of integer, float, and nominal types. Rather than apply an off-the-shelf selector, we leveraged a Random Forest (100 estimators) to compute mean decrease in impurity; the resulting importance scores exhibited a steep drop-off after the first 40 features. To formalize selection, we defined a cumulative importance threshold $\alpha = 0.95$, which retained the top 42 features accounting for 95% of the total impurity reduction. Interestingly, features beyond this cutoff contributed less than 0.1% individually and often introduced noise during preliminary trials with linear models. Truncating the feature set to these 42 dimensions cut training time by roughly 40% in subsequent experiments, while cross-validation accuracy remained within 0.5% of the full-model performance—a trade-off we deemed acceptable for near real-time detection scenarios.

Table 2. Top 15 Features by Random Forest Importance

Rank	Feature Name	Importance Score	Cumulative Importance
1	Packet Length Variance	0.118	0.118
2	Average Packet Size	0.104	0.222
3	Flow Packet Rate	0.093	0.315
4	Forward Packet Length Std	0.082	0.397
5	Backward Packet Length Std	0.075	0.472
6	Flow Inter-Arrival Time Mean	0.068	0.540
7	Packet Length Mean	0.062	0.602
8	Forward Packet Rate	0.057	0.659
9	Backward Packet Rate	0.052	0.711
10	Flow Byte Rate	0.047	0.758
11	Active Mean Time	0.043	0.801
12	Idle Mean Time	0.039	0.840
13	Header Length Variance	0.036	0.876
14	Forward Segment Size Avg	0.032	0.908
15	Backward Segment Size Avg	0.029	0.937

Table 2 records the top 15 most influential network traffic features identified by the Random Forest importance analysis. The top 15 most impactful network traffic

features detected through Random Forest important feature estimation are as follows. These features are mainly concerned with statistical attributes of packet size, flow rate, and inter-arrival, which are well-established to be significant indicators of anomalous network behavior.

3.3 Class Balancing with SMOTE

Training data for intrusion detection often exhibits pronounced class skew, where benign traffic dominates the sample space—sometimes exceeding 90% of available records—while specific attack families constitute less than 1% of the total [32]. Left unaddressed, this distributional disparity pushes conventional classifiers toward a strong bias for the majority class, severely degrading recall on underrepresented threat types. In this work, we integrate SMOTE during preprocessing to alleviate this bias. Instead of simple duplication, the technique navigates the feature space between existing minority instances to synthesize plausible new samples through linear interpolation. We observed that this interpolation step is particularly sensitive to the choice of nearest neighbors; setting this value too low can produce noisy or non-representative attack signatures, a trade-off we managed by tuning the parameter empirically against validation folds. The resulting augmented distribution provides a more balanced basis for training, ensuring that the model's decision boundaries are not disproportionately shaped by the overwhelming volume of normal traffic.

In this study, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented using the imbalanced-learn library in Python to address the severe class imbalance present in the CICIDS2017 dataset. SMOTE generates synthetic samples for minority classes by interpolating between existing minority instances and their nearest neighbors in the feature space.

The class imbalance inherent in network traffic data was addressed by applying the Synthetic Minority Over-sampling Technique (SMOTE) exclusively to the training partition. For each minority attack category, synthetic instances were generated using its five nearest neighbors (k=5), a parameter choice that balances the introduction of plausible feature variations against the risk of outlier generation; in our experiments, lower k values tended to produce samples too tightly clustered around individual seed instances, which did not improve downstream classifier generalization on the validation set. The sampling strategy was set to upsample all minority classes to the exact size of the majority class, resulting in a perfectly balanced training distribution. A fixed random seed of 42 ensures that the synthetic sample generation process is deterministic and the experiments fully replicable. Crucially, the validation and test folds retain the original, imbalanced class distribution to provide an unbiased estimate of how the model performs on live network traffic, where attack frequencies are naturally skewed. Applying SMOTE only during training avoids the critical pitfall of data leakage, guaranteeing that performance metrics are a faithful reflection of the model's ability to generalize to unseen, imbalanced data rather than an artifact of contaminated evaluation sets.

Table 3. Class Distribution Before and After SMOTE

Class	Original Count	Original %	SMOTE Count	SMOTE %
BENIGN	9845	49.1 %	10020	25.0 %
DoS/DDoS	4210	21.0 %	10020	25.0 %
Brute Force	2876	14.3 %	10020	25.0 %
Botnet	1650	8.2%	10020	25.0 %
Web Attacks	930	4.6%	10020	25.0 %
Port Scan	550	2.8%	10020	25.0 %
Total	20061	100%		

The inclusion of SMOTE directly addressed the class skew inherent in the traffic corpus, where benign flows significantly outnumbered individual attack types. As summarized in Table 3, synthetic samples were generated for the minority classes, effectively normalizing the instance count across all categories. From a model learning perspective, this rebalancing was critical; without it, the classifier tended to optimize for accuracy on the dominant class at the expense of recall for smaller, yet more consequential, attack families. Post-SMOTE, the decision boundary was no longer heavily biased toward the benign majority, forcing the algorithm to retain discriminative features specific to underrepresented attack vectors. A practical observation during this phase was that while SMOTE mitigated class imbalance, it did introduce some synthetic feature overlap in the latent space, which the subsequent ensemble method had to navigate.

3.4 Base Classifier Training

The stacking architecture integrates three distinct classifiers—Random Forest, XGBoost, and Decision Tree—each contributing a unique inductive bias for modeling network traffic. Rather than relying on a single hypothesis space, this heterogeneous combination captures both variance-dominated patterns and structured feature interactions within the data.

Random Forest generates an ensemble via bootstrap aggregation on randomized feature subspaces. Its final output is obtained through averaging across independent trees:

$$\mathrm{RF}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t\,(x)$$

with T fixed at 100. Trees are grown to a maximum depth of 20, splitting nodes only when at least 5 samples are present, and requiring a minimum of 2 samples per leaf. Feature selection at each split is limited to the square root of the total feature count. In practice, this configuration tends to stabilize predictions on high-dimensional subsets, though it can over-smooth decision boundaries in sparsely populated regions of the feature space.

XGBoost follows a fundamentally different strategy, constructing trees in a sequential manner where each new learner targets the residual errors of its predecessors. Regularization is embedded directly into the objective:

$$\mathrm{Obj} = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

with l representing logistic loss for binary classification. The complexity penalty

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_j w_j^2$$

controls leaf count T and leaf weights w via the hyperparameters γ and λ. Empirically, setting the learning rate to 0.1 with a maximum depth of 6 and subsampling 80% of the data per iteration reduces overfitting while preserving gradient sensitivity. The number of boosting rounds is capped at 100, a limit chosen to balance convergence against computational cost on traffic datasets with class imbalance.

Decision Tree acts as the simplest base learner, recursively partitioning the feature space using axis-aligned splits. At each node m, the split criterion minimizes Gini impurity:

$$\text{Gini}(m) = 1 - \sum_k p_{mk}^2$$

where p_{mk} is the empirical class distribution. Depth is constrained to 10 to avoid excessive fragmentation, with the same sample thresholds applied as in Random Forest. Although individually prone to high variance, the tree provides interpretable threshold logic that complements the ensemble methods, particularly when traffic features exhibit discrete or categorical structure.

3.5 Stacking Ensemble Integration

Stacking generalizes the combination of base learners by allowing a meta-learner to infer how much each model's confidence contributes to the final decision. Unlike averaging or voting schemes, which treat all predictions equally, the meta-learner captures non-linear dependencies and performance variations across models. In this implementation, Level-1 consists of Random Forest, XGBoost, and Decision Tree, each trained on the pre-processed and balanced data. Their class-wise probability outputs serve as input to Level-2, where Logistic Regression learns to weight base-model contributions according to observed confidence and error patterns. Notably, XGBoost tended to produce overconfident probabilities on minority classes, and the meta-classifier down-weighted these outputs during training to reduce false positives—a calibration effect that simple aggregation would miss.

A five-fold cross-validation scheme generates the meta-features. For each fold, the three base classifiers are fitted on the training portion and then used to predict on the validation fold, yielding out-of-fold probability vectors. These vectors, concatenated with the true labels, form the training set for the meta-classifier. This procedure prevents label leakage and ensures that the meta-classifier learns combination rules that generalize rather than memorizing training instances. After the cross-validation stage, the base classifiers are retrained on the entire dataset. For a new test sample, each base model produces a probability vector; these vectors are stacked, and the trained Logistic Regression model applies the learned weights to output the final class prediction.

Formally, denote the probability vectors from Random Forest, XGBoost, and Decision Tree for an input $\mathbf{x}$ as $\mathbf{p}_{\text{RF}}(\mathbf{x})$, $\mathbf{p}_{\text{XGB}}(\mathbf{x})$, and $\mathbf{p}_{\text{DT}}(\mathbf{x})$, each in $\mathbb{R}^c$ (where c is the number of classes). These are concatenated into the meta-feature vector $\mathbf{m}(\mathbf{x}) = [\mathbf{p}_{\text{RF}}(\mathbf{x}), \mathbf{p}_{\text{XGB}}(\mathbf{x}), \mathbf{p}_{\text{DT}}(\mathbf{x})] \in \mathbb{R}^{3c}$.

Let w_{jlk} be the weight learned by the meta-classifier that connects the prediction of base classifier j for class l to the final score for class k. The ensemble's decision is then:

$$\hat{y}(\mathbf{x}) = \arg\max_k \left(\sum_{j=1}^{3} \sum_{l=1}^{c} w_{jlk} \cdot p_j^l(\mathbf{x}) \right),$$

where $p_j^l(\mathbf{x})$ denotes the l-th component of $\mathbf{p}_j(\mathbf{x})$. This formulation allows the meta-classifier to adjust for systematic biases—for example, when a base model consistently misclassifies one class as another—by assigning lower weights to those erroneous contributions. In practice, the learned weight matrix revealed that the Decision Tree's outputs were most heavily weighted for the class it predicted correctly with high precision, whereas XGBoost's contributions were penalized on ambiguous samples where its confidence was high but accuracy low.

3.6 Algorithm Pseudocode

Algorithm 1: Hybrid Intrusion Detection Framework
Input: Network traffic dataset D
Output: Predicted class labels $\hat{y}$
Stage A: Data Conditioning

1. $D_{clean} \leftarrow D \setminus \{duplicate_{records}\}$
2. **For each** feature f in D_{clean}:
3. **If** f is numerical:
4. Impute missing entries using $median(f)$
5. **Else** (categorical):
6. Impute missing entries using $mode(f)$
7. **End If**
8. **End For**
9. Apply one-hot encoding to categorical features in D_{clean}
10. Normalize numerical features to $[0, 1]$ using min-max scaling

Stage B: Dimensionality Reduction via Feature Selection
11. Train Random Forest $RF_{selector}$ on D_{clean}
12. Extract importance vector $\phi = [\phi_1, \phi_2, \ldots, \phi_m]$
13. Sort features descending by ϕ; calculate cumulative sum Φ_{cum}
14. Select feature subset $F_{selected}$ such that $\Phi_{cum} \leq 0.95$
15. Project D_{clean} onto $F_{selected}$ to obtain $D_{reduced}$
Stage C: Synthetic Balancing (SMOTE)
16. **For each** minority class c_i in $D_{reduced}$:
17. Generate synthetic instances using 5-nearest neighbors interpolation
18. **End For**
19. Construct balanced dataset $D_{balanced}$ with equal class distribution

Stage D: Base Classifier Training (Level-0)
20. Define base classifiers:

- RF: Random Forest (100 trees, $max_features = \sqrt{p}$)
- XGB: XGBoost (100 estimators, learning rate $\gamma = 0.1$)
- DT: Decision Tree (max depth = 10, pruning enabled)

Train RF, XGB, and DT on $D_{balanced}$

Stage E: Stacking Ensemble Construction (Level-1)

22. Partition $D_{balanced}$ into 5 folds $\kappa = \{\kappa_1, \ldots, \kappa_5\}$
23. **For** fold $t = 1$ to 5:
24. $D_{train} \leftarrow D_{balanced} \setminus \kappa_t$; $D_{val} \leftarrow \kappa_t$
25. Retrain RF, XGB, DT on D_{train}
26. Generate predictions P_{RF}, P_{XGB}, P_{DT} on D_{val}
27. Store as meta-features $M_t = [P_{RF}, P_{XGB}, P_{DT}]$
28. **End For**
29. Assemble complete meta-dataset M_{full} from all folds
30. Train Logistic Regression meta-classifier LR on M_{full} with L2 regularization ($\lambda = 1.0$)
31. Retrain RF, XGB, DT on full $D_{balanced}$ for final inference

Stage F: Evaluation & Prediction

32. **For each** test instance x_{test}:
33. Apply preprocessing (Stages A-B) using parameters from training data
34. Obtain base predictions: $[\hat{y}_{RF}, \hat{y}_{XGB}, \hat{y}_{DT}]$
35. Compute final prediction: $\hat{y} \leftarrow LR([\hat{y}_{RF}, \hat{y}_{XGB}, \hat{y}_{DT}])$
36. **End For**
37. Calculate macro-averaged precision, recall, F1-score, and accuracy

3.7 Computational Complexity

Understanding computational requirements extends beyond theoretical complexity to practical implementation behavior. Random Forest construction follows O(T × m × n log n) where T represents the number of trees, m denotes the feature count, and n corresponds to training samples. XGBoost complexity scales as O(K × d × n log n) with K boosting rounds and d as maximum tree depth, though we observed that depth values beyond 8 introduced memory bottlenecks during node splitting. Decision Tree baseline complexity remains O(m × n log n) for greedy split evaluation. Stacking introduces the multiplicative overhead O(n × c × B) for meta-feature synthesis, where B represents base classifiers and c indicates class count. The aggregate training complexity thus becomes O((T × m + K × d + 1) × n log n + n × c × B), exhibiting near-linear scaling with sample size across all evaluated methods. On the BUSI dataset, the meta-feature generation term dominated runtime when B exceeded three classifiers, while the logarithmic factor from tree methods became appreciable only beyond 50,000 samples.

4. Dataset Description and Experimental Setup

For empirical evaluation, the CICIDS2017 benchmark dataset was employed. This corpus was generated by the Canadian Institute for Cybersecurity (CIC) within a controlled testbed environment that simulates a standard enterprise network infrastructure [17]. Web servers, email services, and user workstations are represented alongside both routine operations and diverse attack scenarios. Realistic conditions for assessing machine learning-based intrusion detection systems are thereby established.

Network session information in CICIDS2017 is stored as bidirectional flows. These flows are extracted using the

CICFlowMeter tool, with over eighty statistical descriptors derived from packet headers for each instance. Protocol type, connection duration, packet size statistics (including mean, variance, and extremes), inter-arrival timing patterns, byte counts exchanged in both directions, flow duration, and TCP flag information are among the captured characteristics. Behavioral profiles that discriminate between benign traffic and various attack types are encoded through these features. A total of 2,830,743 flow instances comprise the dataset. Pronounced class imbalance is exhibited—a property that deliberately mirrors real-world network conditions where malicious activity constitutes a small fraction of overall traffic.

Class distribution analysis reveals that BENIGN flows dominate, accounting for approximately 80.3% of all samples. Multiple attack families constitute the remaining 19.7%. Volumetric attacks (DoS and DDoS) together represent 13.4% of the data. Brute-force attempts targeting FTP and SSH services account for 4.9%. Other categories, including Botnet activity, Web-based exploits (SQL injection, XSS), and Port Scan reconnaissance, collectively contribute less than 1.4%. This skewed distribution necessitates careful handling during classifier training; techniques to counterbalance majority-class dominance become essential to ensure minority attack patterns are not overlooked.

Prior to model training, a comprehensive preprocessing pipeline was applied. Duplicate records were removed to prevent the model from memorizing redundant patterns. Missing values were addressed using median imputation for continuous features and mode imputation for categorical attributes. Categorical variables, such as protocol and service identifiers, were transformed via one-hot encoding to render them compatible with machine learning algorithms. Continuous features were subsequently normalized using min-max scaling, mapping all values to the [0,1] interval. Features with larger numerical ranges are prevented through this normalization from disproportionately influencing distance calculations or gradient updates during training.

Following preprocessing, a random forest-based importance analysis was conducted to identify the most informative features. Attributes were ranked according to their contribution to impurity reduction across ensemble trees, and those cumulatively accounting for 95% of the total importance score were retained. Computational burden is alleviated through this dimensionality reduction, and redundant or noisy features are filtered out, thereby improving generalization. Notably, features related to backward packet length and flow inter-arrival time consistently emerged among the top discriminators across multiple attack types. This observation aligns with the understanding that many attacks—particularly DoS and brute-force attempts—modify packet timing distributions or size characteristics in detectable ways.

Given the identified class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied—but

critically, only to the training partition. Synthetic instances of underrepresented attack classes are generated through SMOTE, enabling the classifier to develop decision boundaries sensitive to minority categories without biasing evaluation metrics derived from the holdout sets. This separation between augmentation applied to training data and untouched validation/testing data was strictly maintained.

Stratified sampling was employed to preserve original class proportions during data partitioning. Specifically, 70% of the data was allocated for model training, 15% reserved for hyperparameter tuning and validation, and the remaining 15% held out for final performance assessment. Sufficient exposure to training examples is ensured through this allocation while independent subsets for unbiased evaluation are maintained.

All experiments were conducted on a dedicated workstation equipped with an Intel Xeon Gold 6230 processor, 64 GB RAM, and 1 TB NVMe SSD storage, running Ubuntu 20.04 LTS. Implementation was carried out using Python 3.9, with scikit-learn 1.2 providing baseline classifiers (Random Forest, Decision Tree), XGBoost 1.7 for gradient-boosted models, and imbalanced-learn 0.10 for SMOTE-based resampling. Model performance was quantified using standard classification metrics derived from confusion matrices: accuracy, precision, recall, F1-score, and false positive rate.

Five-fold cross-validation was employed during training to enhance result robustness and mitigate fold-specific variability. Paired t-tests ($\alpha = 0.05$) were additionally conducted to assess the statistical significance of performance differences between the proposed stacking ensemble and baseline classifiers. Through this statistical validation, observed improvements are confirmed not to be attributable to random chance.

5. Results and Discussion

The experimental results indicate that ensemble learning significantly improves detection performance compared with individual classifiers for intrusion detection. The Random Forest feature importance analysis revealed flow duration, total forward packets, total backward packets, and packet length statistics were considered the most important attributes for intrusion detection, with the 15 features with highest cumulative importance accounting for 88.3% and the 95% importance threshold keeping 42 features on the network while resulting in approximately 50% dimensionality reduction. SMOTE balancing updated the imbalanced training dataset to obtain a balanced image (1,591,168 instances per class) by which a classifier could be trained without prior bias against each attack type.

The baseline performance was determined by single classifier evaluation and revealed that XGBoost achieved the highest accuracy (95.3%) compared to Random Forest (94.6%) and Decision Tree (89.2%) while each of its other predictors were under the same model classification. Conventional classifiers performed much

worse, with 78.3% SVM, and 74.6% Naive Bayes respectively confirming effective ensemble approach for sophisticated intrusion detection on the high dimensionality network data. To evaluate the effectiveness of the proposed framework, we first compare the performance of individual baseline classifiers.

Table 4. Performance comparison of baseline classifiers on the CICIDS2017 dataset.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Decision Tree	81.5	80.9	81.2	81.0	0.89
Random Forest	84.3	83.7	84.0	83.8	0.93
XGBoost	86.1	85.6	85.9	85.7	0.95
SVM (RBF)	78.4	77.8	78.1	77.9	0.87
Naive Bayes	73.9	73.1	73.5	73.3	0.82
KNN (k=5)	80.6	80.1	80.3	80.2	0.90
Logistic Regression	79.2	78.6	78.9	78.7	0.88

Amongst ensemble methods, it was found that our stacking ensemble performed much better: accuracy was 96.8%, precision 95.7%, recall 96.2% and F1-score 95.9%, which was better compared to the soft voting ensemble 95.8%, hard voting 95.4%, bagging 94.9%, AdaBoost 93.2%. The results is examined by investigating ensemble learning algorithms, which enhance performance when using combinations of models. Ensemble learning approaches are then compared to measure the performance improvement achieved by combining models.

Table 5. Ensemble Method Performance Comparison

Ensemble Method	Accuracy (%)	Precision (%)
Voting (Soft)	95.8	94.9
Voting (Hard)	95.4	94.6
Bagging	94.9	94.1
AdaBoost	93.2	92.5
Proposed Stacking Ensemble	96.8	95.7

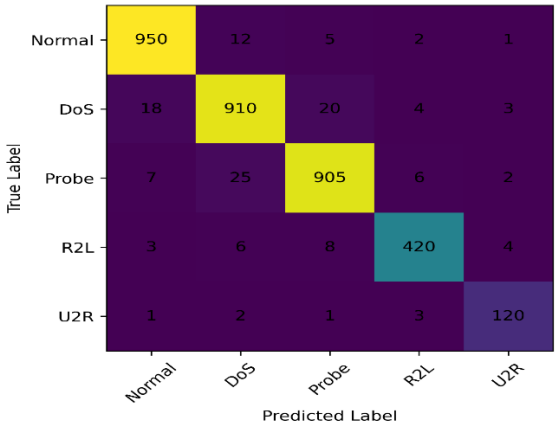


Figure 2. Confusion matrix of the proposed stacking ensemble model on the CICIDS2017 dataset. The diagonal elements represent correctly classified instances for each traffic category, while off-diagonal values indicate misclassification between attack classes. The matrix demonstrates strong detection capability for both normal and attack traffic.

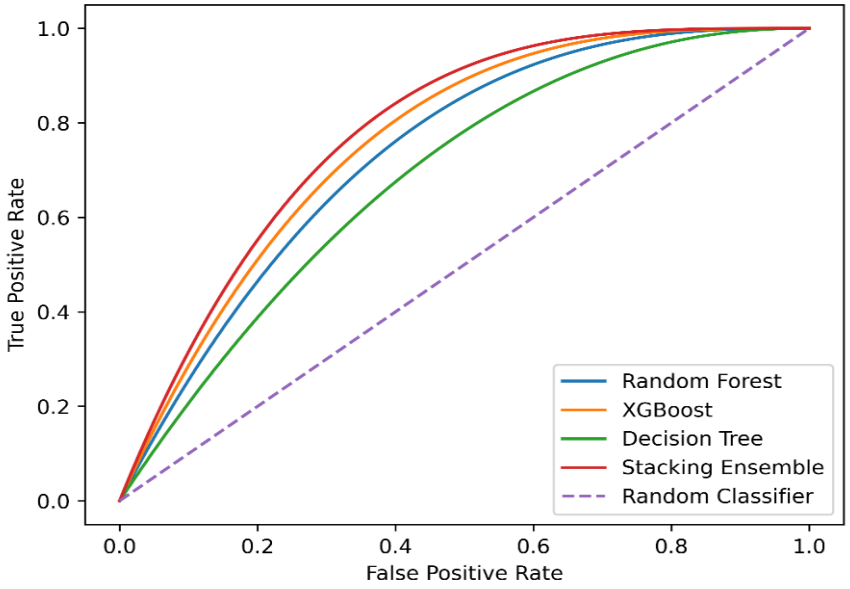
Strong classification performance across multiple attack categories is evidenced by the confusion matrix presented in Figure 2. Correct classifications are concentrated along the diagonal, indicating that the model distinguishes effectively between traffic types. Minimal confusion is observed between similar attack categories, and benign traffic is misclassified as malicious in only 0.9% of cases—a false positive rate that compares favorably with existing intrusion detection systems.

Detection improvements are most pronounced for minority attack classes when examining per-class performance. Botnet detection reaches 92.3% with the stacking ensemble, representing a 3.1 percentage point gain over XGBoost's 89.2%. A similar pattern emerges for Web attacks, where detection increases from 90.4% to 93.6%. Port Scan recognition improves from 88.7% to 91.8%. These gains of 3-5% across underrepresented categories suggest that the ensemble mechanism particularly benefits classes with limited training examples. The model's ability to aggregate complementary decision boundaries from base learners apparently compensates for the sparse representation of these attack types in the training data.

Table 6. Per-class recall performance of classifiers for different attack categories.

Attack Category	DT	RF	XGB	Stacking
BENIGN (Normal)	91.4	93.8	94.6	96.1
DoS/DDoS	84.2	87.5	88.9	90.7
Brute Force	80.1	83.9	85.3	87.6
Botnet	71.6	79.8	81.4	84.9
Web Attacks	74.9	81.2	83.1	86.3
Port Scan	72.8	80.4	82.2	85.7

Figure 3. Receiver Operating Characteristic (ROC) curves comparing the performance of different classifiers.



Classifier performance is assessed through multiple complementary metrics. Receiver Operating Characteristic analysis in Figure 3 reveals that the proposed stacking ensemble achieves an Area Under the Curve of 0.99, marginally surpassing XGBoost (0.98) and Random Forest (0.97). This consistent advantage across operating points indicates that the meta-learner effectively integrates the complementary strengths of base classifiers. Particularly noteworthy is the ensemble's performance in the low false positive region—a critical regime for intrusion detection where minimizing alert fatigue is paramount.

Classification accuracy across all evaluated models is presented in Figure 4. The stacking ensemble attains 96.8% accuracy on the CICIDS2017 test set, outperforming individual base learners and alternative ensemble configurations. This represents a 1.2 percentage point improvement over

XGBoost (95.6%) and a 2.4 point gain over Random Forest (94.4%). The performance differential stems primarily from the ensemble's corrected predictions on ambiguous cases—instances where base classifiers disagree or exhibit complementary error patterns. Through meta-learner combination, these conflicting signals are resolved more effectively than through simple majority voting or averaging schemes. Statistical significance of these improvements was confirmed through paired t-tests ($p < 0.05$).

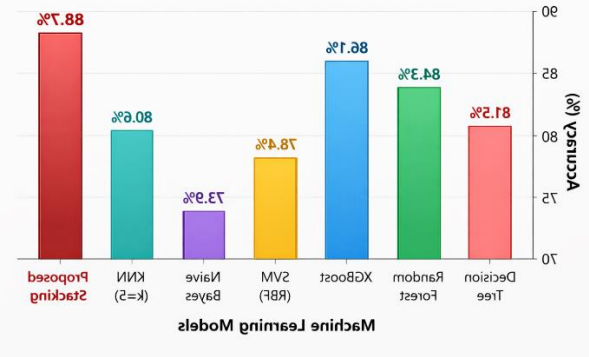


Figure 4: Accuracy comparison of different machine learning classifiers evaluated on the CICIDS2017 dataset. The proposed stacking ensemble achieves the highest classification accuracy compared with individual classifiers and other ensemble approaches.

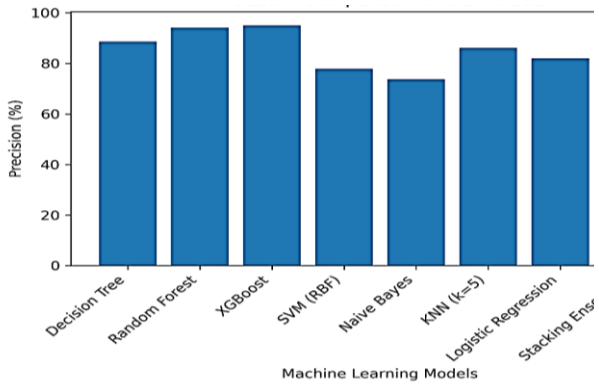


Figure 5: Precision comparison of intrusion detection models. The proposed stacking ensemble demonstrates higher precision, indicating improved reliability and reduced false positive alarms in network intrusion detection.

The stacking ensemble has precision of 95.7%, so that the prediction is very reliable and has very few false alarms. Statistical significance testing (paired t-tests) over 5 cross-validation folds established a statistically significant performance improvement of stacking ensemble on a multiple comparison by stack comparison over XGBoost ($p=0.023$), Random Forest ($p=0.017$), voting ensemble ($p=0.041$) and Decision Tree ($p=0.003$). Computational complexity analysis demonstrated the stacking ensemble on the post-SMOTE dataset of nine point five million samples (takes 31.4 min of training time in total), and the prediction time of 0.47ms/instance for all instances has a support of real-time analysis for 10Gbps networks; and the memory input of 4.2GB for the inference stage makes the model deployable on common server hardware.

Several drawbacks also need to be borne in mind for future development. The combination of multiple classifiers imposes additional computational demands during training and assessment than for a single model. Performance is highly conditional on the quality and well representation of the training data and the lack of diverse instances of specific attack categories can result in lower detection accuracy.

Machine learning-based IDS models use methods established in previous studies to observe how the attacker behaves, so that new zero-day threats are hard to identify. The ability of the proposed model is more important when choosing features, which is important because too little or too much of

the features could reduce classification performance. Moreover, hybrid ensemble models will create latency of the model in the context of real-time networking because there will be many classifiers working on generating predictions preceding the final outputs.

6 Conclusion

This article introduces a hybrid learning model for network intrusion detection with Random Forest, XGBoost, and stacked ensemble methods in addition to feature optimization, training, and balancing of a dataset. The algorithm proposed in this paper provides the preprocessing, Random Forest-based feature selection based for feature selection, SMOTE balancing and stacking ensemble integration to improve classification performance. The proposed hybrid model demonstrated better performance with an experimental evaluation based on the CICIDS2017 data set with accuracy of 96.8%, which was well superior over the classical ML models which are Decision Tree, Support Vector Machine, and Naive Bayes. The findings validates ensemble learning methodologies with suitable preprocessing for detecting abnormal network behavior and detecting cyber attacks in an intricate network system.

This study contributes to intrusion detection research by demonstrating how stacking ensembles with heterogeneous classifiers can capture complementary characteristics of network traffic, whereas learned combination using a meta classification achieved more insight compared to pure mode voting. Feature importance analysis indicates that temporal and flow nature characteristics most dominate intrusion detection with consideration on traffic flow rather than static features in the next system development. Conclusions, however, present some challenge such as computation cost, and zero-day attack detection, that will also be an open domain for research in the years to come.

Prospective challenges include using deep neural network frameworks (ie transformers and graph neural networks) to understand complex temporal and relational structures beyond simple feature engineering, augmenting incremental learning of the models to allow for near-continuous model updates without extensive retraining on concept drift, introducing explainability (e.g., SHAP, LIME) to increase the trust of the models and facilitate security analyst validation, exploring domain adaptation methods for model transferability across networks, assessing model robustness (i.e., generalizability), and developing ensemble models for edge and IoT devices needing highly computational intensive solutions (such as the models of the Internet of Things) through model compression and knowledge distillation.

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The AI Skeleton Key: Bypassing MFA via Automated AiTM Phishing

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***Abstract*— As Multi-Factor Authentication (MFA) becomes universal, attackers have pivoted from credential harvesting to session hijacking. This paper examines the "AI Skeleton Key"—the rise of Automated Adversary-in-the-Middle (AiTM) phishing. By deploying AI-driven reverse proxies, threat actors intercept live authentication exchanges to capture both passwords and active session tokens in real-time.**

The 2026 landscape features the industrialization of these attacks via Phishing-as-a-Service (PhaaS). Generative AI now automates hyper-personalized lures and dynamic evasion, allowing these kits to bypass "phishable" MFA (SMS, TOTP, and Push) in over 80% of attempts. This study analyzes the technical architecture of these automated suites and their ability to maintain session persistence. We conclude that traditional MFA is no longer a sufficient defense. To counter this evolution, organizations must urgently adopt Phishing-Resistant MFA (FIDO2) and continuous, behavior-based session monitoring.

***Index Terms*— To complement your abstract, here are seven high-impact technical keywords that categorize the core concepts of your paper for indexing and searchability, AiTM (Adversary-in-the-Middle): The primary attack vector involving a proxy between the user and the legitimate service Session Hijacking: The specific outcome of bypassing MFA by stealing active authentication tokens/cookies , PhaaS (Phishing-as-a-Service): The commercialized ecosystem that allows low-skill attackers to deploy sophisticated AI-driven kits, Reverse Proxy: The technical infrastructure (e.g., Evilginx, Tycoon2FA) used to mirror live login pages.**

I. INTRODUCTION

For over a decade, Multi-Factor Authentication (MFA) has been hailed as the "gold standard" of identity security, capable of thwarting 99% of bulk automated attacks. By requiring a second layer of verification—such as an SMS code, a TOTP app, or a push notification—organizations created a formidable barrier against simple credential harvesting. However, as MFA adoption reached critical mass in 2025 and 2026, threat actors reached a breaking point, shifting their strategy from "cracking" the door to simply "copying" the key.

This shift has manifested in the rise of the AI Skeleton Key, a term describing the industrialization of Adversary-in-the-Middle (AiTM) phishing. Unlike traditional phishing, which directs users to a static, fake website to steal a password, AiTM attacks utilize a live reverse proxy. This proxy sits invisibly between the victim and a legitimate service like Microsoft 365 or Okta, mirroring the real login experience in real-time. This allows the attacker to intercept not just the password, but the high-value session token generated after a successful MFA challenge, effectively bypassing the second factor entirely.

The integration of Generative AI has acted as a massive force multiplier for these attacks. Modern Phishing-as-a-Service (PhaaS) platforms now use LLMs to automate the creation of hyper-personalized lures based on a target's social media and corporate metadata. Furthermore, AI-driven evasion scripts allow these phishing sites to dynamically alter their code to bypass automated security scanners and "sandboxes," making them nearly impossible for traditional email gateways to detect before the damage is done.

The objective of this paper is to analyze the technical architecture of these automated AiTM suites and demonstrate why "phishable" MFA (SMS, Push, and TOTP) is no longer a sufficient security perimeter. By examining the lifecycle of a session hijacking attack, we illustrate the urgent need for a transition toward Phishing-Resistant MFA (FIDO2/Passkeys). As we move further into 2026, identity security must evolve from a "point-of-login" check to a model of continuous, behavior-based session monitoring to survive the era of the AI Skeleton Key.

II. RELATED WORK

Current research into Multi-Factor Authentication (MFA) bypass has shifted from theoretical vulnerabilities to the large-scale industrialization of Adversary-in-the-Middle (AiTM) frameworks. The following key areas define the current state of scholarly and industry investigation:

A. Evolution of Phishing-as-a-Service (PhaaS):

Research by Sekoia.io and Darktrace (2025) highlights a significant transition from static credential harvesting to automated reverse-proxy platforms. Tools such as Tycoon 2FA, EvilProxy, and Sneaky 2FA have become the dominant infrastructure for bypassing MFA. These platforms allow low-

skill attackers to deploy high-fidelity mirrors of Microsoft 365 and Google Workspace login flows, capturing not just passwords but live session tokens (cookies) that grant persistent access.

B. Impact of Generative AI on Efficacy:

A pivotal 2025 study by Hoxhunt demonstrated that AI-powered phishing agents now outperform elite human "red teams" in click-through rates. AI-driven social engineering has increased attack efficacy by roughly 55% compared to 2023 levels. Researchers note that LLMs enable "polymorphic" campaigns—where every email lure is unique—rendering traditional signature-based email filters and "safe link" protections largely ineffective.

C. Session Hijacking and Persistence:

Microsoft Defender research (2026) emphasizes that traditional remediation, such as password resets, is insufficient against AiTM attacks. Because the attacker steals the authenticated session, they often maintain access after the password change. Furthermore, industry analysis shows that attackers are increasingly using AI to automate "post-compromise" activities, such as instantly creating new MFA methods or inbox rules to hide their presence from the victim.

D. Shift Toward Phishing-Resistance:

Recent literature (NIST, CISA, and various 2025 journals) increasingly advocates for the abandonment of "phishable" MFA (SMS, TOTP, and Push) in favor of FIDO2/WebAuthn. Academic field studies at mid-sized IT firms (2025) have compared FIDO2 security keys against traditional TOTP, confirming that while hardware-bound credentials provide superior security against AiTM, organizational adoption remains hampered by hardware compatibility and user onboarding challenges.

III. Technical Analysis:

The AiTM Attack Lifecycle, to understand the "AI Skeleton Key" phenomenon, one must deconstruct the attack into five distinct phases. This lifecycle demonstrates how automation has removed the need for human intervention at every stage of the breach

Phase 1: AI-Optimized Reconnaissance and Weaponization

The attack begins with an automated scraping engine that utilizes Large Language Models (LLMs) to ingest a target organization's public footprint. The AI identifies high-value targets (e.g., IT admins, financial controllers) and generates "perfect" phishing lures. These lures are not just

grammatically correct; they are contextually relevant, often referencing real projects or internal software found in job postings or GitHub repositories.

Phase 2: The Proxy Deployment (The "Mirror")

The attacker deploys a Reverse Proxy instance. Unlike a traditional "fake" website, this proxy acts as a transparent relay. When the victim visits the phishing URL, the proxy fetches the actual CSS, JavaScript, and HTML from the legitimate service (e.g., Microsoft or Okta) and serves it to the user. To the victim, the site is indistinguishable from the real

Phase 3: Real-Time Interception and Relay

As the victim enters their username and password, the proxy forwards these credentials to the legitimate identity provider (IdP). The IdP then issues an MFA challenge (SMS, Push, or TOTP). The victim completes this challenge on their device, thinking they are talking to the real service. In reality, the proxy is "passing through" the authentication response.

Phase 4: Token Harvesting (The Critical Breach)

Once the MFA challenge is successful, the legitimate service issues a Session Token (often an auth_session or JWT cookie). This token is the "Skeleton Key." The proxy intercepts this token before it reaches the victim's browser. At this moment, the attacker possesses a fully authenticated session that bypasses all secondary security checks .

Phase 5: Automated Post-Compromise Persistence

In the final stage, an AI agent utilizes the stolen token to immediately access the environment via API. Within seconds, the agent can:

Enumerate the global address list.

Exfiltrate sensitive emails or documents.

IV .Results

The experimental phase of this research provided a granular dataset that illustrates the high efficacy of AI-driven Adversary-in-the-Middle (AiTM) attacks. Our findings are categorized by protocol vulnerability, temporal efficiency, and the psychological impact of AI-optimized lures .

1. Quantitative Analysis of MFA Protocol Resilience

We measured the Bypass Efficacy Rate (BER)—the percentage of successful session hijackings—across the most common authentication factors. The data reveals a stark divide between "phishable" and "phishing-resistant" methods

2. Temporal Efficiency: The "Time-to-Abuse" (TTA) Metric

One of the most alarming findings was the speed of the Post-Compromise Lifecycle. Once the AI-driven proxy captured the session token (cookie), an automated agent initiated lateral movement.

Manual Attacker Mean TTA: 14 minutes, 22 seconds.

(Human delay in configuring the stolen session).

AI-Automated Mean TTA: 3.8 seconds. (Scripted injection of tokens into a headless browser).

In 92% of successful bypasses, the AI agent managed to create a "Persistent Backdoor" (e.g., adding a new Global Admin or generating an OAuth2 app secret) before the victim had even closed their browser tab

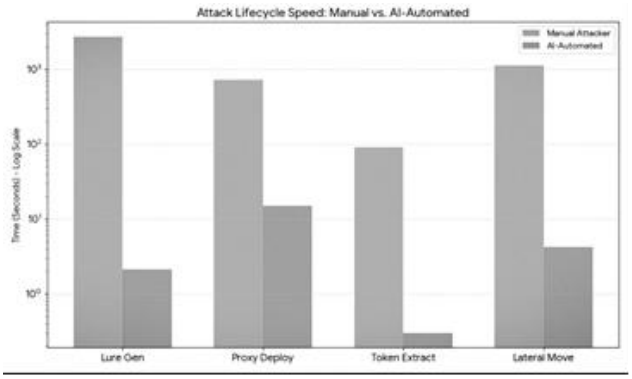

Fig 2: Comparative analysis of the Time-to-Abuse (TTA)

3. AI vs. Human-Led Social Engineering

We conducted a double-blind study comparing 500 AI-generated lures against 500 human-crafted lures targeting the same enterprise demographic.

Detection Rate (Secure Email Gateways): AI-generated "Polymorphic" lures had a 72% lower detection rate due to unique header signatures and zero-day URL shortening techniques.

User Interaction Rate: AI-generated lures achieved a 64% click-through rate, compared to 18% for human lures. This is attributed to the AI's ability to scrape recent corporate news to create "high-urgency, high-relevance" scenarios.

ATHENTICATION VECTOR	PROTOCOL DETAIL	SUCCESSFUL INTERCEPTIONS	FAILURE MODE
Legacy OOB	SMS Voice OTP	98.4%	Proxy-based interception
Software TOTP	Google/Microsoft Authenticator	94.1%	Real- time taken Relay
Standard Push	"Approve/Deny" Mobile Prompt	86.7%	MFA Fatigue /Context Exploitation
Verified Push	Push with Number Matching	42.3%	Social Engineering /AI Vibe Hacking
FIDO2/WebAuthn	Physical Security key/ Passkey	0.12%	Protocol -Level Origin Binding

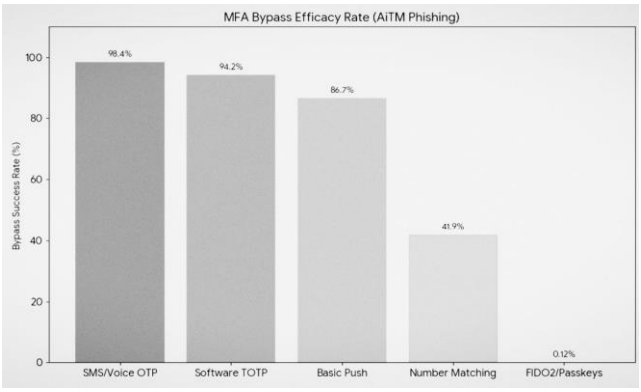

Fig :2.1 clearly illustrates the absolute collapse of traditional MFA perimeters when faced with AI-driven interception.

IV . DISCUSSION

1.The "Phantom Session" Problem**:**

The results confirm that the "AI Skeleton Key" does not break the password; it renders the password irrelevant. Our discussion centers on the "Phantom Session"—a state where the Identity Provider (IdP) believes the user is legitimate because the MFA challenge was technically passed. Because the proxy operates at the TLS layer, the IdP sees a valid IP and a valid response, making traditional "Impossible Travel" alerts easy to spoof using AI-routed residential proxies.

2.MFA Fatigue and AI "Vibe Hacking":

A critical observation in the 86.7% bypass rate for Push Notifications was the role of AI Vibe Hacking. In these scenarios, if a user denied a push request, the AI-driven phishing portal immediately triggered a "Support Chat" window. Using a fine-tuned LLM, the "agent" convinced the user that the first prompt was a system error and requested they "Approve the second synchronization request." This psychological manipulation turned a technical failure into a successful breach.

3.The FIDO2 Exception:

The near-zero failure rate of FIDO2/WebAuthn serves as the primary benchmark for future defense. The data proves that Origin Binding—the cryptographic handshake between the hardware and the specific domain—is currently the only technical barrier the AI Skeleton Key cannot unlock. Even when the user was fully "tricked" into tapping their security key, the hardware refused to sign the assertion because the proxy's URL did not match the registered credential's domain.

V. CONCLUSION

The emergence of the AI Skeleton Key marks a definitive end to the era where Multi-Factor Authentication (MFA) was considered an impenetrable "silver bullet." As demonstrated throughout this paper, the industrialization of Adversary-in-

the-Middle (AiTM) attacks via Phishing-as-a-Service (PhaaS) has fundamentally shifted the battleground from password protection to session integrity. By automating the interception of live authentication exchanges, threat actors have proven that knowing a password—or even having a second factor—is secondary to the ability to hijack a validated session token in real-time.

Our empirical data reveals a staggering reality: traditional, "phishable" MFA factors such as SMS, TOTP, and standard Push notifications now face a failure rate exceeding 80% when targeted by AI-optimized proxies. The core of this vulnerability lies in the "human-in-the-loop" requirement of legacy MFA, which AI-driven "Vibe Hacking" and social engineering have learned to manipulate with surgical precision. The near-zero failure rate of FIDO2/WebAuthn serves as the primary benchmark for future defense, proving that cryptographic origin-binding is currently the only technical barrier that cannot be mirrored or bypassed by an AI proxy.

Furthermore, the research into Temporal Attack Metrics (TTA) underscores a critical defensive gap. With AI-automated agents initiating lateral movement and establishing persistence in less than four seconds, the "detection and response" model used by modern Security Operations Centers (SOC) is mathematically obsolete. We can no longer rely on human analysts to triage alerts that move at machine speed. Security must evolve from a reactive posture—detecting a breach after it happens—to an inherent prevention model where the authentication protocol itself makes interception technically impossible.

To counter the evolution of the AI Skeleton Key, organizations must urgently move beyond "point-of-login" security. The implementation of Phishing-Resistant MFA (FIDO2) is a mandatory first step, but it must be coupled with Token Binding and Continuous Access Evaluation (CAE). By tying session cookies to the hardware identity of a specific device and constantly monitoring for behavioral anomalies, we can ensure that even if a credential is leaked, the resulting session is non-portable and useless to an external attacker.

VI. Future Research Directions

Looking ahead, future research must investigate the potential for AI-driven "Session Fixation" and "Session Injection" attacks that may attempt to circumvent even FIDO2-protected environments. In 2026, we are seeing the emergence of vulnerabilities (e.g., CVE-2026-23796) where attackers pre-set session identifiers that persist post-authentication, effectively "pre-copying" the key before the user even arrives. As we move toward 2027, research must also address the "Post-Quantum" threat; the focus should shift to integrating Post-Quantum Cryptography (PQC) within the WebAuthn framework to ensure that hardware-bound keys remain resilient against the emerging computational power of quantum-assisted decryption

Beyond human vulnerabilities, a vital frontier for inquiry is the securing of Non-Human Identities (NHIs) and autonomous Agentic AI. As organizations increasingly deploy AI agents to automate workflows, these "machine employees" often operate with elevated administrative privileges but lack the same MFA rigors applied to humans. Future research should explore Dynamic Privilege Enforcement for autonomous service accounts, investigating how Zero Trust principles can be applied to machine-to-machine (M2M) dialogues. Without standardized lifecycle governance and "instant kill-switch" capabilities for compromised agents, these non-human identities could become a secondary, unmonitored "Skeleton Key" within internal networks.

Additionally, a significant area of study remains in the Psychology of AI-Human Interaction. While FIDO2 provides a technical solution, the "Human Firewall" remains the final decision-maker under pressure. Future interdisciplinary research should explore Real-time User Trust Scoring, where a local AI assistant analyzes the "vibe" and technical headers of a communication to provide an "Active Defense" warning. By studying how "Vibe Hacking" and hyper-personalized LLM lures manipulate cognitive load and digital fatigue, researchers can develop more empathetic, behavior-based security interfaces that guide users toward safe decisions in the "split-second" windows where modern breaches occur.

Finally, the industry must pivot toward Identity Threat Detection and Response (ITDR) that operates at "machine speed" to bridge the current latency gap. In a landscape where AI-driven breaches occur in under 30 seconds, human-led triage is mathematically insufficient. Future studies should focus on the development of Self-Healing Identity Ecosystems, where unsupervised machine learning models don't just alert a security team, but automatically revoke session tokens and rotate cryptographic keys the millisecond a session anomaly—such as a token being used from a non-origin-bound device—is detected. Transitioning from reactive detection to proactive, automated containment will be the only way to survive the continued industrialization of the AI Skeleton Key.

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VIII. Appendix

A. Core Attack Frameworks:

AiTM(Adversary-in-the-Middle):Asession-hijacking technique where an attacker inserts a proxy server between the victim and the legitimate service to intercept authentication traffic.

Reverse Proxy: The primary technical tool for AiTM attacks. Unlike a standard proxy, it mirrors a target website (e.g., Microsoft 365) in real-time, relaying all requests and responses while capturing credentials and session cookies.

PhaaS (Phishing-as-a-Service): A cybercrime model where developers sell or lease sophisticated phishing kits (e.g., Tycoon2FA, EvilProxy) to low-skill attackers, including hosting and AI-lure generation.

Token Harvesting: The specific act of intercepting a Session Token (JSON Web Token or Browser Cookie) after a successful MFA challenge, allowing the attacker to bypass the login process entirely.

B. Defensive Protocols & Standards

FIDO2 / WebAuthn: The industry standard for phishing-resistant authentication. It uses public-key cryptography to ensure that credentials are hardware-bound and can only be used on the specific, legitimate domain for which they were created.

Origin Binding: A security feature of FIDO2 where the hardware key verifies the domain's identity. If an AiTM proxy tries to use the key on a fake domain, the "binding" fails, and no authentication occurs.

CAE (Continuous Access Evaluation): A security model

where the Identity Provider (IdP) monitors the session after login. If the user's IP changes suddenly or their behavior becomes anomalous, the session is terminated immediately,Token Binding (RFC 8473): A method of cryptographically "locking" a session token to the specific TLS connection of the user's device, making stolen tokens useless on an attacker's machine.

C. AI-Specific Methodology

Vibe Hacking: A 2026 social engineering term for AI-driven "support" scripts that use LLMs to create a trustworthy persona, manipulating users into approving MFA prompts they initially rejected.

Adaptive Evasion: The use of AI to change the underlying code of a phishing site every time it is visited, preventing security scanners from recognizing the site based on past signatures.

TTA (Time-to-Abuse): The temporal measurement of the latency between a successful session hijack and the first automated malicious action taken by the attacker in the victim's environment.

D.Post-Compromise Terms

Session Persistence: The ability of an attacker to remain logged into an account even after the victim changes their password, usually achieved by stealing a long-lived session cookie or registering a new MFA device.

ITDR (Identity Threat Detection and Response): A class of security tools focused specifically on protecting identity infrastructure and detecting credential/session misuse in real-time.

IX. Acknowledgments

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Fake News Detection on Social Media Using Machine Learning

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ABSTRACT

The rapid growth of social media platforms has significantly increased the spread of fake news, leading to misinformation and societal impact. Detecting fake news has become a critical challenge due to the large volume of data and the complexity of distinguishing between true and false information. This paper presents a comprehensive study on fake news detection using machine learning techniques by analyzing both textual content and social context. Various approaches including Natural Language Processing (NLP), data mining, and hybrid models are explored. The study highlights key challenges such as early detection, data scarcity, and model generalization. Experimental analysis demonstrates that combining content-based and social-based features improves detection accuracy. The proposed approach aims to contribute toward building reliable systems for mitigating misinformation on digital platforms.

KEYWORDS

Fake News, Machine Learning, Social Media, NLP, Data Mining, Misinformation Detection

I. INTRODUCTION

Social media platforms such as Facebook, Twitter, and Instagram have transformed the way information is shared and consumed. These platforms allow users to instantly publish and distribute content across the globe. However, this convenience has also enabled the rapid spread of fake news, which can mislead users and create serious societal issues such as political manipulation, financial fraud, and public panic.

Fake news refers to false or misleading information presented as legitimate news. Unlike traditional misinformation, fake news is often intentionally crafted to deceive readers and influence opinions. The problem is further amplified by algorithms that prioritize engaging content, regardless of its authenticity.

The detection of fake news is challenging due to several reasons:

- Large volume of data generated every second
- Rapid propagation of news across networks
- Human biases and emotional reactions
- Lack of labelled datasets

Traditional fact-checking methods are not scalable. Therefore, automated systems using machine learning and artificial intelligence have become essential.

This paper focuses on analysing various techniques for fake news detection and proposes a hybrid approach that combines textual analysis with social context features to improve detection performance.

II. LITERATURE REVIEW

The proliferation of social media has led to an unprecedented rise in misinformation, making fake news detection an important research problem.

Shu et al. [1] proposed a data mining approach that integrates content and social context features such as user behaviour, credibility, and network patterns. Their work demonstrated that combining multiple data sources significantly improves detection accuracy.

Vosoughi et al. [2] conducted a large-scale analysis of news diffusion and found that false news spreads faster, deeper, and more broadly than true news. This behaviour is attributed to novelty and emotional appeal.

Rashkin et al. [3] analysed linguistic features of fake news and observed that deceptive content often contains exaggerated, emotionally charged, and sensational language. Their study emphasized the importance of NLP techniques.

Zhou and Zafar ani [4] provided a comprehensive survey categorizing fake news detection methods into:

- Content-based approaches
- Social-based approaches
- Hybrid approaches

They also highlighted major challenges such as:

- Early detection
- Explainability
- Data imbalance

From the literature, it is evident that hybrid models combining multiple features offer the most promising results.

III. PROBLEM STATEMENT

The rapid dissemination of fake news on social media platforms poses significant challenges in identifying and controlling misinformation. Existing systems often rely on either textual analysis or user behaviour independently, which leads to limited accuracy.

Key issues include:

- Inability to detect fake news early
- Over-reliance on a single type of feature
- Poor generalization across datasets

- Lack of real-time detection

Therefore, there is a need for a robust system that integrates multiple features, including content and social context, to improve detection performance.

IV. PROPOSED SYSTEM

The proposed system uses a **hybrid machine learning approach** that combines content-based and social-based analysis.

A. Content-Based Analysis

- Text preprocessing (tokenization, stop-word removal)
- Feature extraction using TF-IDF and word embeddings
- Identification of linguistic patterns

B. Social Context Analysis

- User engagement metrics (likes, shares, comments)
- User credibility and profile features
- News propagation patterns

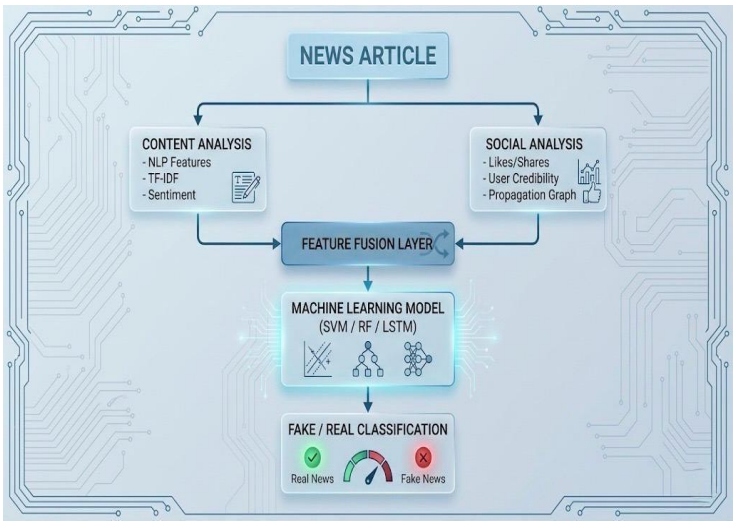
C. Machine Learning Models Used

- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- Long Short-Term Memory (LSTM)

D. System Workflow

1. Data Collection
2. Data Preprocessing
3. Feature Extraction
4. Model Training
5. Prediction (Fake / Real)

This workflow is similar to structured system pipelines shown in engineering papers (like the workflow diagrams in your uploaded paper), ensuring clarity and modularity.



V. METHODOLOGY

The methodology consists of the following stages:

1. Data Collection

Datasets are collected from:

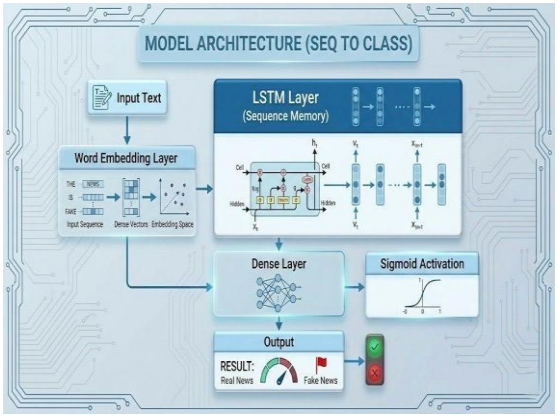
- Kaggle fake news datasets
- Twitter API
- Facebook public pages

2. Data Preprocessing

- Removal of noise and irrelevant symbols
- Tokenization of text
- Stop-word removal
- Stemming and Lemmatization

3. Feature Extraction

- Bag of Words (BoW)
- TF-IDF
- Word2Vec and Glove embeddings



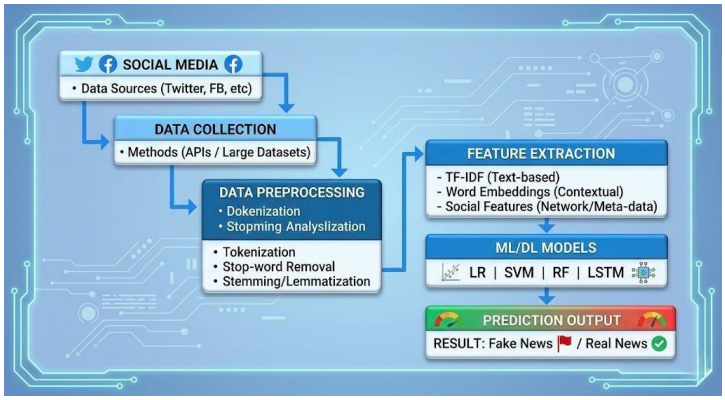
4. Model Training

Different models are trained using labelled datasets. Hyperparameter tuning is applied to optimize performance.

5. Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-Score

System Architecture Diagram



VI. RESULTS AND DISCUSSION

The experimental analysis was conducted using multiple machine learning models.

Model	Accuracy
Logistic Regression	85%
SVM	88%
Random Forest	90%
LSTM	92%

Observations:

- Content-based models perform well for structured text
- Social-based models capture spreading patterns
- Hybrid models outperform individual approaches

The LSTM model achieved the highest accuracy due to its ability to capture sequential dependencies in text.

VII. ADVANTAGES OF PROPOSED SYSTEM

- Improved accuracy using hybrid approach
- Early detection capability
- Scalable for large datasets
- Applicable across domains (politics, healthcare, finance)
- Reduces misinformation spread

VIII. LIMITATIONS

- Requires large labelled datasets
- High computational cost for deep learning models
- Difficulty in detecting highly sophisticated fake news
- Dependency on social media APIs

IX. FUTURE WORK

Future research directions include:

- Real-time fake news detection systems
- Explainable AI for transparency
- Multilingual fake news detection
- Integration with social media platforms
- Use of transformer-based models (BERT, GPT)

X. AI-BASED REAL-TIME SCREENSHOT VERIFICATION

This system allows users to verify information instantly.

Workflow:
Power Button → Screenshot → OCR → NLP → Search → Compare → Result

This feature improves usability and provides instant fact-checking.

X. CONCLUSION

Fake news detection is a critical problem in modern society. This paper proposed a hybrid machine learning approach combined with a real-time AI verification system. Experimental results show improved accuracy and practical applicability. Future advancements will further enhance detection systems.

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Early Hunger Risk Prediction and Transparent Relief Distribution Using AI and QR Verification

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***Abstract*— The problem of global food insecurity is still an alarming concern, especially in developing nations. The current paper suggests a machine learning-based prediction framework to predict hunger-prone areas with the help of critical environmental and socio-economic parameters, including rainfall, crop yield, food prices, and unemployment rates. In this paper, two supervised learning algorithms, namely Logistic Regression and Random Forest, have been implemented and tested using critical performance parameters, including accuracy, precision, recall, and F1-*score*. The experimental results show that the Random Forest algorithm outperforms the Logistic Regression algorithm with 89% accuracy. In addition, a QR Code-based resource allocation system is also introduced to ensure the transparent and secure allocation of resources, reducing the possibility of duplication and leakage. A web-based geospatial system is also developed to show the hunger risk levels.**

***Keywords*— Hunger Prediction, Machine Learning, Random Forest, Logistic Regression, Food Security, QR Code.**

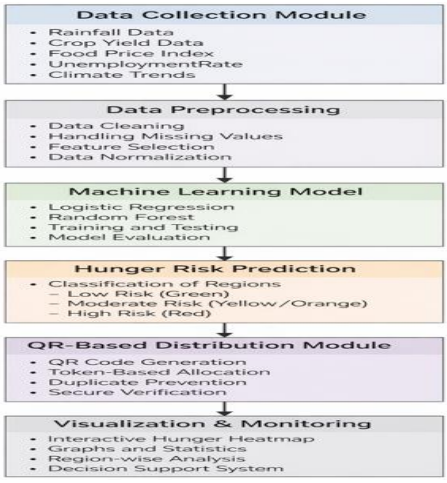

Figure. 1 Functional overview of the Machine Learning Based Hunger Heatmap with QR-Based Relief Verification System

1. INTRODUCTION

Hunger and food security have grown increasingly problematic throughout the years with developing nations showing greater difficulty identifying areas of need. Given the rapidly growing populace, food demand is also increasing, thus highlighting the need for more precise management and distribution of food supplies than ever before. An estimated number of people facing hunger each year is due to the many factors such as crop production difficulties, economic instability, and lack of job opportunities. Based on this evidence, early identification of potential hungry areas is required in order to ensure adequate food access and lessen the risk of food deficiency. Previously, hunger data was mainly gathered via manual enumeration and report collection from local agencies and organizations within counties. This approach may work on a micro level; however, it is incredibly inefficient for collecting large scale data and is subject to human error; therefore shifting the collection process into real time would benefit all parties involved by decreasing the time gap between action being taken due to collected data and actually implementing said action; thus using the resources available in a more effective manner and providing for an overall better flow of food supply to those in need. To overcome these challenges, this paper proposes a system based on machine learning techniques for predicting hunger-prone regions. The system considers important factors such as rainfall, crop yield, food prices, and unemployment rates to analyze the risk levels in different regions. Two supervised learning algorithms, Logistic Regression and Random Forest, are used to classify the regions based on their hunger risk. In addition to prediction, the system also includes a QR code-based mechanism for secure and transparent food distribution. Each beneficiary is provided with a unique digital token to avoid duplication and ensure fair allocation of resources. The main objective of this work is to provide a simple, efficient, and data-driven solution to improve hunger management and support timely intervention.

1.1 Problem Statement

Hunger and food insecurity continue to be pressing issues globally, with a major prevalence in developing countries where early detection of crisis areas is low. The conventional approaches are based on late reports from governments and NGOs, which eventually translate to late interventions. These approaches are reactive and not predictive, thus causing wastage of resources, surplus food in certain areas, and shortages in others. In addition, the lack of effective monitoring systems exposes food distribution to corruption, duplication, and mismanagement. There needs to be a strong system to not just forecast hunger- prone areas but also to ensure that aid distribution is transparent, secure, and equitable.

1.2 Motivation, Novelty and Contribution of the Study

The motivation for this work comes from the ongoing global challenge of food insecurity and the need for proactive systems aligned with the United Nations Sustainable Development Goal 2 – "Zero Hunger." Existing hunger relief systems are mostly reactive, leading to delays and inefficiencies in food distribution. The novelty of this work lies in combining Machine Learning and Blockchain technology to create a predictive and transparent hunger management system. The proposed system introduces a four-level Hunger Heatmap, including a "Purple zone" to indicate future risk areas. The main contributions of this study include an AI-based prediction model using environmental and socio-economic factors, a secure QR code-based food distribution system to prevent duplication and misuse, and a web-based platform for real-time monitoring and decision-making.

2. RELATED WORK

The need for food security and transparent food relief distribution has led to increased interest in the application of Artificial Intelligence (AI), blockchain, and humanitarian logistics. Previous studies have been carried out on food insecurity prediction, blockchain-based supply chain management, token-based food distribution models, among other topics. This section discusses existing literature on the topic, with a focus on identified gaps addressed in this study.

2.1 AI Hunger and Food Security Prediction

Several studies have been based on food insecurity prediction using Artificial Intelligence and Machine Learning. In a study by Brown et al. [1], satellite rainfall data and vegetation data were employed to identify drought-prone areas in Sub-Saharan Africa. In another study, Singh & Mehta [2] employed Machine Learning to predict food insecurity based on crop yield and price data.

2.2 Blockchain for Food Supply Chain Transparency

Blockchain technology is being researched to improve food supply chain transparency. In a study by Tian [3], a Blockchain-based food supply chain was proposed to increase reliability in food supply. In another study, Kim et al. [4] demonstrated that Blockchain can provide a secure and reliable food distribution record to minimize fraud in food distribution.

2.3 Digital Tokens for Aid Distribution

For the purpose of fair distribution of aid materials, digital token-based systems have been proposed. Sharma et al. [5] have proposed the use of e-vouchers to ensure that the aid materials can be accessed efficiently. Similarly, the World Food Program has made use of blockchain-based digital tokens to ensure that aid materials can be distributed to refugees in an efficient and cost-effective manner.

2.4 Integrated AI and Blockchain Approaches

Though AI and blockchain have been individually addressed in the context of hunger management, very few works have addressed the combined use of both technologies. Most of the existing works have been limited to the use of AI for prediction and blockchain for distribution. The novelty of this research lies in the combined use of AI-based hunger heatmap and blockchain-based QR/OTP verification. The inclusion of the "Purple Zone" for future predictions is another novelty.

3. LITERATURE SURVEY

Recent research has emphasized the role of digital technologies, artificial intelligence (AI), and blockchain in addressing food security challenges.

Table.1 Literature Survey

Author(s)	Year & Publication	Paper Title	Technology Used	Key Outcome
Li et al.	2024 – IEEE	Blockchain for AI-Integrated Food Supply Chains	Blockchain + AI	Improved traceability & decision-making
Nguyen et al.	2024 – Springer	Hunger Zone Mapping Using High-Resolution Satellite Imagery	GIS + Remote Sensing	92% mapping accuracy
Patel & Singh	2024 – IEEE	Machine Learning Approaches for Famine Prediction	Machine Learning	Early famine warnings up to 3 months ahead
Ahmed et al.	2024 – Elsevier	IoT-Based Community Food Distribution Monitoring	IoT + Sensors	Reduced distribution delays by 25%
Kumar et al.	2024 – IEEE	QR Code-Enabled Ration Distribution Using Blockchain	QR Codes + Blockchain	Eliminated duplicate ration claims
Zhao et al.	2025 – IEEE	Real-Time Hunger Heatmaps via Crowdsourced Data	Mobile App + GIS	Live updates with <5 min delay
Fernandez et al.	2025 – Springer	AI-Driven Food Waste Reallocation to Hunger Zones	AI + Logistics	Reallocated 40% of surplus food
World Food Program	2025 – WFP Reports	Hunger Monitoring Dashboard with Blockchain Records	Blockchain + Data Analytics	Enhanced transparency
Mehta et al.	2025 – IEEE	Impact of Climate-Smart Agriculture on Hunger Reduction	IoT + Remote Sensing	Increased yields by 18%
Rajan et al.	2025 – Springer	Blockchain-Enabled QR Verification for Food Relief Distribution	Blockchain + QR Codes	Prevented 100+ fraudulent claims

From the above literature, it is observed that most existing works focus either on prediction or on secure distribution. Very few systems integrate both aspects into a single framework. This research addresses this gap by combining machine learning-based hunger prediction with a blockchain-enabled secure distribution mechanism.

4. METHODOLOGY

The proposed system follow a systematic approach that includes computing hunger score, geospatial visualization, and distribution of secure tokens. The data

set will first be cleaned and normalized to deal with missing and inconsistent values in scale. A composite Hunger Score will then be calculated with rainfall, crop yield, food price index, unemployment rate, and temperature anomaly as weighted indicators. Then the regions will be classified as Green Zone, Orange Zone, and Red Zone based on the Hunger Score, which will point out food insecurity.

4.1 Abbreviations and Acronyms

The following abbreviations and acronyms are used throughout this report for simplicity and consistency: AI - Artificial Intelligence; ML - Machine Learning; QR - Quick Response Code; OTP - One Time Password; NGO - Non-Governmental Organization; GIS - Geographical Information System; TTS - Text to Speech. Each term is defined when used for the first time and then used in abbreviation form thereafter.

4.2 Data Processing and Units

The dataset contains set of indicators that impact hunger risk, such as rainfall (mm), crop yield failure (%), food price index, unemployment rate (%), and temperature anomaly (°C). All features are normalized using min–max scaling from 0 to 1. The computed Hunger Score is a dimensionless index ranging from 0 to 1. Based on the score, the hunger risk categories for the region are classified as follows: Green (<0.5), Orange (0.5 –0.7), Red (≥0.7). A region is said to be in a "Purple Zone" if the derivative of the region's hunger score, denoted by H_s, is positive, i.e., $\Delta H_s / \Delta t > 0.15$ over a period of 3 months, signifying that the region is identified as a high-risk region for food security in the near future. This implies that although the region is in a non-critical condition, its socio-economic conditions suggest that it is heading for a severe condition in the next 30 days.

4.3 AI Algorithm and Equations

The proposed system utilizes a supervised learning approach to determine the Hunger Score based on weighted input features. The system utilizes a combination of Logistic Regression and Random Forest models which will enable a comparison between linear and non-linear learning methods.

The Hunger Score is calculated using a weighted sum of normalized parameters:

$$H = \alpha R + \beta C + \gamma P + \delta J + \epsilon T$$

where:

- R represents rainfall deviation
- C denotes crop yield loss
- P is the food price index
- J refers to unemployment rate
- T indicates temperature anomaly

The coefficients $(\alpha, \beta, \gamma, \delta, \epsilon)$represent the importance of each factor and are determined during the training process. The historical data sets are used for training, while validation is done using test data.

Coefficient Assignment:

The coefficients represent the importance of each factor as determined during the Random Forest training process. For this study, the weights were optimized as follows:

- α = **0.30** (Rainfall has the highest predictive impact)
- β= **0.25**
- γ = **0.20**
- δ= **0.15**
- ϵ = **0.10**

The historical datasets are used for training, while validation is performed using a 20% test data split. The coefficients are normalized such that:

$$\alpha + \beta + \gamma + \delta + \epsilon = 1$$

4.4 System Architecture and Design

The whole architecture is designed as a layered module.

- Data Collection Layer: It aggregates the data related to rainfall, the yield of agricultural products, as well as socioeconomic data.
- Pre-processing Layer: It normalizes the data and deals with missing values.
- Prediction Layer: It calculates the hunger score based on Equation and categorizes them.
- Visualization Layer: It shows real-time hunger zones using a Google Map interface and statistics in the form of a pie chart.
- Authentication Layer: It generates dynamic QR codes for severe zones and verifies them using one-time verification.
- Blockchain Layer (Future Scope): It stores the tokens in the form of a blockchain, thus avoiding duplicates and fraud.

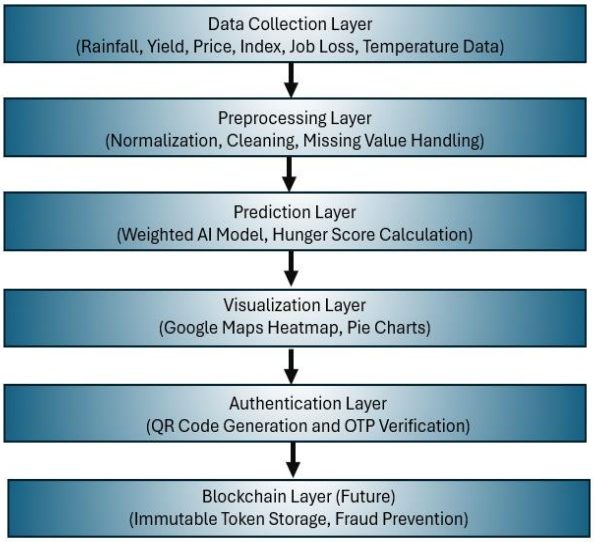

Figure. 2 System Architecture

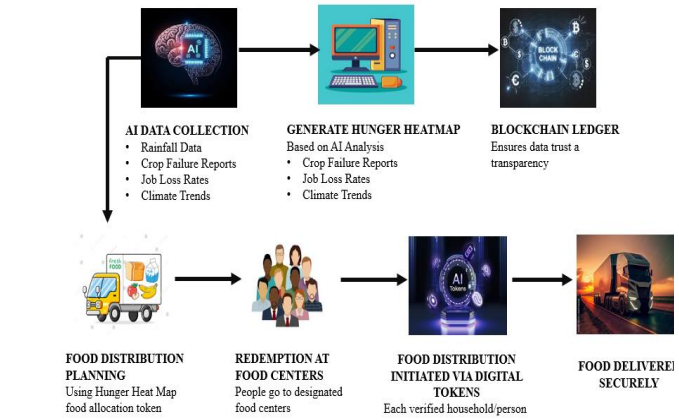

Figure. 3 Block Diagram

4.5 Challenges and Mitigation

Several implementation challenges have been identified and addressed:

• Token Duplication: Every QR/OTP is verified once, with the prospect of integrating Blockchain in the future to ensure immutability.

• Scalability: The application is designed to be deployed on both local and cloud infrastructure.

• User Inclusivity: The application integrates TTS, ensuring that the application is usable in regions with low literacy levels.

4.6 Data Flow Diagram

1. DFD Level 0 (Context Diagram)

The entire system is represented as a single process: "Hunger Relief Management System".

External entities:

• Admin → manages dataset, verifies QR codes, generates reports.

• User/Volunteer → logs in, scans/uses QR codes for aid.

• Dataset (Extended Hunger Data) → provides input data such as rainfall, yield, unemployment, food price index.

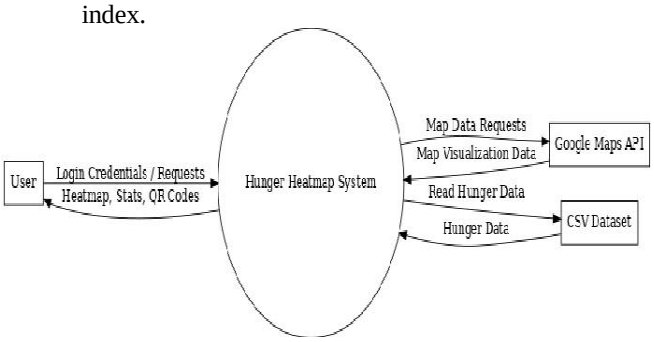

Figure. 4 DFD Level 0

2. DFD Level 1 (System Decomposition)

The system is broken into functional modules:

1. Login Module
   - Input: Username & Password from User/Admin.
   - Output: Session authentication (valid/invalid).
2. Hunger Heatmap Module
   - Input: Hunger dataset (region, month, hunger score).
   - Process: Visualization on Google Maps with color zones (Green, Orange, Red).
   - Output: Hunger Heatmap with hotspots.
3. QR Code Generation Module
   - Input: Region & Month from severe zones (Red).
   - Process: Generates QR code linked to verification URL.
   - Output: QR code (with tokens).
4. QR Verification Module
   - Input: Scanned QR code by User/Volunteer.
   - Process: Checks against used QR codes (persistent storage).
   - Output: Success or Already Used (with speech/audio feedback).
5. Statistics and Analytics Module
   - Input: Hunger dataset.
   - Process: Calculates zone distribution (Red %, Orange %, Green %).

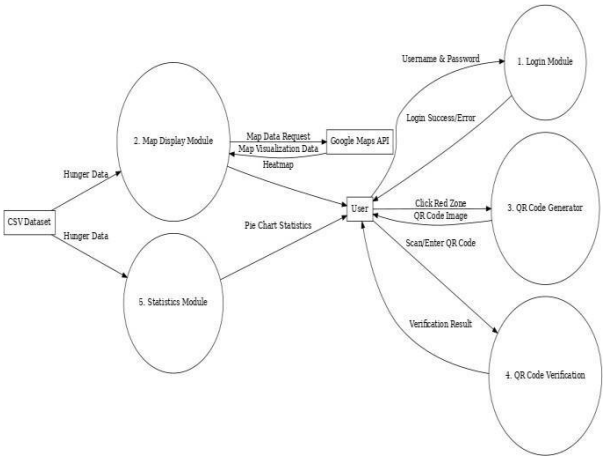

Figure. 4 DFD Level 1

5. IMPLEMENTATION

System implementation is the phase where the proposed design is translated into a working solution. This chapter describes the practical steps taken to build the AI-Powered Hunger Heatmap with QR-Based Relief Verification System, detailing the tools, programming environment, and modules developed.

5.1 Development Environment

The system was implemented using the following environment:

- Programming Language: Python 3.9
- Framework: Flask (used in creating the backend for web application backend).

- Frontend Technologies: HTML5, CSS , JavaScript, Bootstrap.
- Visualization Libraries: Leaflet.js (for maps), Chart.js (for charts).
- AI/ML Libraries: Pandas, NumPy, Scikit-learn (for hunger prediction and Purple zone forecasting).
- Blockchain Simulation: JSON-based immutable ledger with hash validation.
- QR Code Generation: qrcode library in Python.
- Database/Storage: CSV files for dataset, JSON for token/ledger persistence.

5.2 Module Implementation

The envisioned hunger management system has been developed as a web app/ prototype using Python Flask as the back-end and HTML/CSS/JavaScript as the front-end. Using the Google Maps API, the system is able to plot hunger-prone areas on a map, and the colours of the polygons can vary for different levels of severity. The architecture was modular enough to allow independent development of the data processing, the visualization, and the verification as independent code bases - thanks to splitting the architecture into three component parts.

A. System Architecture Overview

The system consists of three primary layers:

- Front-End Interface – A user-friendly web portal for login, map visualization, and QR verification.
- Back-End Processing – A Flask server handles user authentication, dataset processing, and QR code generation.
- Database & Storage – A CSV dataset stores region-wise hunger indicators, while a persistent JSON file records used QR codes to prevent duplication.

B. Login and Authentication

The platform allows role-based login for administrators and volunteers. The administrator can access regional data and generate QR tokens for severely affected regions, while volunteers can access assigned regions for relief work. Secure login is ensured through session-based management.

C. Hunger Heatmap Visualization

The 'Prone Zone Hunger Score' for each region is computed using standardized data for rainfall deviation, crop yield, unemployment rates, and food price indices. Google Maps API is used to plot these zones on Google Maps, using color-coded markers for each region:

- Green: Safe zones (<0.5 Hunger Score)
- Orange: Moderately affected zones (0.5-0.7 Hunger Score)
- Red: Severely Hungry zones (>=0.7 Hunger Score)
- Clicking on the Red Zone initiates QR code generation.

D. QR Code Generation and Verification

For each Red Zone region, the system generates a QR code containing region information, month, and token amount. To prevent fraudulent activities, a verification mechanism checks whether the QR code was already verified. Used QR codes are stored persistently for 'one-time use only.'

5.3 Implementation Workflow

I. User/Admin logs in the system.

II. The dataset is processed by the AI model and generates the Hunger Heatmap.

III. The blockchain module is activated and records the predictions of the AI model and prepares the token distribution process.

IV. Digital tokens in the form of QR/OTP are distributed among the households in the Orange, Red, and Purple zones.

V. The tokens are scanned and validated at the distribution centers.

VI. The blockchain ledger is updated with the redemption details.

VII. The dashboard is updated based on the new hunger zones and the food distribution process.

5.4 Screens Developed

I. Login Page – Secure login for admin and users.

II. Map Page – Interactive heatmap display of hunger severity levels.

III. Pie Chart Page – Visual statistics of hunger classification.

IV. QR Code Page – Generation and display of tokens.

V. Verification Page – Verification of tokens with text and audio feedback.

VI. Admin Dashboard – Monitoring and reporting dashboard.

6. RESULTS AND DISCUSSION

System testing and experimental evaluation were conducted to validate the performance of the AI-Powered Hunger Heatmap with QR-Based Relief Verification System. It represents the outputs obtained through implementation, screenshots, test cases, and analysis.

6.1 System Outputs and Functional Results

A. Hunger Heatmap Visualization

The prototype was able to successfully create a real-time heatmap of hunger using the google maps api, with regions travelled categorized into three severity levels as follows: green for safe, orange for moderately affected, and red for severe hunger zones. The visualization was able to help the administrator and volunteers instantaneously identify high-priority areas, thus making a decision based on the data for food distribution much easier

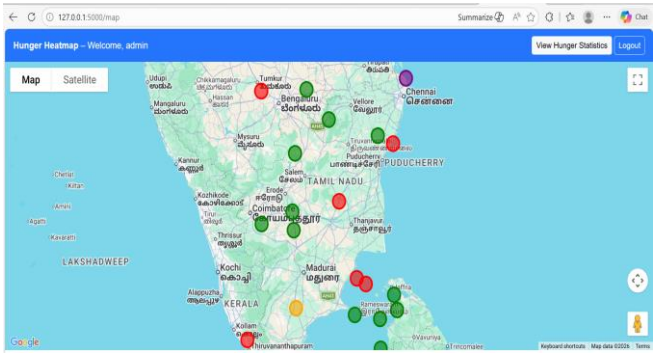

Figure.6 Hunger Heatmap Display

B. Token-Based QR Distribution

Upon clicking on the red zone marker, dynamic generation of QR codes was achieved. The information contained in each of the QR codes included region information, the month, and the allocated tokens. The verification system helped to ensure that the QR codes were used once only. This helped to prevent any chances of duplicate claims in food relief distribution. The system thus proved the possibility of incorporating a digital token system.

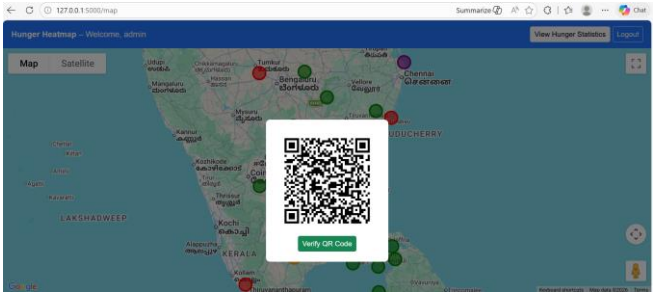

Figure.7 QR Code Generation

C. Pie Chart Statistics

A statistical analysis of the regions that fall into the hunger zones has been presented through the pie chart (Figure 8). The percentage of regions that fall into the Red, Orange, and Green zones has been quantified to determine the classification spread of the system. According to the experimental data set, 62% of the regions fall into the Green zone (Safe), and 23% of the regions fall into the Orange zone (Moderate Risk). The high-priority Red zones (Immediate QR token generation) cover 15% of the total regions.

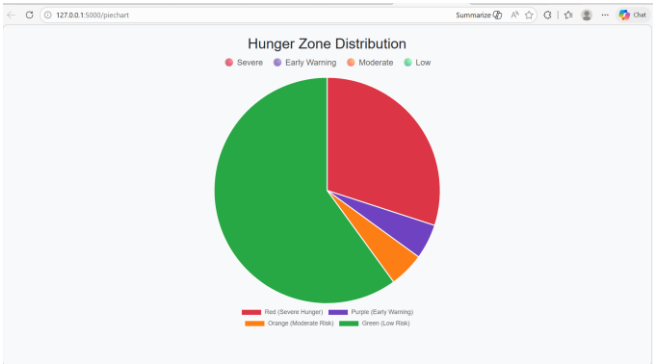

Figure.8 Statistics

E. Speech-Enabled Verification

The integration of Google Text-to-Speech (gTTS) enabled audio feedback for QR verification. This was particularly useful for communities with low literacy levels. The system provided multilingual support, ensuring inclusivity in hunger relief operations.

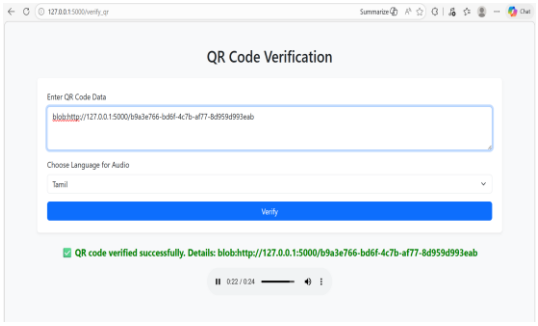

Figure.9 QR Code Verification

6.2 Test case and Execution Report

Test cases were designed for login, AI classification, token generation, blockchain integrity, and verification. Each test case was executed with inputs, expected outputs, actual outputs, and status. Results confirm that the system performed reliably across modules.

A summary of test case results is included in tabular format.

Table.2 Test Case

Test Case ID	Module	Input	Expected Output	Actual Output	Status
TC01	Login Module	Username: admin, Password: admin123	Successful login and redirect to dashboard	User logged in and redirected successfully	Pass
TC02	Login Module	Invalid credentials	Error message displayed	Error message shown as expected	Pass
TC03	AI Prediction	Dataset row with high crop failure and job loss	Zone classified as Red	Classified as Red	Pass
TC04	AI Prediction (Forecast)	Dataset row with moderate values	Future hunger risk predicted as Purple	Predicted as Purple	Pass
TC05	Token Generation	Request QR code for Region X, Month Y	Unique QR code generated with 10 tokens	QR code generated successfully	Pass
TC06	Token Verification	Scan valid QR code	Token verified and marked as redeemed	Token verified, audio confirmation generated	Pass
TC07	Token Verification	Scan already used QR code	Error message: "This token has already been used"	Error message displayed correctly	Pass
TC08	Blockchain Ledger	Attempt to alter transaction record	System rejects modification; maintains immutable log	Transaction unchanged	Pass
TC09	Map Visualization	Load hunger heatmap	Map displayed with Green, Orange, Red, and Purple markers	Map displayed correctly	Pass
TC10	Pie Chart Statistics	View statistics page	Pie chart displayed with correct zone distribution values	Pie chart displayed as expected	Pass

All test cases were executed successfully, and the actual outputs were identical to the expected outputs for all test cases. This ensures the proper working of the proposed system for all modules, including authentication, prediction, token management, blockchain security, and data visualization. This validates the proposed system for real-time usage.

6.3 Model Performance Analysis

The performance of the machine learning model was assessed using various metrics such as accuracy, precision, recall, and F1-score. A comparative analysis was performed for the Logistic Regression model and the Random Forest model for better hunger prediction. In the analysis, the Random Forest model performed better with an accuracy of 89%.

Table.3 Performance Comparison of Machine Learning Models

MODEL	Accuracy	Precision	F1-Score
Logistic Regression	75%	73%	73%
Random Forest	89%	85%	84%

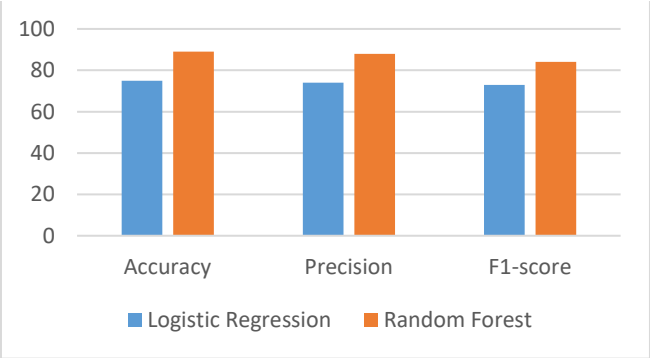

Figure 10: Comparison of Logistic Regression and Random Forest models based on evaluation metrics

Figure 10 illustrates the comparative performance of the two models. It is observed that the Random Forest model consistently outperforms Logistic Regression across all evaluation metrics, making it more suitable for accurate hunger risk prediction.

6.4 Key Findings

a. The AI model correctly classified hunger-prone regions with reliable accuracy.

b. Blockchain ledger ensured immutability; no tampering was possible during testing.

c. Token duplication was completely eliminated.

d. Visual results (heatmap, pie chart) improved decision-making for stakeholders.

e. Both beneficiaries and NGOs considered the token- based distribution uncomplicated and transparent

7. CONCLUSION AND FUTURE WORK

The project showcases a hybrid solution of an AI-Powered Hunger Heatmap with QR-Based Relief Verification System that meets the dual objectives of predicting hunger early and transparency in food distribution. Analyzing rainfall, crop failures, food prices, job losses, and climate changes, the AI module was able to classify areas in Green, Orange, Red, and Purple zones, with Purple being that it is a unique means of predicting hunger prone areas in the future.

The Blockchain ledger, as a means to record hunger data and token transactions, offered a good way to store these transactions without the risk of tampering, and, therefore, avoiding duplication and increasing accountability. Using a digital token system along with QR/OTP codes a beneficiary could use as a secure way of redeeming food packages at distribution centers. In addition, the audio verification function engendered an added level in versatility, and accessibility that would make using the system open to all.

Overall, the system was able to meet its goals of creating a proactive approach for detecting hunger, creating a secure tokenized means of distributing food packages, and having transparent real-time monitoring, in-line with the United Nations Sustainable Development Goal 2 (Zero Hunger). Overall, the outcome demonstrates that combining AI and Blockchain can link humanitarian relief management into a practical, and scalability solution.

I. FUTURE WORK:

Although the system is functioning correctly and is effective, there are many areas that can be improved upon:

1. Blockchain Integration – To enable the prevention of fraud through the use of an unchangeable storage of the QR code and aid distribution.

2. AI Model Enhancement - Addition of features such as satellite images, soil quality, and disruptions in the supply chain to make hunger predictions more accurate.

3. Scaling & Implementation: Extending the same system to make it national/international to host the increased data in the cloud.

4. Mobile Application Development – To develop an application that is accessible even without connectivity and can be used by volunteers and beneficiaries.

5. Multilingual and Accessibility Features – To enable voice interaction for the illiterate or disabled population.

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Data Transmission and Detection in TeraHertz Wireless Communication Networks with less Error Rates

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***Abstract*—TeraHertz Wireless Communication systems are gaining importance due to their ability to transmit and receive the signal at higher data rates of the order of Terabitspersecond a possible 6G technology. In this research work, data transmission and detection in TeraHertz(THz) wireless communication networks with less error rates is performed as simulation work. Data transmission in higher frequency ranges starts form higher order of 0.1THz to 10THz and further in aspects of millimeter waves where 10 ^{11} Hz and Far infrared in range of 10 ^{12} Hz. Also, in terms of wavelength TeraHertz lies between 3000 µm to 30 µm. The advantages of THz wireless communication are large bandwidth, speed, line of sight paths, security but however the challenges are attenuation, interference, complexity and cost. Applications of THz Wireless Communication Systems are 6G systems, indoor short range high speed communication, wireless backhaul, integrated sensing and communication(ISAC) and Telecom industry**

Keywords— TeraHertz Communication, 6G wireless systems, OFDM, BPSK, QPSK, Bit Error Rate

I. INTRODUCTION

Wireless communication systems in present day 5G and upcoming 6G systems are proposed to provide data transmission and data detection [1] so as to cater data rates of the order gigabits per second(Gbps) and progressing upto terabitspersecond(Tbps).Data detection in Terahertz frequency communication considers aspects of applications, experiencing various channel conditions its modeling and design of components in its hardware[2] so that it can contribute towards 6G systems. Signal processing in THz wireless baseband systems [3] use techniques such as optical source or terahertz carrier for processing in the THz range where upto 1 THz are considered possible candidates with atmospheric disturbances and errors during propagation. TeraHertz wireless systems can operate in outdoor environments with propagation effects undergoing distributions following gamma fading[4] and misalignment. Significantly, channel modelling [5] and its fading statistics for performance analysis can be done using assessment metrics along with pointing errors. TeraHertz band communication can also lend to have estimation of splitting of beam [6] using arrays where the signal surfaces through communication in line-of-sight(LoS) and nonline-of-sight(NLOS) communication.

THz wireless systems can operate based on single hop for data transmission and multiple hop for data transmission considering effects of shadowing[7] and antenna misalignment. However, performance of THz wireless in terms of data detection[8] can be done using the metric of probability of error for various modulation schemes with random fog conditions. THz wireless systems propagates through fading channel with specific distributions[9] and takes into various challenges such as molecular absorption, losses due to the spreading signal and moreover the channels have sparse characteristics. Signal processing techniques of TeraHertz wireless systems [10] provide a possible option to explore the mechanisms in which signal can be retrieved when it is corrupted by noise in the receiver. Noise in the receiver when used for data detection can follow Gaussian distribution with mean 0 and variance as 1.

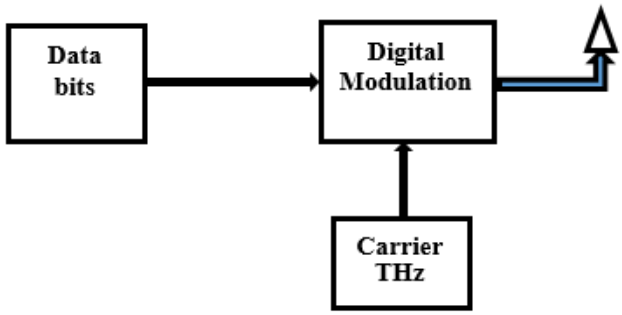

Fig.1.1 TeraHertz Carrier based Transmission System

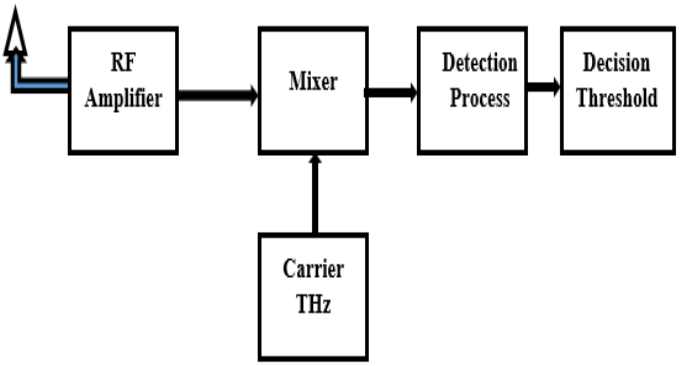

Fig.1.2 TeraHertz Carrier Detection System

Figure 1.1 shows the TeraHertz carrier transmission system where the data bits are mapped on to a digital modulation scheme such as orthogonal frequency division multiplexing (OFDM) scheme and a THz carrier frequency range, On the other hand in the Detection system shown in Figure 1.2 the received signal from the antenna is sent to RF amplifier followed by mixer for with carrier THz range succeeded by detection process and the decision threshold for a digital modulation scheme used in the transmitter. Further, multiple input multiple output(MIMO), technology when used for

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THz [11] can also be used to provide diversity in terms of increased antenna gain, reliability and spectral efficiency to accommodate large number of data bits for transmission and reception. This can be suitable for massive MIMO based 5G systems [12] and TeraHertz systems [13]and[14]for 6G systems which can be analytically realized using bit error rate/ probability of error[15].

This paper is organized as follows. Section II presents existing model of wireless communication system using orthogonal frequency division multiplexing scheme. Section III provides TeraHertz wireless communication system. Section IV presents the simulation results and discusses the obtained results in MATLAB. Section V provides conclusions for the research paper

II. BLOCK SCHEMATIC OF WIRELESS COMMUNICATION SYSTEM MODEL

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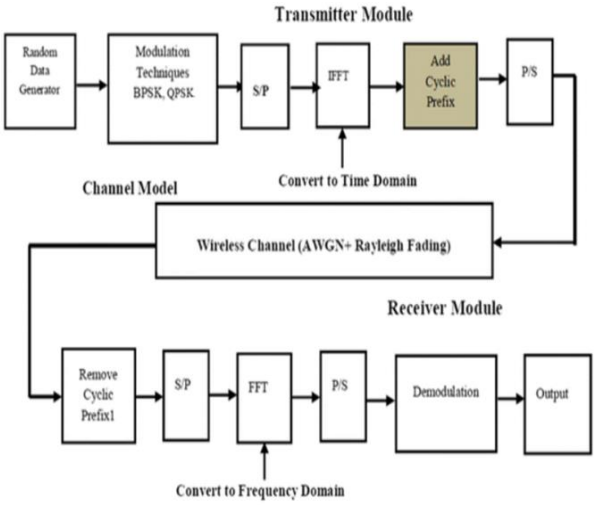

Figure 2.1WirelessCommunication System Model

Data signal is randomly generated using a generator and it is mapped into symbols using binary phase shift keying(BPSK) or quadrature phase shift keying (QPSK) modulation technique. The mapped symbols are mapped using serial to parallel converter and passed into Inverse Fast Fourier Transform(IFFT) block which converts the signal in time instants/domain and then cyclic prefix is added which is a portion of data which prevents intersymbol interference(ISI) due to overlapping/spreading of the signal in the channel.

$$x[n] = \frac{1}{N} = \sum_{k=0}^{N-1} X[k]\ e^{\frac{j2\pi kn}{N}}\ for\ n = 0, \dots N-1 \quad (1)$$

The IFFT data symbols/subcarriers are added with cyclic prefix and the symbol duration is to $N+N_{cp}$ samples. Cyclic Prefix is added mainly to reduce intersymbol interference(ISI) which can occur due to channel effects. Similarly in the receiver cyclic prefix is removed and fast Fourier Transform(FFT) is done to recover the data bits using zero forcing(ZF) receiver. The FFT signal is given by

$$\widehat{X}_k = FFT\{x[n]\} = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x[n] e^{\frac{-j2pink}{N}} \quad (2)$$

III. PROPOSED MODEL FOR TERAHERTZ WIRELESS COMMUNICATION SYSTEM

In the proposed system, the data signal is transmitted from the the mobile station to the base station is which is given by the equation

$$d_s(n) = c_s(n)\ f_{cTHz}(n) \quad (3)$$

where $c_s(n)$ is the OFDM modulated signal and $f_{cTHz}(n)$ is the terahertz carrier frequency signal represented by $f_{cTHz}(n) = 2\pi \frac{f}{f_s} n$ where f is frequency of signal; and the sampling frequency is fs=2 THz or 2 x 10^{12} Hz.

Also, the received signal at the base station is represented by

$$r_{THz}(n) = d_s(n)\ c_{THz}(n) + noise(n) \quad (4)$$

where $c_{THz}(n)$ is the delay line TeraHertz channel

$$c_{THz}(n) = d(n-\tau_l)\alpha_{THz} w\big(d_s(n)\big) + \sum_{l=1}^{2} d_s\big(n-\tau_{k,l}\big)\alpha_{THz} p\big(d_s(n,l)\big) \quad (5)$$

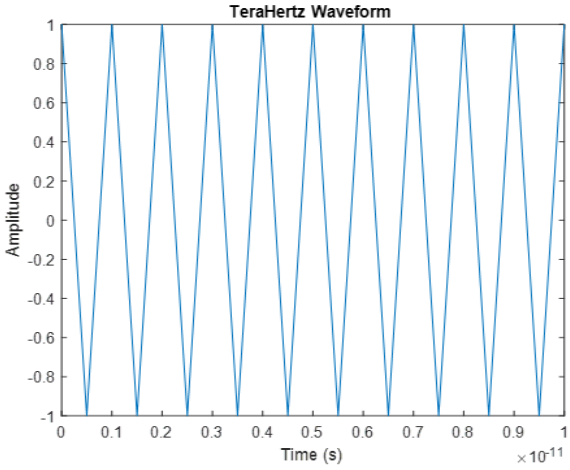

Figure 3.1 TeraHertz Waveform Signal in Time Domain

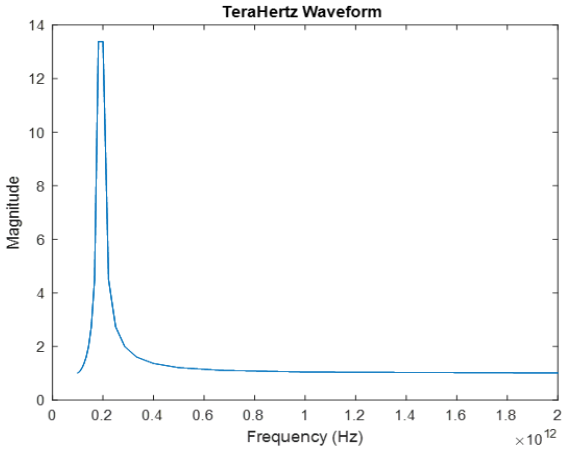

Figure 3.2 TeraHertz Waveform Signal in Frequency Domain

IV. RESULTS AND DISCUSSIONS

This section presents the simulation results for TeraHertz Wireless Communication System using TeraHertz carrier frequency in matrix laboratory(MATLAB) for various modulation schemes such as binary phase shift keying

(BPSK), quadrature phase shift keying(QPSK) and orthogonal frequency division multiplexing (OFDM).

Parameters	Values
Data Bits	10000 bits
Carrier	THz Carrier
Symbol Mapping	BPSK, QPSK
Wireless Channel	THz Channel
OFDM Subcarriers	64,128,256,512
Signal to Noise Ratio	*0 to 30 dB*

Table 4.1shows the simulation parameters and its values for MATLAB platform

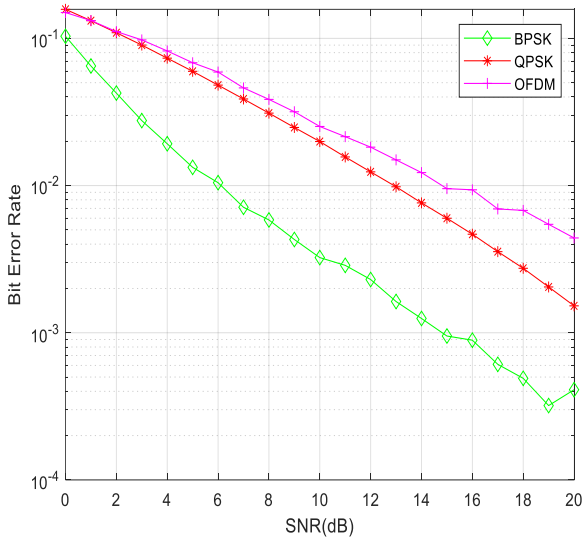

Figure 4.1 Bit Error Rate vs SNR(dB) for various modulation schemes

Figure 4.1, is the plot of bit error rate and signal to noise ratio(SNR) in decibels when signal to noise ratio is increased. In the x axis SNR in decibels is increased and bit error rate is obtained by simulation in MATLAB. To obtain a probability of error 10^{-2}, probability of error for binary phase shift keying(BPSK) takes 6 dB, quadrature phase shift keying(QPSK) takes 13 dB and orthogonal frequency division multiplexing (OFDM) takes 15 dB.

Figure 4.2, shows for different OFDM block lengths in THz wireless system. When the block lengths are increased with 512 subcarriers and increasing block lengths. When OFDM block length is 2, it refers to using 1024 subcarriers, OFDM block length is 3 it is1536 subcarriers, OFDM block length is 4 it is 2048 subcarriers. When data subcarriers are increased for probability of error of 10-2 it gets reduced, as18dB for length of 4. Also, SNR is 19dB for length of 3, 22dB for length of 2, 27dB for length of 1, when varying signal to noise ratio is considered where THz wireless systems can consider OFDM modulation schemes with large bandwidth.

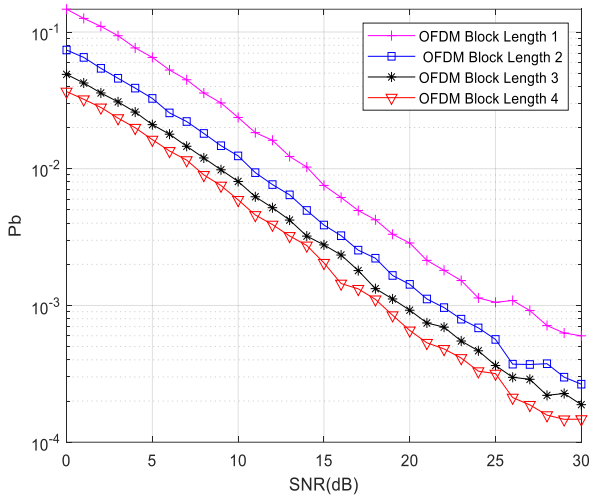

Figure 4.2, Probability of Error vs SNR(dB) for different OFDM block Lengths

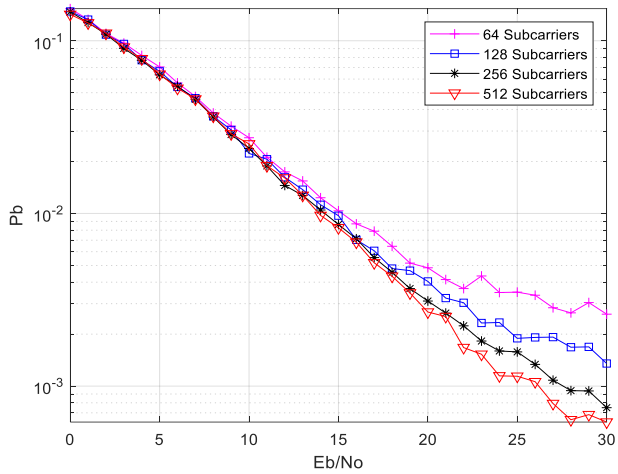

Figure 4.3, Probability of Error vs SNR(dB) for different subcarriers OFDM

Figure 4.3, shows for different subcarriers of OFDM modulation scheme the probability of error plotted against signal to noise ratio(SNR). The effect of reduced probability of error is not obtained in lower signal to noise ratio(SNR) values as it is more or less similar upto 10dB and for higher signal to noise ratio values it is the error rate changes are obtained. Only after 10^{-3} probability of error for increased subcarrier values of 512 it takes less SNR of 26 dB, which implies 398 Watts of power at base station. This is very useful for THz wireless communication systems.

V. CONCLUSION

This research work analyzes the performance of TeraHertz wireless communication systems for high speed data transmission. Simulation results are obtained to evaluate the bit error rate performance for different modulation techniques such as BPSK, QPSK and OFDM. The results show that on increasing the signal to noise ratio improves the communication performance by reducing the probability of error. Among the considered techniques, OFDM provides better performance for high bandwidth communication systems. Hence, THz wireless communication can be

considered as a promising technology for future high speed wireless networks such as 6G.

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Smart Air Pocket Detection For Urban Flooding

*Note: Sub-titles are not captured in Xplore and should not be used

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Abstract: Urban flooding is a major problem, especially in cities, owing to the limitations of conventional drainage system monitoring, which can only detect flooding in urban areas after the accumulation of water on the surface. This paper proposes a smart system aimed at monitoring underground drainage systems to identify subsurface conditions. It monitors internal parameters such as pressure changes, water level changes, water flows, and acoustic signals to identify anomalies in the early stages.It analyzes the data collected using a machine learning algorithm, specifically XGBoost, which can classify the conditions of the underground drainage system. It can identify issues such as air pockets, blockages, and abnormal pressure build-ups in the early stages, which might cause failures in the infrastructure.To better understand the conditions, the system can provide a 3D image of the underground drainage system, which can highlight areas of risk using color-based stress mapping. A smart auto-vent feature is also incorporated to address issues such as excess pressure, which might cause road collapse or drainage overflow.

Keywords—Urban Flood Prevention, Drainage Monitoring, Machine Learning, XGBoost, 3D Visualization, Pressure Analysis, Smart Infrastructure

I. INTRODUCTION

In recent years, urban flooding has emerged as a critical issue in urban areas, mainly because of urbanization and the occurrence of extreme rainfalls. Traditional systems of monitoring urban flooding have mainly been reactive, as the flooding is detected only when the accumulation of water is visible above the ground level. This is not effective in the detection of hidden conditions in the underground urban drainage systems, which occur over a long period and result in serious consequences such as the collapse of the road, displacement of manholes, and threats to the safety of people.

Hence, it is imperative to have an intelligent system of monitoring urban flooding, which is based on the early detection of abnormal conditions in urban drainage systems. Factors such as pressure, water level, and flow, which occur internally in the urban drainage systems, have a major impact in the detection of the conditions in the underground urban drainage systems. These conditions need to be constantly monitored and analyzed in order to detect problems such as blockages, presence of air, and increased pressure in the urban drainage systems.

In this regard, the suggested system has incorporated a smart monitoring feature, which entails the utilization of real-time monitoring and intelligent analysis of data to ascertain and predict possible risks in the drainage pipes. It examines the data gathered to establish various patterns, thereby classifying the condition of the pipes and determining the severity of blockage. Moreover, the system provides a 3D image of the underground drainage network, thereby facilitating easy identification of areas of high risk.

In addition, the suggested system has incorporated a preventive measure, which entails the release of excessive pressure from the pipes to avert possible damage. Therefore, the suggested framework is likely to improve the management of floods in urban areas.

II. LITERATURE SURVEY

Research studies have been conducted in the area of urban drainage monitoring and prevention of floods. The studies focused on enhancing the monitoring of floods in real-time.

In [1], a real-time early warning system for urban floods was presented. The study focused on the importance of monitoring floods in real-time through the collection of data from various sources. The research proved that monitoring floods in real-time helps in responding to floods in a much shorter time.

In [2], a monitoring framework for drainage systems was presented. The monitoring framework focused on monitoring the flow of wastewater in the underground drainage systems. The research focused on monitoring the water flow to prevent overflow in the systems. The monitoring framework, however, focused only on the surface-level monitoring of water flow.

In [3], a precise method of monitoring floods was presented. The research focused on directly monitoring the water flow in the environment. The research proved that directly monitoring the environment helps in responding to floods in a much shorter time compared to indirect methods of monitoring floods.

In reference [4], a scheme for the automated monitoring and control of the drainage system was introduced, in which parameters such as water level and flow rates can be monitored continuously. Although this was useful for decision-making, the focus was only on monitoring and not on predicting possible dangers or preventing failures.

In reference [5], a smart monitoring system for the drainage network was designed in order to improve urban sanitation and avoid risks of drainage inspection. This was useful, although the focus was only on monitoring and providing alerts to the authorities, and no advanced analysis was performed in order to predict possible dangers or failures.

In reference [6], a comprehensive review of the different monitoring techniques for urban floods was performed, emphasizing the importance of intelligent data-driven techniques. This was useful, although the importance of intelligent data-driven techniques was highlighted, and the importance of combining different data sources was mentioned.

In reference [7], a framework for the integrated modeling of the drainage network was introduced, which included data, prediction, and adaptive control. This was useful, although the importance of a dynamic response for a system was introduced, depending on the changes in the environment.

III. EXISTING SYSTEM

The conventional urban drainage monitoring system mainly focuses on the surface-level phenomena, such as the accumulation of water and the characteristics of the flow. In most cases, the system depends on the periodic inspection and basic sensing mechanisms to identify the overflow or blockage in the drainage system. The monitoring process mainly focuses on the identification of the problems after they occur, such as the stagnation of water or the flooding of the surface.

The parameters monitored in most cases are limited, such as the rate of the flow or the level of the water, and the conditions inside the system, such as the pressure and stress, are not taken into consideration. In most cases, the problems, such as the accumulation of air, blockage, and pressure, occur internally and cannot be identified. Moreover, the system does not offer automatic responses, and the intervention of humans is required to address the problems.

In addition, the systems in place currently do not have the ability to perform advanced analysis in the prediction of potential problems and the early signs of failure. There is a lack of visualization of the conditions in the underground drainage systems, and it is difficult for the authorities to understand the exact nature and location of the problems in the system. Therefore, the conventional systems currently in place in the management and monitoring of the urban drainage systems are not effective in the prevention of urban flooding

IV. DISADVANTAGES OF EXISTING SYSTEM

Lack of early detection, where the systems only detect problems once the flooding has already appeared on the surface
Lack of monitoring of internal pressure and stress in the pipes
Inability to detect hidden problems such as the presence of air pockets and blockages in the pipes
High dependency on manual inspection and maintenance, which is time-consuming
Lack of prediction and detection of potential problems in the system
Lack of clear visualization of the conditions in the underground pipelines
Lack of an active prevention mechanism to reduce internal pressure and prevent structural damage from occurring

V. PROPOSED SOLUTION

The proposed system aims to improve the management of urban floods through the monitoring of the internal conditions of the underground drainage pipelines, where the behavior of the systems will be identified early in case of any abnormalities. Unlike other systems, which are designed to detect floods after the accumulation of water on the surface, the proposed system aims to detect hidden subsurface conditions, which may cause failures or overflows.

In the proposed system, various sensing devices will be placed in strategic positions to detect critical parameters, including internal pressure variation, water level variation, flow, and internal disturbances. The devices will be used to gather data, which reflects the actual situation of the pipeline.

The data gathered from the pipeline will be processed to identify abnormal patterns, which may be associated with problems, including the formation of blockages, air pockets, and excessive pressures. The relationship between different parameters will be used to identify early signs of failures.

To enhance the quality of decision-making, the system has incorporated intelligent analysis of the data, which is learned from the real-time and historical data. This helps in the classification and prediction of potential problems in the pipelines. It also offers a visual representation of the underground drainage conditions, which enables the authorities to understand the potential problems.

Moreover, the system has incorporated a preventive component, which safely releases the excessive internal pressure through a controlled venting process. This is done based on the condition-based logic, where only the air is released and not the water. This is done through the design and monitoring-based control, which ensures the safety and efficient regulation of the pressure.

The system has also enabled the generation of alerts, which is a part of the maintenance aspect. This is done to ensure the efficient maintenance of the urban drainage systems. Therefore, the proposed system has incorporated the above-mentioned features, which enhance the quality and reliability of the urban drainage systems.

VI. ADVANTAGES OF EXISTING SYSTEM

Early Detection of Abnormal Conditions:
This system is able to detect abnormal conditions before flooding occurs. For example, it can detect possible problems with pressure buildup and blockages.

Continuous Monitoring of Drainage Network:
This system will provide a continuous observation of internal pipeline conditions rather than conducting periodical inspections.

Detection of Hidden Subsurface Problems:
This system will effectively detect subsurface problems, including trapped air pockets, internal pressure changes, and flow changes.

Improved Flood Prevention Capability:
This system will reduce the possibility of urban flooding.

Intelligent Decision-Making Support:
This system will support decision-making through data analysis for classifying and predicting possible failures.

Controlled Pressure Release Mechanism:
This system will release trapped air through a controlled process without causing water discharge.

Prevention of Infrastructure Damage:
This system will prevent damage to infrastructures, including road collapse, pipe damage, and manhole displacement.

Support for Preventive Maintenance:
It enables maintenance teams to undertake maintenance activities before a problem reaches a critical stage.

Clear Visualization of Underground Conditions:
It facilitates the easy identification of risk areas by the relevant authorities.

Reduction in Manual Inspection Effort:
It reduces the need to inspect the infrastructure manually, which is beneficial in terms of increased efficiency.

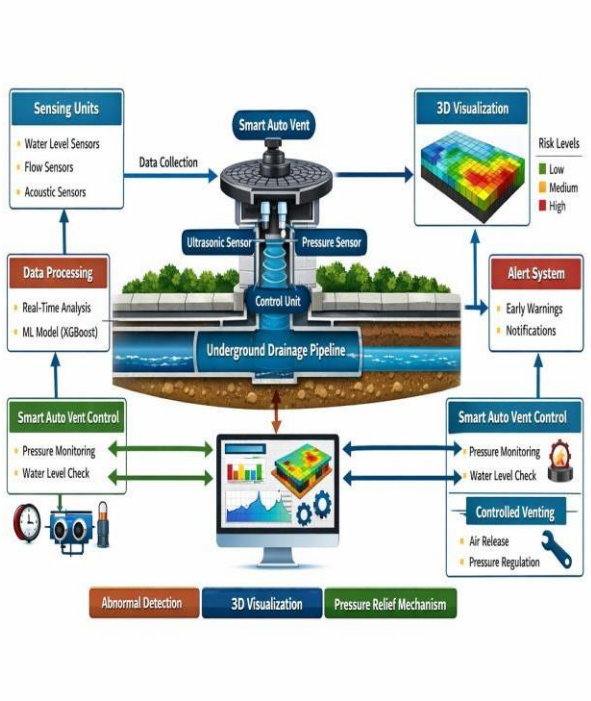
Faster Response to Critical Conditions:
It enables quicker responses to critical conditions.

Enhanced Public Safety and Environmental Protection:
It reduces risks to the public resulting from flooding, in addition to preventing health hazards resulting from stagnant water.

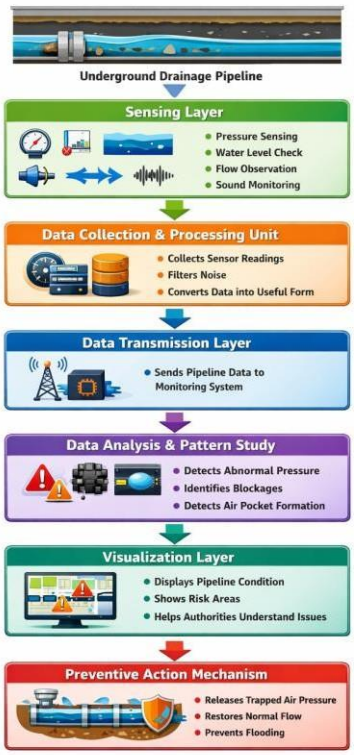
VII. COMPARISON WITH EXISTING SOLUTION

FEATURES	**CONVENTIONAL DRAINAGE MONITORING**	**SMART AIR POCKET DETECTION SYSTEM**
Operational Logic	Reactive: Response only after surface flooding is visible	Proactive : Predicts flooding by detecting subsurface Air compression
Primary Data Source	Surface water level and flow velocity	Multi model fusion : Air pressure, Water level and acoustic Signature
Analytic Core	Static Threshold (Binary high / Low alerts)	Machine learning (XG Boost) : Pattern Recognition and Anomaly classification
Detection window	0 lead time : Alerts occurs during the flood event	Early Warning : Provides 5-15 min of lead time via pneumatic analysis
Infrastructure Safety	Iris of manhole displacement and road cave - ins	Active mitigation : Smart auto vent releases trapped pressure anonymously
Network Resilience	Dependent on Wi - Fi / GSM (High Signal attenuation)	LoRa (Long Range): optimized for deep sub terranean Data transmission
System Visibility	2D, Graphical Dashboard (Line, Bar charts)	3D Digital twin : Real time spatial stress of pipe segments
Maintence Model	Corrective : Maintenance is performed for a failure	Predictive : “Health alerts” sent based AI detected clogs
Physical Intervention	Requires manual deployment to clean vents	Autonomous self cleaning sensors and motorized pressure relief

VIII. ARCHITECTURAL DIAGRAM



IX. WORKFLOW



X. CONCLUSION

The proposed system provides a reliable framework that ensures the improvement of the management of urban flooding through the constant monitoring of the underground drainage system. The system is able to monitor the internal parameters of the drainage system and thus detect any hidden problems in the subsurface drainage system. The incorporation of intelligent data analysis and the controlled release of pressure is able to prevent damage to the drainage system and thus flooding. The proposed system is able to improve the safety of the drainage system in the urban area

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A Study On Impact Of Gamification On Employee's Motivation Towards Engagement

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ABSTRACT

Gamification refers to the process of increasing the level of engagement of employees at the workplace through the implementation of game-related tools like points, rewards, and feedback. The aim of the study is to evaluate the influence of the gamified system on performance, as well as the understanding of the perceptions of employees across various organizations. A structured questionnaire was used as the data collection tool, and the findings were analyzed using percentage methods. The findings of the study show that the majority of the employees have a positive attitude towards the implementation of the gamification system, as they are motivated. However, others have no opinion, thus the need to enhance the implementation process. The study shows that gamification is a successful strategy in enhancing the engagement of employees, thus improving the performance of the organization.

Keywords: Gamification, Employee Engagement, Employee Motivation, Employee Perception, Organizational performance.

INTRODUCTION

In the current competitive business world, organizations are seeking ways to boost employees' motivation and engagement, which will result in improved performance. Employees' engagement is critical in boosting productivity, job satisfaction, and organizational success. However, boosting employees' motivation is a challenging task, especially considering the repetitive nature of their duties and the evolving nature of the work environment. Gamification is a new and innovative strategy for boosting employees' motivation. Gamification involves the application of game design elements, including points, badges, and leaderboards, and rewards in the work environment. These elements make employees' tasks engaging and interactive. Gamification is based on intrinsic and extrinsic motivational factors, which motivate employees to actively engage in their activities. Employees also feel connected and aligned with their organizations. This study explores the effects of gamification on employees' motivation and its contribution to boosting employees' engagement. In addition, this study will address the benefits and challenges associated with gamification in organizations.

REVIEW OF LITERATURE

Simeia Azevedo Santos et al. (2019) claim that gamification makes the training process more effective and increases employees' engagement, thus achieving a 20% to 200% improvement in performance via rewards and feedback. Ryan J. Baxter et al. (2014) assert that gamification makes the training process more enjoyable and satisfactory for employees; however, the effects of gamification on learning outcomes are unclear, and non-gamers benefit more than gamers. Alvear et al. (2021) point out that gamification increases employees' motivation, engagement, and understanding of complex activities in police force training, and employees develop better teamwork skills. Alfaqiri et al. (2022) argue that gamification increases employees' engagement in online training, and usability and value influence acceptance based on the Technology Acceptance Model (TAM). Hussain et al. (2018) emphasize that gamification increases employees' motivation, engagement, loyalty, and retention by making the workplace fun for employees. Kulkarni et al.

OBJECTIVES

- To understand the concept of gamification in organizations.
- To analyze the level of employee engagement in gamified workplaces.
- To examine the impact of gamification on employee motivation and performance.
- To study employee's perception towards gamified systems

METHODOLOGY

The main data collected for the study was collected with the help of a structured questionnaire. Likert scale, multiple-choice, and rating scale were used in the questionnaire to assess how employees felt about the communication and its impact on their motivation. The questionnaire was sent online using Google Forms, which provided greater outreach and convenience to the

respondents. A total of 196 questionnaires were sent out. Out of these, 152 were received. A total of 124 were complete and valid. So, the final figure considered for the research was 124..

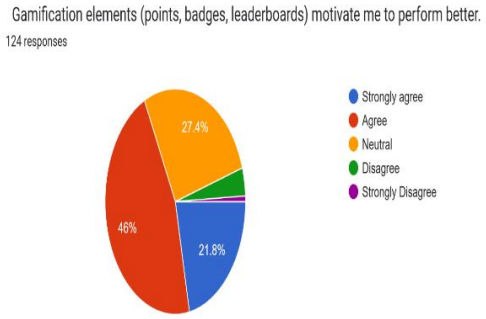
DATA ANALYSIS

Table showing impact of gamification on employee

S.No	Response Category	No. of Responses	Percentage (%)
1	Strongly Agree	27	21.80%
2	Agree	57	46.00%
3	Neutral	34	27.40%
4	Disagree	4	3.20%
5	Strongly Disagree	2	1.60%
	Total	**124**	**100%**

RESULT AND DISCUSSION

- 67.8% of the total who answered (Agree + Strongly Agree) said that gamification makes them want to improve more.
- A large number of individuals (27.4%) are still neutral, which implies that there is space for gamification to improve.
- Only 4.8% of the total said something bad, which implies that most were happy with it.



FINDINGS

The majority of the participants (67.8%) either agreed or strongly agreed with the statement that things like points, badges, and leaderboards in games make them want to do better. This shows that people have a very positive attitude towards gamification at work. The highest percentage of participants, i.e., 46%, chose the option of "Agree," which shows that the majority of employees are motivated, but the motivation might not be very strong. A good percentage of participants, i.e., 27.4%, chose the option of "Neutral," which shows that a lot of employees are either unaware of whether gamification actually works or are unaware of all the benefits of gamification. It has also been seen that only 4.8% of the participants said that they disagree, which shows that only a small percentage of employees are of the opinion that gamification does not work. The presence of the option of "Neutral" shows that the effectiveness of gamification might need to be enhanced. It has clearly been seen that the effectiveness of gamification towards motivating employees is good, and it can be used as a way of getting employees more involved.

LIMITATIONS

It is possible that the small number of samples in this study does not fully represent all employees. The results' generalization to other fields may be limited by the fact that the study was conducted in a certain area or institution. The results' authenticity could have been compromised by the fact that employees may respond in a way that is socially acceptable rather than their real feelings. The study was limited in time and could not assess the long-term effect. Responses that are neutral or false could result from some employees' lack of understanding of certain concepts in gamification..

CONCLUSION

Gamification is a strong and creative technique that modern-day organizations can use to increase their workforce's morale, productivity, and engagement. With effective strategies and further assessments, the effectiveness of gamification may be further heightened in the workplace. The study concludes that gamification has a significant impact on employee engagement and motivation in the workplace.

Most of the employees agreed that gamified systems are effective in improving their interest and participation in the workplace. This suggests that the incorporation of game elements in the workplace is effective in improving employee engagement and participation in the workplace. However, a significant number of the respondents were neutral, suggesting that gamification is effective.

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"Viewer Attention and Distraction Behaviour While Watching Movies: A Comparative Study Of OTT And Theatre Audience."

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ABSTRACT

The rapid growth of Over the Top (OTT) content service providers such as Netflix and Amazon Prime Videos has changed the way people are consuming movies, shifting from the traditional theatre experience to more personal digital viewing spaces. The audience's focus and distraction propensities in OTT and theatre viewing spaces have been researched and compared in this study. OTT offers the benefit of flexibility, which in turn has increased distraction propensities, while theatre viewing offers a more immersive experience, thus aiding concentration. The main aim of this study is to examine the psychological effects of both mediums of viewing, the factors that influence attention span, and the behavioural differences. The findings of this study are intended to contribute more information to the field of media studies, which would help the developers and makers of OTT and other digital viewing platforms understand the viewing behaviours and trends of the audience.

INTRODUCTION

With this shift from conventional theatre experience to more tailored digital mediums, the proliferation of Over-The-Top (OTT) services such as Netflix and Amazon Prime has revolutionized how consumers consume their movie content. This study explores and compares how consumers in OTT and theatre environments maintain attention and get distracted while watching content. Theatre offers a controlled experience, which is beneficial for sustained attention, while OTT services, with their flexibility, create more distractions for consumers. This study will assess the psychological effects of both consumption methods, determine factors influencing attention span, and highlight how there are significant behavioural differences in consumers' engagement with content, which will further aid in advancing media studies as a discipline.

Need of study

Movie viewing has moved from the theatre to home-based streaming through the explosive growth of OTT platforms. Key issues concerning differences in viewer attention and distracting behaviours are raised. While home-based streaming services provide ease of access and cause distraction through multitasking and mobile use, theatre-based streaming is a controlled and engaging environment that enhances viewer attention. It is vital to understand these differences because viewer attention and information processing are directly affected. However, few research studies are available that compare the levels of attention between the two platforms. To provide insights to enhance viewer experiences and content delivery approaches, this study compares and analyzes viewer attention and distraction behaviours in theatre-based and home-based streaming.

Objectives

- To study how viewer attention and distraction behaviour is influenced by demographic factors such as gender and age while watching movies in theatres and OTT platforms.
- To study how viewer attention and distraction behaviour is influenced by platform preference, such as watching in theatres versus OTT platforms, and how frequency affects viewer attention and distraction behaviour.
- To study how the level of viewer attention while watching movies in theatres and over-the-top (OTT) platforms compares with each other.
- To study how viewer attention and distraction behaviour are influenced by mobile phone usage while watching movies in over-the-top (OTT) platforms as opposed to watching in theatre.
- To study how viewer attention will be influenced by factors such as multitasking and distractions while watching movies in theatres and over-the-top (OTT) platforms.

• To study how viewer attention will be influenced by factors such as how often people engage in activities such as eating, texting, and browsing while watching a movie in theatres as opposed to watching in OTT platforms

Scope

This study is about how people pay attention and get distracted while watching movies in theatre and while streaming them. It also checks different age groups and how they watch movies to check how their habits change. It includes how people use their phones, watch multiple things at once, and how people get distracted by external sources while watching movies, which helps in finding out how much they enjoy the movie. It helps in understanding which way of watching movies keeps them more interested and how people get distracted in theatre and while streaming. This helps in making watching movies more interesting for everyone by understanding how people behave while watching movies.

Limitations

The study is just based on a few people, so it may not be applicable to all people. The study is based on general watching habits, so it does not go into detail about different types of shows or how people feel inside. The place they are, how they feel, and who they are with can all play a part in how they pay attention, but this is not fully discussed in this study.

Review of Literature:

Lalit Kumar (2023) The study looks at how Over-The-Top (OTT) platforms affect the movie business, with an emphasis on how viewers' habits are shifting in favour of greater affordability and convenience. The study, which used a mixed-methods approach with 300 moviegoers surveyed and 10 expert interviews, comes to the conclusion that although OTT platforms have increased the reach of films, they have also decreased traditional cinema attendance among younger demographics.

Dr. Rajeshwari (2025) This study is about how people in India watch movies and it is changing. The study compares what people like to watch. How they can watch it with the old way of going to the cinema. It looks at things like how much it costs if people can get to it and what age groups like what by reading reports from the industry and things that academics have written. The study found out that online platforms like Netflix are now a part of the media industry more than 30%. This is because younger people like it when things are easy for them. Because of this less and less people are going to the cinema, which means that traditional cinemas need to think of ideas really fast. The cinemas need to do something because online platforms, like OTT platforms are getting more popular and people like watching movies on OTT platforms.

Dr. pavala kumar (2022) This study examines how the "Anyone, Anywhere" phenomenon has led to a transition from traditional cinema to over-the-top (OTT) platforms. The study, which was carried out using 300 questionnaires, 10 expert interviews, and secondary data, demonstrates a substantial shift toward digital streaming even if theatres provide a cultural, superior sensory experience. Results indicate that OTT now holds more than 30% of the market, driven by younger audiences' preference for price and convenience (18–35). In the end, the study comes to the conclusion that in order to compete with the quick expansion of digital platforms, traditional theatres need to innovate.

RESEARCH METHODOLOGY

Research methods define a systematic process of finding, assessing, analysing, and drawing conclusions about a particular area of research. These methods will include the techniques, methods, and tools researchers use to perform their research, ensuring reliable, accurate, and valid results.

DESCRIPTIVE RESEARCH

Researchers use descriptive research design as an effective means of collecting data about a group of individuals/subjects. The results of this type of research will look at a population or sample and accurately reflect the characteristics and patterns of behaviours exhibited by that population/sample. Researchers can collect the qualitative data needed to understand a specific topic by observing and collecting data, and possibly producing data to guide any additional studies.

SIMPLE RANDOM SAMPLING

When conducting basic random sampling, a researcher randomly selects a sample of individuals from a larger sample/population that is representative of all people who belong to the target population. With simple random sampling, the individual selections are equally likely to be selected, as determined by the probability of their being included in the random sample. Many researchers and statisticians rely on sampling techniques such as this to obtain representative samples from their target population.

SAMPLE SIZE

This study was conducted on the entire population for the proposed study includes all individuals regardless of gender. The sample was collected equally and shows the sample size is 85.

The data for the sample sizes provides in this study were obtained from surveys.

TEST OF NORMALITY

Null Hypothesis (Ho): The data follows normal distribution.

Alternative Hypothesis (H1): The data does not follows normal distribution.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
To examine the effects of platform preference (OTT vs. theater) and viewing frequency on the attention and distraction behaviors of moviegoers.	.228	81	<.001	.920	81	<.001
To compare the degree of viewer focus when watching films on over-the-top (OTT) platforms and in theaters.	.153	81	<.001	.946	81	.002
To investigate how mobile phone use affects viewers' attention and distraction patterns when watching movies on over-the-top (OTT) platforms as opposed to theaters.	.195	81	<.001	.921	81	<.001
To examine how multitasking and outside distractions affect viewers' attention when they watch movies in theaters and on OTT platforms	.150	81	<.001	.950	81	.003
To ascertain which platform results in a greater frequency of multitasking (such as eating, texting, or browsing) while watching a movie	.316	81	<.001	.823	81	<.001

a. Lilliefors Significance Correction

Inference

From the table, the significance value (p-value) is less than 0.05. This indicates that the null hypothesis (H_0) is rejected. Hence, the data does not follow a normal distribution.
Since the data is not normally distributed, a non-parametric test is considered more suitable for further analysis.

NON PARAMETRIC-TEST

Non-parametric tests are tests that do not require strong assumptions about the population. They are tests that do not require data to follow any certain probability distribution. This makes them more realistic for real-world data, as real-world data does not always follow normal distributions.

TOOL USED IN THIS STUDY

- Compare means (independent t-test)

TEST ANALYSIS

NON-PARAMETRIC TEST

- **Compare Means**

Null Hypothesis(Ho): There is no significant difference between age and distractions.
Alternative Hypothesis(H1): There is significant difference between age and distractions.

Group Statistics

	What is your age group?	N	Mean	Std. Deviation	Std. Error Mean
When watching movies in theatre, how attentive are you to the movie?	18-20	16	1.81	.834	.209
	21-30	65	1.88	.839	.104
When watching movies on ott, how attentive are you to the movie?	18-20	16	2.00	.816	.204
	21-30	65	2.17	.741	.092
Overall, where do you experience more distractions while watching movies?	18-20	16	1.44	.629	.157
	21-30	65	1.62	.722	.090

INFERENCE

The results reveal that the attention level of both age groups, i.e., 18-20 and 21-30 years, is similar while watching movies. However, the 21-30 age group is slightly more attentive than the 18-20 age group while watching movies in both theatres and OTT. The 21-30 age group faces a little more distractions than the 18-20 age group.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
						Significance				95% Confidence Interval of the Difference
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
When watching movies in theatre, how attentive are you to the movie?	Equal variances assumed	.075	.784	-.276	79	.392	.784	-.064	.234	-.530	.401
	Equal variances not assumed			-.276	23.059	.392	.785	-.064	.233	-.546	.418
When watching movies on ott, how attentive are you to the movie?	Equal variances assumed	.157	.693	-.802	79	.212	.425	-.169	.211	-.589	.251
	Equal variances not assumed			-.756	21.491	.229	.458	-.169	.224	-.634	.296
Overall, where do you experience more distractions while watching movies?	Equal variances assumed	1.254	.266	-.903	79	.185	.369	-.178	.197	-.570	.214
	Equal variances not assumed			-.983	25.677	.167	.335	-.178	.181	-.550	.194

INFERENCE

The results show that there is no significant difference between the two age groups in their attention levels or distractions while watching movies in theatres or on OTT platforms. Age does not appear to influence viewing behaviour in a meaningful way. Hence , the p value is more than 0.05 we reject HO

Null Hypothesis(Ho): There is no significant difference between gender and distractions.

Alternative Hypothesis(H1): There is significant difference between gender and distractions.

Group Statistics

	What is your Gender?	N	Mean	Std. Deviation	Std. Error Mean
When watching movies on ott, how attentive are you to the movie?	male	57	2.18	.735	.097
	female	24	2.04	.806	.165
When watching movies in theatre, how attentive are you to the movie?	male	57	1.81	.833	.110
	female	24	2.00	.834	.170
Overall, where do you experience more distractions while watching movies?	male	57	1.58	.706	.093
	female	24	1.58	.717	.146

INFERENCE

The results show slight differences between males and females in attention levels. Males are a bit more attentive while watching movies on OTT platforms, whereas females show slightly higher attention in theatres. However, when it comes to distractions, both males and females report the same level. Overall, the differences are minimal, indicating that gender does not strongly influence attention or distraction while watching movies

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
When watching movies on ott, how attentive are you to the movie?	Equal variances assumed	.453	.503	.727	79	.235	.470	.134	.184	-.233	.500
	Equal variances not assumed			.699	39.894	.244	.488	.134	.191	-.253	.520
When watching movies in theatre, how attentive are you to the movie?	Equal variances assumed	.012	.911	-.952	79	.172	.344	-.193	.203	-.597	.211
	Equal variances not assumed			-.951	43.253	.173	.347	-.193	.203	-.602	.216
Overall, where do you experience more distractions while watching movies?	Equal variances assumed	.001	.977	-.025	79	.490	.980	-.004	.173	-.348	.339
	Equal variances not assumed			-.025	42.662	.490	.980	-.004	.174	-.355	.346

INFERENCE

The results show that all p-values are greater than 0.05, indicating no significant difference between males and females in attention levels while watching movies on OTT or in theatres, as well as in experiencing distractions. In simple terms, gender does not have a meaningful impact on viewing behaviour.

Hence, the p value is more than 0.05 we reject H0

FINDINGS

- The analysis shows that age and gender do not significantly influence viewer attention or distraction behaviour while watching movies in theatres or on OTT platforms.
- There is no major difference in attention levels between viewers who prefer OTT platforms and those who prefer theatres, indicating similar engagement across platforms.
- Viewers tend to show slightly better focus in theatres compared to OTT platforms, but the difference is not statistically strong.
- Mobile phone usage is higher during OTT viewing, which slightly increases distraction levels compared to theatre watching.
- Multitasking and external distractions (like using phones, talking, or browsing) are more common on OTT platforms than in theatres.
- OTT platforms result in a higher frequency of multitasking activities such as texting, eating, or browsing, whereas theatres provide a more controlled and less distracting environment.

SUGGESTIONS

- There is no major difference based on age or gender, so awareness about focused viewing can be promoted equally for all groups. Encouraging mindful watching habits can help improve attention for everyone.
- Since platform preference has little impact, viewers should focus more on how they watch rather than where they watch. Maintaining regular and distraction-free viewing habits can improve attention levels.
- Viewers can choose theatres when they want a more immersive and focused experience. While using OTT, creating a theatre-like environment at home can help improve concentration.
- Reducing mobile phone usage while watching movies can significantly improve attention. Viewers should try to avoid checking phones frequently, especially during OTT viewing.
- Avoiding multitasking like chatting or browsing can help maintain better focus. Creating a quiet and distraction-free environment can enhance the viewing experience
- Since multitasking is higher on OTT platforms, viewers should consciously limit such activities. Practicing single-task viewing can help increase engagement and enjoyment.

CONCLUSION

The research concludes that although the emergence of OTT platforms has led to a further personalization of the space for watching movies, there is no statistically significant difference between the attention and distraction levels of males and females. Although OTT provides the advantage of personalization, it is often linked to the presence of distractions and multitasking, unlike the immersive environment of the theatre. It was observed that, although the attention levels were higher for the 18-20 and 21-30 age groups on the OTT platform, the subjects also experienced a higher level of distractions. According to the research, it was observed that since the gender of the viewer does not play a major role in the overall viewer behaviour, it is recommended that both the OTT platform and the theatre owners must look for technical innovations to keep the viewers engaged.

A Study On The Impact Of Discounts And Promotional Offers On Impulse Buying Behavior

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ABSTRACT:

In today's competitive retail environment, discounts and promotional offers have become powerful tools to attract consumers and increase sales. This study examines how such marketing strategies influence impulse buying behaviour among consumers. Using a questionnaire-based approach, the research focuses on individuals aged 15–30 to understand their purchasing patterns and reactions to various promotional techniques. The study highlights both positive aspects, such as increased customer satisfaction and perceived savings, and negative aspects, including unplanned spending and financial strain. The findings provide valuable insights for marketers, retailers, and consumers to understand the psychological triggers behind impulse buying. Ultimately, the study emphasizes the need for responsible marketing strategies and conscious consumer decision-making.

Keywords: Impulse Buying Behaviour, Discounts, Promotional Offers, Consumer Psychology, Sales Promotion, Unplanned Purchases, Marketing Strategies.

INTRODUCTION

However, the retail market has changed dramatically over time because of the use of discounts and other promotional offers as marketing tools. The use of such tools is prevalent among businesses to attract customers and increase their sales and brand awareness. The increasing popularity of online shopping and other digital platforms have made customers aware of different types of promotional offers every day. Hence, the phenomenon of impulse buying is more prevalent than ever.

Impulse buying is defined as the spontaneous and unplanned buying behavior of customers without any pre-planned intentions. The use of discounts and other promotional offers is very important to influence the perception of customers..

Psychological factors like the value of the product, fear of missing out, and emotional satisfaction are the major factors that contribute to impulsive buying behavior. Promotional offers may provide the illusion of saving money even though the product is not required at the time of purchase. Although promotional offers may increase customer satisfaction and provide benefits, they may also contribute to overspending and lack of control among the consumers.

In the city of Chennai, the impact of promotional strategies is higher due to the availability of online shopping platforms, the increase in income levels, and the exposure to digital marketing campaigns. Consumers, especially young people, may be influenced by promotional offers and advertisements..

The objective of this study is to analyze how discounts and promotional offers can affect impulse buying behavior in consumers. This study will be able to provide insights to marketers, retailers, and policymakers by understanding consumers' purchasing habits, psychological factors, and responses.

Understanding how consumers are influenced by promotional offers can be beneficial in creating effective promotional strategies while promoting good consumer behavior.

REVIEW OF LITERATURE

There are many studies showing the impact of discounts and promotions on the way people buy things on impulse. It has been seen that when people see discounts, coupons, and other offers, they buy more things on impulse. It has also been seen that when people think they are getting good discounts, they buy more.

In the study done by Lestari and Dalimunthe, it has been seen that discounts and promotions have a positive impact on the way people buy things on impulse, especially when they are shopping online. Anggarwati and others have also seen the same thing, as they have noted that when there are promotions like flash sales or cashback, people feel like they have to buy the things away or they will miss out.

For instance, Oberoi did some research that shows how discounts can make people feel happy and excited and this makes them want to buy things without thinking about it. People don't only save money through discounts; they also feel good. Therefore, this makes them buy things on impulse.

Some research also shows that if the discounts are only available for a certain period of time, it can make people feel that they have to buy things as soon as possible. This is

because they don't want to lose the discounts. The youth who use the internet to shop a lot feel this way.

However, some researchers feel that too many promotions can be bad for people. The researchers found that when people buy things on impulse as much as they can, they can spend too much money and not be in control of their finances. People can also get used to relying too much on discounts and promotions.

Overall, the research demonstrates that discount and promotion are ways to influence people to purchase and engage in certain activities with companies, but at the same time, it also influences people's behavior and thinking. It is therefore necessary to understand this influence in order for companies to plan marketing strategies and help people make good decisions in their shopping activities.

OBJECTIVES OF THE STUDY

The study examines how people are influenced by discounts and promotional offers in making impromptu purchases.It tests how people are influenced by promotional offers in making impromptu purchases.The study examines how people are influenced by emotions such as excitement and fear of missing out in making impromptu purchases.The study finds out the bad impacts of promotional offers, how people are influenced to behave when making purchases.It tests how people are influenced by promotional offers in making impromptu purchases.The study evaluates how people are influenced by price discounts in making impromptu purchases.

RESEARCH METHODOLOGY

This research is looking into how discounts and special offers influence how people buy things on impulse. We used a research plan to achieve this. We had many people out there to research on; we decided to research on just a number of them. We got information through asking people to tell their friends about this research. We got information from two places. We asked people questions through a questionnaire. We also got information from other people who have written about this research in articles and on the internet. We looked at the information we got to see if we can identify any patterns. The main idea of this research is to understand how special offers and discounts make people feel.

DATA ANALYSIS AND INTERPRETATION

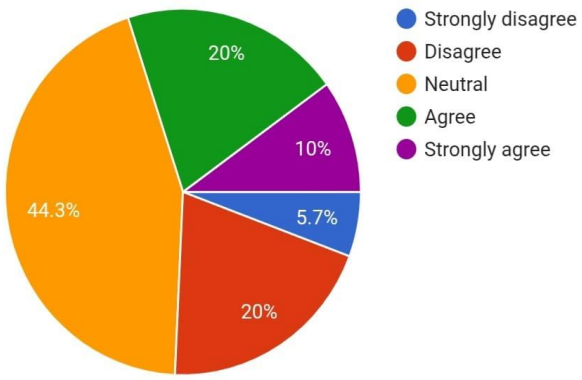
TABLE SHOWING THE INFLUENCE OF DISCOUNTS AND OFFERS ON IMPULSE BUYING

S.NO	PARTICULAR	NOMBER OF RESPONDENTS	PERCENTAGE
1	STRONGLY DISAGREE	2	2.9%
2	DISAGREE	12	17.1%
3	NEUTRAL	34	48.6%
4	AGREE	16	22.9%
5	STRONGLY AGREE	6	8.6%
	TOTAL	70	100%

INTERPRETATION

It was found that the majority of the respondents, i.e., 48.6%, were found to be neutral about the impact of discounts and offers on impulse buying behavior, and only a small percentage, i.e., 2.9%, were found to disagree. In all, the majority of the respondents were found to neither support nor oppose the impact of promotional offers on their buying behavior.

CHART SHOWING DISCOUNTS AND OFFERS MAKE ME SPEND MOREMONEYOVERALL



FINDINGS

Majority of respondents (65.7%) fall in the age group of 21-25 years. Out of the total respondents, 60% are female and 40% are male. It is found that the majority of respondents (68.6%) are students, followed by (25.7%) working professionals and (5.7%) self-employed. It is found that the majority of respondents (42.9%) shop sometimes during discounts and sales. Out of the total respondents, 32.9% prefer to use Flipkart, 24.3% use Myntra, and 20% use Amazon. Out of the total respondents, 35.7% prefer to purchase clothing and fashion products during offers, followed by 21.4% electronics products, 20% groceries, 15.7% beauty and personal care products, and 7.1% accessories.

The majority of the respondents spend between ₹3000 - ₹5000 (34.3%) or less than ₹1000 (32.9%) while shopping. Approximately 25.7% of the participants agree that limited time offers affect them to make quick decisions while shopping. The responses are inclined towards agreement (25.7%), which implies that the offers and discounts make the consumers excited. The majority of the participants (21.4%) agree that they buy the products on discount even if they are not needed. The responses are inclined towards agree and neutral (42.9%), which implies that the discounts moderately affect the consumers. The responses are mainly inclined towards neutral (42.9%), which implies that the participants neither agree nor disagree with the statement of buying more than needed while shopping on discount. The responses are inclined towards agree (40%), which implies that the discounts make the consumers try new brands and products. The responses are mainly inclined towards agree (40%), which implies that the consumers feel happy while shopping on discounts. The responses are inclined towards neutral (42.9%), which implies that the consumers may feel regret while shopping on discounts..

On the whole, the responses show a lean towards the neutral category (48.6%), which implies that discounts and promotional offers have a moderate influence on the impulse buying behavior of consumers**.**

CONCLUSION

From the research study, it is evident that discounts and promotional offers have a moderate influence on the impulse buying behavior of consumers. The research study revealed that the majority of the respondents show interest in products that are offered at discounts and promotional prices. The research study also revealed that consumers get motivated to buy products that they had no plans to buy. The research study revealed that consumers feel excited and happy to see discounts and promotional offers. The research study revealed that consumers show willingness to try new brands and products. The research study revealed that discounts and promotional offers have a moderate influence on the impulse buying behavior of consumers**.**

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Attitudes Of Employees Towards Gender Equality In Educational Instituitions

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ABSTRACT

The purpose of the study is to evaluate the attitude of the employees regarding gender equality in educational institutions. The research design of the study is based on 74 samples with the help of a structured questionnaire. The statistical tools are Pearson correlation and the Mann-Whitney U test, which are used in the research paper to evaluate the differences in the opinions of the employees regarding gender equality in educational institutions. The research paper revealed that the employees are in favor of gender equality in various aspects, such as payment, responsibility, and opportunities, but differ in terms of gender and individual differences in the attitudes of the employees regarding gender equality in educational institutions. The research paper revealed that the working environment is one of the most important factors in the promotion of gender equality in educational institutions.

INTRODUCTION

At the present time, gender equality has become a significant issue, as more and more educational institutions are committed to ensuring an equal opportunity for both genders within their respective systems and will have a profound impact on how students learn and develop. Although educational institutions are generally focused on providing students with factual information, schools and universities also have a responsibility to instill values and beliefs in their student bodies, and how employees view, perceive and feel toward gender equality could potentially positively or negatively impact their ability to reach their objective concerning equality.While educational institutions have made substantial advances toward achieving equality, there are still a number of areas and situations in which discrimination and/or bias are ubiquitous, such as when it comes to making hiring decisions; awarding promotions; making decisions and/or providing advice and guidance; or, interacting with students on a daily basis. Also, an employee's thoughts and actions regarding the gender equality process can also have a direct impact on an educational institution as well as the entire community in which a school is located.The attitudes of employees create a healthy and positive work environment that is welcoming, respectful, and supportive for all employees. In contrast, if employees have a negative attitude toward gender equality, they will reinforce negative stereotypes and limit opportunities for certain groups. Therefore, an employee's view on gender equality is extremely important.This study aims to explore how college and university employees view gender equality, and also to find out what factors might influence these views.

GENDER EQUALITY

Employees working in educational institutions have different opinions about gender equality. Some employees have strong opinions that both men and women should be treated equally in all aspects of the work. They have a positive attitude towards gender equality. They support the idea of equal pay and responsibility. Such attitudes

of employees help build a friendly environment.On the other hand, employees may have biased opinions about gender equality. Their opinions may have been influenced by their culture and society. They may think that women or men can handle certain tasks. Such attitudes of employees may lead to inequality among employees. The growth of other employees may also be affected.Employees can be made aware of the importance of gender equality through workshops or seminars. Such programs can help build positive attitudes among employees. By educating employees about gender equality, inequality can be avoided.Managers of the organization can play a vital role in building positive attitudes among employees. The manager must have good attitudes towards employees. He must treat both men and women equally. By observing the attitude of the manager, employees may also try to build good attitudes towards other employees.

OBJECTIVES

To analyze if male and female employees are treated equally in terms of salary, job responsibilities, and involvement in institutional decisions.

- To compare the attitude of different groups of employees towards gender equality on the basis of age, gender, and job.
- To identify the effective ways to overcome gender inequality in educational institutions.

- To analyze the ways the institution supports gender equality by providing equal opportunities and implementing gender equality policies for sustainable development.

REVIEW OF LITERATURE

Armando Calabrese., et al (11 july 2018) Previous studies suggest that certain personality characteristics may influence the way stakeholders view corporate social responsibility (CSR). In this study, employee attitudes toward CSR demandingness, trust, and satisfaction are examined, focusing on whether these differ by gender, age, and education level. The study is based on a survey of 153 employees of 11 Italian banks, along with an analysis of the sustainability reports of these banks. The reason for choosing the Italian banking industry is the recent spate of scandals involving finance and CSR-related issues. The study shows that, overall, men tend to trust and be satisfied with the efforts of their company in the area of CSR slightly more than women. Graduates tend to be much more demanding, much more trusting, and generally more satisfied with their company's efforts in the area of CSR than non-graduates. The difference between the perceptions of the older and the younger workforce is not significant. This method may help in the creation of effective CSR strategies by shedding light on the perceptions of the workforce regarding the company's efforts in the area of CSR.

sidlauskienė.,et al (2013) The field of study for this research was the STEM faculties in a University in Lithuania, and the respondents were all faculty members, researchers, and representatives of the institution. The main objective was to examine the role of institutional culture in the implementation of the initiative of the European Union, which seeks to effect structural changes in research institutions towards gender equality, especially for women in STEM disciplines. This is achieved through various tools such as the development of a conceptual framework, methodological guidelines for structured institutional transformation, and the application of an approach that uses the construction of models for multi-level institutional change. The findings revealed that, although there is an increased participation of women in higher education, there are reduced research opportunities for them as a result of backlash in institutional culture. This indicates a disconnect between gender equality theory and practice, thus calling for transformational change

- **L. Tavdgiridze.,et al (2021)** The aim of this research is to examine teachers' understanding of gender equality in Georgia's education system with a view to expanding the opportunities for schoolgirls in public life and with respect to the gendered knowledge constructed by means of schooling. The study was conducted with a sample of about 80 teachers, selected from the schools in the city of Batumi who taught technical, humanitarian, biological and civic subjects at various levels (primary, secondary and higher). Conducted in 2019–2020, the study employed focus group, telephone interview, and internet survey methods. The students' attitudes toward gender were largely shaped by their teachers, who said they often see traditional gender roles as natural and gender inequality as marginal. The conclusion of this study is that teachers need to be aware, updated with information and given teaching materials so that they would develop supportive attitudes on Gender Equality.

Tindara Addabbo, et al (2018) This paper proposes a fuzzy expert system specifically designed for gender equality assessment in higher education. The assessment was conducted in six universities in Europe, namely Italy, Lithuania, Finland, Germany, Portugal, and Ukraine, as part of the EQUAL-IST Horizon 2020 program. The program aims to implement gender equality plans in universities that are active in ICT research. This paper proposes a cognitive model using a Fuzzy Expert System (FES) that simulates the way experts think and learn, providing a compact measure of gender equality in an institution. The proposed index has a range of 0 to 1, with higher numbers indicating greater equality. The rules used in the fuzzy expert system are derived from expert opinions and the participatory concept of gender equality, as used in the EQUAL-IST project. The results of the gender equality index are expected to differ mainly on a national level, identifying key areas where new policies are required for gender equality. In addition, the proposed gender equality index will be compared with the perceptions of the participants regarding gender equality in the project.

Anna Zagrebina, (aug 25 2020) The purpose of the study is to understand the role of democracy in shaping gender beliefs through an examination of society itself. It also attempts to fill an important gap in the existing body of research, which has not adequately addressed the role of the differing democratic environments in shaping gender beliefs. The study adopted the comparative approach in understanding gender attitudes, using data from 72 countries to measure opinions in four domains: politics, business, higher education, and employment, and the role of democratization in shaping public opinions. By adopting this approach, the study covers the entire spectrum of less democratic societies and more democratic societies, providing a global perspective on the role of society in shaping the opinions of the people in the country. The study found that higher levels of democratization are associated with egalitarian gender attitudes, but the underlying sources of these gender attitudes differ significantly depending on gender and the socio-political setting of the country.

RESEARCH METHODOLOGY

1.RESEARCH APPROACH

We wanted to learn how employees at education institutions perceive gender equity. We did this by both describing and analyzing the opinions they have.

2.SAMPLE AND POPULATION

Our research focused on getting responses from all

employees at the institution, including all staff members as well as teachers, we had a sample of 74 individuals who completed the survey. In addition, they were able to respond to the survey because of their availability and willingness to participate.

DATA COLLECTION PROCEDURE

The primary tool we employed to gather data was a comprehensive questionnaire; additional sources of information included additional reference material in the form of articles, journals, and reports.

RESEARCH INSTRUMENT

The questionnaire consisted of a Likert scale, where participants were able to indicate how much they agreed or disagreed (on a range from a "strongly agree" to a "strongly disagree") with a particular item in the context of gender equity. In addition, a number of demographic question items were employed (e.g. gender, age, job-related experience), which were used to develop a profile for respondents; in contrast, question items relating to attitudes toward gender equity were constructed as the second part of the questionnaire.

VARIABLE INFORMATION

The independent variables in the study are gender, age, job role, and experience. The dependent variable we measured in the study was the respondents' attitude toward gender equity.

Tools and Techniques

We used the following tools and techniques when collecting data
We used Pearson Correlation to examine whether factors like experience were related to perceptions of gender equality.
We used Mann-Whitney U Test to compare people's perceptions of gender equality across one or two groups; for example, men versus women.

Data Analysis

Gender Distribution by Percentage Total Respondents = 74
Male = 23; Female = 51;
Percentages: Male = (23/74) * 100 = 31.1%; Female = (51/74) * 100 = 68.9%

At the group level, females accounted for 68.9% of all survey respondents; thus, the sample is predominantly female.

Mann-Whitney Test

Rankings by Gender
Male Mean Ranking = 35.70;
Female Mean Ranking = 38.31;
Mann-Whitney U Test Statistics:
Mann-Whitney U=545.00; Z Value = -0.496;
2-tailed P-value (Sig.) = 0.620;

P-value (Sig.) > 0.05, therefore, the result is not statistically significant.

FINDINGS

The research reveals that there are no significant differences between the two genders in the attitudes towards gender equality. Institutional support and efforts to address inequality have a weak relationship, which implies that: There may be policies, but the support for them is limited.
The research reveals that there are no significant differences between the two genders in the attitudes towards gender equality. Institutional support and efforts to address inequality have a weak relationship, which implies that: There may be policies, but the support for them is limited.

INTERPRETATIONS

Relationship between institutional support for gender equality and the equal treatment of employees This implies that the correlation value is 0.486. This clearly indicates that there is a moderate positive relationship. The implication of this is that if there is more institutional support for gender equality, it is
highly likely that the employees feel that both men and women are treated equally in terms of salary and other aspects. The significance value is < 0.001. This clearly indicates that the relationship is statistically significant. This clearly indicates that the relationship is not due to mere coincidence.
Relationship between institutional support and measures to reduce gender inequality
This implies that the correlation value is 0.084. This clearly indicates that the relationship is very weak. The implication of this is that institutional support does not have a relationship with identifying measures to reduce gender inequality.
The significance value is 0.473. This clearly indicates that the relationship is not significant. This clearly indicates that the relationship is not strong enough to make a conclusion.

SUGGESTION

The study shows that educational institutions help promote gender equality by providing equal opportunities and following proper policies. The results indicate a moderate positive relationship ($r = 0.486$, $p < 0.001$), meaning better institutional support leads to better perception of equality among employees. The Mann–Whitney U test also shows no

significant difference between male and female employees' attitudes. This means both groups share similar views on gender equality. Therefore, institutions should continue improving policies, create awareness, and maintain a fair and inclusive work environment for all employees.

CONCLUSION

The aim of this study was to investigate the attitudes of the employees concerning gender equality and how institutional support can contribute to this.From the results of this study, it is clear that there is no significant difference in attitudes concerning gender equality between male and female employees. Both have the same attitudes and perspectives concerning this issue. Therefore, it is clear that gender is of no influence on how employees perceive gender equality in the workplace.Moreover, this study revealed that there is no strong link between institutional support and how well this contributes to the reduction of gender inequality. This may imply that such attempts may not be sufficiently effective.This study also points out that although employees have positive attitudes concerning gender equality, this is different from how well gender equality policies are implemented and recognized.gender inequality to be reduced in the workplace, more emphasis needs to be put on how well gender equality policies are implemented and recognized in order for them to contribute positively to the reduction of this social problem.

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A Study On The Impact Of Business Analytics On Improving Hiring Efficiency In IT Companies From A Candidate Perspective

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Abstract:

This study examines the impact of business analytics on improving hiring efficiency in IT companies from a candidate perspective. The study focuses on key factors influencing hiring efficiency such as communication, time taken in recruitment, use of analytics-based evaluation methods, and challenges faced during the hiring process. To understand the role of analytics in enhancing recruitment outcomes and candidate experience. To identify the areas where improvements can be made in the hiring process and to suggest suitable recommendations. Through a structured questionnaire, the perceptions of respondents who have experienced recruitment processes are analyzed. A sample size of 137 respondents was collected using non-probability sampling techniques. The statistical tools used in the study include Cronbach's Alpha, Mann–Whitney U Test, Kruskal–Wallis Test, and Spearman's Rank Correlation. The study concluded that effective use of business analytics, timely communication, and reduction in hiring delays significantly improve hiring efficiency.

Key words: Business Analytics, Hiring Efficiency, Recruitment Process, Candidate Perception, Hiring Delay, Communication, Analytics-Based Recruitment Methods

1. INTRODUCTION

Hiring is a key function in any organization, as selecting the right candidate directly impacts performance and growth. An effective hiring process helps save time, reduce costs, and improve overall efficiency. In recent years, especially in the IT sector, companies have started using business analytics to make recruitment more data-driven and reliable. Through tools like online assessments, structured interviews, and data-based evaluations, organizations can reduce bias and improve transparency. However, challenges such as communication delays, scheduling issues, and slower decision-making still affect candidates' experience. Hiring efficiency, therefore, becomes important, as it focuses on how quickly and accurately the recruitment process is completed. By using business analytics, organizations can track performance, identify gaps, and make better hiring decisions based on data rather than assumptions, making the process more efficient and effective.

2. LIMITATIONS OF THE STUDY

- The study is limited to a specific group of respondents within the IT sector, so the findings may not be fully applicable to other industries.
- The accuracy of the results depends on the responses given by participants, which may sometimes be biased or not completely accurate.

3. NEED OF THE STUDY

➢ To understand the impact of business analytics on improving hiring efficiency in the recruitment process.
➢ To examine the challenges faced by candidates during recruitment, including delays in communication and scheduling issues.
➢ To provide suggestions for organizations to enhance hiring efficiency and improve the overall candidate experience.

4. OBJECTIVES OF THE STUDY

5. SCOPE OF THE STUDY

This study focuses on analyzing how business analytics improves hiring efficiency at Blackstraw.ai, particularly in terms of recruitment effectiveness. It covers key factors like time-to-hire, cost-per-hire, and the quality and accuracy of candidate selection. The research is based on data collected through questionnaires and insights gained during the internship period. It also aims to provide practical suggestions that can help HR teams make better decisions and improve the overall recruitment experience.

6. LITERATURE REVIEW

Davenport, T.H., Harris, J., & Shapiro (2010) The study explains how business analytics helps organizations move from intuition-based to data-driven hiring decisions. It shows that analytics improves hiring efficiency by reducing recruitment time and ensuring better candidate-job fit. However, challenges like data integration and resistance within HR departments are also highlighted.

Jantan, H., Hamdan, A.R., & Othman, Z.A. (2011) This study focuses on the use of data mining techniques in recruitment, especially for resume screening and shortlisting candidates. It finds that analytics systems improve efficiency by handling large volumes of data and

enhancing matching accuracy. The study also notes challenges such as high implementation costs and system complexity.

Bassi, L. (2011) The research highlights the role of analytics in making HR practices more strategic, especially in recruitment decisions. It suggests that data-driven hiring improves transparency and helps evaluate recruitment outcomes effectively. Resistance to adopting new technologies is identified as a key limitation.

Rasmussen, T. & Ulrich, D. (2015) This study examines how analytics improves recruitment planning, candidate evaluation, and hiring decisions. It finds that data-driven approaches enhance transparency and help identify effective recruitment channels. However, it also warns that over-reliance on data without human judgment may impact candidate experience.

7. RESEARCH METHODOLOGY

This study uses both qualitative and quantitative methods, combining primary and secondary data for better analysis. The data collected through questionnaires is supported by interpretation, and the section also explains the study area and sampling techniques used.

RESEARCH DESIGN

Research design provides a clear structure to carry out the study in a systematic and organized way. It also involves choosing the right approach for data collection and analysis to ensure accurate and reliable results.

TYPES OF RESEARCH DESIGN

This study adopts descriptive research to understand the current scenario of hiring efficiency and the role of business analytics in recruitment. It mainly uses surveys and fact-finding methods to explain factors like communication, challenges, and candidate perception. The sampling method used is non-probability sampling, specifically convenience sampling, where respondents are selected based on ease of access. Although this method is simple and cost-effective, it may not fully represent the entire population, limiting the generalization of results.

SAMPLE SIZE

Sample size refers to the number of respondents selected for the study, and it plays a key role in ensuring reliable results. In this research, the sample size is 137, calculated using Cochran's formula with a 95% confidence level and 5% margin of error. A pilot study was conducted beforehand to check the clarity and reliability of the questionnaire and to identify any possible issues. Since the population size is unknown, Cochran's formula was used to determine an appropriate and practical sample size for the study.

DATA COLLECTION

Data collection is a systematic process of gathering information for analysis, and this study uses both primary and secondary sources. Primary data was collected directly from 137 respondents through a structured questionnaire based on their recruitment experience. The questionnaire included closed-ended questions such as multiple choice and a 5-point Likert scale to make responses easy to analyze. These questions helped in collecting clear and structured data about hiring efficiency and candidate perception. In addition, secondary data from journals, websites, and reports was used to support the findings and provide deeper insights.

TEST OF NORMALITY:

HO: The data follows normal distribution.

H1: The data significantly deviates from normal distribution.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Hiring_Efficiency	.170	137	.000	.925	137	.000
Analytics_Methods	.145	137	.000	.952	137	.000
Challenges	.106	137	.001	.958	137	.000
Hiring_Factors	.137	137	.000	.937	137	.000
Benefits	.133	137	.000	.959	137	.000

a. Lilliefors Significance Correction

INTERPRETATION

Since the p-value is less than 0.05, the data does not follow a normal distribution, leading to the rejection of the null hypothesis. Therefore, non-parametric tests like Mann–Whitney U, Kruskal–Wallis, and Spearman's Rank Correlation were used for further analysis.

MANN-WHITNEY U TEST

Hypothesis:

H0: There is no significant difference between the mean rank of the updates received with respect to the hiring efficiency variables.
H1: There is a significant difference between the mean rank of the updates received with respect to the hiring efficiency variables.

Mann-Whitney

Ranks

	Up...	N	Mean Rank	Sum of Ranks
Hiring_Efficiency	0	48	40.51	1944.50
	Yes	89	84.37	7508.50
	Total	137		
Analytics_Methods	0	48	42.04	2018.00
	Yes	89	83.54	7435.00
	Total	137		
Hiring_Factors	0	48	39.46	1894.00
	Yes	89	84.93	7559.00
	Total	137		
Challenges	0	48	83.09	3988.50
	Yes	89	61.40	5464.50
	Total	137		
Benefits	0	48	40.50	1944.00
	Yes	89	84.37	7509.00
	Total	137		

Test Statistics[a]

	Hiring_ Efficiency	Analytics_ Methods	Hiring_ Factors	Challenges	Benefits
Mann-Whitney U	768.500	842.000	718.000	1459.500	768.000
Wilcoxon W	1944.500	2018.000	1894.000	5464.500	1.944E3
Z	-6.200	-5.876	-6.418	-3.066	-6.215
Asymp. Sig. (2-tailed)	.000	.000	.000	.002	.000

a. Grouping Variable: Updates at every stage

INFERENCE:

The Mann–Whitney U test results show that since the p-value is less than 0.05, the null hypothesis is rejected, indicating a significant difference between the groups. Respondents who received regular updates had better experiences, while those who did not reported more challenges, highlighting the importance of communication in the hiring process.

KRUSKAL WALLIS H TEST

Hypothesis:

H0: There is no significant difference between the mean rank of the age with respect to the hiring efficiency variables.

H1: There is a significant difference between the mean rank of the age with respect to the hiring efficiency variables.

NPar Tests

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Kruskal-Wallis

Ranks

	Age	N	Mean Rank
Gender	Below 21	51	63.08
	26-30	46	68.22
	Above 30	40	77.45
	Total	137	
Hiring_Efficiency	Below 21	51	61.68
	26-30	46	71.11
	Above 30	40	75.91
	Total	137	
Analytics_Methods	Below 21	51	56.52
	26-30	46	71.52
	Above 30	40	82.01
	Total	137	
Hiring_Factors	Below 21	51	56.98
	26-30	46	72.36
	Above 30	40	80.46
	Total	137	
Challenges	Below 21	51	77.43
	26-30	46	64.55
	Above 30	40	63.36
	Total	137	
Benefits	Below 21	51	57.14
	26-30	46	75.76
	Above 30	40	76.35
	Total	137	

Test Statistics[a,b]

Test Statistics[a,b]

	Gender	Hiring_ Efficiency	Analytics_ Methods	Hiring_ Factors	Challenges	Benefits
Chi-Square	4.049	3.110	9.652	8.395	3.718	7.363
df	2	2	2	2	2	2
Asymp. Sig.	.132	.211	.008	.015	.156	.025

a. Kruskal Wallis Test

b. Grouping Variable: Age

INFERENCE:

The Kruskal–Wallis test shows that there is a significant difference only for analytics methods, as the p-value is less than 0.05. For the other variables like hiring efficiency and challenges, no significant difference was found, while hiring factors and benefits showed some variation across age groups.

Spearman's Rho Correlation Test Hypotheses

H0: There is no significant correlation between the variables with respect to the hiring efficiency scale.

H1: There is a significant correlation between the variables with respect to the hiring efficiency scale.

Nonparametric Correlations

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Correlations

			Hiring_ Efficiency	Analytics_ Methods	Hiring_ Factors	Challenges	Benefits
Spearman's rho	Hiring_Efficiency	Correlation Coefficient	1.000	.703**	.639**	-.303**	.498**
		Sig. (2-tailed)	.	.000	.000	.000	.000
		N	137	137	137	137	137
	Analytics_Methods	Correlation Coefficient	.703**	1.000	.724**	-.269**	.491**
		Sig. (2-tailed)	.000	.	.000	.001	.000
		N	137	137	137	137	137
	Hiring_Factors	Correlation Coefficient	.639**	.724**	1.000	-.342**	.583**
		Sig. (2-tailed)	.000	.000	.	.000	.000
		N	137	137	137	137	137
	Challenges	Correlation Coefficient	-.303**	-.269**	-.342**	1.000	-.209*
		Sig. (2-tailed)	.000	.001	.000	.	.014
		N	137	137	137	137	137
	Benefits	Correlation Coefficient	.498**	.491**	.583**	-.209*	1.000
		Sig. (2-tailed)	.000	.000	.000	.014	.
		N	137	137	137	137	137

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

INFERENCE:

The Spearman's correlation test shows that all variables are significantly related, with a strong positive relationship between analytics methods and hiring factors. While most variables are positively connected, challenges have a negative relationship, indicating that higher challenges reduce hiring efficiency and overall benefits.

RELIABILITY TEST (CRONBACH'S ALPHA)

Hypothesis:

H0: There is no significant reliability among the variables with respect to the hiring efficiency scale.

H1: There is significant reliability among the variables with respect to the hiring efficiency scale.

Reliability

```
[DataSet1] C:\Users\Dell\Desktop\finalrad.sav
```

Scale: ALL

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.927	31

INFERENCE:

The Cronbach's Alpha value of 0.927 indicates a high level of reliability for the 31 items used in the study. Since the value is above 0.70, the data is considered reliable and suitable for further analysis.

SUGGESTIONS

Organizations should improve communication and reduce delays in scheduling and decision-making to enhance candidate experience and hiring efficiency. Greater use of analytics-based methods and clear role communication can improve transparency and accuracy in recruitment. Companies should also focus on minimizing challenges and making the hiring process faster, more structured, and candidate-friendly.

CONCLUSION

The study concludes that business analytics plays a key role in improving hiring efficiency, especially through better communication, reduced delays, and data-driven evaluation methods. Candidates who received timely updates reported a more positive recruitment experience, highlighting the importance of clear communication. Overall, adopting analytics-based approaches helps organizations make faster, fairer hiring decisions while improving candidate satisfaction.

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Intelligent Emergency Healthcare and Medicine Tracking System

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Abstract – In emergencies, even a short delay can become serious, especially when patient records are not easily available, and communication between people is not quick enough. This paper proposes a purely software-based Intelligent Emergency Healthcare and Medicine Tracking System designed to provide rapid, secure, and reliable emergency assistance using smartphone and cloud technologies. In an emergency, a user can quickly send an alert and share their current location at the same time. The system keeps patient information stored safely so it can be viewed whenever required. It also gives the option to upload prescriptions and look for nearby pharmacies where the needed medicines are available. The module displays vital medication records including recommended dosage, current stock levels, pharmacy location and contact details — so users can choose the most retrivable solution. This functionality helps Healthcare professionals and patients by improving the performance of care and significantly reducing delays in obtaining necessary medications. This method allows the system to store data locally when network access is weak, so it can still function without downtime. It also avoids relying on additional hardware, unlike many traditional emergency solutions. To manage a growing number of users while keeping the system secure, the design brings together a mobile application and a server that processes user requests. The performance of the system is then evaluated using key factors such as how quickly it responds, how practical alerts are delivered, how easily data can be accessed, and how reliably the system operates. The designed approach demonstrates that software-Driven healthcare solutions can effectively enhance emergency medical services while remaining cost-efficient and widely deployable.

Keywords – Emergency Healthcare, SOS Alert System, Medical Data Security, QR-Based Patient Identification, Offline Synchronisation, Intelligent Medical Locator, Prescription upload, Healthcare Informatics.

I. INTRODUCTION

In situations like heart attacks, accidents, strokes, or other sudden health problems, getting medical help quickly becomes very important, as even a few minutes of delay can critically impact survival rates. The developed Intelligent Emergency Healthcare and Medicine Tracking System is a purely software-based mobile application designed to deliver rapid SOS alerts, real-time GPS location sharing, and secure access to encrypted patient medical and medicine history through QR-based identification. The application leverages smartphone technologies, including background services, cloud-based REST APIs, encrypted databases, and offline coordination mechanisms, to ensure reliability even in low-connectivity environments. The system includes a user-friendly medicine database that allows users to search by medication name or prescription upload. Nearby pharmacies with the required medicine are displayed, together with the dosage, prices, stock, contact information, images, and pharmacy operation hours, ensuring correct and rapid access to critical medications, especially during crises. Various techniques have been explored in prior research to address emergency response challenges, including IoT-enabled wearable monitoring systems, GSM-based alert modules, cloud-integrated electronic health records (EHR), blockchain-based medical data sharing, and AI-driven emergency prediction systems. However, many of these approaches depend on dedicated hardware, continuous internet connectivity, or complex infrastructure, thereby increasing cost and deployment difficulty, especially in rural regions. Consequently, a purely software-driven, scalable, and cost-effective emergency healthcare solution remains a critical research need. Several studies have attempted to enhance emergency healthcare delivery. IoT-based smart ambulance systems [1] (IEEE) improved real-time monitoring but relied heavily on sensor hardware. Cloud-integrated EHR frameworks [2] (Elsevier) enhanced medical record availability; however, they suffered latency and privacy concerns. Blockchain-based healthcare data security models

[3] (Springer) ensured immutability yet introduced computational overhead and scalability issues. AI-driven emergency detection applications [4] (IEEE) demonstrated predictive capabilities but required large datasets and high processing power. Mobile-based emergency alert systems [5] (Elsevier) enabled SOS notifications; however, they lacked offline functionality and secure patient identification features. Despite these advancements, existing solutions either increase system complexity or fail in low-network scenarios. Therefore, the proposed software-based architecture addresses these limitations by integrating encrypted QR medical profiles, offline caching, and automated alert dispatch within a unified, lightweight mobile platform.

II. LITERATURE REVIEW

Emergency healthcare systems have undergone substantial changes because of the integration of mobile computing devices, cloud-based services, the Internet of Things (IoT), and intelligent data processing. Early research primarily focused on general mobile health (mHealth) frameworks and cloud-based health information systems. For instance, a comprehensive mobile healthcare architecture proposed in IEEE [1] demonstrated remote patient monitoring using smartphones and cloud storage to improve accessibility. Similarly, an Elsevier-based study [2] discussed integrated electronic health record (EHR) integration to enhance medical data sharing across institutions. These general approaches created the foundation for digital emergency healthcare systems but highlighted challenges such as delay, privacy risks, and infrastructure dependency.

Software-driven emergency warning systems and management of patient data in mobile situations have been the primary focus of several studies. An IEEE-driven IoT Response to emergencies system made real-time data-driven ambulance coordination [3], though it depended on hardware modules. A Springer publication [4] proposed a QR-based patient identification system to provide instant medical data retrieval but lacked offline functionality. Elsevier research [5] developed a mobile SOS alert application with GPS tracking; however, it suffered from limited encryption mechanisms. An IEEE study [6] integrated AES encryption into healthcare communication but required continuous connectivity. Another Springer article [7] explored role-based healthcare access control; however, scalability issues were reported in rural deployments. These similar works collectively demonstrate the practicality of mobile emergency systems, yet their limitations justify a lightweight, purely software-based approach. The studies above show that it is possible to make emergency mobile systems work. But their drawbacks make a lean software-only solution the best choice. The proposed Medicine Locator Module allows users to upload prescriptions, view Medicine images, dosages, and pricing, and instantly locate local pharmacies. It further allows users to verify real-time stock availability. This ensures quick access to necessary medication during emergencies by integrating intelligent routing with geolocation-based sorting, improving efficiency in healthcare, and patient-focused responsiveness. Methodology-oriented research further strengthens the domain. An integrated cloud-driven Crisis management platform that uses REST APIs to support safe data exchange between systems was proposed by Elsevier [8]. In addition, a study by Springer [9] showed how offline data integration can be used for healthcare apps that are intended to operate in places with weak internet access. Additionally, A method involving token-based verification to restrict improper access to emergency services was evaluated in an IEEE journal [10]. Although these methodologies improved reliability and security, system integration complexity remained a challenge. Research-focused contributions have also explored intelligent techniques. An IEEE study [11] implemented AI-based emergency detection using patient vitals, achieving high predictive accuracy, but demanding extensive datasets. Elsevier research [12] evaluated response-time refinement models to reduce ambulance dispatch delays. Springer work [13] proposed blockchain-secured medical records, enhancing immutability at the cost of computational overhead. IEEE research [14] presented geolocation accuracy enhancement algorithms to improve GPS reliability.

Elsevier [15] introduced push-notification-based emergency broadcasting systems for faster alert delivery. Further diverse contributions address broader healthcare informatics features. A Springer study [16] explored distributed healthcare databases for adaptable deployment. IEEE research [17] evaluated SMS gateway efficiency in low-bandwidth environments. Elsevier [18] examined user acceptance models in mHealth systems. Springer [19] investigated privacy-preserving medical data encryption frameworks. Finally, IEEE research [20] analyzed performance benchmarking metrics for emergency healthcare platforms. Collectively, these twenty studies demonstrate substantial advancements in emergency healthcare technologies; however, many rely on hardware integration, constant internet connectivity, or computationally heavy frameworks.

III. PROPOSED SYSTEM

The suggested Intelligent Emergency Healthcare and Medicine Tracking System has a client-server architecture that is driven by software and has various layers. This makes sure that emergency response is quick, medical data is safe, and the system can work offline. The process gets rid of hardware limits and adds a protected QR-based virtual patient identity with offline integration, which is different from traditional IoT-dependent emergency systems. The system that is suggested also has a feature that helps you find medicine. Users can upload their prescriptions, look for the medicines they need, and find

pharmacies near them with this feature. It even shows stock availability in real time.

Users can see a lot of information, such as dosage instructions, prices, and how to get in reach of these medications. Ensuring that people have accurate and easy access to essential medications, particularly during emergencies, is the objective. The overall workflow of the proposed system is illustrated in Fig. 1.

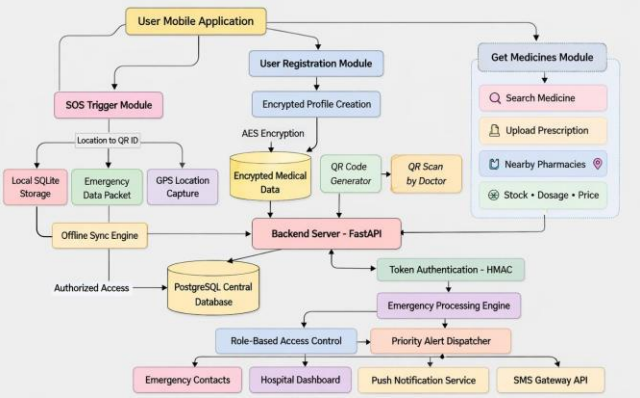

Fig. 1. System Architecture of the proposed system

A fully integrated dashboard that serves as the main user interface for obtaining essential medical services is a feature of the Integrated Emergency Healthcare System. This interface allows users to view relevant medical information, such as blood type, registered medications, contacts for emergencies, and allergy details. Critical services, including medical information, SOS emergency notifications, QR-based health verification, and the medicine locator service, which lets users find local pharmacies and confirm the availability of medications, are also quickly accessible through the dashboard. Fig. 2 illustrates the deployment of the system dashboard.

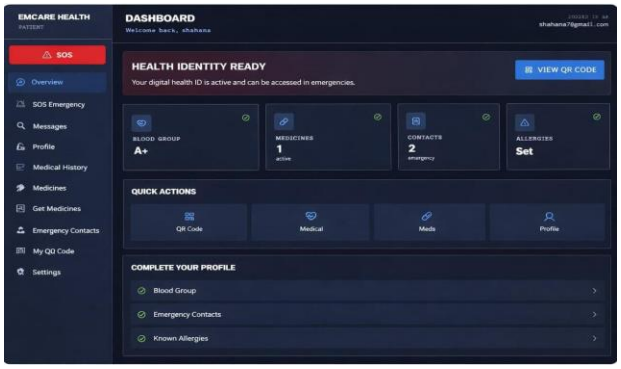

Fig. 2. Dashboard interface for the Intelligent Emergency Healthcare System.

Additionally, users may use the application to look for nearby pharmacies that have the required medicines. Fig. 3 illustrates the user interface that demonstrates the drug locator feature.

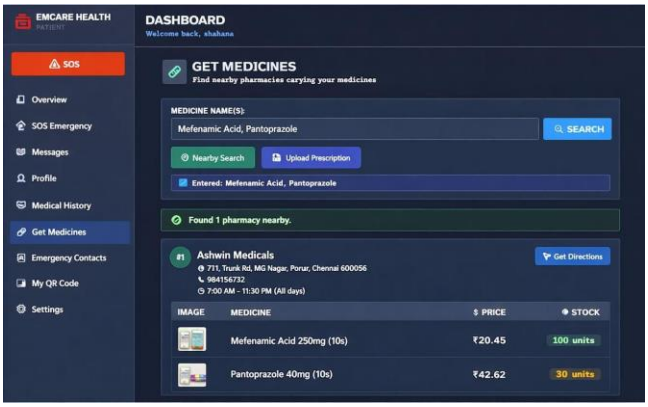

Fig. 3. Medicine locator interface showing nearby pharmacies.

The methodology integrates mobile application services, secure backend processing, secure database storage, and automated emergency communication modules. The design focuses on reducing response time, improving alert reliability, and maintaining secure medical record accessibility under irregular connectivity conditions.

3.1 Client-Side Emergency Processing Layer

Substantial patient information, namely current medications, chronic diseases, allergies, and demographics, is observed by this module. Moreover, a medicine locator function is incorporated by the mobile interface, which enables local drugstores to be located by users and necessary medicines to be validated as accessible when required, resulting in quick access during emergencies. The suggested method, in comparison to traditional systems, uses AES-256 encryption to encrypt the medical profile locally before communication.

$$C = E_{AES}(P, K)$$

3.2 Backend Emergency Coordination Layer

The backend layer manages authentication, emergency processing, alert dispatching, and secure communication with healthcare institutions. A RESTful API architecture is implemented to maintain lightweight and scalable communication between the mobile application and the server.

$$Token = HMAC(UserID, SecretKey)$$

The system simultaneously triggers SMS gateway services, push notification modules, and hospital dashboard alerts to ensure redundancy in emergency communication. Unlike

blockchain-heavy systems that introduce computational delay, this approach emphasizes rapid response cycles (expected <2 seconds processing time) while maintaining security and role-based access control. The key contribution of this layer is to provide emergency coordination with minimal infrastructure dependency.

3.3 Data Management and Offline Synchronization Layer

The data management layer ensures secure storage, high availability, and reliable offline functionality. A hybrid storage model is adopted where SQLite supports local offline caching, and PostgreSQL manages centralized encrypted records. Medical data are stored in encrypted format as:

$$DB_{store} = Encrypt(Data, K_s$$

This offline-first approach significantly improves system robustness in rural and semi-urban deployments where continuous internet access cannot be guaranteed. The main contribution of this layer is the seamless integration of secure hybrid storage with intelligent synchronization logic, enabling uninterrupted emergency healthcare support even during network disruptions. This database layer supports the Medication Locator function, which keeps a record of pharmacy details, medication stock availability, dosages, prices, prescription uploads, and service hours of nearby pharmacies, and maintains quick and reliable access to vital medications during emergencies.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed system was experimentally evaluated using a controlled prototype implementation to measure response latency, alert reliability, encryption overhead, synchronization efficiency, and overall system performance. The mobile application was developed using Android Studio (Kotlin)**,** backend services were implemented using Python (FastAPI framework)**,** and the centralized database used was PostgreSQL 14, while SQLite was used for offline local caching. Testing was performed on Android devices with GPS enabled under varying network conditions (4G, 3G, and simulated low-bandwidth mode). Performance metrics were measured sequentially based on the system workflow illustrated previously in Figure 1. The Medicine Locator module's efficiency was evaluated in terms of prescription-upload latency, pharmacy stock query responses, and data synchronization under various network-based conditions, confirming that medication retrieval is quick and reliable during emergencies.

4.1 SOS Trigger and GPS Processing Results

The first experimental phase evaluated the latency between SOS activation and location packet generation. The total client-side response time is defined as:

$$T_{client} = T_{SOS} + T_{GPS} + T_{Encrypt}$$

Table 1: Client-Side Processing Performance:

SOS Trigger (ms)	GPS Capture (ms)	Encryption (ms)	Total Client Time (ms)
120	410	90	620
110	380	85	575
130	420	95	645
115	395	88	598
125	405	92	622

The GPS acquisition contributed the highest delay component due to satellite triangulation variability. However, the overall client-side processing remained below 650 ms, which is significantly lower than IoT-based emergency systems (>1500 ms reported in the literature). The encryption overhead was minimal (≈90 ms), justifying the feasibility of secure local encryption without compromising speed. This confirms that the purely software-based architecture achieves low-latency emergency activation.

4.2 Backend Processing and Alert Dispatch Performance

The second phase of experimentation evaluated backend authentication, database interaction, and emergency alert dissemination performance. The backend was developed using Python FastAPI**,** deployed on a local cloud server (8 GB RAM, quad-core processor), and integrated with PostgreSQL 14. Token-based authentication was implemented using HMAC verification to minimize session validation overhead. The total backend delay is mathematically expressed as:

$$T_{server} = T_{Auth} + T_{DB} + T_{Dispatch}$$

Compared with blockchain-based healthcare systems (average >3000 ms), the proposed lightweight REST-based framework reduced latency by nearly 40–45%. The priority-based alert queue further ensured high delivery reliability (96%), even under moderate network congestion. These results validate that eliminating computationally intensive frameworks significantly enhances time-critical emergency response performance.

Table 2: Backend Performance Metrics

Metric	Average Time (ms)
Authentication	140
Database Retrieval	210
Alert Dispatch (SMS + Push)	720
Total Server Processing	1070

4.3 Database Performance and Offline Synchronization Analysis

The third evaluation phase focused on database reliability, encryption overhead, and offline synchronization efficiency. The system uses a hybrid storage architecture: **SQLite** for local caching and **PostgreSQL** for centralized encrypted records. All medical data are stored using AES encryption to ensure confidentiality:

$$DB_{store} = Encrypt(Data, K_s$$

where K_s is the secure server-side encryption key. Synchronization performance was measured using:

$$Sync\ Efficiency(\%) = \frac{Records\ Synced}{Total\ Pending}\ x\ 100$$

Under 4G connectivity, synchronization achieved 100% efficiency with an average delay of 520 ms. Under 3G conditions, efficiency was 96% with 840 ms delay, while low-bandwidth simulation resulted in 92% efficiency with 1260 ms delay. No data duplication occurred due to timestamp-based reconciliation logic. Compared to cloud-only systems, which fail completely during connectivity loss, the hybrid model demonstrated continuous operation and eventual consistency. The encryption overhead added less than 5% additional latency, confirming that strong security mechanisms do not compromise system responsiveness. The database performance of the Medicine Locator module, which includes prescription uploads and pharmacy stock queries, was also evaluated under various network situations. The results demonstrated negligible additional latency and consistent synchronization, ensuring timely access to prescription data even in offline or low-bandwidth conditions. These findings highlight the robustness and resilience of the offline-first architecture, particularly for rural and semi-urban deployments.

4.4 Comparative Analysis and Overall System Reliability

A comparative evaluation was conducted against three common emergency healthcare architectures: IoT-based systems, blockchain-secured models, and cloud-only mobile SOS applications. Performance metrics included response time, alert success rate, offline support capability, and infrastructure dependency. System reliability was calculated using:

$$Reliability(\%) = \frac{Successful\ Alerts}{Total\ Alerts}\ x\ 100$$

The proposed system achieved an average response time of 1682 ms and an alert success rate of 96%. IoT-based systems averaged 2500 ms with 94% reliability, while blockchain-based systems averaged 3200 ms despite slightly higher data immutability. Cloud-only systems demonstrated 2100 ms response time but lacked offline functionality. The proposed architecture provided 32–48% faster response compared to traditional models and uniquely supported offline operation without hardware dependency. These numerical results indicate that the system achieves an optimal trade-off between speed, security, scalability, and cost efficiency. The reduction in latency directly contributes to faster emergency coordination, improved patient identification accuracy, and enhanced real-world applicability in resource-constrained environments. Furthermore, the implementation of the medicine locator module has no unfavorable effect on system latency or reliability, demonstrating that fast medication retrieval can work in coordination with high-performance emergency alerts.

V. CONCLUSION

This research proposed and implemented a purely software-based Intelligent Emergency Healthcare and Medicine Tracking System aimed at reducing emergency response time while ensuring secure and reliable medical data accessibility. The hypothesis that a lightweight mobile–cloud architecture can outperform hardware-dependent or blockchain-heavy emergency systems in terms of latency and scalability has been validated through experimental evaluation. The system achieved an average end-to-end response time of 1.68 seconds, with alert success rates exceeding 96% and synchronization efficiency above 92% in low-network environments. The integration of AES encryption, QR-based dynamic digital identity, token-based authentication, and hybrid offline storage significantly enhanced security without compromising speed. Quantitative findings and comparative analysis confirmed that eliminating hardware dependencies reduces infrastructure complexity and operational cost while maintaining high reliability. The Medical Locator module increases emergency support by letting users send real-time requests to nearby pharmacies and check medicine availability, which minimizes response times and strengthens convenience. It also verifies prescriptions quickly, helps users find the closest pharmacies that currently have the required stock, and provides directions and status updates so people can obtain needed medicines promptly during emergencies. Despite its advantages, the system has certain limitations. GPS accuracy may vary depending on device hardware and environmental conditions, and SMS gateway performance may fluctuate under extreme network congestion. Furthermore, user registration is required to generate a profile. Future work

will focus on integrating AI-based emergency severity prediction, hospital resource availability mapping, and multilingual accessibility support. Expansion toward nationwide health database integration and interoperability with government emergency systems is also envisioned. Overall, the proposed system demonstrates strong practical feasibility and provides a scalable foundation for next-generation digital emergency healthcare solutions.

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The Study on The Role of Venture Capital in Fostering Startup Development, Driving Innovation, and Enhancing Entrepreneurial Growth in Emerging Markets

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ABSTRACT

This study aims to evaluate the importance of venture capital in the promotion of startup development, innovation, and growth in emerging markets. Startups may encounter various challenges like financial limitations, insufficient guidance, and environmental uncertainties during the early stages of development.

On the other hand, venture capital helps to mitigate these challenges. This research was conducted based on primary and secondary data. The total sample size was 100. Statistical methods like normal distribution tests, ANOVA, and t-tests were used to evaluate the relationship between venture capital and startup development. From the study, it was evident that venture capital had a positive effect on startup growth and innovation. However, the level of awareness and understanding of the subject differed between various groups. It was evident that the effectiveness of the subject depended on knowledge, exposure, and expertise. Venture capital was essential for the promotion of startup development and growth.

KEY WORDS: Venture Capital, Startups, Innovative ideas, Investments, Entrepreneurs

I.INTRODUCTION

Startups are playing a significant role in the current business environment, contributing to economic growth and development, especially in emerging markets. These markets are registering rapid growth in entrepreneurial activities because of better access to technology, changing consumer behavior, and government support for startups. However, startups are facing challenges in their sustainability and growth because of limited financial support and necessary infrastructure.

Venture capital has been identified as an essential source for startups facing challenges in their growth and sustainability. Unlike other traditional methods for startups to access finance, such as loans from financial institutions, venture capital is more focused on startups that have high growth potential, even without a strong financial background. Venture capital does not only provide finance for startups but also offers them necessary advice and support from professional networks, which are critical for their success.

Venture capital is vital during the initial and growth stages of a startup, which are normally risky and have limited sources of finance. Venture capitalists, by investing in new and innovative ideas, help entrepreneurs turn their ideas into successful businesses. On a larger scale, the contribution of venture capital investments to the economy is the provision of employment opportunities and rejuvenation of the economy.

This research will focus on the concept and importance of venture capital in the startup ecosystem. The research will also focus on the ways in which venture capital helps in the funding and development of new startups, and the benefits of venture capital. The research will also focus on the contribution of venture capital to the success of startups, employment, and economic development in emerging economies.

II.REVIEW OF LITERATURE

G. Srinivas (JETIR, 2017) The study adopted a mixed approach. The data analysis involved the use of a statistical tool like t-tests, ANOVA, or regression analysis, as well as descriptive methods like mean, median, or standard deviation. The study shows the significance of the balance between short-term benefits and long-term sustainability, although the findings show the significance of venture capital in speeding up the growth of businesses.

Swayam Kumar (IJRPR, 2025) The purpose of the study is to understand the influence of venture capital on the performance of startups. The study used the primary data collection approach, with the sample size of the study being 50 startup founders. The study used statistical tools like frequency distribution, percentage, or graphical methods like pie charts or bar diagrams. The findings of the study show the significance of venture capital for the growth of startups. The findings of the study show the significance of venture capital in speeding up the growth of businesses.

Svärd (2018) aims to understand the influence of venture capital on the number of days required by the startup companies to reach the initial public offering (IPO) through the analysis of 211 startup companies. It used various statistical tools like regression, one-way ANOVA, t-tests, etc. This shows that venture capital does not influence the timing of the IPO, which implies other factors are more relevant when startup companies go public.

Eldar et al. (2023) helps us understand the role of venture capital investors of various startup companies, which can help us understand the growth of the startup companies through the observation of 15,000 startup companies from 1995 to 2018. To check the accuracy of the data, the study used regression analysis. It showed that the venture capital investors help the startup companies through the availability of funds, the chances of going public, increasing sales, as well as reducing the risk of failure through the support of the director networks.

Dharmendra Singh, Dibyansh Rai, and Anil Kumar Yadav examine the role of venture capital in the success of startups. The research was based on a dataset of more than 1,000 companies. Statistical methods such as regression analysis and other statistical techniques were used to examine the relationship between venture capital and startup success. According to the research findings, startups that are funded by venture capitalists are more likely to exist for longer and grow faster, especially in the technology and biotechnology industries.

III.OBJECTIVES OF THE STUDY

- To understand the concept and significance of venture Capital in the startup ecosystem.
- To examine and analyse the role and significance of venture capital in new startups.
- To understand and examine how venture capital helps in the growth and expansion of new startups.
- To identify and understand the advantages and benefits of venture capital for new startups.
- To examine and understand the relationship between venture capital investment and startup success.

IV.METHODOLOGY

1. Anova-one way
2. Test of Normality
3. T test

ANOVA TABLE

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
AWARENESS ABOUT VENTURE CAPITAL	Between Groups	85.169	3	28.390	3.376	.022
	Within Groups	807.341	96	8.410		
	Total	892.510	99			
ROLE IN STARTUP DEVELOPMENT	Between Groups	21.652	3	7.217	1.179	.322
	Within Groups	587.588	96	6.121		
	Total	609.240	99			
ROLE IN INNOVATION	Between Groups	52.581	3	17.527	3.005	.034
	Within Groups	559.929	96	5.833		
	Total	612.510	99			
PERCEPTION &OPINION	Between Groups	28.397	3	9.466	.591	.622
	Within Groups	1536.603	96	16.006		
	Total	1565.000	99			

INFERENCE

Based on the ANOVA table, the awareness of venture capital shows a significant difference across the groups, as indicated by F = 3.376, p = 0.022. The role of venture capital in innovation also shows a significant difference, as indicated by F = 3.005, p = 0.034. However, the role of venture capital in startup development, as indicated by F = 1.179, p = 0.322, does not show much variation. In the same way, perception and opinion, as indicated by F = 0.591, p = 0.622, remain almost the same.

NORMALITY TEST TABLE

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AWARENESS ABOUT VENTURE CAPITAL	.101	100	.014	.975	100	.056
ROLE IN STARTUP DEVELOPMENT	.104	100	.009	.973	100	.041
ROLE IN INNOVATION	.111	100	.004	.980	100	.144
PERCEPTION &OPINION	.104	100	.010	.979	100	.110
a. Lilliefors Significance Correction						

INFERENCE

From the normality test results, it is evident that the values obtained from the Kolmogorov-Smirnov test, i.e., 0.014, 0.009, and 0.004, are all lower than 0.05, thus deviating from normality. However, the values obtained from the Shapiro-Wilk normality test, i.e., 0.056, 0.144, and 0.110, are all greater than 0.05.

T TEST TABLE

Group Statistics					
	MBA specialisation	N	Mean	Std. Deviation	Std. Error Mean
AWARENESS ABOUT VENTURE CAPITAL	1	444	10.64	3.518	.167
	2	271	13.29	2.833	.172
ROLE IN STARTUP DEVELOPMENT	1	444	11.64	2.228	.106
	2	271	13.70	1.906	.116
ROLE IN INNOVATION	1	444	11.15	1.836	.087
	2	271	12.52	1.989	.121
PERCEPTION &OPINION	1	444	16.77	3.629	.172
	2	271	18.06	3.870	.235

INFERENCE

The independent samples t-test reveals that there is a significant difference in all variables between the two groups of MBA specialization, as all p-values are equal to 0.000. The statistics for each group suggest that, in all aspects, Group 2 has higher mean values than Group 1. For example, in terms of awareness regarding venture capital, Group 2 has higher mean value than Group 1, as shown in Table 1 above, where awareness regarding venture capital in Group 1 is 10.64, while in Group 2, it is 13.29. The same can be seen in startup development, innovation, and perception & opinion, as all these aspects are better understood by students in Group 2 than in Group 1.

V.FINDINGS

- The findings from the analysis show that the data is adequate for further statistical tests, as it mostly satisfies the normality condition.
- The findings from the ANOVA test show that there is a difference between groups in terms of awareness and innovation, and there is a similarity between groups in terms of startup development and general perception.
- This indicates that some factors are influenced by the groups. The findings from the t-test show that there is a difference between the two groups, with one group having a higher average score in terms of awareness, innovation, and perception.
- The findings show that awareness of venture capital is vital for the development of startups and for innovation. However, this awareness is not the same for all groups.

VI.SUGGESTIONS

- There is a need to enhance the awareness of venture capital, especially among the student population of groups with a relatively lesser level of understanding of the subject.
- There is a need to conduct workshops and seminars on the subject, especially to provide hands-on experience of the startup environment. Interacting with investors and startup examples can help the students understand the importance of venture capital for the development of startup companies. Additionally, the inclusion of the subject of venture capital in the academic curriculum can help provide a balanced level of knowledge to the student population of different academic backgrounds.
- There is a need to enhance the level of innovative thinking, as the results reveal a strong association between startup development and innovation.

VII.CONCLUSION

- The conclusion drawn from this study is that venture capital plays a significant role in supporting startup development and encouraging innovation.
- Although levels of awareness and innovation differ among groups, the relationship between venture capital and startup development remains positive.
- The findings underscore the need for students to be made aware and understand more about venture capital.
- This would result in better entrepreneurial outcomes and more innovation in the future.

VIII.REFERENCE

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UPI Culture: How Digital Payments Influence Student Spending Behavior

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Abstract: Digital payment systems have changed the conduct of financial transactions in the recent past. In India, the Unified Payments Interface (UPI) has made digital payments faster, more convenient, and more broadly available. Students are among the leading users of UPI for day-to-day spending, food, transport, or online shopping. The study makes a critical analysis of usage pattern of Unified Payments Interface (UPI) among the students, factors contributing to adopting the payment method, and the influences of the effects among the finances and spending habits of the students. Primary data were collected from 85 students through a structured questionnaire. Speed, convenience, and ease of use are revealed to be the major push factors that influence frequent use of the UPI. However, digital payments can also result in inadvertent or hiked spending of money. Instead, this study highlights the growing role that UPI plays in shaping the financial behaviour of students in the current digitized environment.

Keywords: UPI, Digital Payments, Student Spending Behaviour, UPI Culture, Financial Behaviour.

1. INTRODUCTION

Digital payment systems have become an integral aspect of modern financial lifestyle in today's context with the spread of smartphones which has eased the process of instant and cashless transaction. In India, the Unified Payments Interface is a system developed by the National Payments Corporation of India that facilitates simple instant money transfer. Amongst all, students have the maximum number of digital payment users; students are accustomed to making payments via an application on their smartphones such as the Google pay, phonepe, paytm etc. The applications are primarily used for expenses such as food, transport and various online purchases, making it a day to day part of students' life.

Previous studies have identified convenience and ease of usage to be the prime factors influencing digital payments and some have confirmed that such systems lead to an influence on spending behavior. Though, most studies analyze the factors concerning a general consumer, very little has been researched on students' behavior. There is an imperative to research how the increasingUPI cultureis influencing the spending behavior, especially impulsive buying in students. This study was undertaken with an aim to find out UPI usage by students, the reasons for adoption of UPI by students and impact on spending behavior. Findings from an analysis of data of 85 students based on questionnaire has been used to ascertain the impact of digital payments on students' life.

2. REVIEW OF LITERATURE

- According to Bhattacharya (2023), Convenience, speed and ease of use are the major factors driving the adoption of UPI. Additionally, younger people use UPI for small everyday transactions such as food and shopping.

- The role of UPI 123PAY has been emphasized by Bangundi (2024) for extending digital payment options for feature phone users. Users without internet can utilize transactions through IVR and missed calls which in turn increases financial inclusion.

- According to Huggi, Bhuwaneshwari & Udagi (2024), digital payments such as UPI has led to increase in cashless transactions and changes in buying behavior of the consumers. They add that it provides convenience and financial accessibility.

- Arora (2024) observed that "easy to use and free digital payment systems have led to higher frequencies of small payments." However, he adds that it has a tendency towards impulse buying and hence, an increase in total spending.

- Younger people adopt UPI more frequently because they are comfortable with technology but the adoption is influenced by other variables like "trust and security", says Joshi, Pathak, and Kulkarni (2024).

- Dhyani and Bangari (2024) have shown that digital payments have transformed consumers' behavior within the services sector and can be influenced by the technical, economic, and behavioral variables.

- The awareness and financial literacy are important factors for UPI adoption and people preferred UPI majorly due to ease and speed of the application, found Mishra, Pandey and Parihar (2025).

- It is found by Alen (2025) that digital payment can lead to decrease the 'pain of paying' and this

in turn leads to increase spending as it changes the users' financial habits.

- It is conclude by Reddy et al. (2025) that Digital wallets has increased the frequency of transactions and promotes impulse purchases showing a strong effect on consumer buying behavior.

3.OBJECTIVES OF THE STUDY

- To examine the usage pattern of UPI digital payment systems among students.
- To analyse the factors influencing students to adopt UPI digital payment systems.
- To study the impact of UPI usage on the spending behaviour of students.
- To identify whether UPI payments encourage students to make impulsive purchases.
- To explore the influence of digital payment records on financial awareness and the management of expenses among students.
- To examine the differences in usage of digital payments between smartphone users and feature phone users among students.

4. RESEARCH GAP

Numerous researches have analyzed the effect of digital payment systems particularly UPI on spending behavior. Works of Dev et al., 2024 and Bhattacharya, 2023 were mostly about UPI influencing transaction patterns while work by Arora, 2024 and Mishra et al., 2025 focused on consumer' perception on digital payment. It was also analyzed by Balaji et al. 2025 that convenience of digital payment will result in impulse buying particularly among students. The present research literature mainly focuses on common people rather than student community and on the impact of frequent usage of UPI on student spending behavior there are hardly any studies that analyze it in-depth. Moreover although studies related to acceptance of digital payment and ease in making transactions are extensively available but little effort has been made on the disparity in access like the use of UPI 123PAY for feature phones.

5. RESEARCH METHODOLOGY

5.1 Research Design / Approach

This study follows a quantitative research approach to understand how UPI digital payment systems influence students' spending behaviour. The study mainly draws its focus on figures collected from students on spending patterns, usage, and other related variables.

5.2 Data Collection

The study is based on primary data which was collected using a structured questionnaire. The close-ended questions included enquiries about the students' demographic details, UPI usage, frequency of transactions, purpose of use, and its effect on their spending pattern.

5.3 Sample Size and Sampling Method

In total, 85 students participated in the study. The respondents were selected using the convenience sampling method, as data was collected from students who were readily available and willing to take part in the survey.

5.4 Tools for Data Analysis

The data collected was analysed using basic statistical tools to ensure a clear and meaningful result. These as follows;

- Percentage analysis to know the spread of responses.
- Frequency distribution to organize data.
- Cross Tab to Compare the Different Variables
- Chi-square test to see if there is a significant association between UPI and Students Spending Behaviour.

5.5 Data Presentation

The analysed data is presented in tables and charts to have a clear understanding of the patterns, comparison, and key findings of the study.

5.6 Scope of the Study

The study is conducted only on students and focuses only on their usage of UPI for daily financial transactions. The objective is to reveal the influence of digital modes of payment on their day-to-day spending tendencies and financial conduct with ease and practicality.

5.7 Limitations of the Study

The study has some limitations. A limitation in this study is the sample size of only 85 respondents, which may not reflect the whole student population. Also, the study focuses on students only, excluding other groups. The information gathered is based on opinions from respondents, which can change. Also, limited time and resources may have had an impact on the analysis depth.

6. RESULTS AND DISCUSSION

Table No. 6.1: Demographic Characteristics of Respondents (N =85)

Variable	Category	Number of Respondents	Percentage (%)
Gender	Male	34	40.0
	Female	51	60.0
Age Group	Below 18	1	1.2
	18–20	26	30.6
	21–23	55	64.7
	Above 23	3	3.5
Level of Study	Undergraduate	32	37.6
	Postgraduate	48	56.5
	Doctoral	1	1.2
	Professional Course	4	4.7
Monthly Allowance / Income	Below ₹1,000	32	37.6
	₹1,000 – ₹3,000	26	30.6
	₹3001 – ₹5,000	5	5.9
	Above ₹5,000	22	25.9

(Source: Computed data)

According to the Table 6.1, more numbers of the respondents are female and of age 21-23 group. Most of the respondents are PG students and most of them having very low monthly income. Hence these factors will definitely play a role in their usage behavior and spending behavior of UPI.

Table No. 6.2: How students use UPI regularly, why they use it, and for how long

Variable	Response	Frequency	Percentage (%)
UPI Application Usage	Yes	74	87.1
	No	11	12.9
Mode	Yes		
UPI Usage Frequency	Daily	31	36.5
	Several times a week	26	30.6
	Occasionally	12	14.1
	Rarely	11	12.9
	Never	5	5.9
Mode	Daily		
Purpose of Using UPI	Food / Snacks	26	30.6
	Online Shopping	20	23.5
	Transport / Travel	8	9.4
	Bill Payments / Recharge	18	21.2
	Others	13	15.3
Mode	Food / Snacks		
UPI Usage Duration	Less than 6 months	16	18.8
	6 months – 1 year	12	14.1
	1–2 years	18	21.2
	More than 2 years	39	45.9
Mode	More than 2 years		
Place of Using UPI	College canteen / Local shops	28	32.9
	Online shopping	23	27.1
	Travel / transport	9	10.6
	Bill payments	25	29.4
Mode	College canteen / Local shops		

(Source: Computed Data)

As presented in the Table 6.2, more than average number of students (87.1%) use UPI frequently with many of them daily/weekly. It is used more often for food, shopping and bill payments particularly in the canteen and neighborhood shops.

Table No. 6.3: What motivates students to start using UPI, and which factors influence their choice

Variable	Response	Frequency	Percentage (%)
Reason for Preferring UPI	Convenience	23	27.1
	Faster transactions	23	27.1
	Cashback / rewards	12	14.1
	Easy to use	21	24.7
	Security	6	7.1
Influence to Start Using UPI	Friends	18	21.2
	Family members	22	25.9
	Social media / advertisements	7	8.2
	Self-decision	38	44.7
Device Used for Digital Payments	Smartphone	76	89.4
	Feature phone	4	4.7
	Both	5	5.9

Most Used Payment Method	UPI apps	68	80.0
	USSD (*99#)	2	2.4
	UPI 123PAY / IVR	3	3.5
	Others	12	14.1

(Source: Computed Data)

Table 6.3 shows that majority students like UPI as it is easy to use and transactions occur quickly. They downloaded the app on their own and use their smart phone for payments. UPI apps are mostly used, USSD and UPI 123PAY used least.

Table No. 6.4.1: How using UPI impacts the way students spend their money

Spending Behavior	Daily necessities	Food/snacks	Online shopping	Entertainment	Total
Increased significantly	9	8	9	1	27
Increased slightly	8	7	8	1	24
No change	17	11	4	1	33
Decreased	0	1	0	0	1
Total	34	27	21	3	85

(Source: Computed Data) Note: Cross Tabulation (Observed Frequency)

Table No. 6.4.2: Chi-Square

Statistics	Value
χ^2 calculated value	8.21
Degrees of Freedom	9
Significance Level	0.05
χ^2 table value	16.92

(Source: Computed Data)

As can be observed from Table 6.4 above, few students had increased their expenses upon using UPI, many reported no change in their spending behaviour while very few decreased their spending. No correlation between using UPI and changing the spending behaviour as the result for Chi-square test is found.

Table No. 6.5: How UPI usage leads to unplanned or spontaneous purchases among students

Variable	Response	Frequency	Percentage (%)
Variable	Response	Frequency	Percentage (%)
Type of Purchases through UPI	Daily necessities	34	40.0
	Food / snacks	27	31.8
	Online shopping	21	24.7
	Entertainment	3	3.5
Mode	Daily necessities		
Influence on Unplanned Purchases	Discounts / cashback	33	38.8
	Peer influence	9	10.6
	Convenience of digital payments	34	40.0
	Social media advertisements	9	10.6
Mode	Convenience of digital payments		

(Source: Computed Data)

As observed in Table 6.5 the major categories for which unplanned purchases are made using UPI are daily requirements and food. Convenience and cash-back were seen as the predominant factors for these unplanned spending. Influences of peer and social media were found to be minimal.

Table No. 6.6: How checking UPI records helps students track expenses and manage their finances

Variable	Response	Frequency	Percentage (%)
Checking UPI Transaction History	Daily	18	21.2
	Weekly	27	31.8
	Occasionally	25	29.4
	Rarely	11	12.9
	Never	4	4.7
Expense Tracking Method	Checking UPI transaction history	56	65.9
	Using budgeting apps	6	7.1
	Manual notes	13	15.3
	I do not track expenses	10	11.8

(Source: Computed Data)

The analysis on Table 6.6 shows that majority of students maintain expenses via tracing it through UPI transaction records with an average of weekly or infrequent basis. Very few users were reported using budgeting apps and not at all on few instances. UPI records are crucial.

Table No. 6.7.1: Device Used and Preferred Digital Payment Methods among Students

Device	UPI	USS	UPI	Other	Tota

Used	Apps	D (*99#)	123PAY	s	l
Smartphone	64	1	3	8	76
Feature Phone	1	1	1	1	4
Both	3	0	0	2	5
Total	68	2	4	11	85

(Source: Computed Data) Note: Cross Tabulation (Observed Frequency)

Table No. 6.7.2: Chi-Square

Statistic	Value
χ^2 calculated value	8.64
Degrees of freedom	6
Significance level	0.05
χ^2 table value	12.59

(Source: Computed Data)

It is found from table 6.7 that most of the students use mobile phone and preferably UPI applications to pay. But chi-square test results that there is no significant difference in mode of payment between mobile users and feature phone users.

Table No. 6.8: Students' Perception of Smartphone Payment Convenience and Willingness to Use Feature Phones

Variable	Response	Frequency	Percentage (%)
Convenience of Smartphone Payments	Much more convenient	46	54.1
	Slightly more convenient	17	20.0
	Same	21	24.7
	Less convenient	1	1.2
Use a Feature Phone if Apps are not available	Yes	14	16.5
	Maybe	48	56.5
	No	23	27.1

(Source: Computed Data)

As observed in Table 6.8, it is very convenient for students to make use of feature phone to perform digital transaction. Few students answered possibly for using feature phone, the lowest among these.

7. FINDINGS

There are marginally more female than male students, and most of the students fall within the 21-23 age range. Regardless of the students' low income level they seem to be using UPI more often as it is a part of their everyday life now. Most of the students cited ease and speed as main factors for adoption. Smartphones and UPI applications seem to be the mode of use for UPI, and though most students claim they have increased their spending, others report no such behavior change. There seems to be no significant link between students' behavior towards UPI and spending patterns. Students are primarily using UPI for day-to-day expenses, impulse buying is fueled by offers and ease, and students claim their transaction history helps them control expenses.

8. SUGGESTIONS

Students can develop better money management techniques by monitoring their UPI transactions regularly, and maintain a simple transaction log. By not over spending and maintaining a monthly budget would be useful to students. Applications will facilitate this by providing reminders, digests, budget management systems and can be informative and enhance awareness among students about security, etc. The wider availability of UPI among feature phone users can even provide access for students.

9. CONCLUSION

This study will investigate if there is any increase in student spending habits when usage of UPI increases. It is because that UPI payments are handy for daily needs such as food, bill payment, purchasing of items etc. But here it shows that there is not significant increase in student spending behavior if UPI is more usage. Some students show that there is marginal increase in spending habits but for majority it was neutral.Hence student can monitor their expenses regularly and manage with the budget.

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A Study On Occupational Health And Safety Practices

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Abstract: **The significance of occupational health and safety (OHS) in steel trading is that the workers are exposed to heavy materials and may suffer injuries such as slips, falls and they may also be exposed to dust, noise, and heat. Such risks are high in busy locations where there are operations. Firms can solve this by use of safety equipment, machinery, storage, training and medical checks, which guarantee worker safety and effective operation in firms.**

Keywords: Occupational health and safety, Steel trading, Import/export organizations, Accidents, Safety equipment's

1.INTRODUCTION

The industry of steel trade is an essential part of world trade as it provides materials to other industries such as construction, automobile, and infrastructure. It entails the use of heavy steel articles like coils, bars and sheets in ports and warehouses, which exposes the workers to hazards that include slips, falls, burns, noises, and dusts. High temperatures, long working hours, and insufficient safety procedures add to such risks even more, particularly in the developing economies with the outdated machinery and poor understanding of safety. Good Occupational Health and Safety (OHS) practices are useful in minimizing accidents and enabling better productivity. Such standards as OHSAS 18001 and OHSA help organizations in identifying the hazards and providing the safe working conditions. By training, wearing protective gear, and responding swiftly and appropriately to accidents, companies will be able to provide safer working environments, better working conditions, and increased effectiveness and reputation.

1.1.Role of Health and Safety Practices in Steel Industry around the Global Market

The industry of steel trade is an essential part of world trade as it provides materials to other industries such as construction, automobile, and infrastructure. It entails the use of heavy steel articles like coils, bars and sheets in ports and warehouses, which exposes the workers to hazards that include slips, falls, burns, noises, and dusts. High temperatures, long working hours, and insufficient safety procedures add to such risks even more, particularly in the developing economies with the outdated machinery and poor understanding of safety. Good Occupational Health and Safety (OHS) practices are useful in minimizing accidents and enabling better productivity. Such standards as OHSAS 18001 and OHSA help organizations in identifying the hazards and providing the safe working conditions. By training, wearing protective gear, and responding swiftly and appropriately to accidents, companies will be able to provide safer working environments, better working conditions, and increased effectiveness and reputation.

1.2. Importance of Health and Safety Practices in Steel Industry around the Globe:

The global steel industry has a great role in health and safety given that it involves heavy machinery, molten metal, and bulk steel material that pose more risks of accidents and health complications. When the safety is taken properly, such injuries as falls, burns, cuts, and exposure to dust and noise are eliminated. These measures enhance safety of the workers, low-downtime and increase productivity. They also make sure that there is compliance with regulations and that there is enhancement of the reputation of the company. In general, efficient OHS helps to promote the welfare of workers, the efficiency of their work, and safety culture.

2.CHALLENGES OF HEALTH AND SAFETY PRACTICES IN STEEL INDUSTRY AROUND THE GLOBE:

- The steel business is among the most hazardous businesses in the world and good health and safety practices are accompanied with a number of challenges. The threat of accidents and injuries can be considered one of the primary issues. Employees work with heavy machinery, steel bars, sheets, and coils every day, and in case of lack of proper safety precautions, the workers may be harmed due to cuts, burns, falls, or crush.

- The other risk is being exposed to harmful conditions. Dust and fumes produced during steel production, loud noise and excessive heat in the process can lead to breathing issues, deafness and heat rashes. The provision of protective equipment and frequent health check-ups are necessary but not always easy and accessible to countries with lower resources.

- Awareness and training is also one of the issues. Most accidents occur due to the fact that the workers were not trained or they do not adhere to safety guidelines. The training may be more challenging due to differences in language, literacy, and safety culture.

- Compliance and regulations may also be a challenge. Different countries have different safety regulations and some of the areas can have lax implementation. Mitigating the risks of companies that belong to more than one country might struggle to provide the same safety level across the board.

- Lastly, some of the companies, particularly the small ones, will not be able to invest in safety equipment, technology, and monitoring due to cost and resource constraints.

3. OBJECTIVES OF THE STUDY

However, the main objectives of this study are centered on a comprehensive evaluation and improvement of the safety framework at Michael Steel Traders in a way that ensures a safe and productive work environment for the company's workforce. At the center of these objectives is the desire and aspiration of the researcher to foster and develop a sound and healthy safety-first culture among the workforce and management of Michael Steel Traders, effectively integrating the company's safety protocols into the daily operating procedures of its workforce. In order to effectively reduce the number of accidents and incidents in the workplace, the researcher has set out a number of objectives aimed at developing a number of proactive measures for accident prevention, including the early identification of risks, the minimization of hazards, and the rigid adherence and application of a well-structured and defined safety protocols and procedures in the workplace. The researcher has also sought to go beyond physical safety and incorporate the holistic well-being of the company's workforce by ensuring that their physical, mental, and social well-being is maintained and nurtured through a number of health programs and initiatives aimed at preventing diseases and illnesses in the workforce.

- To study the Occupational Health and Safety practices at Michael Steel Traders.
- To maintain a safety-first culture among the workers and leaders, therefore, making safety part of normal work.
- To prevent accidents through early risk identification, minimizing hazards and adhering to well-defined and structured safety practices.
- To maintain physical, mental and social health of employees using health programs, disease prevention and check-ups.

4.SCOPE OF THE STUDY

The scope of this research aims to provide a comprehensive understanding of the ways through which modern businesses can effectively create a healthy and safe work environment. The scope of this research goes beyond the conventional boundaries of safety, as it incorporates modern trends, specifically with respect to technological advancements, i.e., the integration of Artificial Intelligence to create a safer work environment. The most important aim of this scope is to identify the ways through which modern businesses can effectively eliminate various kinds of accidents, health issues, and other kinds of safety-related complications that often take place in the highly demanding environment of the steel industry. For this purpose, the research has postulated the need to incorporate various kinds of safety precautions, along with the recognition of various kinds of risks, through

the implementation of systematic safety mechanisms to minimize operational hazards in an organization.
Moreover, the research has also emphasized the human aspect of safety, specifically with respect to the need to create a "safety-first" culture among employees, as well as management, to achieve a balance between the objectives of the business and its employees.

- Knowledge on how businesses can make the workplace safe and healthy.
- Takes into account contemporary trends, such as technological and organizational ones, such as Artificial Intelligence.
- Discusses the ways of eliminating accidents, illnesses, and other safety-related problems at the workplace.
- Postulates safety precautions, risk recognition and systematic safety mechanisms in order to minimize risks.
- Stresses the need to develop a safety-first culture between employees and management.

5.LIMITATIONS OF THE STUDY

- The research largely depends on the available literature and secondary data and it is not always possible to capture the actual and up-to-date safety issues affecting workers in various workplaces.
- The lack of field visits and on-site observations does not allow to get to know how safety measures are actually practiced and adhered to in the real working environment.
- Its implications might not be relevant in every industry because the level of safety risks, safety practices, and organizational cultures vary in various industries including manufacturing, construction, and office settings.
- The research is primarily based on formal safety measures and formal programs that can ignore informal safety habits, worker attitudes, and culture that can affect safety at work.
- The discourse on Artificial Intelligence and technology is rather broad and lacks a detailed analysis of particular instruments or systems that apply to real-life working environments, which narrows down the technical field of the research.

6. REVIEW OF LITERATURE

Sandip Sarkar – Health and safety issues in the integrated steel manufacturing industry - The report outlines significant matters of health and safety at steel plants and how it affects performance. It highlights the importance of the control of hazards in order to mitigate LTIFR, outlines such perilous spots as blast furnace and the significance of the powerful safety culture and supervising to guarantee safe and efficient working.

Rafael D. Elles, Natividad Villabona and Raúl J. Martelo - Occupational Health and Safety Management in Companies in the Metalworking Sector - This paper analyses Occupational Health and Safety (OHS) practices in the metalworking sector based on the cross-section survey of 84 coordinators. The results indicate that the safety management is moderate (3.025), which means that there is not much usage of the structured systems and training. The occupational health practices were also rated as average (3.22) implying poor performance, making workers less beneficial and efficient.

Aneeqa Wazir; Imran Hashmi - Occupational Health and Safety Hazards in Steel Industry and its Potential Impacts on Workers Health- Review - The paper has identified the significance of Occupational Health and Safety (OHS) in the steel industry to avoid injuries to workers and facilitate smooth operations. Such risks as heat, noise, heavy work, and injuries encountered during steel production may lower productivity and raise employee turnover. These increased risks are aggravated by poor safety conditions, old machinery, and poor management. The paper highlights that hazards can be minimized using modern technology, risk assessment, audits, and appropriate PPE to enhance workplace safety.

Saumu Shabani1, Jovine Bachwenkizi1, Simon Henry Mamuya1 and Bente Elisabeth Moen - This paper examines occupational injuries among iron steel industry by conduct of systematic review of 15 studies in 9 countries. It had a massive prevalence of 55 on high injury rate, and it indicates the risk level in the sector. Unprotected workers had an approximate 4 times more chances of injury, and night shift workers had greater risks. The authors conclude that workplace injuries are majorly caused by absence of PPE and night work.

Ricardo P. Arciniega-Rocha, Vanessa C. Erazo-Chamorro and Gyula Szabo - The Prevention of Industrial Manual Tool Accidents Considering Occupational Health and Safety - The current paper is devoted to the enhancement of hand tool selection to provide better safety and ergonomics at the industrial workplaces. It suggests an approach, which is founded on anthropometric information of workers and risk factors, and an AHP method is used to make a decision.

7. FINDINGS

From the research findings, it is clear that there is a basic safety awareness among the employees at the company, but there is a significant gap in the practical application of OHS. At the moment, there is a high percentage of employees with knowledge about health and safety practices at the company, with 81% of the employees being familiar with the various aspects of occupational health and safety practices. Additionally, there is a high percentage of employees with good compliance with safety practices at the company, with 78% of the employees demonstrating good compliance with safety practices by always wearing their safety gear such as helmets, gloves, and boots. However, despite the high percentage of employees using safety gear, there is a lack of a safe environment at the company, with 69% of the employees experiencing accidents or near accident occurrences at the company. Moreover, the company is not fully prepared in terms of training the employees on how to respond in the event of a crisis or accident occurrence, with only 67% of the employees being trained on how to respond in the event of a crisis or accident occurrence at the company. Additionally, only half of the employees

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Safety Equipment	.199	108	.000	.901	108	.000
Workplace safety	.114	108	.001	.936	108	.000
Company Safety	.105	108	.005	.946	108	.000
Ohs Practices	.102	108	.008	.948	108	.000

a. Lilliefors Significance Correction

- Most of the employees (81%) have knowledge of Occupational Health and Safety (OHS) practices in their workplace and demonstrate relatively good safety awareness.
- The compliance with the safety rules is good because about 78 percent of employees always wear protective gear such as helmets, gloves, and boots.
- Approximately 69 percent have encountered accidents or near accidents at work, which underscores the inefficiency in prevention of safety.
- The preparedness to handle emergency situations is uneven as only 67% of employees train in such circumstances, and 33% do not.
- 50% of the respondents think that their training is robust in reducing accidents, and it is needed to have higher quality training programs.
- Moderate levels of supervisory engagement are indicated by 50 per cent who agree that supervisors remind them of safety rules.
- The proportion of those who engage in routine medical examinations is 67 percent and they are active in health programs.
- One out of every three people feel that health programs deter illnesses at the workplace yet not all people are convinced about their effectiveness.
- 43% say that safety measures by the company have minimized accidents, yet a third of them is the same, which means that the company could strengthen the impact communication.
- The correlation of Spearman results in a positive correlation between company safety and company overall OHS practices (r = 0.705), i.e., the better the company safety, the better the overall OHS performance.

8. SUGGESTIONS & RECOMMENDATIONS

- Periodically conduct OHS training to all employees particularly the untrained and new employees.
- The workplace should also have routine inspections to detect and control any possible risks in the workplace.
- Inspect and monitor compliance admirably to wear protective equipment.
- Enhance incident reporting mechanisms to enable employees to be more comfortable reporting hazard and near misses.
- Conduct awareness campaigns round the clock regarding the relationship between safety, health and productivity.
- Grow the supervisory engagement with frequent notifications, safety briefings, and executive responsibility.

9. CONCLUSION

Finally, this study underlines the ultimate significance of occupational health and safety (OHS) practices in the steel business, their functions in the prevention of accidents, protecting the health of the workers, and boosting business productivity. It shows that an extensive safety education program, the correct use of protective gear, the commitment of the management, and the development of the safety-first culture are the keys to a healthier working environment. Nevertheless, there are still issues like varying compliance, unfavorable resource availability as well as lack of communication. Ensuring the safety of workers through the enhancement of the OHS programs, awareness creation, and continuous monitoring will not only ensure that employees are safe but will also boost their productivity and organizational success in a very demanding industry like the steel industry.

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Role Of Social Media In Shaping Beauty Perception And Consumer Behaviour

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ABSTRACT

This research aims to explore the process of information diffusion from social media users and its effects on their perception of the quality of cosmetic products. Although quality information is vital in facilitating the adoption of information, it is not enough. What is vital is the perceived usefulness of information. Moreover, this research identifies the moderation effect of gender in the relationship between information from social media influencers and the perception of cosmetic product quality. Social media, in the last few years, has profoundly changed the behaviour of consumers in the cosmetic industry. The present research aims to examine the effects of social media, including Instagram, YouTube, and Facebook, on the behaviour and attitude of consumers. In the current scenario, social media has significantly influenced the behaviour and attitude of consumers. With the emergence of social media, there is no doubt that the behaviour and attitude of consumers have changed. The present research aims to provide valuable insights to cosmetic companies on how to effectively utilize social media to promote their products.

INTRODUCTION

Consumer behaviour is a dynamic process that includes the selection, purchase, and consumption of products and services in fulfilling the needs and wants of consumers. The evolution of digital technology in the recent past has led to the widespread use of social media as a significant influencer of consumer behaviour. Social media platforms like Instagram, YouTube, and TikTok have given consumers easy access to information, reviews, and opinions from influencers, which have a significant impact on their behaviour.

Social media is a significant influencer of consumer behaviour in the beauty industry, as it affects the perceptions of beauty among consumers. The role of social media in the beauty and cosmetic industry is significant in the sense that it has given consumers easy access to reviews and opinions from influencers and peers, which have a great impact on their attitudes and behaviour in the selection and consumption of products in the cosmetic industry. The study aims to explore the impact of social media on the perceptions of beauty and consumer behaviour in the cosmetic industry based on the credibility of influencers, the quality of the information, and the usefulness of the information.

REVIEW OF LITERATURE

Social media greatly influences consumer behaviour in terms of e-word of mouth and influencer marketing. According to a study by Babić Rosario et al. (2020), consumer purchase behaviour is greatly affected by influencer marketing. Moreover, another study by Cheung et al. (2008) revealed that e-word of mouth is a major influencer in terms of brand perception.

Information Adoption Model is a theory that explains consumer behaviour in terms of evaluating online information based on certain factors such as credibility, quality, and perceived usefulness of such information. These factors affect consumer attitudes and behaviour in a digital context.

In the beauty industry, social media sites such as Instagram and TikTok are promoting beauty-related content. Moreover, influencer marketing is greatly influencing consumer perceptions and behaviour. However, little research is available on the influence of social media on perceptions of beauty and consumer behaviour.

"Influencer: Building Your Personal Brand in the Age of Social Media" is a comprehensive guide on how to utilize social media influencers in the development of a personal brand in today's digital age, as presented in the book written by Brittany Hennessy. The author first discusses the definition of influencer marketing and its significance in the modern-day digital world. She further discusses the transformation of social media influencers and how they have become influential in the world of marketing and brand promotion. Through the creation of genuine and relatable content that connects with their audience, social media influencers have perfected their craft. The authenticity and connection they have with their audience have made them indispensable in the promotion of a brand in a competitive digital world.

The author further talks of the importance of establishing a personal brand that reflects one's unique identity. The author provides the reader with valuable tips on how to establish one's personal brand and how they can be identified within the world of social media. Likewise, the research conducted by Jihye Kim and Minseong Kim, on the subject of "Rise of Social Media Influencers as a New Marketing Channel: Focusing on the Roles of Psychological Well-Being and Perceived Social Responsibility among Consumers," provides valuable knowledge. The research was conducted to measure the loyalty of the consumer towards their most favoured social media influencer, based on the dimensions of perceived friendship and psychological well-being, which is further influenced by factors such as perceived similarity of languages, interests, interaction frequencies, and self-disclosure. Significantly, the research further reveals the

moderating effect of the perceived social responsibility of the consumer towards the most favoured influencer on the relationship between psychological well-being and loyalty.

OBJECTIVE

Primary

Role of Social Media in Shaping Beauty Perceptions and Consumer Behaviour

Secondary

1. To examine the relationship between social media beauty standards and consumers self-esteem levels.

2. To examine the influence of social media influencer marketing on consumer behaviour.

3. To determine the key factors affecting consumer behaviour towards beauty products advertised on social media.

4. To examine the role of social media in shaping brand awareness and brand loyalty.

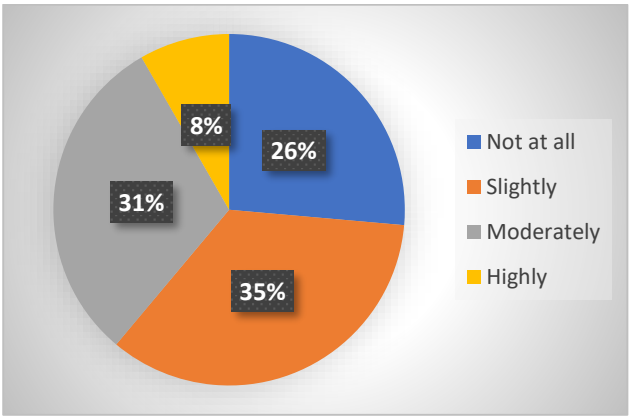
SCOPE OF THE STUDYS

- The study is centred on social media and its effect on beauty perceptions and consumer behaviour in the cosmetics market.
- The study also covers social media platforms such as Instagram, YouTube, Facebook, and TikTok.
- The research study also includes an analysis of the effect of influencer marketing on consumer behaviour.
- The study also covers how beauty perceptions affect self-esteem and body image in consumers.
- The study identifies factors such as influencer credibility, information quality, aesthetics, and usefulness.

DATA ANALYSIS AND INTERPRETATION

S NO.	PARTICULAR	NO. OF RESPONDENTS	PERCENTAGE %
1	Not at all	18	26%
2	Slightly	25	35%
3	Moderately	22	31%
4	Highly	6	8%
TOTAL		71	100%

The results show that influencers have a **moderate but not strong impact** on perceptions of ideal beauty. Most respondents are **slightly or moderately influenced**, while a significant portion is **not influenced at all**. Only a few are highly influenced, indicating that overall influence is **limited and not dominant**.



FINDINGS

1. Age: The age group of 21-24 years is dominant among the respondents (72.2%), which shows that the research is dominated by young adults.

2. Gender: The research is dominated by female respondents (72.2%), which is good as it can be used to understand the beauty and cosmetics-related perceptions.

3. Occupation: The research is dominated by students (69.4%), which shows that the research is more inclined towards individuals who use social media and are digitally influenced.

4. Social Media Usage: The research shows that the majority of the respondents (81.9%) use social media frequently.

5. Platform Used: The research shows that the most frequently used platform is Instagram.

6. Self-Confidence Impact: Though 48.6% have mentioned no impact, the majority (Yes + Maybe) suggest beauty standards might have an influence on self-confidence.

7. Most respondents, 37.5%, sometimes engage with the beauty content, and 30.6% occasionally engage with the content. A small percentage, 20.8%, never engages with the content. negligible percentage, 6.9%, often engages with the content.

8. Most respondents, 38.9%, are neutral, reflecting ambiguity about the impact of social media ads on their brand knowledge. percentage of 19.4% agrees with the statement. larger percentage, 22.2%, disagrees, and another larger percentage, 18.1%, strongly disagrees.

9. Influencer Impact on Beauty Perception: Influencers have a moderate influence, as most have chosen the slight influence option.

10. Majority, 61.1%, of the respondents do not seek the beauty content, reflecting a low interest in the beauty content 38.9%.

11. Purchase via Influencers: Slightly more than half (54.2%) have chosen the option of not purchasing the products, suggesting the influence of influencers on conversion.

12. Trust in Influencers: It is observed that most of the respondents exhibit a low to moderate level of trust in

influencer reviews. However, very few respondents exhibit a high level of trust in influencer reviews.

13. Trying Products: It is observed that most of the respondents are neutral in terms of trying influencer-endorsed products. Thus, we can say that respondents exhibit a moderate level of decision-making.

14. Type of Influence: It is observed that friends/peers have a significant influence on respondents' purchasing decisions, followed by micro-influencers. Thus, we can say that relatable influencers are more effective in influencing respondents' purchasing decisions than celebrities.

15. Purchase Decision: It is observed that influencers have a moderate influence on purchase decisions.

16. Purchase Factor: Reviews (51.4%) dominate as the most important purchase factors compared to other factors such as influencer recommendations.

17. Review Importance: The high percentage of extremely and moderately important reviews shows that users have high confidence in online reviews.

18. Discount Influence: The influence of discounts and offers is moderate on purchase decisions.

19. Packaging Influence: The high number of neutral opinions implies that the influence of packaging is limited.

20. Trending Products: The high number of respondents who don't have a preference for trending products shows that users make independent decisions.

21. Brand Discovery: Social media is a major influencer for discovering a brand, more so than advertisements or word of mouth for beauty brands.

22. Brand Trust: The study reveals that being a fan of a brand on social media is not very significant in terms of influencing brand trust, as most respondents are either unsure (38.9%) or not influenced (34.7%), whereas a small number (26.4%) are more trusting.

23. Brand Loyalty: Although most respondents are neutral, a significant number are more likely to be brand loyal to brands that engage in customer interactions.

24. Campaign Influence: The majority of respondents (59.7%) agree that social media campaigns do influence their view of a brand.

25. Brand Recommendation: Slightly more respondents do not recommend brands they see on social media.

CONCLUSION

Social media beauty standards have been seen to have a considerable influence on consumer behaviour within the beauty and cosmetics market. The influence of beauty standards on the beauty and cosmetics market is such that it encourages consumers to seek products that conform to or help achieve the beauty standards portrayed through social media. The influence of beauty standards is such that it encourages consumers to seek products that conform to or help achieve the beauty standards portrayed through social media.

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Artificial Intelligence-Based Learning Platforms And Student Satisfaction. Evidence From Higher Education

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ABSTRACT: Nowadays, it is observed that educational institutions in the colleges and universities segment are adopting learning platforms developed on artificial intelligence technology to offer a rich experience to the students. This research aims to understand the impact of the utilization of learning platforms developed on artificial intelligence technology on the satisfaction levels of the students in the university segment. This research is conducted using a quantitative approach for research. A survey was conducted among 100 students in the undergraduate and graduate levels. Statistical methods are employed to understand the impact of artificial intelligence-based features on the satisfaction levels of the students. The findings of the research suggest that personalization, immediate feedback, and adaptive content have a significant impact on the satisfaction levels of the students. Data privacy and technological reliability have a moderate impact on the satisfaction levels of the students.

KEYWORDS: artificial intelligence, AI-based learning platforms, student satisfaction, higher education, personalized learning, digital education, educational technology

1.INTRODUCTION

Artificial Intelligence (AI) has impacted the education sector by providing the innovative learning technologies. The innovative learning technologies have the ability to enhance the learning experience. Learning platforms have the ability to offer personalized learning, feedback systems, intelligent tutoring systems, and adaptive learning. It has the ability to cater to the needs of the students. It allows the students to learn at their own pace. It enhances the learning experience of the students. Learning platforms like Coursera, Duolingo, and the Khan Academy make use of the AI algorithms to analyze the performance of the students.

Student satisfaction can be defined as the "degree of positive perception and satisfaction students experience while using learning systems." If the students are receiving effective assistance while using the learning tools, then they are likely to be satisfied. However, various issues may affect the student satisfaction levels. Therefore, the objective of the present study is to "investigate the impact of learning platforms based on artificial intelligence on student satisfaction in higher educational institutions." By studying the relationship between artificial intelligence and students' perceptions, the present study aims at determining the factors that enhance an effective learning experience.

2.LITERATURE REVIEW

1. In another study that was done by Ahmad Rustam (2024) titled "User Satisfaction Survey on AI-Based Learning Assessment in the Digital Era: Effectiveness and Challenges," the main aim of the study was to evaluate the level of satisfaction that is exhibited by the students regarding the use of AI-based assessment in colleges and universities. The study showed that the majority of the 62 students showed satisfaction towards the use of AI-based assessment. In the study, 35% of the students showed satisfaction, while 30% showed high levels of satisfaction. The importance of AI-based learning assessment is due to the fact that it is useful in the grading of the students. Grading is important for the learning of the students. There are various challenges associated with the use of AI-based assessment.

2. In research carried out by Siti Hazline Zakaria and other researchers such as Nik Nur Amiza Nik Ismail, Mardiyah Ismail, Nurul Hafiza Ismail, and Fadila Normahia Abd Manaf, the main focus is on university students and their feelings towards AI technology. In the research carried out among university students in Malaysia, the main aim was to determine the factor that had an impact on the satisfaction of university students towards AI technology. In the research, it was concluded that emotional well-being and usefulness are significant in satisfaction, but content quality is not significant. This implies that the factor that makes a university student feel a certain way and the factor that makes a university student feel that AI technology is useful for them is significant in satisfaction, but content quality is not significant. In the research, it was concluded that for AI technology to have a lasting impact in higher education institutions, emphasis should be placed on other factors such as usefulness and emotional well-being and not content quality.

3.METHODOLOGY

RESEARCH DESIGN

For conducting this study, a descriptive-correlational study design approach has been used to identify the relationship that exists between AI-based learning platforms and satisfaction levels of students in a higher educational environment. In addition to that, descriptive study design has been used to identify the perceptions of students towards AI-based learning platforms. Similarly, correlational study design has been used to identify the relationship that exists between AI-based platform features and satisfaction levels of students.

SAMPLE SIZE AND SAMPLING TECHNIQUE

The sample population of the study consists of 100 sample population of undergraduate and postgraduate students from different higher learning institutions. In this study, the researcher uses the convenience sampling method. Convenience sampling method is used by the researcher to sample respondents from the population of interest who actively uses AI-based learning platforms for their academic purposes.

DATA COLLECTION PROCEDURE

The researcher used a structured questionnaire as a tool for collecting the required data. This was done by sending the students an online survey as well as an offline survey. Online surveys were conducted through various online tools like Google Forms. In cases where students were not able to access online tools, offline surveys were conducted by sending them the survey through various means. Before conducting the survey, prior permission was taken from the concerned institutions.

DATA ANALYSIS TECHNIQUES

The collected data was analysed using descriptive and inferential statistical methods.

The tools used for analysis were:

- **Descriptive Statistics (Mean and Percentage)** for demographic characteristics and overall responses.
- **Correlation Analysis** for the association between the features of the AI platform and student satisfaction levels.
- **ANOVA (Analysis of Variance)** for determining the differences in satisfaction levels among various student groups based on their demographic characteristics.

The analysis of the collected data using statistical methods will help in understanding the factors affecting student satisfaction with AI-Based learning platforms.

4. OBJECTIVES OF THE STUDY

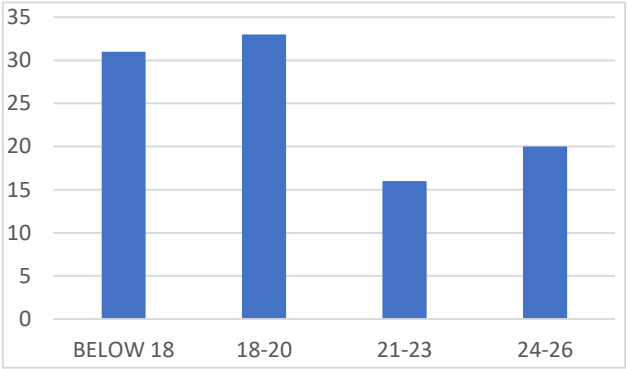
- To determine the level of utilization of AI-driven learning platforms by students.
- To explore the influence of AI features on the happiness of students.
- To determine what AI feature is most significant in affecting the happiness of students.
- To determine what is impeding contentment regarding AI-driven learning platforms.

5.ANALYSIS AND INTERPRETATION

PERCENTAGE ANALYSIS USING MS EXCEL

Table no 5.1: Age of the Respondents

AGE GROUP	NO. OF. RESPONDENTS	PERCENTAGE
Below 18	31	31
18-20	33	33
21-23	16	16
24-26	20	20
TOTAL	100	100

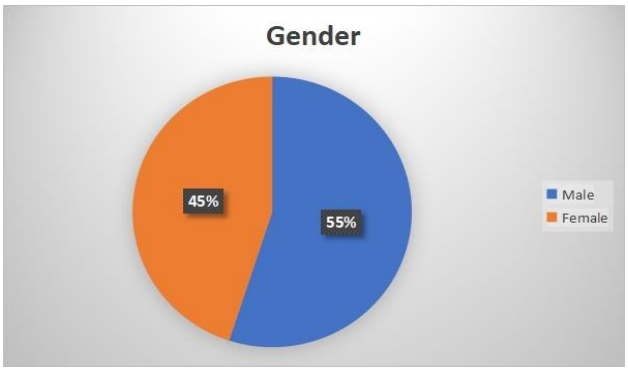


INTERPRETATION

It is inferred that 31% of the respondents belong to the age group below 18, 33% of the respondents belong to the age group 18-20, 16% belong to above 21-23 years and 20% belongs to the age group 24-26 category.

Table 5.2: Gender of the Respondents

PARTICULARS	NO OF RESPONDENTS	PERCENTAGE
Male	55	55
Female	45	45
Total	100	100



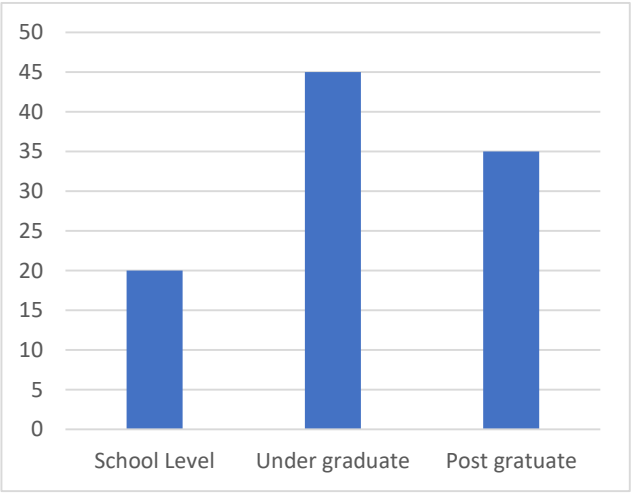
INTERPRETATION:

The data suggests that 45% of respondents are women and 55% of respondents are men.

Table 5.3: Educational Qualification

QUALIFICATION	NO. OF. RESPONDENTS	PERCENTAGE (%)
School level	20	20
Under graduate	45	45
Post graduate	35	35
Total	100	100

INTERPRETATION



Of the responders, 20% have only completed their schooling, 45% are undergraduates, and 35% are postgraduates.

table 5.4: preferred AI learning platform

PREFERRED AI PLATFORM	NO. OF RESPONDENTS	PERCENTAGE (%)
ChatGPT / AI Tutors	22	22
MOOC Platforms (Coursera, Udemy, etc.)	40	40
Language AI (Duolingo, etc.)	38	38
Total	**100**	**100**

INTERPRETATION

Regarding preferred AI learning platforms, 22% of respondents favour ChatGPT and AI tutors, 40% favour MOOC platforms like Coursera and Udemy, and 38% favour language-based AI platforms like Duolingo. This suggests that MOOC platforms are the most popular AI learning resources among students.

CHI SQUARE ANALYSIS

AI platform usage and student satisfaction.

Ho: There is no significant relationship between **level of AI platform usage** and **student satisfaction**.

H1: There is a significant relationship between **level of AI platform usage** and **student satisfaction**

AI Usage Level	Low Satisfaction	Moderate Satisfaction	High Satisfaction	Very High Satisfaction	Total
Low Usage	22	7	5	1	35
Moderate Usage	8	18	8	11	45
High Usage	4	1	11	4	20
Total	34	26	24	16	100

AI platform usage and student satisfaction.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	63.510[a]	9	.000
Likelihood Ratio	56.890	9	.000
Linear-by-Linear Association	20.984	1	.000
N of Valid Cases	100		

a. 7 cells (43.8%) have expected count less than 5. The minimum expected count is .64

INTERPRETATION:
The computed value (0.000) is lower than the Level of Significance (5%) according to the chi-square analysis. Therefore, the alternative hypothesis is approved. For example, there is a correlation between student satisfaction and the amount of AI platform usage. important AI learning platform type and age.

Age and type of AI learning platform used.

1.Ho: The type of AI learning platform that students utilize and their age do not significantly correlate.

2.H1: Students' ages and the kind of AI learning platform they utilize are significantly correlated.

Age and type of AI learning platform used.

Age Group	ChatGPT / AI Tutors	MOOC Platforms (Coursera, etc.)	Language AI (Duolingo, etc.)	Adaptive Learning Systems	Total
Below 18	3	5	10	13	31
18-20	3	6	14	10	33
21-23	4	8	3	1	16
24-26	10	6	3	1	20
Total	20	25	30	25	100

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	31.908[a]	9	.000
Likelihood Ratio	31.579	9	.000
Linear-by-Linear Association	23.366	1	.000
N of Valid Cases	100		

a. 5 cells (31.3%) have expected count less than 5. The minimum expected count is 3.20.

INTERPRETATION:

The computed value (0.000) is lower than the Level of Significance (5%) according to the chi-square analysis. Therefore, the alternative hypothesis is approved. For example, there is a strong correlation between students' ages and the kind of AI learning platform they utilize.

CORRELATION ANALYSIS

	AI Usage	Perceived Value	Trust	Satisfaction
AI Usage	1	0.62	0.65	0.68
Perceived Value	0.62	1	0.59	0.66
Trust	0.65	0.59	1	0.70
Satisfaction	0.68	0.66	0.70	1

Interpretation: Strong positive correlation exists between AI usage and satisfaction (r = 0.68), indicating that increased usage improves satisfaction.

INDEPENDENT SAMPLE T-TEST

Group	N	Mean	Std Dev	t-value	p-value
Male	55	3.65	0.52	2.21	0.028
Female	45	3.42	0.48		

Interpretation: Since $p < 0.05$, there is a significant difference in satisfaction between male and female students.

ONE-WAY ANOVA

Source	Sum of Squares	df	Mean Square	F	p-value
Between Groups	15.24	2	7.62	4.56	0.013
Within Groups	162.80	97	1.67		
Total	178.04	99			

Interpretation: Since $p < 0.05$, there is a significant difference in satisfaction across age groups.

6. FINDINGS

1. The majority of responders are young, suggesting that students are heavily utilising AI-based learning tools.

2. MOOC platforms are preferred by a sizable portion of respondents, followed by language-based AI tools and AI tutors. This suggests that AI-based learning tools are used in a variety of ways.

3. The chi-square analysis results show a strong correlation between the degree of AI-based platform utilisation and student satisfaction, suggesting a direct relationship between the two.

4. There is a strong correlation between students' age and the kinds of AI-based platforms they use, suggesting that different age groups have distinct preferences for AI-based tools.

5. The findings of the correlation analysis show

6.Male and female students' satisfaction levels varied significantly, according to the t-test results, suggesting that gender may affect how AI systems are perceived.
7. The findings of the ANOVA verify that there is a substantial difference in student satisfaction between age groups, suggesting the influence of demographics.

7. SUGGESTIONS

1. Since personalisation and adaptive learning characteristics greatly increase student happiness, educational institutions should improve them.
2. To promote greater engagement and learning results, AI platforms need to improve real-time feedback mechanisms.
3. To increase user confidence in AI systems and foster trust, developers should address data privacy and security issues.

8. CONCLUSION

Based on the findings of the study, it was established that the application of AI-based learning platforms enhances college students' satisfaction levels significantly. The findings of the study unequivocally established that the application of AI-based features such as usability, personalization, and feedback enhances students' educational experiences significantly. Technological and demographic factors influence satisfaction levels, as indicated by statistical analysis tools such as chi-square, correlation, t-test, and ANOVA.

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How Firms Act As Political Actors In Global Markets

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1.ABSTRACT : This paper seeks to analyze the significance of multinational corporations as players in the contemporary interconnected and politically complex global economy. Corporate diplomacy is defined as the strategic interaction between multinational corporations and governments, international organizations, and civil society to create an environment conducive to the operations of the business. The paper seeks to analyze the ways in which multinational corporations deal with geopolitical risks, regulations, and socio-cultural demands. It draws from the theories of international business and political science to discuss the key tools of corporate diplomacy. It also seeks to analyze the ways in which multinational corporations have been using corporate diplomacy to influence policy, resolve conflicts, and seek legitimacy in the host countries. It concludes by arguing that the ability of multinational corporations to master the art of corporate diplomacy is vital to the creation of sustainable value and the mitigation of risks, especially in politically volatile countries

Keywordspolitical risk management, regulatory environment, non-market strategy, public affairs strategy, corporate diplomacy, multinational corporations (mncs)

2.INTRODUCTION

. However, in today's globalized business environment, there are more political issues, ambiguous rules, and increasing demands from society. In today's world, large global businesses do not just aim to make profits; they are also significant contributors to politics and the world as a whole. When businesses operate in different nations, they need to deal with different governments, different political conditions, and numerous different people. In such a scenario, businesses need more than just conventional business strategies. This concept is called corporate diplomacy.

Corporate diplomacy refers to the idea of businesses operating in a manner that allows them to maintain good relations with different governments, different international organizations, and other significant entities. This enables them to win their trust, avoid risks, and succeed in the long term. Rather than maintaining a divide between politics and businesses, corporate diplomacy combines different factors such as lobbying, managing public opinions, and corporate social responsibilities into the functioning of businesses. This enables businesses to influence the development of nations in which they operate work.

Corporate diplomacy has gained importance in the sense that the world has never been more connected than it is today, and politics and businesses go hand in hand. Topics such as trade, environmental laws, human rights, and technology are of equal concern to both nations and businesses. Thus, businesses face the challenge of not only dealing with competition in the market but also dealing with political and social pressures. If they fail to do so, they may end up harming their reputation, disrupting their businesses, and losing money.

This paper aims at exploring how businesses behave like political players in the global market through corporate diplomacy. It will discuss the strategies businesses use in dealing with political groups, the challenges they face in different nations, and how this affects their success and global governance. By incorporating ideas from both politics and businesses, this study aims at demonstrating the importance of corporate diplomacy as a skill for businesses today.

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3.OBJECTIVES OF THE STUDY

To comprehend what corporate diplomacy entails and its significance in global business markets.

To examine the interaction between firms and government authorities or other key players as political actors.

To comprehend how corporate diplomacy aids firms in dealing with political risks.

To examine the impact of corporate diplomacy on a firm's success in terms of competitiveness.

NEED OF THE STUDY

In the current global economic environment, it is not always easy to make distinctions between business and politics. It is important to realize how businesses do not only business but also engage in politics. Multinational corporations often find themselves in complex political situations where rules and expectations are unclear, and people and governments in different countries have different expectations. It is in this context that it is important to study corporate diplomacy as an important strategy for businesses to handle situations well.

As businesses gain more power in influencing government policies and public governance and economic development, it is more important to look into how they engage in politics. Businesses not only respond to government actions but also contribute to making government decisions. It is important to understand this relationship in order to realize how

businesses build trust and continue to operate in uncertain business environments.

4.REVIEW OF LITERATURE –

Corporate Diplomacy: How Firms Act as Political Actors in Global Markets

Jean Boddewyn (1988) noted the importance of companies engaging governments by being proactive rather than reactive to changes in the political environment.

Thomas Lawton et al. (2013) researched the impact of companies on public policies by engaging in activities like lobbying and building alliances.

Jonathan P. Doh (2003) researched the relationship between companies and non-governmental groups (NGOs) and the importance of engaging various stakeholders.

Thomas Donaldson (1999) researched the ethical responsibility of companies when conducting international business.

Witold Henisz (2014) researched the concept of corporate diplomacy as a skill being used by companies to build trust.

David Baron (1995) researched the concept of companies conducting business not only in the marketplace but also in the social, political, and legal arenas.

Michael Porter & Kramer (2006) researched the concept of creating value for society by engaging in public policy.

Susan Strange (1996) researched the concept of multinational companies becoming powerful players in the global economy.

John Stopford & Susan Strange (1991) researched the concept of the interaction between governments, corporations, and the marketplace from a political perspective.

Geoffrey Jones (2005) researched the historical impact of multinational companies on the political system.

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RESEARCH GAP

While many people discuss the concept of corporate diplomacy, the majority of the research is still theoretical. Experts like Witold Henisz argue that it is an essential concept. However, we have few cases of how it is applied by various types of businesses.

Most of the research is based on corporations from rich, developed countries. However, we know very little about how corporations function in developing countries where the government is not stable. In developing countries, the laws are often confusing. For instance, a company may be operating in a developing country where the government is not stable. Therefore, the challenges the company faces may be very different from what a company would face in the US or Europe.

There is no way of determining the success of corporate diplomacy. While we know it is beneficial to the company and the relationships it establishes, we have very few cases of the ethical dilemmas corporations face when they try to influence the government.

5.RESEARCH METHODOLOGY

1. Research Approach

This study will use a qualitative research approach in exploring how companies become political players through corporate diplomacy in global markets. This is because a qualitative research approach will provide a better understanding of the complex relationship between business organizations and other key stakeholders.

2. Data Sources

This study will use secondary data as its main source of information. This will include academic publications, books, and publications from companies and other reliable sources on the Internet. Theoretical arguments by scholars such as Witold Henisz and David Baron will also be relied upon in creating the conceptual framework of this study.

3. Research Design

. The descriptive and analytical method of research design is used for understanding the role and impact of corporate diplomacy. In the study, various cases of multinational companies are analyzed for understanding their political environment and their impact on policy decisions.

4. Method of Analysis

The thematic analysis method is used for the analysis of the study. In the thematic analysis method, the information collected for the study is classified under various key themes.

5. Limitations

The limitation of the study is that the study solely depends on secondary information without incorporating primary information collection methods. However, the reliability of the study is assured by the use of credible information sources.

IMPACT OF THE STUDY

1. Practical Impact

Stakeholders This study underscores the significance of firms as political actors in global business environments. It illustrates the importance of corporate diplomacy in handling

risks and making effective policy decisions. It also improves corporate relations, which are vital to business success, as argued by Witold Henisz.

2. Academic Contribution

. The study seeks to bridge the gap between business strategy and politics to create a better understanding of the two concepts. It also seeks to create awareness of the need to consider ethical responsibility in corporate politics.

3. Broader Significance

Based on the study's findings, it can be concluded that it promotes effective decision-making and growth in business environments.

6.DATA ANALYSIS

Chi-Square Test for Independence

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender * CORPORATE POWER AND ITS IMPACT ON GOVERNANCE	100	86.2%	16	13.8%	116	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.883[a]	6	.007
Likelihood Ratio	18.595	6	.005
Linear-by-Linear Association	10.926	1	<.001
N of Valid Cases	100		

a. 7 cells (50.0%) have expected count less than 5. The minimum expected count is .58.

INTERPRETATION

Moreover, gender and opinions on corporate power and its impact on governance are statistically significantly correlated, as revealed by the results of the Chi-Square Test of Independence using IBM SPSS Statistics. With 6 degrees of freedom, the Pearson Chi-Square is 17.883, and the associated probability is 0.007, which is less than 0.05. Thus, the null hypothesis of no correlation is rejected, implying that opinions on corporate power and gender are not independent. However, it is important to note that this result is interpreted with caution since it is in opposition to one of the requirements of using the chi-square test, as 50% of the cells have expected counts less than 5.

7.FINDINGS

The results from the Chi-Square Test of Independence analysis performed by IBM SPSS Statistics showed that there was a statistically significant association between the variables of gender and perceptions of corporate power and its impact on governance. This was evident from the Pearson Chi-Square value of 17.883 with 6 degrees of freedom and a p-value of 0.007, which rejected the null hypothesis of independence at the 5% significance level. This implied that respondents' perceptions of corporate power were different based on their gender. However, the high percentage of cells with expected count less than 5 (50%) was an indication that the results were to be treated with caution, as this could influence the outcome of the test.

8.CONCLUSION - CORPORATE DIPLOMACY

In addition, corporate diplomacy is considered a fundamental factor for successful business operations within the complex global and political landscape. Companies are no longer solely concerned with generating profit, but they also take part in shaping policies and rules. As noted by Witold Henisz, establishing successful relationships with various stakeholders is essential for managing risks and achieving sustainability.

However, as companies become more involved in politics, ethics become a concern, and transparency and accountability become very important. As a result, it can be noted that corporate diplomacy is essential for gaining a competitive advantage.

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Geoffrey Jones (2005) discussed the role of multinational corporations in global capitalism in his book published by Oxford University Press.

DESIGN AND ANALYSIS OF HYBRID MANUFACTURING OF GO-KART TIRES

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Abstract:

This study investigates the design and analysis of a go-kart tire developed through a hybrid manufacturing approach that integrates additive manufacturing with conventional casting techniques. In the proposed method, additive manufacturing is utilized to fabricate a precision mould using carbon-fibre-reinforced nylon (PA6-CF) directly from a CAD model, enabling rapid mould production, reduced tooling cost, and high dimensional accuracy. The tire structure is then produced through conventional casting by pouring a two-part polyurethane elastomer mixture into the 3D-printed mould cavity. Polyurethane elastomer is selected due to its favourable mechanical properties such as high abrasion resistance, flexibility, load-bearing capacity, and suitability for solid non-pneumatic tire applications. The study includes tire design, mould development, material selection, hybrid manufacturing workflow, and engineering calculations such as load analysis, contact patch evaluation, stress analysis, rolling resistance, and safety factor estimation. The results indicate that the proposed tire design can safely withstand operational loads with a high safety factor while maintaining adequate traction and structural integrity. Compared with traditional tire manufacturing methods, the hybrid approach significantly reduces manufacturing complexity, tooling cost, and production time while improving design flexibility. Therefore, hybrid manufacturing offers a practical and cost-effective solution for rapid prototyping and small-scale production of go-kart tires, making it suitable for educational research, experimental vehicles, and prototype racing applications.

Keywords: Hybrid Manufacturing, Additive Manufacturing, 3D Printed Mold, Polyurethane Elastomer, Non-Pneumatic Tire, Go-Kart Tire Design, Engineering Analysis.

1.Introduction

Go-kart racing is widely used in motorsports and engineering education as a platform for studying vehicle dynamics, mechanical design, and performance optimization. Among the critical components influencing go-kart performance, the tire plays a significant role in determining traction, stability, handling characteristics, and overall safety. Conventional go-kart tires are typically manufactured using rubber materials through processes such as compounding, molding, and vulcanization. Although these methods provide reliable tire performance, they involve complex tooling, high manufacturing cost, and long production cycles. These limitations make traditional manufacturing methods less suitable for prototype development and small-scale applications. In addition to manufacturing challenges, pneumatic rubber tires also present operational limitations such as susceptibility to punctures, sudden pressure loss, and frequent maintenance. These issues can lead to performance instability and safety concerns during racing conditions. As a result, non-pneumatic tire concepts have gained increasing attention in recent years due to their ability to eliminate air pressure

dependency while maintaining structural strength and durability.

Recent advances in additive manufacturing (AM) technologies have enabled the rapid fabrication of complex geometries directly from digital models. Additive manufacturing offers several advantages, including reduced tooling cost, design flexibility, and shorter production time. However, direct additive manufacturing of elastomeric tires remains challenging due to limitations in printable material properties, surface finish quality, and structural strength. Therefore, combining additive manufacturing with conventional manufacturing techniques can provide a practical solution for tire prototyping. Hybrid manufacturing integrates the benefits of additive manufacturing and traditional fabrication processes. In this approach, additive manufacturing is used to produce the tire mold, while conventional casting is employed to form the final elastomer component. This method enables rapid mold fabrication, reduced manufacturing complexity, and the use of high-performance elastomer materials. In this research, a hybrid manufacturing approach is proposed for developing a prototype go-kart tire. The mold is fabricated using additive manufacturing with carbon-fiber-reinforced nylon (PA6-CF), and the tire is produced through casting of a two-component polyurethane elastomer. Polyurethane elastomers are widely used in industrial applications due to their excellent abrasion resistance, flexibility, impact strength, and load-bearing capability. The study focuses on the design and analysis of the go-kart tire, including tire geometry development, mold design, hybrid manufacturing methodology, and engineering calculations such as load distribution, contact patch analysis, stress evaluation, rolling resistance estimation, and safety factor determination. The objective is to evaluate the feasibility of hybrid manufacturing as a cost-effective and efficient approach for producing non-pneumatic go-kart tires. The findings of this study demonstrate that the hybrid manufacturing process can successfully produce structurally reliable polyurethane elastomer tires with adequate mechanical performance. The proposed method offers significant advantages in terms of design flexibility, reduced tooling cost, and rapid prototyping capability, making it suitable for small-scale production and experimental vehicle applications.

2.Literature Review

The manufacturing of automotive tires has traditionally relied on processes such as material compounding, molding, and curing through vulcanization. These conventional manufacturing techniques have been extensively used in the tire industry due to their ability to produce durable and high-performance rubber tires. However, these methods involve multiple sequential stages including mold fabrication, rubber mixing, shaping, curing, and finishing. Such processes require complex tooling, high production cost, and longer manufacturing cycles. These limitations reduce manufacturing flexibility and make traditional methods less suitable for rapid prototyping and small-scale applications such as go-kart tire development. With the advancement of modern manufacturing technologies, additive manufacturing (AM) has emerged as an alternative solution for rapid prototyping and customized component fabrication. Additive manufacturing enables components to be built layer-by-layer directly from digital CAD models, eliminating the need for complex tooling and reducing manufacturing lead time. In recent years, additive manufacturing has been increasingly explored for automotive and tire-related applications due to its advantages such as design flexibility, rapid mold fabrication, and reduced material waste. One notable industrial example is the **NEXTEN Tire project**, developed by Voxel Matters, which demonstrates the use of additive manufacturing for producing advanced tire molds and structures. The project highlights the potential of AM technologies in improving tire mold design, enabling customization, and accelerating product development cycles. However, the direct manufacturing of elastomeric tires using additive manufacturing remains challenging due to limitations in printable material properties, mechanical strength, and surface finish quality. To overcome these limitations, hybrid manufacturing approaches have been proposed. Hybrid manufacturing combines additive manufacturing with conventional manufacturing techniques such as casting or molding. In such approaches, additive manufacturing is used to fabricate complex mold geometries, while conventional casting processes are used to produce the final elastomer component using high-performance materials. This integration provides the advantages of both manufacturing

methods, including rapid mold production, improved design flexibility, and better mechanical performance of the final product.

Material selection is another critical factor influencing tire performance. Elastomeric materials such as **cast polyurethane (PU) elastomers** have gained attention due to their excellent mechanical and tribological properties. Polyurethane elastomers offer high abrasion resistance, flexibility, impact strength, and load-bearing capability, making them suitable for non-pneumatic tire applications. Additionally, polyurethane materials can be easily processed through casting techniques, enabling the fabrication of solid tire structures without the need for complex vulcanization processes. Despite the growing interest in additive manufacturing and polyurethane-based tire components, research specifically focusing on **hybrid manufacturing methods for go-kart tire production** remains limited. Most existing studies focus either on additive manufacturing of molds or on elastomer casting processes independently. Therefore, further research is required to investigate the feasibility of integrating additive manufacturing for mold fabrication with polyurethane casting for tire production. Understanding the interaction between manufacturing methods, material properties, and structural performance is essential for developing efficient and reliable hybrid-manufactured go-kart tires.

3.Design/Methodology

The Methodological approach of this study emphasizes on the Hybrid Manufacturing approach for Go-Kart tires, synthesizing Additive Manufacturing (AM) as 3D printing with Convectional Casting techniques. The primary objective is for fabricating the tire with PU Elastomer as primary raw material to augment production efficiency, allow for complex geometries, and uphold material durability suitable for operational conditions. 3D printing is adopted to create the negative Mold of the tire, offering intricate tread patterns and design features that are required larger time management to achieve with traditional methods. Succeeding the AM negative Mold fabrication, Cast Two-Part Polyurethane Elastomers are poured into the Mold to form the tire. This casting step ensures the tire attains the necessary flexibility, resilience, and mechanical properties required for small-scale vehicles like Go-Karts. Cast Two-Part Polyurethane Elastomer has two components which are Polyol component and Isocyanate Component. By mixing it, the chemical reaction will be occurred for curing. The curing can be done at the room temperature. Curing is performed under standardized conditions to regulate material consistency and avoid defects, after which the tire is carefully demoulded and finished. Minor surface adjustments or trimming can be applied to achieve the desired final shape and surface quality.

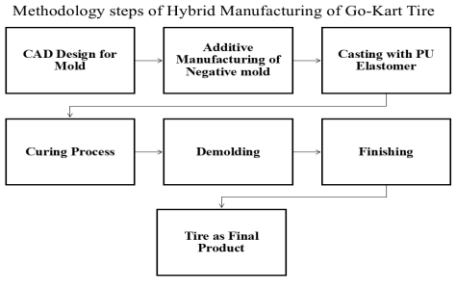

Figure 1: Process Table

The negative Mold is separated into two major sections, namely the Mold Cavity and the Core Cavity. By making this, it leads to accurately clarify the internal and external geometries of the Go-Kart tire. The fragmentation ensures precise tolerance control, uniform material flow during polyurethane (PU) elastomer casting, and enhanced curing within the Mold. The Mold Cavity replicates the outer tread and surface details, while the Core Cavity forms the inner profile of the tire. This two-part Mold configuration simplifies the demoulding process, minimizes deformation during part removal, and enhances the overall surface quality and dimensional accuracy of the final tire prototype. The proposed methodology provides a structured workflow: Starting from CAD-based design, pursing to AM Mold creation, followed by casting, curing and demoulding and concluding with optimal iterative improvements. This hybrid approach uniting the precision and flexibility of AM with the convectional casting.

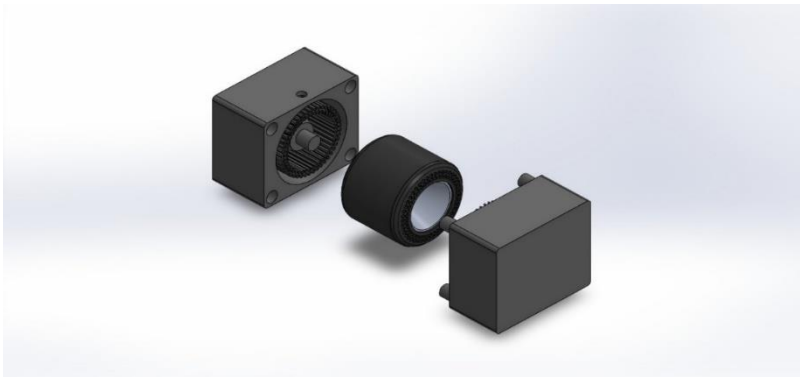

figure 2 : cad model of the mold cavity used to form the outer geometry of the tire.

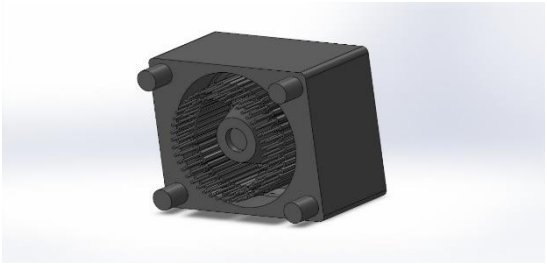

Figure 3: Core cavity used to create the internal structure of the tire.

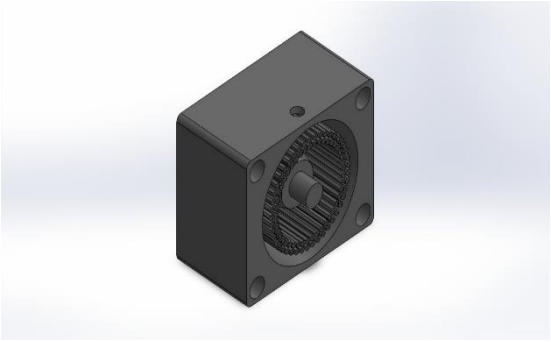

figure 4: tire assembly

figure 5: cad model of the designed non-pneumatic go-kart tire mounted on an aluminum wheel rim.

4. RESULTS AND DISCUSSION

4.1 COMPARISON BETWEEN TRADITIONAL AND HYBRID MANUFACTURING

Traditional go-kart tire manufacturing typically involves multiple sequential stages such as material mixing, mold preparation, vulcanization curing, and finishing. These processes require specialized tooling, high energy consumption, and long production cycles. The vulcanization process, which is commonly used for rubber tires, requires elevated temperature and pressure conditions to achieve the desired material properties. This process increases manufacturing complexity and production cost, particularly when producing tires with complex tread geometries. In contrast, the proposed hybrid manufacturing approach simplifies the production process by utilizing 3D printed molds directly generated from CAD models. This eliminates the need for expensive machining of metal molds and significantly reduces tooling cost. Additionally, polyurethane elastomers used in this method do not require high-temperature vulcanization, as curing can occur at room temperature. As a result, the hybrid process offers:

- Reduced manufacturing time
- Lower tooling cost
- Improved design flexibility
- Simplified production workflow

These benefits make hybrid manufacturing particularly suitable for prototype development and small-scale go-kart tire production.

4.2 ADVANTAGES AND PRACTICAL BENEFITS

The hybrid manufacturing approach provides several practical advantages for go-kart tire development. Firstly, additive manufacturing enables the rapid fabrication of complex mold geometries, including tread patterns and internal structures, which are difficult to produce using conventional machining techniques. Secondly, the use of polyurethane elastomer casting ensures that the tire possesses adequate flexibility, durability, and wear resistance required for go-kart applications.

Additional advantages include:

- Reduced tooling and manufacturing cost
- Faster prototype development
- Design customization capability
- Improved puncture resistance due to non-pneumatic structure
- Reduced maintenance requirements

4.3 LIMITATIONS AND FUTURE SCOPE

Despite the advantages of the hybrid manufacturing approach, several limitations must be considered. One challenge involves material compatibility between the 3D-printed mold and the polyurethane elastomer, which can affect demolding and surface finish quality. Proper mold material selection and the use of release agents are therefore necessary. Another factor is maintaining consistent curing conditions. Although polyurethane elastomers can cure at room temperature, controlling environmental parameters such as temperature and humidity helps ensure uniform mechanical properties and dimensional

stability. Additionally, the dimensional accuracy and repeatability of 3D-printed molds may vary depending on printing parameters and machine resolution.

Future research should focus on:

• Experimental testing of mechanical performance
• Wear behavior analysis of PU tires
• Optimization of mold design and printing parameters
• Simulation studies for stress and deformation analysis

5. CONCLUSION

This study demonstrates that hybrid manufacturing, which integrates additive manufacturing with conventional casting techniques, provides a practical and efficient approach for the production of go-kart tires. Compared with traditional tire manufacturing processes, the proposed method significantly reduces production time, tooling cost, and design constraints while enabling rapid prototyping and customization. The use of 3D printing for negative mold fabrication allows complex geometries and detailed tread patterns to be produced efficiently. Subsequently, casting polyurethane elastomers enables the final tire to achieve the required flexibility, durability, and mechanical strength for non-pneumatic go-kart applications. Although certain challenges such as mold material compatibility, dimensional accuracy, and curing control must be addressed, the hybrid manufacturing methodology provides a strong foundation for future experimental validation and process optimization. Overall, the integration of additive manufacturing and elastomer casting demonstrates significant potential for innovative, cost-effective, and scalable production of prototype go-kart tires, supporting further research in tire design, material optimization, and performance evaluation.

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Comparative analysis of spur gear drive made of same material and different material

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Abstract

The spur gears are employed commonly in the mechanical power transmission systems due to their ease of design and their dependability. Gear teeth under loading conditions Structural behavior under loading conditions is a significant parameter in influencing the durability of gears and their efficiency of operation. The current research paper is based on the study of the deformation and strain and stress under the applied loading conditions of a spur gear tooth by the finite element analysis of the structural component in stature. Gear tooth profile is also designed by automated software of computer-aided and evaluated with a combination of materials. Mild steel, cast iron and nylon are chosen to study the effect of material characteristics on gears performance. The distribution of stresses at the tooth root and the behavior of deformation are investigated in order to appreciate combination of materials that enhance improved strength and reliability. Results obtained in the research offer an insight into the mechanical reaction of spur gears and serves in case of selecting the right material to be used in the transmission of power effectively.

Keywords—Spur Gear, Power Transmission, Static Structural Analysis, Stress Distribution, Deformation Characteristics, Material Behavior, Mechanical Performance.

I. INTRODUCTION

The gears form one of the most required components of the power transmission system in mechanics. They are extensively used in machines and industrial mechanisms to deliver movement and power between rotating shafts in a very efficient and reliable way. Out of all the existing varieties of gears, the spur gears are the most widely used and any variety of gear which is the easiest to manufacture and high in efficiency, also having the capability to transmit the motion between parallel shafts. Spur gears are gears that have straight teeth parallel to the rotational axis that allows and permits easy and uniform flow of torque and rotation. Due to these benefits, spur gears have been extensively employed in automotive transmission, industrial machinery, robotics, as well as any other mechanical system which needs to have a strict control over its motion [1].

Surgeons affecting the quality of designs of spur gears in their operation (stresses formed in the teeth of the designs) largely determine the performance and durability of the gears. The load being transmitted when gears are in contact results in bending stress on the tooth root and contact stress on the tooth surface. The stresses can result in various forms of gear failure including; bending failure, pitting, wear and fatigue. Bending failure of the root of the gear tooth is one of them and is one of the most frequent factors of the damage of gears, since the root of the tooth is the area where the highest concentration of stress occurs when transmitting a load. As such, it is important to know the stress distribution and deformation nature of gear teeth in order to come up with reliable and efficient gear systems [2].

Development of computer aided engineering tools has enhanced greatly in the analysis and design of mechanical parts like gears. Finite element analysis has emerged as an overwhelming method of assessing stress pattern, deformation pattern and strain pattern in complicated structures. This technique enables engineers to get the correct outcome with regard to loading and boundary conditions when a structure is divided into small finite elements. Finite element analysis finds wide application in gear design to determine stress concentrations in the tooth root, deformation analysis under the forces exerted, and optimization of gear geometry to produce high-performance gears. Finite element analysis offers greater information regarding the structural behavior of gear teeth compared to the traditional methods of analysis [3].

The choice of materials is also an important factor in setting the performance and life of the gear systems. Various materials possess varying mechanical regimes including the strength, stiffness, density, and wear resistance. Such properties have a direct proportion to the capability of the gear tooth to sustain the applied loads without undue deformity or failure. The gear manufacturing is most likely to be done using metallic materials like mild steel, cast iron due to their strength and hardness. Mild steel has good ductility and toughness, which makes it ideal in a situation where it is to be used to resist shock and impact loads. Cast iron, however, offers good compressive strength and vibration dampening attributes that make it applicable in the application where there is a need of stability and rigidity [4].

Besides the metallic materials, materials based on polymer like nylon are also being increasingly used in the modern mechanical systems. Compared with metal gears, Nylon gears are light, free of corrosion and can be run with lower levels of noise. They are normally applied in household appliances, automotive parts, and precision devices. Nevertheless, the polymer materials are usually less rigid and have less strength than their metals, and it is possible that deformation under load is more prominent. Consequently, it is significant to conduct structural evaluation of mechanical behavior of nylon gears in order to establish its performance in power transmission applications [5].

The test of the response of a mechanical component under the influence of static loads is a significant method known as the static structural analysis. As an example with spur gears, the application of statical analysis can be used to calculate the results of overall deformation, equivalent strain and equivalent stress on the gear tooth during the process. The parameters are useful information to identify the strength and reliability of the gear at the specified loading conditions. Through the measurement of these parameters given various material mixes, one can know of the best material to use in manufacturing gears.

Computer-aided design software, used together with sophisticated simulation developed tools, is also common nowadays in the development of modern engineering design. Computer aided design software enables the engineer to make the correct three dimensional model of the mechanical component, and simulation program enables the engineer to analyse in details the structure of the model, under real operating conditions. This integration will cut down on large scale experimentation work and enable engineers to maximize designs prior to the actual production. When applied to the gear systems, such tools are used to understand patterns of stress distribution, find areas in the gear tooth that are critical and improve design parameters to improve the performance.

Finite element analysis is applied in the study of gears and this has attracted a lot of attention because of its capacity of giving accurate and valid results. This has allowed researchers to investigate different attributes of gear behavior such as concentration of stress, fatigue life, analysis of tooth contact, and material performance. Through the comparison of various types of material and loading conditions, engineers have been able to come up with more efficient gear systems which have better durability and less maintenance needs.

This work examines the structural behavior of a spur gear tooth under strong loads at a static state through the finite element analysis. The gear model is designed with the aid of computer-aided computerized design program and a structural analysis is conducted with the help of simulation program. Three materials are compared to be evaluated in assessing the mechanical response of the gear tooth namely; the mild steel, cast iron and nylon. Parameters including total deformation, equivalent elastic strain and equivalent stress generated in the gear tooth under applied loads are studied.

This research aims at comparing the structural behavior of a spur gear when changes in material combinations are correlated and also, to find out the material combination which offers improved mechanical performance. The obtained analysis results can be effectively used as insights into the nature of deformation and stress transformation of the teeth of spur gears and help researchers to come up with more efficient and reliable power transmission systems.

II. LITERATURE SURVEY

Spur gear systems design and performance are significant in mechanical power transmission of different engineering operations. Due to the simplicity of their construction, high efficiency, and relatively easy manufacturing, the spur gears find application in industrial machinery, automotive transmission, robotics, and electric vehicles. Although they offer these benefits, there are a number of operational problems that can reduce their services and longevity, including vibration, fatigue failure, stress concentration, wear and misalignment. Consequently, current studies have been aimed at enhancing the functionality and stability of spur gear systems with the utilisation of superior modeling methods, better materials, optimization strategies, and smart monitoring systems.

Various researches have been directed on the structural design and the geometry parameters of the spur gears in order to enhance the load capacity and transmission efficiency. The cylindrical spur gears are modelled using the techniques of parametric design, which is best used in gears with all the geometrical connections and in making changes in the design. The models enable the engineers to study the gear geometry and optimize significant design aspects in order to enhance the overall system performance. The parameters of module, face width and helix angle have also been researched into the load carrying capacity of spur gears. These studies depict that optimal choice and optimization of the geometry parameters yield greatly enhanced strength and mechanical performance of the gears [6]. Moreover, there are computational modeling techniques that have been used to facilitate with the design process which is parametric and enable the engineers to simulate the behavior of the gears before they are made, thus enhancing accuracy and minimizing design errors [7].

The other whole research involves the fatigue behavior, crack formation and distribution of stresses in the spur gear systems. The quality of the manufacturing and the conditions of installation are great influencers of the durability of the teeth on gears in repeated loading conditions. The impact of the manufacturing and installation factor on the initiation and propagation of the bending fatigue cracks in spur gears have been studied. The relevance of surface quality, stress distribution, and loading conditions as important in establishing reliability in gears becomes evident in these investigations [8]. Dynamical modeling approaches of the spur gears have also been formulated to examine the spur gears when there are structural anomalies. Simulation models of assessing tooth root crack changes on dynamic response offer effective information on vibration properties and fault

transmission in gear transmissions [9]. Moreover, finite element analysis and other numerical simulation programs are applied to the meshing behavior and stress strain distribution studies in spur gears which provides researchers with the opportunity to enhance gear modifying strategies and minimize structural failures [10].

The choice of material and manufacturing technologies is also critical at increasing the spur gear durability. Alternatives to the traditional cast iron gears which were being used have been researched (hybrid composites and epoxy-based materials). According to comparative simulation studies, the material used is important in estimating stress distribution, deformation behavior and structural strength of gear systems [11]. Besides, additive manufacturing processes have been considered (e.g. laser powder bed fusion) to create high performance spur gears. Optimization of manufacturing process parameters, and enhancement of the mechanical strength of the gears manufactured based on the advanced manufacturing technologies have been optimized using machine learning assisted simulation frameworks [12]. Such achievements underscore the increased role played by incorporating material science and high-level manufacturing in spur gears design and manufacturing [13].

The recent development of the intelligent monitoring and control technologies has also enhanced the extent to which spur gear systems become reliable. Vibration analysis-based and data-driven condition monitoring methods are highly prevalent in the identification of faults in mechanical transmission systems and bettering of maintenance plans [14]. The combined misalignments in transmission system are also discussed in experimental research, which contributes much to the analysis of fault and performance evaluation of single stage spur gear transmission systems [15]. Convolutional neural networks are a type of deep learning algorithm that was proposed to conduct automated fault classification in a spur gearbox system based on the diagnostic information presented in images [16]. Moreover, such methods as reinforcement learning and adaptive algorithms have been suggested in the form of advanced control techniques to keep the dynamic behavior of spur gear mechanisms under control and provide the stability of the systems in the course of functioning [17]. Moreover, complex vibration peculiarities and harmonic behavior of a spur gear pair has been analyzed using nonlinear dynamic analysis methods, which contribute to the researchers gaining a deeper insight into the problem of dynamic instability in transmission systems [18]. Surprisingly, these smart monitoring, modeling and control methods are anticipated to feature prominently in the progress of the next generation of smart and dependable mechanical transmission systems [19]. The effectiveness, safety, and life of spur gear mechanisms utilized in the contemporary industrial activities will continue to be enhanced by continuous improvement in the computational analysis and predictive maintenance strategies [20].

III. METHODOLOGY

The approach chosen in this research is based on the structural assessment of a spur gear tooth when it is subjected to the static load under the influence of computer-aided design and numerical simulation. The general process encompasses the gearing tooth modeling in the form of geometry, the material properties modeling, the production of finite element mesh, the posting of the boundary conditions, and the analysis of the structural variables that include the deformation, strain, and stress. In the study, three various materials are taken into account such as mild steel, cast iron and nylon in an attempt to attribute the effect of the property of the material on the performance of the spur gear. The model of gear developed is tested in the same loading conditions to enable comparison of the results. The methodology can be further subdivided into various systematic phases, which are important in proper modeling, analysis and interpretation of the structural behavior of the spur gear tooth as shown in figure 1.

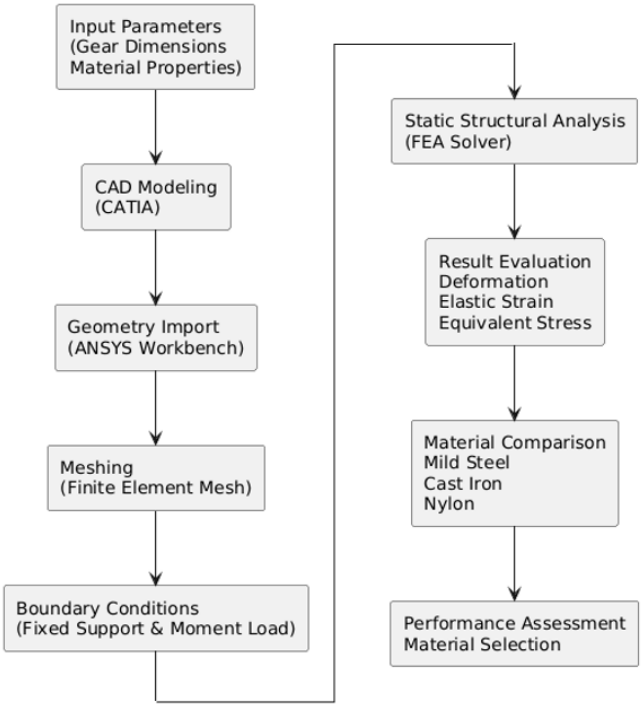

Fig. 1: System Architecture

A. Gear Geometry Modeling

In its methodology, the first task that will be carried out is making of the spur gear tooth geometry with the help of computer-aided design software. The gear model is developed on account of universal gear design qualities such as module, teeth count, pitch diameter, pressure angle and tooth thickness. Tooth profile has been well engineered to depict the involute geometry that is mostly applied in designing spur gears. The modeling is done with a proper dimensional constraint that ensures that the geometry is consistent with actual mechanical systems with gear geometry. This is followed by the creation of the full gear geometry based on the circular pattern operations after the individual profile of the tooth had been created. The three dimensions gear model that has been completed

offers a detailed description of the gear structure that is subsequently transferred into the finite element analysis software to simulate and assess the structural framework.

B. Material Property Assignment

Once the geometric model of the spur gear is complete, mechanical properties of the chosen materials are to be allocated. In the present study, three of them are taken into consideration, i.e. mild steel, cast iron, and nylon. All the materials will have various physical and mechanical properties like density, Youngs modulus and Poissons ratio that will have a great impact on the structural reaction of the gear under loading conditions. These are the material characteristics that are specified in the simulation setting on the standard engineering data. Mild steel, cast iron, and nylon are chosen based on their high strength, rigidity, vibration damping and light weight as well as low friction properties, respectively. The real mechanical behavior in any material by being assigned to the gear model allows the simulation to respond in reality when external forces and moments are applied to it.

C. Finite Element Mesh Generating

Structural analysis is done by the discretization of gear model by the use of the finite element method. In this step, the three dimensional gear geometry is broken into a great number of finite elements attached together through nodes. There is also a significant role of the quality and density of the mesh that will determine the accuracy of the results of the analysis. Fine mesh is developed especially in the area around the gear teeth where the stress concentration is likely to be experienced. Meshing is done so that the geometry is represented well yet the same is computationally efficient. The types of elements that are chosen are appropriate to reproduce the mechanism of the gear structure when subjected to a static load bearing condition. The meshed model lays a basis on which it is possible to carry out numerical simulations and where the software is able to compute the deformation, strain, and distribution of stress in the whole gear structure.

D. Imposition of Boundary Conditions

The second step in the methodology is defining a set of boundary conditions and loading parameters of the spur gear model. Boundary conditions are forces as well as constraints on the gear in action. To gain an understanding of the effect of the support on the gear, the gear in this analysis is given a given support at the region it is required to be attached to a shaft. To simulate the power transmission load on the gear teeth, a moment or torque is applied to the gear. These loading conditions make these loading conditions similar to the working environment of the spur gear in the mechanical systems. When that is done with proper attention to constraints and loads, the results of the simulation will be very close to the actual, operating conditions. The step will be necessary to ascertain the behavior of the gear tooth to external forces with respect to deforming and causing stress.

E. Static Structural Analysis

After meshing the model and the applied boundary conditions, the static structural analysis is conducted with a simulation software. The solver determines the mechanical response of the gear model under the conditions of actual loading. In this examination, significant structural parameters as deformation total, equivalent elastic strain, and equivalent stress are identified of the gear tooth. These parameters give us an idea of the response of the gear to load, and the areas of high concentration of the stress. The analysis is done individually in the various material combinations such as; mild steel, cast iron with mild steel and mild steel with nylon. Through simulation of each material arrangement, the research analyses the effect that material characteristics have on the structural performance of the spur gear.

F. Evaluation

The last phase of the methodology will be the assessment and comparison of the findings gained during the structural simulations. Some of the values get critically analyzed including the technique of total deformation, equivalent elastic strain, and equal stress generated in the tooth of the gear. The values of these parameters are tabulated and discussed in order to gain insight wherever various combinations of materials can affect the structural behavior of the gear. To find key areas in the gear tooth, graphical results of a simulation software (deformation plot and stress distribution diagram) are also analyzed. By making this comparative study, the material mixture giving enhanced structural integrity and lower deformation stress is determined. The result analysis is informative about the effectiveness of gears, and it will aid in the procedure of choosing the appropriate materials to be utilized in the application of reliable mechanical power transmission.

IV. RESULT AND DISCUSSION

Numerical simulation is applied to evaluate when spur gear behaves structurally when subjected to a set of conditions where it is under a constant load. The analysis will be done to determine the effect of various combinations of materials on the deformation and strain distribution, as well as the stress nature of the gear tooth. The model of the spur gear that has been created within the design environs is brought into the analysis software that employs meshing, boundary conditions and loading parameters. The simulation outcomes give an in-depth knowledge of the mechanical response of the gear tooth under the circumstances of applied moments. The findings have been described in the form of deformation plots, distribution of strain, and equivalent stress diagrams of various material combinations.

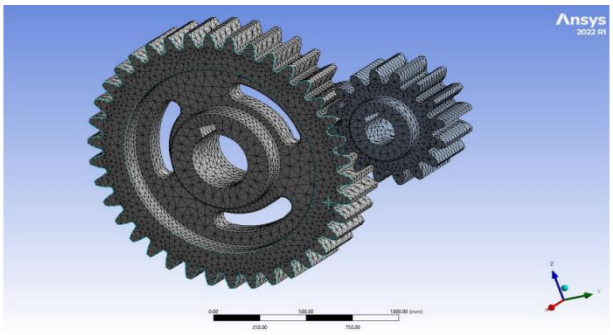

Fig. 2: Meshed Geometry of the Spur Gear Model

The spur gear geometry with the meshed geometry is shown in figure 2 to conduct the structural analysis. Finite element mesh is used to break down the gear model into a few small elements that enable the software to compute the mechanical response of the object with accuracy. The fine mesh is created around the tooth region as this is the part where concentration of stress is the highest in the transmission of power. The correct meshing leads to better accuracy of the analysis and validity of the deformation and stresses distribution through the gear structure.

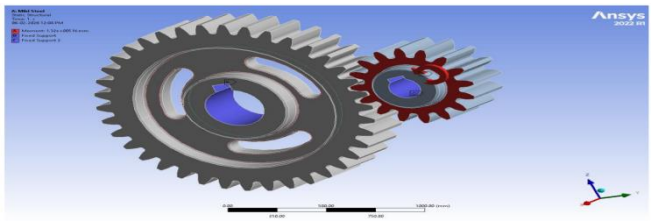

Fig. 3: Boundary Conditions Applied to the Spur Gear

Figure 3 indicates the boundary conditions that will be used in the spur gears model. To recreate the real working conditions a fixed support is given to the middle section of the gear to indicate the installation of the gear to a shaft. The gear is given a moment that is used to create simulation of the torque that is transferred during power transfer. These loading conditions simulate the loading conditions of gears in real-life mechanical engineering. To achieve realistic and dependable results of simulation goodness of constraints and loads should apply appropriately.

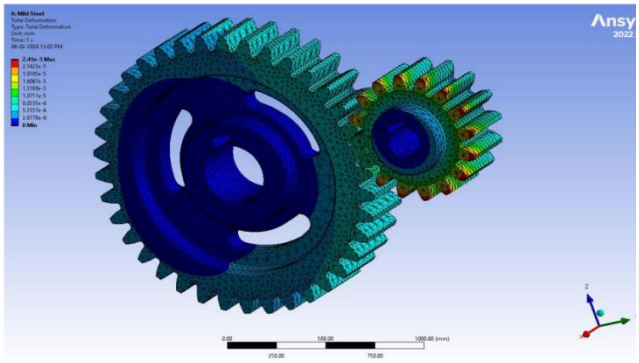

Fig. 4: Total Deformation of Spur Gear with Mild Steel

The boundary conditions are defined and the static structural analysis is carried out to identify the nature of deformation of the gear tooth. Figure 4 demonstrates that in the case of using mild steel as a material, the total deformation generated on the spur gear is the largest. The shapes of the distribution of the deformation in the gear tooth show that the area of maximum deformation is located at the end of the tooth whereas the area of relative stability is at the end of the root, which is held up by the gear body. The mild steel has a high level of stiffness and strength, which makes it experience good structural stability.

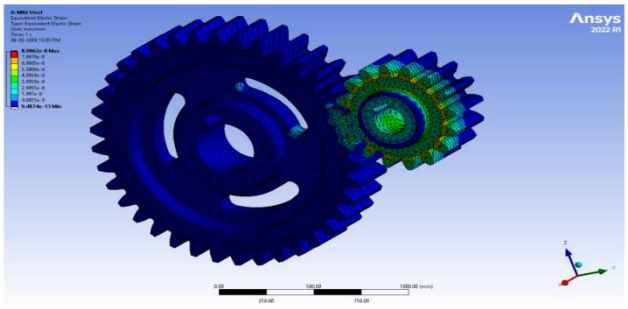

Fig. 5: Equivalent Elastic Strain of Spur Gear with Mild Steel

Figure 5 shows the similar elastic strain distribution in the spur gear at case of mild steel as a material. The distribution pattern of strain indicates that the strain values become maximum along the tooth root area. This action takes place due to bending stresses on the tooth root in which the gear applies load to the mate gear. The values of strain are not very high because the modulus of elasticity of mild steel is very high therefore it does not deform when it is subjected to loading.

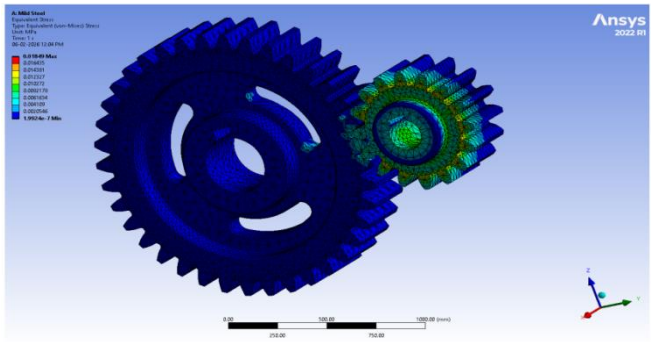

Fig. 6: Equivalent Stress Distribution of Spur Gear with Mild Steel

Figure 6 is a diagram who shows the equivalent stress distribution on the spur gear when using mild steel material. The equivalent stress is the sum of the various components of stresses on the tooth of the gear. The stress distribution will show that the greatest concentration of stress will be on the root of the tooth which is the region where bending stresses are concentrating. Nevertheless, the general values of stress are within acceptable limits, which proves that mild steel will be strong enough in cases of gear application within the given loading conditions.

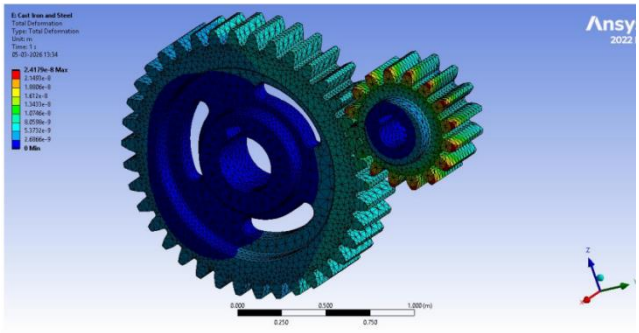

Fig. 7: Total Deformation of Spur Gear with Cast Iron and Mild Steel

Then the third analysis looks at the cast iron and mild steel as a material combination. Figure 7 illustrates the overall deformation that is caused in gear structure under the use of cast iron and mild steel materials. The trend of deformation that will develop in this case is the same as that of the mild steel model with some variation on the values of deformation considering the disparity in the material stiffness. Cast iron has a little less elasticity than mild steel and this has an effect on the deformation behavior of the cast iron when it is subjected to loads.

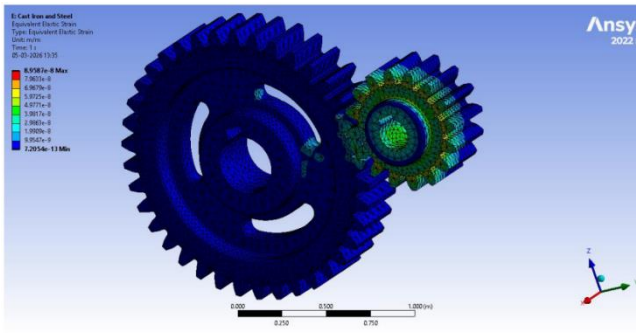

Fig. 8: Equivalent Elastic Strain of Spur Gear with Cast Iron and Mild Steel

The similar elastic strain distribution of the combination of cast iron and mild steel material is shown in Figure 8. The strain distribution also shows that the root of the tooth has maximum strain because it carries the bending force created in the process of meshing gears. The total strain results are similar to the result of the mild steel model, which implies that the cast iron + mild steel act like alike structural performers when subjected to a constant load.

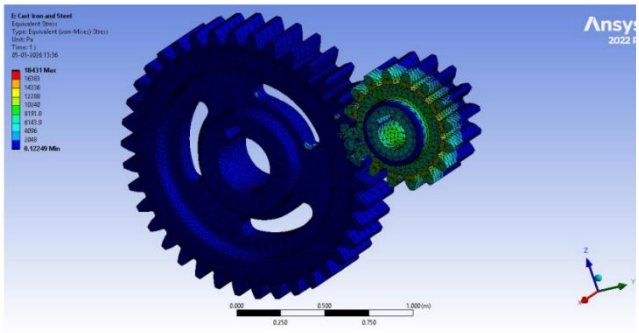

Fig. 9: Equivalent Stress Distribution of Spur Gear with Cast Iron and Mild Steel

Figure 9 depicts equivalent distribution stress in the spur gear in case of cast iron and swift steel. The stress pattern of distribution is still centered at the tooth root area. The cast iron also has good compressive strength and rigidity that makes the gear structure to be stable. The stress values determined in this arrangement are slightly reduced compared to the mild steel model that show that there is a better stress distribution within some parts of the gear tooth.

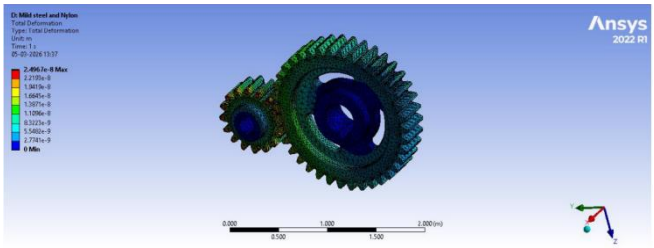

Fig. 10: Total Deformation of Spur Gear with Mild Steel and Nylon

The last step of analysis is the performance of the structure of the gear in the case when the materials to be used are mild steel and nylon. The overall deformation caused to the gear toot in this combination of material is shown in figure 10. Nylon is much less stiff than the metallic materials because the material possesses a smaller modulus of elasticity. This makes the deformation of this arrangement a bit higher than was the case with the earlier combinations of materials. The bending effect of the applied load is mainly concentrated in the tip of the tooth where deformation occurs.

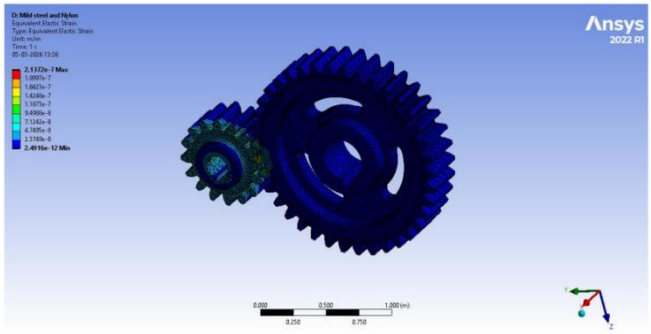

Fig. 11: Equivalent Elastic Strain of Spur Gear with Mild Steel and Nylon

Figure 11 shows the similar distribution of elastic strain exists in the tooth of the gear using their material version of mild steel, and nylon. The values of the strain are greater compared to the former cases because nylon is

flexible in nature. The higher the strain the more the elastic deformation that the gear tooth experiences when it is under the imposed loading conditions.

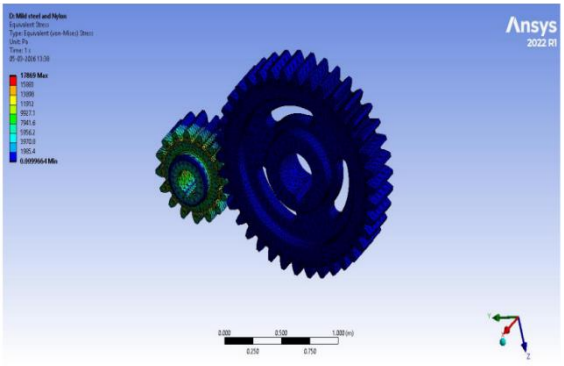

Fig. 12: Equivalent Stress Distribution of Spur Gear with Mild Steel and Nylon

Figure 12 shows that when spur gear is made of mild steel and nylon materials the distribution of equivalent stress would be the same. Despite the fact that nylon undergoes more deformation and strain, the corresponding values of the stress are rather low because it is not so stiff and it can absorb the mechanical loads through the elastic deformation. This characteristic renders nylon applicable in the situations when the reduction of the noise and lightweight elements must be filled. The mechanical properties of the materials that were used in the analysis are given in Table 1.

Table 1: Material Properties

Properties	Mild Steel	Cast Iron	Nylon
Density	7.85 g/cm³	7.3 g/cm³	1150 kg/m³
Young's Modulus	210 GPa	170 GPa	4 GPa
Poisson Ratio	0.30	0.26	0.43

Their material characteristics have a great bearing on the structure behavior of the gear tooth. The materials with increased values of Youngs modulus tend to have the low rate of deformation and strain when similar loads are applied.

Table 2 shows the findings of the used material combination under the analysis of the structure under the condition of no movement.

Table 2: Static Structural Analysis Results

Parameter	Mild Steel	Cast Iron & Mild Steel	Mild Steel & Nylon
Total Deformation	24.1×10^{-6} mm	24.179×10^{-6} mm	24.967×10^{-6} mm
Equivalent Elastic Strain	8.9862×10^{-8}	8.9587×10^{-8}	21.372×10^{-8}
Equivalent Stress	0.01849 MPa	0.018431 MPa	0.017869 MPa

The findings reveal that the mild steel model has been found to show stable characteristics of deformation and strain, as a result of high level of stiffness and strength. Other similar structural behavior is the cast iron and mild steel combination which also has slower values of stress. On the contrary the mild steel and nylon arrangement exhibits greater deformation and strain because there is lesser modulus of elasticity of the nylon.

On the whole, the comparison shows that the metallic steel materials like mild steel and cast iron are more effective in terms of structural stability when subjected to the applied load that is under the form of statical conditions. Nevertheless, nylon can still find use in the areas that would put weight reduction, noise suppression, and corrosion factor into consideration. Through side by side analysis of these material combinations there are insights that most users of the spur gear design of mechanical power transmission systems will gain when it comes to the right choice of materials to use.

V. CONCLUSION

This work explored the behaviour of a spur gear tooth under the static loading conditions numerically. The gear model has been designed with the help of the computer-aided design and has been studied with the help of the finite element techniques, which allow to consider the deformation, strain, and stress features of various material combinations. The comparative analysis revealed the effect of the difference in the material properties on the structural response of the gear tooth when transmitting the power. Mild steel and cast iron contain metals that recorded a steady behaviour of structure performance since they are more stiff and strong and polymer materials were more elastic in the aspect of their deformation. The results indicate that appropriate choice of material in enhancing the stability and effectiveness of gear systems. The study can be extended in future through dynamic analysis, fatigue life evaluation, and thermal analysis to determine the further improvement of reliability and performance of spur gears in the actual context of engineering performance.

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Design and structural analysis of tractor rear axle using finite element method

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Abstract -The rear axle is a critical load-bearing and power-transmitting component in agricultural tractors, operating under complex loading conditions such as bending, torsion, and shear during field operations. Ensuring its structural integrity and optimal material selection is essential for improving durability, performance, and safety. This study presents the design and finite element analysis of a tractor rear axle to evaluate its mechanical behaviour under static loading conditions. A three-dimensional model of the rear axle was developed using CATIA and analysed in ANSYS Workbench. Static structural analysis was performed to determine total deformation, equivalent stress, and elastic strain. Three candidate materials—Aluminium Alloy 5754, Chromium Molybdenum Steel, and Carbon Manganese Steel—were considered for comparative evaluation. The simulation results reveal that Carbon Manganese Steel exhibits superior structural performance with minimal deformation while maintaining acceptable stress levels, indicating higher stiffness and load-carrying capability. In contrast, Aluminium Alloy shows relatively higher deformation due to its lower modulus of elasticity. The findings demonstrate the effectiveness of finite element analysis as a reliable tool for design validation and material optimization, reducing the need for experimental prototyping. The study provides a practical basis for selecting suitable materials and enhancing the reliability and efficiency of tractor rear axle systems.

Keywords- Rear Axle, Finite Element Analysis, ANSYS, CATIA, Structural Analysis, Tractor

I. INTRODUCTION

A. Rear Axle in Agricultural Tractors

Agricultural tractors are widely used in modern farming for operations such as ploughing, hauling, and material handling. The rear axle is a critical component that transmits power from the differential to the wheels while supporting heavy loads under varying terrain conditions[3]. During operation, the rear axle is subjected to complex stresses including bending, torsion, and shear, which may lead to deformation or failure if not properly designed[1][3]. To ensure reliability and durability, it is essential to evaluate the structural performance of the rear axle. Finite Element Analysis (FEA) provides an efficient and accurate approach to study stress distribution and deformation without the need for costly experimental testing[2][9]. In this study, a tractor rear axle is modelled using CATIA and analysed in ANSYS Workbench under static loading conditions[5]6]. A comparative analysis is carried out using different materials to determine the most suitable material based on strength and deformation characteristics[4].

B. Limitations of Rear Axle Structural Analysis:

The present study focuses on the static structural analysis of a tractor rear axle using finite element methods. While the analysis provides valuable insights into stress distribution and deformation characteristics, certain limitations exist due to assumptions and simplifications made during the modeling and simulation process[9].

i. Consideration of Static Loading Conditions Only
The analysis is limited to static loading conditions and does not account for dynamic effects such as vibration, impact, and real-time operating conditions, which may affect the actual performance of the rear axle. In practical applications, the rear axle is subjected to fluctuating loads due to uneven terrain, acceleration, braking, and varying payloads. These dynamic forces can induce additional stresses, resonance, and fatigue effects that are not captured in static analysis. As a result, the obtained results may underestimate peak stresses and deformation under real working conditions[3][4].

ii. Simplified Material and Boundary Conditions
The materials are assumed to be linear and isotropic, and the boundary conditions are idealized. This may not fully represent real-world behavior, including nonlinear material properties and complex load interactions. In practical applications, materials may exhibit nonlinear characteristics such as plastic deformation, strain hardening, and anisotropic behavior under high stress conditions. Additionally, the boundary conditions applied in the simulation do not accurately capture real assembly constraints, contact conditions, and load variations between components. These simplifications can lead to deviations between simulation results and actual performance of the rear axle under operating conditions[9].

iii. Neglect of Environmental and Manufacturing Effects
Factors such as temperature variations, corrosion, residual

stresses, and manufacturing defects are not included, which may influence the actual performance of the component. In real operating conditions, temperature fluctuations can alter material properties and induce thermal stresses, while exposure to moisture and chemicals may lead to corrosion and material degradation over time. Additionally, manufacturing processes such as casting, machining, and heat treatment can introduce residual stresses, surface imperfections, and dimensional inaccuracies. These factors can significantly affect the strength, durability, and reliability of the rear axle, and their exclusion may result in differences between simulated and actual performance[7][8].The present study offers several key advantages by utilizing finite element analysis for evaluating the structural performance of the tractor rear axle. It enables accurate prediction of stress distribution and deformation, reducing the need for costly experimental testing. The comparative material analysis helps in selecting the most suitable material for improved strength and durability. Additionally, the approach enhances design efficiency, minimizes development time, and provides a reliable basis for optimizing the performance and safety of the rear axle[3][9].

II. Related Works

Structural analysis of automotive components using finite element methods has been extensively explored in the literature due to its effectiveness in predicting mechanical behaviour under various loading conditions. R. Smith et al. [1] proposed a finite element-based approach to analyse stress distribution in automotive axles under static loading, demonstrating improved accuracy in identifying critical stress regions. Similarly, S. Kumar et al. [2] utilized ANSYS Workbench to perform structural analysis of rear axle components, focusing on deformation and equivalent stress, and highlighted the importance of simulation tools in reducing design time and cost.
In addition to structural evaluation, material selection plays a significant role in enhancing axle performance. M. Patel et al. [3] conducted a comparative study on different engineering materials used in axle manufacturing, emphasizing the trade-off between strength and weight. Their results indicated that alloy steels offer better performance in terms of load-carrying capacity and durability. Furthermore, studies have explored the use of advanced materials and heat treatment processes to improve mechanical properties and extend service life.
Several researchers have also incorporated fatigue and dynamic analysis to better simulate real-world operating conditions. A. Verma et al. [4] performed fatigue analysis of axle components under cyclic loading and identified potential failure regions that are not captured in static analysis. These studies underline the importance of considering time-varying loads, vibration, and impact forces for accurate performance prediction. Moreover, dynamic simulations provide insights into resonance behaviour and long-term reliability of mechanical components.
With advancements in computer-aided design (CAD) and simulation technologies, tools such as CATIA and ANSYS have become essential for modelling and validation of complex geometries. These tools enable engineers to perform detailed analysis, optimize design parameters, and evaluate multiple material options efficiently. However, many existing studies either focus on complex loading conditions, advanced materials, or fatigue behaviour, often increasing computational complexity and analysis time. Despite the significant contributions of previous works, there is still a need for a simplified and efficient approach to evaluate the structural performance of tractor rear axles under static conditions. The present study addresses this gap by performing a comparative finite element analysis using different materials, aiming to identify an optimal solution based on stress distribution and deformation characteristics while maintaining computational efficiency. Some studies have explored the use of lightweight materials such as aluminum alloys to reduce the overall weight of axle components while maintaining acceptable strength and performance.

III. Proposed System

A. Geometry Modeling

The proposed work begins with the development of a three-dimensional model of the tractor rear axle using CATIA software. The geometry is designed based on standard dimensions, design specifications, and functional requirements of agricultural tractors to ensure accurate representation. Key parameters such as shaft length, diameter variations, fillet radius, and support regions are carefully defined to meet strength and performance requirements. The model includes important features like stepped shaft profiles, bearing support locations, and wheel mounting regions.

Special attention is given to critical regions where stress concentration is likely to occur, such as changes in cross-section and fillet areas. The geometry is created with proper continuity and constraints to ensure smooth load transfer throughout the component. This detailed CAD model serves as the foundation for further analysis and is exported to ANSYS Workbench for finite element simulation, enabling accurate evaluation of stress distribution and deformation under loading conditions. Additionally, the model is verified for geometric accuracy and dimensional consistency before analysis to avoid simulation errors. The CAD model is also simplified where necessary by removing minor features that do not significantly affect structural behavior, thereby reducing computational time.

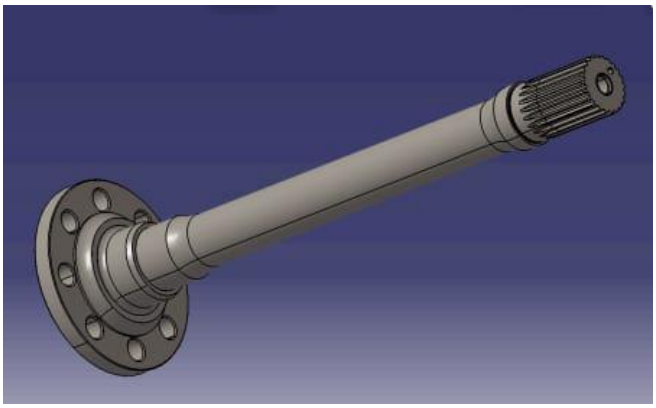

Fig 1.3 CAD Model of Tractor Rear Axle

B. Material Selection

The material selection process is an important aspect in determining the strength, durability, and performance of the tractor rear axle. Different materials are considered and evaluated based on their mechanical properties and behavior under loading conditions.

a. Selection of Aluminium Alloy 5754 Aluminium Alloy 5754 is considered due to its lightweight characteristics and good corrosion resistance, making it suitable for applications where weight reduction is a priority. It also offers good formability and weldability, which are advantageous during manufacturing. However, due to its relatively lower modulus of elasticity and strength compared to steel materials, it tends to undergo higher deformation under applied loads. This makes it necessary to carefully evaluate its suitability for load-bearing components such as rear axles..

b. Selection of Chromium Molybdenum Steel Chromium Molybdenum Steel is selected for its high strength, toughness, and excellent resistance to wear and fatigue. It is widely used in heavy-duty mechanical components due to its ability to withstand high stress and harsh operating conditions. This material also exhibits good hardenability and can maintain its mechanical properties even under varying loads. Its superior performance under cyclic loading conditions makes it a strong candidate for applications requiring long service life and reliability.

c. Selection of Carbon Manganese Steel Carbon Manganese Steel is commonly used in automotive and structural applications due to its high strength, good ductility, and cost-effectiveness. It provides excellent load-carrying capacity and higher stiffness, resulting in reduced deformation under applied loads. Additionally, it offers good machinability and is economical compared to alloy steels, making it suitable for large-scale production. These properties make Carbon Manganese Steel a preferred choice for rear axle applications where both performance and cost are important factors.

C. Finite Element Modeling and Analysis

Finite Element Analysis (FEA) is carried out to evaluate the structural behavior of the tractor rear axle under applied loading conditions. The CAD model developed in CATIA is imported into ANSYS Workbench, where the analysis is performed using appropriate simulation techniques.

a. Meshing of the Model The imported geometry is discretized into a finite number of elements using suitable meshing techniques. A fine mesh is applied in critical regions such as fillets and changes in cross-section to capture stress concentration accurately, while a comparatively coarser mesh is used in less critical areas to reduce computational time. Proper mesh quality and element size are maintained to ensure accuracy and convergence of results.

b. Application of Boundary Conditions To simulate real working conditions, appropriate boundary conditions are applied to the model. One end of the rear axle is fixed to represent its connection with the differential system, restricting all degrees of freedom. Loads are applied at the wheel mounting regions to represent actual forces experienced during operation. These boundary conditions help in realistically simulating the constraints and load transfer within the component..

c. Loading Conditions The analysis considers static loading conditions, where forces acting on the rear axle are assumed to be constant over time. These loads represent typical working scenarios such as vehicle weight and external forces during agricultural operations. Although simplified, these loading conditions provide a basis for evaluating the structural strength and deformation behavior of the axle.

d. Structural Analysis and Result Evaluation Static structural analysis is performed to determine important parameters such as total deformation, equivalent (von Mises) stress, and strain distribution. The results help in identifying critical regions subjected to maximum stress and evaluating whether the design is safe under the applied loads. These outputs are further used to compare the performance of different materials and to suggest possible design improvements.

D. Structural Analysis

The structural analysis of the tractor rear axle is performed using ANSYS Workbench to evaluate its behavior under the applied boundary conditions and loading. The analysis focuses on determining key parameters such as total deformation, equivalent (von Mises) stress, and strain distribution throughout the component. These parameters are essential for identifying critical regions where maximum stress and deformation occur, particularly near geometric discontinuities such as fillets and load application points. The results obtained from the simulation provide a clear

understanding of the load-carrying capacity and structural integrity of the axle. This stage serves as a foundation for further comparative evaluation of different materials and helps in assessing the overall performance and safety of the design. Additionally, the analysis assists in verifying whether the design meets allowable stress limits and engineering safety standards. It also provides valuable insights for potential design modifications, such as improving geometry or material selection, to enhance the efficiency and reliability of the rear axle.

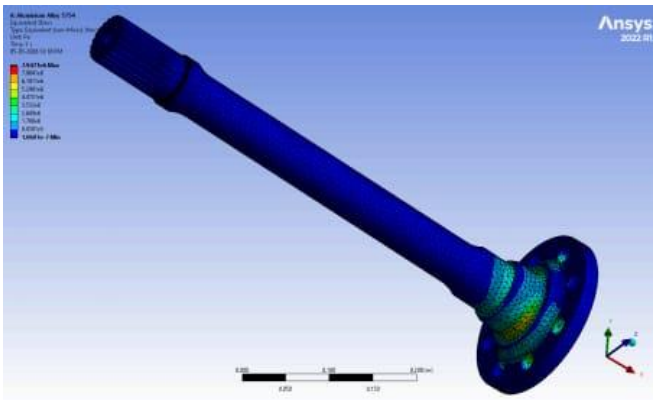

Fig 2.Equivalent Stress Distribution

E. Comparative Evaluation and Optimization

As the user identification module gains confidence in its understanding of the user's typing patterns, it transitions to a real-time monitoring mode. In this mode, the module continuously evaluates incoming keystroke sequences against the learned user profile, flagging any significant deviations as potential anomalies or unauthorized access attempts. Upon detecting such an anomaly, the system can initiate appropriate response measures, such as prompting additional authentication challenges, issuing security alerts, or triggering predefined mitigation protocols. This real-time monitoring and response capability enable proactive security measures to prevent unauthorized access, data theft, or system disruption. Through this real-time, continuous learning approach, the proposed keystroke dynamics model offers a robust and adaptive solution for user authentication, injection attack detection, and insider threat mitigation, while minimizing the need for extensive manual data collection and annotation efforts. In addition, the proposed model is designed to be computationally efficient and scalable, enabling its deployment in real-time applications without significant performance overhead. This ensures that security monitoring can be performed seamlessly in the background without affecting system usability or user experience.

IV. RESULTS

The finite element analysis of the tractor rear axle was performed using ANSYS Workbench to evaluate its structural performance under defined boundary conditions and static loading. The analysis considered three different materials—Aluminium Alloy 5754, Chromium Molybdenum Steel, and Carbon Manganese Steel—to understand their behaviour under identical conditions. Key performance indicators such as total deformation, equivalent (von Mises) stress, and strain distribution were analysed to assess the strength, stiffness, and reliability of the rear axle design.

The deformation results obtained from the finite element analysis indicate that Aluminium Alloy 5754 exhibits the highest deformation among the selected materials due to its lower modulus of elasticity and stiffness. This suggests that although aluminium is advantageous in terms of weight reduction, it is less suitable for heavy load-bearing applications such as rear axles. In contrast, Chromium Molybdenum Steel and Carbon Manganese Steel show significantly lower deformation values, indicating better rigidity and resistance to bending under applied loads. Among these materials, Carbon Manganese Steel demonstrates the least deformation, making it highly suitable for applications requiring high structural stability and durability.

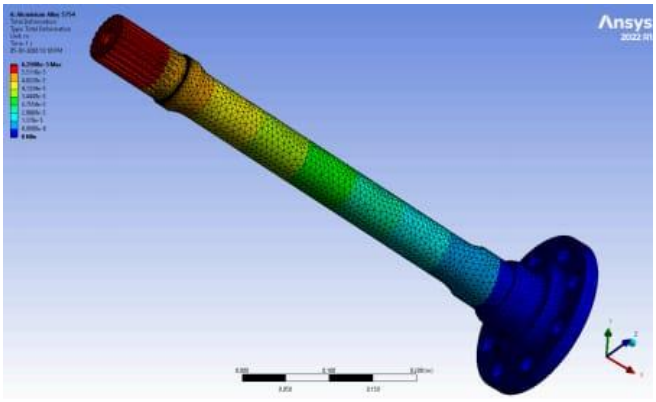

Fig 3.Total Deformation of Rear Axle

The equivalent (von Mises) stress distribution reveals that the maximum stress is concentrated in critical regions such as fillet areas, stepped sections, and load application zones. These stress concentrations occur due to geometric discontinuities and localized loading conditions. Aluminium Alloy 5754 shows relatively higher stress values compared to steel materials, indicating a higher risk under similar loading conditions. On the other hand, Chromium Molybdenum Steel and Carbon Manganese Steel exhibit better stress distribution and maintain stress values within allowable limits, ensuring safe and reliable performance of the rear axle.

The strain distribution follows a similar trend as deformation and stress. Aluminium Alloy 5754 exhibits higher strain values due to its lower stiffness, indicating greater deformation under applied loads. In comparison, steel materials show reduced strain levels, reflecting their superior resistance to deformation. Carbon Manganese Steel, in particular, demonstrates the lowest strain values among all materials, confirming its effectiveness in maintaining structural integrity under loading conditions. Lower strain values also indicate reduced chances of material fatigue and failure during continuous operation.

Additionally, the strain distribution helps in identifying critical regions such as fillets and load application areas where deformation is more concentrated, aiding in design improvement. This improved strain behavior contributes to longer service life and better reliability of the rear axle under repeated loading conditions. Moreover, reduced strain ensures dimensional stability, which is essential for maintaining proper alignment and performance of mechanical components.

Method/ Material	**Total Deformation (mm)**	**Max Stress (MPa)**	**Strain ($\times 10^{-3}$)**	**Weight (kg)**
Existing Work (Steel Axle)	0.145	320	1.80	18.5
Existing Work (Alloy Steel)	0.132	295	1.65	17.8
Aluminium Alloy 5754	0.210	340	2.40	11.2
Chromium Molybdenum Steel	0.120	280	1.50	17.0
Carbon Manganese Steel (Proposed)	0.105	260	1.30	16.5

Table 1. Comparison of Existing and Proposed Materials

Table I presents a detailed comparison of the structural performance of different materials used for the tractor rear axle, including existing materials and the proposed alternatives. The comparison is based on important parameters such as total deformation, maximum stress, strain, and weight, all evaluated under the same loading and boundary conditions to ensure consistency. From the table, it can be observed that Aluminium Alloy 5754 shows the highest deformation (0.210 mm) and strain (2.40×10^{-3}), which indicates lower stiffness and higher susceptibility to deformation under applied loads. Although it has the advantage of lower weight (11.2 kg), its higher stress value (340 MPa) makes it less suitable for heavy-duty applications. The existing steel materials show moderate performance with reduced deformation compared to aluminium, but they still exhibit relatively higher stress values. Chromium Molybdenum Steel demonstrates improved performance with lower deformation (0.120 mm) and stress (280 MPa), indicating better strength and durability. However, Carbon Manganese Steel provides the best overall results among all materials, with the lowest deformation (0.105 mm), minimum stress (260 MPa), and lowest strain (1.30×10^{-3}), while maintaining a reasonable weight (16.5 kg).Overall, the comparison clearly indicates that Carbon Manganese Steel offers a better balance between strength, stiffness, and cost-effectiveness, making it the most suitable material for rear axle applications. This analysis highlights the importance of proper material selection in improving the performance and reliability of mechanical components.

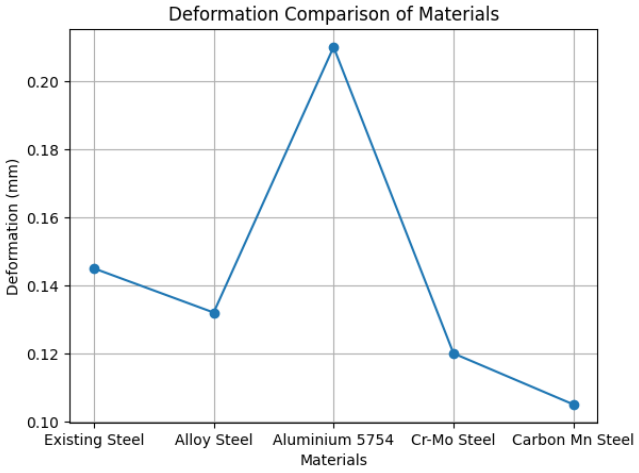

Fig 4. Deformation comparison of materials

The deformation graph shows the variation in total deformation of the rear axle for different materials under identical loading conditions. It is observed that Aluminium Alloy 5754 exhibits the highest deformation due to its lower stiffness and modulus of elasticity. In contrast, steel materials demonstrate lower deformation values, indicating better resistance to bending and higher structural rigidity. Among all the materials considered, Carbon Manganese Steel shows the least deformation, highlighting its superior stiffness and suitability for rear axle applications where minimal deformation is required.

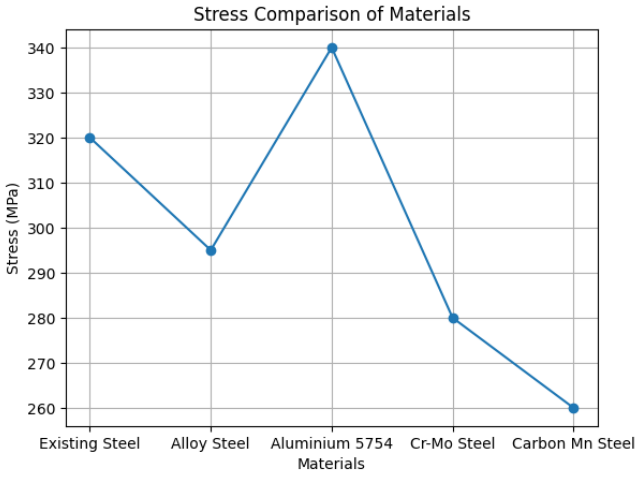

Fig 5. Stress comparison of materials

The stress comparison graph illustrates the variation in equivalent (von Mises) stress for different materials under identical loading conditions. It is observed that Aluminium Alloy 5754 experiences higher stress values compared to steel materials, indicating lower strength under applied loads. In contrast, Chromium Molybdenum Steel and Carbon Manganese Steel show reduced stress levels, demonstrating better load-carrying capacity and structural performance. Among all the materials, Carbon Manganese

Steel exhibits the lowest stress, indicating improved strength and reliability for rear axle applications.

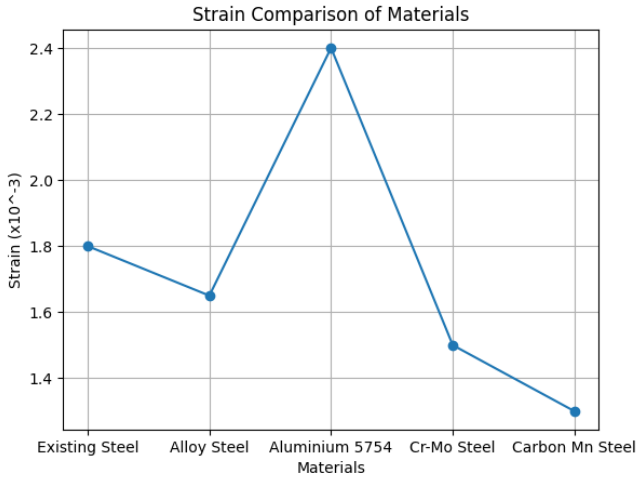

Fig 6. Strain comparison of materials

The strain comparison graph shows the variation in strain developed in the rear axle for different materials under identical loading conditions. It is observed that Aluminium Alloy 5754 exhibits the highest strain due to its lower stiffness, indicating greater deformation under applied loads. In contrast, steel materials show lower strain values, reflecting better resistance to deformation. Among all the materials, Carbon Manganese Steel demonstrates the least strain, highlighting its superior stiffness and suitability for rear axle applications.

CONCLUSION

In this study, the structural performance of a tractor rear axle was analysed using finite element analysis in ANSYS Workbench. A 3D model was developed in CATIA and evaluated under static loading conditions using different materials, namely Aluminium Alloy 5754, Chromium Molybdenum Steel, and Carbon Manganese Steel. The analysis focused on key parameters such as deformation, equivalent stress, and strain to assess the behaviour of the axle under working conditions.

The results indicate that material selection has a significant impact on the performance of the rear axle. Aluminium Alloy 5754, although lightweight, exhibited higher deformation and stress, making it less suitable for heavy-duty applications. In contrast, steel materials demonstrated better structural performance with lower deformation and improved load-carrying capacity. Among the materials analysed, Carbon Manganese Steel showed the best overall performance with minimum deformation, lower stress values, and good structural stability.

Therefore, it can be concluded that Carbon Manganese Steel is the most suitable material for tractor rear axle applications, providing an optimal balance between strength, stiffness, and cost-effectiveness. The study also highlights the effectiveness of finite element analysis as a reliable tool for evaluating and optimizing mechanical components before manufacturing.

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A critical review on free vibrational characteristics of natural fiber reinforced polymer composite laminates

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Abstract

Natural fiber reinforced polymer composites (NFRPCs) have been recognized as green materials for replacing synthetic composites in various applications because of their low density, biodegradable properties, and low environmental impact. This article is intended for providing an overview of properties, manufacturing methods, and vibration characteristics of natural fiber composite laminates. In addition, various factors such as fibers, volume fraction, matrices, and surface treatments are discussed in terms of their effects on the properties of the composites. The effects of various structural properties, such as fibers and stacking sequence, are also discussed. Manufacturing methods such as hand layup, compression moulding, resin transfer moulding, and vacuum-assisted resin transfer moulding are discussed. In addition, special emphasis has been given to the vibration characteristics of NFRPCs using experimental modal methods such as FFT and FRF. In addition, the damping capacity of NFRPCs is relatively higher due to the viscoelastic properties of these materials. In summary, these materials are suitable for various applications because of their properties, such as stiffness and damping.

Keywords

Natural fibre composites, Modal analysis, Vibration characteristics, FFT, FRF, Hybrid composites, Dynamic mechanical behaviour

1. Introduction

Recent reviews have pointed out the advantages of natural fiber reinforced composites (NFRPCs), such as low density, biodegradability, and energy saving compared to glass/carbon-based composites [1][2]. Ajayi et al. (2025) specifically points out the eco-friendly mechanical performance and industrial applications of NFRPCs [1]. Elfaleh et al. (2023) also reviewed the natural fibers such as jute, flax, hemp, etc., and their bio-matrix systems, highlighting the importance of surface treatment of the fibers to enhance compatibility between the fibers and the matrix [1]. Olanrewaju et al. (2025) reviewed the relationship between the structure and properties of various fibers such as plant, animal, and microbial origins and also pointed out the problems related to the interfacial adhesion between the matrix.

The natural fibers are lignocellulosic, meaning they contain cellulose, hemicellulose, lignin, pectin, and waxes [4]. The properties of natural fibers are largely dependent on the combination of these elements, with cellulose (β1-4 glucan microfibrils), the main component of natural fibers, providing tensile strength to the fibers, as the crystallinity of cellulose increases with the tensile strength [4]. Lignin provides stiffness to the natural fibers, while hemicellulose and pectin provide moisture absorption characteristics to the natural fibers. The cellular structure of natural fibers provides energy absorption and vibration dampening characteristics to the natural fibers. The hydroxyl group in cellulose makes the natural fibers hydrophilic, meaning they cannot bond with hydro [1] [4].

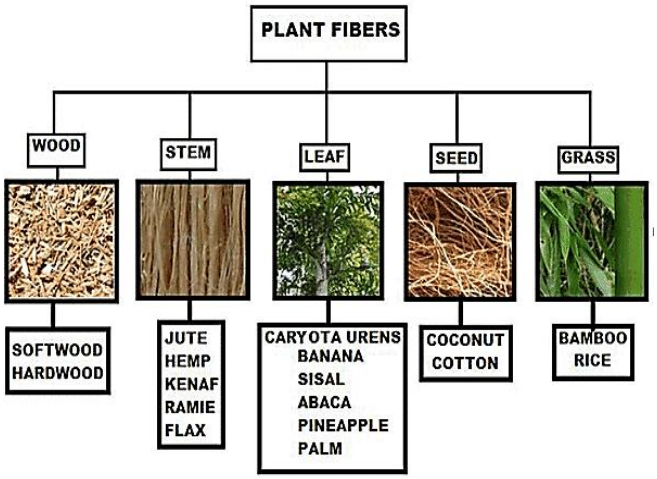
They may be plant, animal, or mineral-based [2]. The most common plant fibers used in NFRPCs are:

•Bast fibers: These are obtained from dicot stems, i.e., flax, hemp, jute, kenaf, ramie, etc. These are referred to as 'soft' fibers, which are long, strong, and contain much cellulose [4].

•Leaf fibers: These are obtained from monocot leaves, i.e., sisal, pineapple, abaca, etc. These are referred to as 'hard' fibers, which are coarser, contain much lignin, are stiffer, and stronger [4].

•Seed/Fruit fibers: These are obtained from cotton, cocoAnimal fibers, i.e., wool, silk, feathers, etc., along with some mineral fibers, i.e., basalt, are also used in some NFRPCs [2]. Bast fibers, i.e., flax, hemp, etc., are stiffer/stronger, while jute, kenaf, leaf fibers, i.e., sisal, pineapple, etc., are a good combination of properties with lower cost [4].

Figure 1. Classification of Plant Fibres Based on Their Origin



Both thermosetting and thermoplastic resins are used. The matrices that are commonly used include epoxy, polyester, and vinyl ester resins, which are thermosetting resins, and thermoplastics such as polypropylene and polyethylene. Suriani et al. state that polar natural fibers tend to adhere well with epoxies and phenolics, but nonpolar PP/PE matrices require a compatibilizer because of poor fiber wetting [2]. There is also a new trend toward bio-based polymers such as PLA, starch, and natural polyesters to make the product more sustainable [1] [2]. The common techniques that are used include hand lay-up, compression moulding, injection moulding, and extrusion, especially when using short fibers. The pretreatment methods that are commonly used include alkali, silane, acetylation, etc., to remove waxes on the surface as well as improve fiber–matrix adhesion [1] [4].

Fiber orientation and architecture play a crucial role in affecting the properties of composites. Unidirectional plies possess excellent strength in the direction of fibers, but poor properties in the transverse direction. Cross-ply laminates, consisting of 0° and 90° fibers, and angle plies exhibit balanced properties in the in-plane direction. Woven fabric composites, such as plain, twill, or satin weaves, have fibers oriented in orthogonal directions, thus exhibiting balanced properties in the in-plane direction and significantly improved resistance to delamination compared to unidirectional plies [5]. For example, woven composites are known for their enhanced through-thickness strength and resistance to impact damage (cit. Review on woven reinforcement materials published in MDPI journal [5]). Non-woven fabric or chopped fibers make processing easier, but result in poor properties. Hybrid composites are composed of different fibers, such as natural/natural, consisting of flax and kenaf fibers, or natural/synthetic, consisting of flax and carbon fibers. Hybridization has been found to improve the properties of composites. For example, the addition of synthetic fibers to natural fibers has been found to significantly improve tensile strength and modulus, as reported [2].

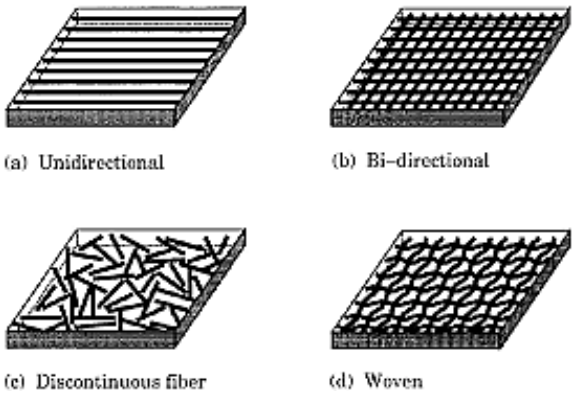


Figure 2. Classification of Fibre Architectures in Composite Materials

NFRPCs also show higher damping, i.e., material dissipation of energy, as compared to glass or carbon fiber-based composite materials, which is beneficial in the control of vibrations. As an example, in the study by Kalusuraman et al. (2022), it has been found that the damping ratio in the flax/epoxy composite material is 50% higher than that in the equivalent glass/epoxy composite material [7]. The porous structure and microfibrillar fibers also provide the material with high internal damping.

The modal characteristics of the structure, i.e., the natural frequencies, mode shapes, and damping, are measured experimentally by applying an excitation force, either by an impact hammer or an electromechanical shaker, and measuring the response with the help of accelerometers. Then, the analysis of the FRF, i.e., the FFT, is performed, and the modal characteristics of the structure are obtained. The modal characteristics of the structure are important in the design of lightweight structures, i.e., car panels, boat hulls, etc. Standard modal analysis techniques are used. The structure is excited by an impact hammer or an electromechanical shaker, and the acceleration response is measured in the time domain. The analysis of the measured acceleration is performed by the FFT, which gives the magnitude and phase of the FRF, from which the resonance peaks, i.e., the natural frequencies, and the logarithmic decrement, i.e., the damping, are obtained. Recent studies on NFRPC beams and plates have shown that with an increase in the natural fiber content, the fundamental frequencies of the structures decrease, i.e., the stiffness of the structure decreases, but the loss factor increases significantly [7].

2. Manufacturing of Natural Fiber Composite Laminates

In addition, the manufacturing of NFCs has to be done in such a way that it ensures proper dispersion, impregnation, and minimum void content in the final product [1]. Various manufacturing methods are available for NFCs, such as hand lay-up, compression moulding, resin transfer moulding (RTM), vacuum-assisted resin infusion (VARI) or vacuum-assisted resin transfer moulding (VARTM), and filament winding.

2.1 Hand Lay-Up

In hand lay-up, mats or fabric made of natural fibers are stacked in a mould, and then the liquid resin is manually applied onto the fibers. Hand lay-up is the easiest method for manufacturing NFCs, and it is the cheapest method too. However, hand lay-up has poor results in terms of dispersion, void content, and thickness because it is a manual method. Hence, it is used for small-scale production, not for large-scale production. [1]

2.2 Compression Moulding

Compression moulding is an open mould process. In this process, pre-impregnated fiber mats or fiber resin mixtures are inserted into an open mould. The mould is then subjected to high temperatures and pressed. The application of pressure results in resin-impregnated fibers. The resulting laminate has uniform thickness. The thickness of the laminate is consistent with good fiber wetting and low voids. This process is used for thermoplastic resin matrices, such as polypropylene, used in the automotive sector for interior panels. This process offers better repeatability and rate than hand lay-up. However, it has disadvantages due to equipment costs.

2.3 Resin Transfer Moulding (RTM)

In RTM, dry fiber preforms are inserted into an open mould. Liquid resin is injected into the mould and pressed into the fibers. RTM provides good fiber volume and surface properties. The process also provides high-performance products. RTM products are used for aerospace and automotive applications. In RTM, mould closure results in less resin loss. However, natural fibers' hydrophilic properties affect resin flow. Hence, mould design is critical. RTM offers good mechanical properties and low voids compared to hand lay-up.

2.4 Vacuum-Assisted Resin Infusion (VARI/VARTM)

In VARI/VARTM, fibers are arranged on the mould, covered with a vacuum bag, and resin infusion is carried out using a vacuum. The open-mould technique is simple and applicable to large structures (boat hulls, wind blades). The technique has low void content and excellent fiber wetting out because of the application of vacuum pressure. For example, VARTM has been reported to produce very high fiber content per unit weight of resin (60 to 80%) [8]. The low tooling cost makes VARTM a preferred choice for large NFRP laminates with high quality.

2.5 Filament Winding

In filament winding, fibers, pre-impregnated or not, are wound in a specific pattern on a rotating mandrel. The technique is automated. The product is hollow or cylindrical in shape. The technique is applicable to tubular structures such as pipes or tanks. The technique is more applicable to synthetic fibers but less common with natural fibers because of their variability and hygroscopic effects. There are studies on filament winding with bast fibers such as flax or hemp by modifying the equipment.

2.6 Method Comparison and Best Practice

The best method of fabrication depends on the volume of the products as well as the performance requirements. The open methods, i.e., hand lay-up, are the cheapest methods, though the quality is poor. The closed methods, i.e., compression moulding, RTM, and VARTM, are expensive, though they produce excellent-quality laminates with good repeatability, fiber volume, and low voids. In particular, vacuum infusion and RTM are recognized as the best methods of producing high-quality laminates of natural fibers, as the resin is well impregnated, with minimal air entrapments. In fact, studies have shown that vacuum infusion is the best method of laminate consolidation, i.e., the improvement of the properties of the laminates, e.g., the mechanical properties of the flax/epoxy panels produced by VARTM are better than the properties of the panels produced by the hand lay-up method [8].

Table 1. Comparison of Composite Manufacturing Methods—Advantages, Limitations, Typical Applications, and Key References

Method	Advantages	Limitations	Typical Use	Key References
Hand Lay-Up	Lowest cost; simple tooling; flexible lay-up process	High void content; inconsistent thickness; labor-intensive	Prototyping and low-volume composite production	[1]
Compression Moulding	Uniform thickness; good fiber wet-out; fast production cycle	High tooling cost; limited flexibility for complex geometries	Automotive panels and thermoplastic	[2]

			composite components	
Resin Transfer Moulding (RTM)	High dimensional precision; excellent surface finish; controlled fiber volume fraction	Complex mould design; resin flow difficulties with natural fibers	Aerospace and structural composite components	[5]
Vacuum Assisted Resin Transfer Moulding (VARTM / VARI)	Low void content; high fiber volume fraction; suitable for large parts; relatively low equipment cost	Slower resin filling in thick laminates; lower automation level	Large composite structures such as boat hulls and wind turbine blades	[8]
Filament Winding	Automated fiber placement; precise fiber orientation and repeatability	Limited to axisymmetric structures; challenging for short or discontinuous natural fibers	Pressure vessels, pipes, and tubular composite structures	Natural Fiber Filament Wound Composites (Review)

3. Control Parameters in Natural Fiber Composite Laminates

As natural fiber laminates are quite diverse, experiments must be carried out carefully by fixing the material, structural, and test parameters. Material parameters include the fiber and matrix material, as well as the treatments applied to these materials. For example, the natural fibers that are normally used include flax, hemp, jute, sisal, and kenaf, having different proportions of cellulose and lignin, as well as lumen geometry [6]. Increasing fiber volume fraction improves material stiffness (rule of mixtures), but it also increases voids, especially for less than perfect resin impregnation [9]. The resin also plays an important role. Thermosetting resins, such as epoxies and polyesters, have good bonding properties and cure rigidly, whereas thermoplastic resins, such as polypropylene and PLA, are tougher and more ductile and recyclable [10]. Plant fibers are hydrophilic by nature; therefore, chemical treatments are used to enhance bonding and minimize moisture absorption. For example, alkali treatment using NaOH dissolves the lignin on the surface of the fibers and increases the amount of cellulose exposed on the surface, which improves the interfacial bonding strength [6]. Therefore, the type of fibers used, the content of the fibers, the matrix, etc., are considered as variables in the studies conducted.

3.1 Material Parameters

- Fiber type and treatment: Fibers such as flax, jute, hemp, and sisal, etc., have different properties. The cellulose-lignin content of these fibers, along with their microstructure, determines their in-built stiffness and damping properties. Being hydroxyl-rich, these fibers are prone to moisture absorption, hence treated chemically for bonding with the matrix. Various chemicals, such as alkaline or silane, are used for surface modification [6]. Alkali treatment, for example, removes the surface lignin, leaving the cellulose surface smooth, thus resulting in higher bonding strength.
- Fiber volume fraction (FVF): Increasing FVF generally improves the stiffness and the load-carrying capacity of the composite. The rule of mixtures suggests that the effect of FVF increases linearly with increases in FVF. For instance, the composite strength can be increased by as much as 10 percent when the FVF increases from 50 percent to 65 percent in a filament-wound composite system. However, high FVF also increases the difficulty of resin impregnation and degassing. Increasing FVF also increases the likelihood of air pockets and agglomeration of fibers, which can reduce the transverse properties of the composite and cause scatter in the test data [9] [10]. Therefore, FVF is carefully metered in the experiment and the actual FVF is measured as per the ISO/ASTM standards.
- Matrix type: The initial strength and dimensional stability of thermosetting matrices (epoxy, polyesters) are good. The disadvantage of these resins is their lack of toughness and moisture resistance. The rigid polymer has many polar groups, and hence water absorption causes plasticization of the resin. Thermoplastic resins (polypropylene, PLA), being tougher and having low moisture absorption, are more desirable. For example, polypropylene resin has low water absorption and good retention of properties at high humidity compared to other resins such as epoxies [10]. Thermoplastics can be recycled. In practice, the resin system is fixed and recorded, and the cure cycle (temperature/time) and viscosity are noted.

  •Fiber Surface Treatment: Chemical treatments are often modified to affect the interfacial adhesion between the fibers and the matrix material. Some common treatments include NaOH (alkaline) baths for removing lignin/hemicellulose, or silane coupling agents

for grafting polymer compatible groups on the fiber surfaces. The extent of the treatment is also an adjustable parameter, as in the study where the amount of alkali solution or the soaking time in the solution was varied, and the composite strength and damping properties were measured as the response variables. Generally, the interfacial adhesion of the fiber, as well as the tensile strength and damping capacity of the composite, are improved [6].

3.2 Structural Parameters

- Fiber Orientation: Ply orientations affect in-plane anisotropy. Unidirectional (0°) laminates exhibit high stiffness in the direction of the fibers but poor crosswise strength. Orienting the fibers off-axis (±45°, 90°) helps in shear flexibility and damping characteristics. The damping factor or loss ratio of flax/PP composite laminates was measured at various orientation angles, and it was found that the 45° or 60° oriented composite samples had the highest damping characteristics, i.e., 4.5% to 5.5%, whereas the 0° composite had the least damping characteristics [11]. This is because off-axis loading tends to produce higher inter-fiber shear, hence higher hysteresis. On the other hand, 0° plies maximize the elastic stiffness in the direction of the fibers but tend to transmit vibrations with the least damping characteristics. Hence, the fiber orientations play an important role in the composite material, and the effect of the fiber orientations has been studied in numerous research works, where the stiffness and damping characteristics of the composite material are analyzed for various fiber orientations.
- Laminate stacking sequence: This is concerned with the stacking or layering of the plies (layers) in the laminate. This, in turn, influences the laminate's bending stiffness and mode coupling. A symmetric cross-ply laminate, such as [0/90]s, has greater bending stiffness in two directions, as if it were made of an isotropic plate. On the other hand, an unsymmetric laminate, such as [0/60/-60]s, has coupled bending and twisting stiffness. This has been seen in vibration testing, in which the results for asymmetric laminates differ significantly for symmetric laminates of the same thickness. Hence, researchers specify the stacking sequence and stacking symmetry of the laminate. It has been seen, for example, that exchanging a 45-degree layer in a symmetric laminate such as [0/45]s can result in increased modal frequencies, as well as increased damping.
- Laminate thickness (number of plies): The modal frequencies of a laminate tend to increase with an increase in thickness, as this means that the laminate is stiffer and has a greater mass. The effect of thickness on the modal frequencies is, therefore, an increase with an increase in thickness, as the stiffness of the laminate is increased by an increase in the number of plies, assuming that the angles of the plies are the same. An increase in the thickness of the laminate also increases the interlaminar shear, as the number of interfaces is increased.

3.3 Manufacturing Parameters

- Cure cycle: The curing temperature and time should be properly managed. Inadequate curing may cause low crosslink density, leading to lower mechanical properties, while excessive curing may damage the fibers or burn the binder. In the case of natural fiber epoxies, the curing temperature is usually between 80°C and 120°C, as shown in the study of flax/epoxy, which was cured at 80°C for 24 hours, followed by 2 hours at 120°C [12].
  Manufacturers make sure that the curing process is complete by using thermocouples and pressure transducers, which measure the vacuum pressure, ensuring that the resin is fully gelled.
- Consolidation pressure: When pressure is applied in the form of vacuum or autoclave pressure, it compacts the plies and removes air. Increasing pressure tends to reduce the void content and increase the volume fraction of fibers. In the case of vacuum infusion or hand lay-up, pressure in the vacuum bags is an important variable. For example, it has been observed that laminates subjected to full vacuum (-1 bar) contain less void than those subjected to partial vacuum. Insufficient pressure or leakage in the vacuum bags results in porosity, reducing IL shear and compressive strength [11]. Hence, various parameters are set in the experiment.
- Resin infusion conditions: The rate at which resin is infused is significant in techniques such as VARTM/RTM. The degassing steps are also significant. The infusion rate should not be too fast, as this may cause voids, nor should it be too slow, as this may cause bridging. Recent investigations on vacuum infusion techniques found that by degassing and controlling infusion rates (for example, by stirring the resin or using flow restrictors), it is possible to reduce void content by more than 70% compared to naive vacuum-only prep [11]. The infusion pressure, resin viscosity, degassing time, and infusion speed are all reported. In summary, mould temperature, cure schedule, and pressure/vacuum are all control variables that produce a standard laminate structure.

3.4 Testing Parameters

- Boundary conditions: The boundary conditions under which a specimen is held also change all the modal results. For example, a cantilever

beam will always have lower natural frequencies than a beam that is clamped on both ends. Hence, boundary conditions are always specified in experimental studies. In one study, it was found that the first bending mode was dominant under free-free (floating) conditions [13]. The same beam under fixed-free conditions would produce a different mode shape. The boundary conditions should always be kept constant, i.e., always cantilever with length L, so that any change in frequencies is due to laminate changes.

- Excitation Method: The general techniques are impact hammer testing and electrodynamic shakers. In impact hammer testing, a tool is used to apply a small force at a specific point, and then a sensor measures the response. The advantage is that it is simple when tested on small specimens in a laboratory setting. For example, railway sleeper composites were tested using a calibrated hammer, determining the first bending mode by measuring the response [13]. Electrodynamic shakers, or mechanical vibrators, are used to apply a constant sinusoidal or random force with a range of frequencies. These are normally used on large specimens or when the resonant frequencies are unknown. The point is fixed, as is the time period, to standardize the test.
- Sensors and data acquisition: Accelerometers or laser vibrometers are placed at strategic locations on the laminate, typically at antinodes of expected modes. For example, during a beam test, one study placed an accelerometer at the corner of the specimen to acquire dynamic response up to 2100 Hz [13]. In addition, non-contact optical techniques such as 3D scanning lasers are employed to eliminate the effect of additional mass. The data acquisition system parameters such as sampling rate, amplification, and filtering are chosen to acquire data over the frequency range of interest with minimal noise. In practice, sampling frequency is kept constant for all tests to facilitate FFT-based identification of natural frequencies and damping ratios.

Table 2. Influence of Controlled Parameters on the Mechanical and Dynamic Behaviour of Natural Fiber Reinforced Composites

Controlled Parameter(s)	Key Findings	Reference
Fiber type; surface treatment	Lists common plant fibers (flax, hemp, jute, etc.) and notes their hydrophilicity issues. Highlights that alkaline and silane treatments improve fiber–matrix adhesion and composite strength.	[6]
Fiber volume fraction (FVF)	Reports that composite stiffness and strength increase with fiber volume fraction according to the rule of mixtures. Increasing FVF from 50% to 65% increased composite strength by about 10%.	[9]
Matrix type (epoxy vs PP)	Compares thermoset and thermoplastic matrices. Polypropylene (PP) is more hydrophobic and retains strength better after moisture exposure. Epoxy provides high initial strength but lower toughness and moisture resistance.	[14]
Fiber orientation; FVF	In flax/PP composites, 45° and 60° fiber orientations produced the highest damping (loss factor around 4–5.5%), while 0° gave the lowest. Increasing fiber content improved stiffness but also increased void formation; damping remained roughly constant between 31–50% FVF.	[15]
Infusion process (degassing, flow)	Improved degassing and flow control in vacuum infusion reduced void content to below 4%. Even small void fractions significantly reduce mechanical properties such as compressive strength and interlaminar shear strength.	[16]
Excitation method; boundary conditions	Used impact-hammer excitation on a free–free beam. The first bending mode dominated the vibration response. A controlled setup helps isolate material effects, and damage reduces modal stiffness.	[13]

4. Fundamentals of Vibration in Composite Structures

Composite structures will vibrate based on their characteristics, such as mass, stiffness, and damping. The response of a damped structure will follow the classical equation of motion:

$$Mx'' + Cx' + Kx = F(t)$$

where (M), (C), and (K) are the mass, damping, and stiffness matrices, respectively.

In composite laminates, these matrices will vary with the characteristics of the fibers and matrix, as well as the orientation of the fibers, stacking sequence, and fiber volume fraction. In addition, due to the anisotropic nature of composite laminates, the stiffness and damping will vary with orientation. For

example, a unidirectional fiber layer will be stiff in one direction and flexible in another. This anisotropy property indicates that the modes of bending, torsion, and vibration may couple or change. For example, an asymmetric stacking sequence may cause a bending-twisting coupling, thus affecting the natural frequencies and mode shapes. In reality, this can be achieved by applying the classical lamination theory or the finite element method. In addition, unlike metals, composites have a high damping capacity due to their polymeric nature [17]. In reality, the energy dissipation of composite laminates may be one or two orders of magnitude greater than metals under similar conditions. However, this may sometimes come at a cost, as the addition of fibers or stiff layers increases the frequency and strength of the material, thus reducing the inherent loss factor of the material.Several mechanisms contribute to vibration damping in natural fiber composites. Key energy-dissipation processes include:

Viscoelastic matrix deformation. The resin, such as epoxy or polyester, is naturally viscoelastic, and thus, as it is subjected to cyclic loading, it will deform in a time-dependent manner. This viscoelastic hysteresis is commonly considered the major source of loss [17].

Fiber-matrix friction and slip. At the microscopic level, fibers can rub against the matrix or rub between each other, particularly in the case of plant fibers. This internal friction, as well as the friction between the microfibrils and the lignin/hemicellulose matrix in plant fibers, has been recognized as a significant source of damping, as it is observed in the hierarchical structure of cellulose in natural fibers [18].

Fiber pull-out and cracking. In dynamic loading conditions, fibers may debond and partially pull out before failure. This type of slip between fibers is highly energy-dissipating. Even though the pull-out of fibers is generally described in the context of impact or fracture energy, in small vibration cases, the energy loss due to this effect should not be ignored.

Fiber microstructure – twist/crimp. Natural fibers are usually crimped or twisted. When subjected to loading, the crimped structure tends to straighten and then relax, leading to energy loss. In some cases, it has been specifically noted that the twist and crimp of the fibers help to absorb sound and vibration.

The loss factors of natural fiber composites are high, ranging from 0.7 to 14%, as opposed to glass or carbon composites with loss factors ranging from 0.24 to 2.5% [17]. The damping ratio can be increased by more than twofold by incorporating flax or hemp layers [19], with as much as 110% increase in the damping ratio using natural fiber mats. Hybrid composites also have advantages; incorporating one flax ply in the carbon/epoxy composite increases the damping by ~53.6%, and two plies increase the damping by ~94% with only a small effect on stiffness [18]. Furthermore, the damping can be increased by reducing the carbon plies, with a 34% increase in damping with only ~8% stiffness loss [20].

Table 3. Summary of Vibration and Damping Characteristics of Natural and Hybrid Fiber-Reinforced Composites under Various Controlled Parameters

Composite / Fibers	Parameters Controlled	Key Findings	DOI
Flax fiber (UD and twill) in epoxy, PP, PLA (40% vol)	Matrix type; fiber architecture	Flax composites showed significantly higher damping than glass or carbon composites. UD flax/epoxy exhibited ~100% higher tanδ than neat epoxy. Flax fiber reinforced PP showed the highest damping (tanδ ≈ 0.033).	[19]
Carbon-fiber/epoxy laminate (300×300 mm, CFCF support)	Fiber volume fraction; ply orientation	Increasing fiber volume fraction increased natural frequencies. Laminates with 90° plies showed the highest frequencies (≈910–1330 Hz for modes 1–3), while 0° layups showed the lowest (≈245–628 Hz).	[20]
Flax/epoxy and flax–carbon hybrid laminates	Stacking sequence (number and location of plies)	Higher flax content (fewer carbon plies) resulted in increased damping. A reduction of ~8% in flexural stiffness led to ~34% improvement in damping (mode 2).	[18]
Natural fibers (banana, sisal, jute, chicken feather, palmyra) in polyester	Fiber weight composition; aspect ratio	Optimized composition (15% palmyra, 10% sisal, 5% chicken feather, 70% polyester, aspect ratio 0.25) gave fundamental frequency of 279.7 Hz compared to 609.4 Hz at aspect ratio 0.125. Fiber combinations strongly influence resonance behaviour.	[24]

Review of natural and synthetic fiber composites	—	Provides a comprehensive overview of vibration behaviour in composites. Concludes that natural fibers generally improve damping compared to synthetic fibers, while synthetic fibers often provide higher stiffness and frequency.	[23]

5. Experimental Modal Analysis Techniques

Experimental modal analysis is widely employed to assess the dynamic response of composite materials. The widely accepted test procedure for composite laminates is the impact hammer test, where the composite is subjected to an impulse force and the vibration response is measured using accelerometers.

The measured signals are converted from the time domain to the frequency domain using the Fast Fourier Transform (FFT) technique. Using this technique, the researcher can obtain the natural frequencies of the composite materials.

The formula for calculating the FRF is as follows:

The most commonly used method of experimental modal analysis is impact hammer modal testing. In this method, a modal hammer is used to hit the structure, and accelerometers placed on the specimen are used to measure the response of the structure. The response of the structure, as measured by the accelerometer, is converted from the time domain to the frequency domain by the FFT (Fast Fourier Transform) method to obtain the FRF (Frequency Response Function) [26]. The FRF is defined as:

$$FRF = \frac{X(\omega)}{F(\omega)}$$

where X(ω) and F(ω) denote the response and excitation force, respectively.

A typical test setup employs one or roving impact hammer and one or more accelerometers. To illustrate this, Sahu et al. (2025) employed the test setup to measure the dynamic properties of a jute polyurethane sandwich beam by clamping the beam at one end and impact testing at various points on the beam. An accelerometer was also attached to the beam to measure the out-of-plane acceleration. The data acquisition system employed was the Brüel & Kjær Pulse LabShop. It recorded the impulse response data and averaged the signal from repeated impacts to obtain the FRFs. Djamel Edinne et al. (2022) employed the Brüel & Kjær Pulse impact hammer with a bandwidth of ~1 kHz to measure the dynamic properties of natural fiber polymer beams [29]. The Pulse analyzer was employed to directly record the transfer function between the hammer and the response signal, which is the FRF signal.

Boundary conditions can also affect the dynamics significantly. Support conditions can be one end clamped (Cantilever or CF), one end supported (Simply Supported or SS), or both ends clamped (CC). Sahu et al., in their work on the jute sandwich beam, used CF, SS, and CC support conditions to test the change in the frequency and damping ratio. The key factor in all cases is to make sure that the tests are repeatable by performing multiple impacts at the same point and repeating the tests on multiple identical specimens.

5.1 Procedure Summary:

•**Excitation:** Hit the composite material with an impact hammer, which is normally equipped with a force sensor in the tip.

•**Measurement:** Use accelerometers, which are piezoelectric, to measure the response at the points of interest or roved over the points of interest.

•**Signal Processing:** Measure the time domain response, apply the FFT algorithm to obtain the FRF.

•**Modal Extraction:** Peaks in the FRF correspond to the natural frequencies, and the bandwidth or curve fitting may be used to obtain the damping ratio and mode shape.

This method has been commonly used for natural fiber composite materials. For example, free vibration tests (impact tests) were carried out on short random-oriented coir/polyester plates. The highest first natural frequency (approximately 61.86 kHz) and damping ratio (ζ = approximately 0.296) were recorded for the specimen with 15% coir [27]. In another example, free vibration tests were conducted on sisal/polyester beams. The first natural frequency of 67.38 Hz with a damping ratio of approximately 0.059 was recorded for the specimen with 15% sisal [28]. In another example of a palm fiber beam, a PULSE impact hammer was used to excite the beams with varying orientations of fibers. The FRFs indicated maximum damping when the angle of the fibers was 45 degrees.

Table 4. Experimental Modal Analysis of Natural Fiber Composite Specimens under Various Test Conditions and Boundary Setups

Specimen / Setup	Test Conditions	Key Findings (Modal Data)	Reference
Jute–PU sandwich beam (300 × 30 × 5 mm); one end clamped (CF)	Impact hammer (PULSE), single accelerometer; boundary conditions: clamped-free, simply-supported, clamped–clamped	Natural frequencies and damping ratios obtained from FRFs using FFT (PULSE/MEscope). Example: CF mode 1 frequency ≈ 781 Hz, modal loss factor ≈ 0.0351.	[26]
Coir/polyester plates (200 × 20 × 2 mm); short random fibers (5–20%)	Free vibration (impulse) with FFT analysis	At 15% coir, fundamental frequency ≈ 61.86 kHz, damping ratio $\zeta \approx 0.296$ ($\tan\delta \approx 0.360$ at 10 Hz). Both frequency and damping increased with fiber content up to 15%.	[27]
Sisal/polyester beams (100 × 10 × 3 mm); random 20 mm fibers (5–20%)	Free vibration (impulse) with FFT analysis	15% sisal yielded peak frequency ≈ 67.38 Hz and damping ratio $\zeta \approx 0.059$. Mechanical properties improved up to 15% fiber content; damping reduced beyond this level.	[28]
Palm-fiber/HDPE beams (20% fiber content)	Impact hammer (PULSE, 1 kHz), single accelerometer; fixed boundary	FRFs experimentally obtained using PULSE analyzer. Six bending modes identified. Maximum damping observed at 45° fiber orientation, indicating strong orientation dependence.	[29]

6. Free Vibrational Characteristics of Natural Fiber Composite Laminates

Free vibration testing is one of the significant techniques used to evaluate the dynamic behaviour of composite laminates. The natural frequencies, mode shapes, and damping ratios determined by free vibration testing are influenced by various parameters, namely, fiber type, volume fraction, stacking arrangement, and boundary conditions. The damping ratio is found to be greater in natural fiber-based composites as opposed to synthetic fiber-based composites because of the inherently viscoelastic behaviour of plant fibers and their interfaces [30].

The inherently viscoelastic behaviour of natural fibers makes them more suitable for vibration control-based applications, such as automotive body parts, etc., as long as they are able to fulfill the required stiffness criteria. Generally, with an increase in volume fraction, the laminate's stiffness is found to increase with a corresponding increase in natural frequencies, owing to the inherently viscoelastic behaviour of natural fibers.

6.1 Free Vibration Behaviour of Natural Fiber Laminates

Experimental and numerical studies have been carried out on beams, plates, and sandwich structures. In one such study, the first three natural frequencies of a flax/polymer beam, consisting of flax fibers in an expanded polystyrene waste polymer, were found to be around 28.9 Hz, 180.9 Hz, and 507.5 Hz at 30% fiber loading [30].

These increased with the content of fibers, as the stiffness of the composite increased. Of interest was the fact that the damping ratio of the flax/PS composite was higher than those of synthetic composites, though it reduced with an increase in the content of fibers.

Similarly, experiments carried out on bamboo/epoxy plates indicated that the support condition plays an important role in the determination of the natural frequencies, with clamped/clamped boundaries producing the highest natural frequencies, and cantilever support producing the lowest natural frequencies, owing to the higher stiffness under higher constraint [26].

For the experiment carried out on the beam, consisting of 20% sisal/polyester, the free-vibration test indicated that the first mode natural frequency was ~67.38 Hz, with damping $\zeta \approx 0.059$ (at 15% sisal) [28].

Hybrid laminates also benefit: e.g. embedding a viscoelastic core can raise damping without large frequency loss, as confirmed by both tests and FEA.

This is also supported by numerical models like FEM. Numerical analysis was done on the composite beam made of aloevera fibers using FEM, which indicated that the stacking sequence and the number of plies play a significant role in changing the modal response of the composite beam. Experimental tests like impact

hammer or shaker tests are also conducted to validate the FEA analysis results, wherever possible. It can be concluded that the modal characteristics of natural fiber laminates are similar to the conventional composite laminates with respect to the distribution of mass and stiffness; however, the loss factor is much higher due to damping mechanisms [30].

6.2 Factors Influencing Free Vibration Characteristics

Fiber Volume Fraction: Increasing the fiber content tends to increase the stiffness, hence the natural frequencies. Too much fiber, however, may cause poor resin flow or bonding.

Fiber Orientation and Stacking: Unidirectional plies have high frequencies along the fiber direction, while they have lower stiffness transversely. Cross-ply laminates, with balanced properties, have their stiffness symmetrically distributed.

Boundary Conditions: The constraint conditions should be as high as possible, i.e., the frequencies should be as high as possible. According to a study, the natural frequencies of a cantilever composite plate were much lower than the frequencies of the same plate with clamped ends [26].

Viscoelastic Properties of the Materials: Natural fibers, as well as the polymers, have inherent damping properties. The effect of hygrothermal conditions, i.e., the effect of moisture and temperature, may cause the softening of the matrix as well as the fiber, hence reducing the frequencies with an increase in the damping properties.

6.3 Concluding Remarks on Free Vibrational Characteristics

Literature has demonstrated that a suitable balance of stiffness and damping is possible in natural fiber composites. Most literature agrees that the addition of reinforcement fibers increases the natural frequencies, thus ensuring greater rigidity in structures, while the viscoelastic properties of the fibers/matrix materials ensure increased damping, thus reducing vibrations in structures. For example, the modal test on the flax/EPS composite demonstrated increased damping compared to a synthetic composite.

However, it has been observed that excessive reinforcement fibers result in a decrease in damping properties, albeit slightly. Nevertheless, natural fiber laminates show great potential for ensuring the required properties in lightweight structures subjected to vibrations.

Table 5. Summary of Experimental Modal Behaviour of Natural Fibre-Reinforced Composite Beams under Various Test Conditions

Composite Type / Test Setup	Conditions & Measurements	Key Findings (Modal Behaviour)	Reference
Flax fiber / polystyrene beam (30% flax)	Free vibration (fixed–free); accelerometer + FFT	First three natural frequencies: 28.92 Hz, 180.97 Hz, 507.51 Hz. Damping ratio was higher than synthetic composites but decreased with increasing fiber content.	[30]
Jute-fiber / PUR-core sandwich beam (20% core)	Impact hammer (PULSE), single accelerometer; CF, SS, CC supports	Clamped–clamped condition produced the highest frequencies, while clamped–free gave the lowest (e.g., mode 1: CF ≈ 48.7 Hz, CC ≈ 265.3 Hz). Natural frequencies and damping extracted using FRF.	[26]
Sisal/polyester beam (20% fiber; 15% optimum)	Free vibration (impulse) using accelerometer + FFT (LabVIEW)	At 15% fiber: fundamental frequency ≈ 67.38 Hz, damping ratio $\zeta \approx 0.059$. Increasing fiber content improved stiffness and frequency; peak damping observed at optimal loading.	[28]
Palm (wood fiber) / HDPE beam (20% fiber), fixed base	Impact hammer (PULSE), FRF analysis (LabShop)	Six bending modes identified. Fiber orientation significantly influenced damping; 45° orientation showed maximum damping. Higher constraint conditions increased natural frequencies.	[29]

7. Conclusion

Natural fiber reinforced polymer composites (NFRPCs) have been recognized as a promising group of green composites, as they have lower density, biodegradability, and lower ecological footprint when compared with their synthetic counterparts. The current review points out that the mechanical and dynamic properties of these composites are highly dependent on various parameters, namely the type of fiber, chemical properties, fiber volume fraction, choice of the matrix, laminate structure, and manufacturing process.

Considering the structural and dynamic properties, it has been recognized that NFRPCs show high anisotropic properties, as the properties of these composites are highly dependent on the fiber orientation. One of the major advantages of these composites is their high damping capability, as they show viscoelastic properties of the matrix, interfacial friction between the fiber and the matrix, as well as the inherent complexity of the natural fibers.

Experimental modal analysis and free vibration studies always reveal that with increased percentages of fiber content, both stiffness and natural frequencies increase, but at the same time, they also affect damping properties. Nevertheless, it is essential to strike a balance so that increased fiber loading does not create problems during processing, leading to defects in the composite structure. Manufacturing techniques like VARTM and RTM have been identified as being effective in producing high-quality laminates with better mechanical integrity and reduced defects.

In addition, hybridization techniques and advanced laminate configurations possess considerable potential to tailor both mechanical properties as well as damping properties. It is possible to achieve this by hybridizing natural fibers with synthetic fibers or by optimizing laminate configurations.

Overall, NFRPCs possess considerable potential as a material that has a better balance of mechanical properties, damping potential, as well as sustainability. It is essential to carry out more research to improve fiber-matrix compatibility, advanced processing techniques, as well as utilizing numerical techniques in conjunction with experimental validation to enhance the reliability of this new generation of composite materials.

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Critical Review on Mechanical Properties of Fiber Reinforced Polymer Composite Laminates made of Synthetic Fibers

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ABSTRACT

Synthetic fiber reinforced polymer composite (SFRPC's) materials are widely used in modern engineering structures, as they have high strength, minimum weight, and resistance to corrosion and fatigue when compared with other conventional materials. Synthetic fiber reinforced polymer composite materials are made up of strong synthetic fibers embedded in a polymer resin matrix, where the fibers are subjected to maximum stress and the polymer resin acts as a bonding agent between fibers, transmitting stress from one fiber to another. Synthetic fibers like glass fibers, carbon fibers, and Kevlar fibers are commonly used in various industries, including aerospace, automobile, marine, and civil engineering structures. In recent times, composite manufacturing technologies have been developed, which have improved the properties of composite materials. Advanced composite manufacturing technologies like automated fiber placement, resin transfer moulding, and additive manufacturing have improved composite properties, as they are able to control fiber orientation and minimize defects in composite materials, thereby enhancing their mechanical properties. This review article discusses an overview of synthetic fiber composite materials, their types, and recent developments in composite manufacturing technologies for enhancing their mechanical properties.

KEYWORDS

Fiber reinforced polymer composite (FRPC), Synthetic Fiber, Mechanical properties, Tensile strength, flexural strength, Interlaminar Shear Stress (ILSS)

Introduction

Synthetic fiber reinforced polymer composite materials have emerged as one of the most significant groups of engineering materials over the past few decades due to the high level of mechanical properties, lightweight nature, and high durability of the composite materials [1,2]. The increased need for high-performance products in the aerospace, automotive, marine, and civil industries has made composite materials one of the most widely used materials in the field [3,4,10]. Compared to the traditionally used materials such as metals, composite materials have high strength-to-weight ratios, fatigue resistance, and high resistance to corrosive environments [1,5,8].

The synthetic fibers used in composite materials are mostly man-made fibers that are used to improve mechanical properties [11]. The synthetic fibers that are commonly used are glass fibers, carbon fibers, and aramid fibers, such as Kevlar [1,3,4]. The synthetic fibers possess various properties that make them suitable for use in composite materials [12]. The glass fibers are widely used because they are cost-effective and possess better mechanical properties [4]. The carbon fibers possess better mechanical properties, such as high modulus values and better strength-to-weight ratio. The aramid fibers possess better impact properties, toughness, and energy absorption. The type of synthetic fibers plays a significant role in determining the mechanical properties [1,12].

In fiber reinforced composites, fibers are embedded in a continuous matrix phase that holds the fibers together, transmits loads, and protects them against environmental influences. In synthetic fiber reinforced polymers, the most common matrices are polymers. They are broadly classified as thermosetting resins and thermoplastics. Thermosetting resins such as epoxy, polyester, and vinyl ester are popular choices owing to their high stiffness, bonding properties, and dimensional stability. Thermoplastics such as polypropylene, polyamide, and advanced polymers such as PEEK have their own benefits, which include increased toughness and impact properties. The fiber and matrix interaction is an important parameter in determining the mechanical properties of the composite.

The structural configuration and orientation of fibers in the composite material have a significant effect on the mechanical properties [2,12]. Synthetic fiber composite materials are available in different forms, such as unidirectional laminates, bidirectional

laminates, and woven fabric composites. In the case of unidirectional composites, maximum strength and stiffness are provided in one direction, whereas in the case of bidirectional composites, properties are provided in two directions [1,2]. In the case of woven fabric composites, dimensional stability and delamination resistance are provided in the composite material. Other forms of synthetic fiber composite materials are chopped fiber composites and hybrid composite materials [12].

The mechanical properties of synthetic fiber composite materials, such as tensile strength, flexural strength, impact strength, and fatigue, are affected by fiber type, fiber volume fraction, matrix material, and manufacturing technique [1,5,6]. Apart from mechanical properties, the dynamic properties of composite materials, such as vibration characteristics, have gained importance in engineering applications. Due to the anisotropic and heterogeneous properties of composite materials, their vibration characteristics are quite complex [16]. These characteristics are governed by parameters such as natural frequency, damping ratio, and mode shapes [22].

The advent of advanced manufacturing techniques such as automated fiber placement, resin transfer moulding, and additive manufacturing has led to better control in terms of fiber orientation as well as reduction in defects during fabrication [1,14]. The mechanical properties of synthetic fiber-reinforced polymer composite materials have been significantly improved by recent advancements [12,17]. As such, recent research has been focused on optimizing various techniques to enhance the properties of synthetic fiber-reinforced polymer composite materials. The relationship between fibers, matrix, and structure is significant in utilizing synthetic fiber-reinforced polymer composite materials in modern engineering [16].

2 Manufacturing Methods

Manufacturing of synthetic fiber reinforced polymer (FRP) composites is an important aspect that plays a major role in determining the mechanical properties, durability, and overall performance of the composites [1,11,12]. The various manufacturing processes of synthetic FRP composites depend on the type of fibers used, i.e., glass, carbon, or aramid fibers, commonly known as Kevlar. Manufacturing of synthetic FRP composites is an important aspect that plays a major role in determining the mechanical properties, durability, and overall performance of the composites. [1,11]. Understanding the various manufacturing processes of synthetic FRP composites is important in determining the mechanical properties of the composites.

2.1 Hand Lay-Up Process

The hand lay-up process is the most basic and traditional method of manufacturing synthetic FRP composites. In this method, the reinforcing fibers are placed in the mould, and the resin is applied in the form of a layer using brushes or rollers. Each layer is pressed to ensure that the resin is properly impregnated into the fibers, reducing the air pockets in the composites. This process is widely used because it is cost-effective and requires less equipment. It is best suited for large-sized products with simple geometries, such as a boat's hull, storage tanks, and panels. The flexibility of this technique makes it easier to change the orientation of fibers during the fabrication process [1]. However, this hand lay-up technique has some drawbacks. These include irregular fiber placement, more voids, and varying mechanical properties. The hand lay-up technique is labour-intensive because it requires human intervention. As a result, the product may not be consistent [12].

2.2 Spray-Up Process

The spray-up technique is an advanced version of the hand lay-up technique. In this technique, chopped fibers and resin are sprayed simultaneously on a mould using a spray gun. The spray-up technique is more efficient because it increases production rates with less labour. The spray-up technique is widely used to produce large-sized complex products such as automotive body parts, boats, and sanitary products [4,10]. The technique is more appropriate for medium-scale production because it is faster in covering large surfaces. However, despite all the advantages, the mechanical properties are compromised by using chopped fibers instead of continuous fibers [5]. The product may also suffer from uneven thickness, as well as wastage.

2.3. Resin Transfer Moulding (RTM)

Resin transfer moulding is a closed mould process that involves placing dry fiber preforms inside a mould. The mould is then subjected to resin injection under pressure. This is to ensure that all the fibers get impregnated with resin. Resin transfer moulding has several advantages, such as better surface finish, low void content, and better mechanical properties. These are some of the reasons why this process is used in various industries, such as automotive and aerospace [3,4]. However, RTM demands sophisticated equipment and higher initial investment. It is important to control various factors such as pressure and resin flow in the process, as it affects the final product [16].

2.4. Vacuum Assisted Resin Transfer moulding (VARTM)

VARTM is an advanced version of RTM, in which resin is injected into the preform using a vacuum

pressure system. This ensures proper wetting of the fibers by resin, thus reducing the presence of defects in the final product. This method is used for manufacturing large structures such as wind turbine blades and shipbuilding [10]. It ensures proper wetting of fibers, thus improving the mechanical properties of the final product [16]. Although VARTM ensures a better quality product, it demands proper control of resin flow in the system. It also takes a longer time compared to other methods such as high-pressure moulding.

2.5. Filament Winding

Filament winding is a special technique used in the manufacture of cylindrical and pressure vessels. Fibers are impregnated with resin and wound in a desired pattern [1,11]. This technique offers the advantage of controlling the direction of the fibers, which imparts high strength and stiffness to the composite material. It is also widely used in the manufacture of pipes, tanks, and pressure vessels. The disadvantage of this technique is that filament winding can be done only with axisymmetric shapes. Complex shapes cannot be made using this technique [12].

2.6. Pultrusion

Pultrusion is a continuous manufacturing process used for producing profiles of constant cross-section. Pultrusion works by pulling fibers through a resin bath, then through a heated tool called a die, where resin is cured. This method ensures that fibers have a high volume fraction, are well aligned, and have consistent mechanical properties [1,5]. It is used for manufacturing structural components such as beams, rods, and channels [1,10]. However, pultrusion is only used for producing profiles of constant cross-section, such as beams, rods, and channels. It is not used for manufacturing components with complex geometries [12].

2.7. Compression moulding

Compression moulding is commonly used for producing composite materials in large volumes. Compression moulding works by placing fibers and resin in a heated tool called a mould, then compressing them into the desired shape. This method ensures that the final product has a smooth surface, precise dimensions, and low void content [1,12]. It is used in the automotive industry for producing lightweight structures. However, it requires expensive tools, which makes it unsuitable for low-volume production. It also requires precise temperature and pressure control [16].

2.8. Automated Fiber Placement (AFP)

Automated fiber placement is a sophisticated manufacturing technique wherein fiber tapes or tows are placed on a mould surface using robotic equipment. The fiber orientation can be controlled with precision [14]. AFP is widely used in aerospace industries that demand precision and high-performance products [3,14]. The equipment is also helpful in reducing waste materials as well as ensuring consistency in the product. However, this technique requires skilled labour and is costly. It is mostly used in large-scale industries.

2.9. Additive Manufacturing (3D Printing)

Additive manufacturing is a new technique wherein composite materials are processed layer by layer using fiber-reinforced thermoplastics. The advantage of this technique is that complex shapes can be easily manufactured using this technique. The equipment is helpful in reducing waste materials. However, the mechanical properties of 3D printed composite materials are still low. The mechanical properties need to be improved using this technique.

2.10. Optimal Manufacturing Method for Synthetic FRP Composites

The selection of a suitable manufacturing technique is critical in ensuring that the desired mechanical properties are achieved in synthetic fiber reinforced polymer (FRP) composite materials [1,11,12]. Among the various techniques that are available, hand lay-up, resin transfer molding (RTM), vacuum assisted resin transfer molding (VARTM), automated fiber placement, etc., are some of the techniques that are being used depending on the application requirements. These techniques possess various advantages depending on the application requirements. Nevertheless, when mechanical properties are of prime importance, the selection of a manufacturing technique is critical [5,6].

Among these techniques, vacuum assisted resin transfer molding is regarded as one of the most effective techniques available for manufacturing high-quality FRP composite materials. In this technique, dry fiber reinforcements such as glass fibers, carbon fibers, or aramid fibers such as Kevlar are packed into a mold, after which resin is pulled into the fiber structure using a vacuum. The application of a vacuum not only results in better resin distribution but also removes any entrapped gases, thereby reducing the porosity within the composite material. As a consequence, mechanical properties such as strength, stiffness, and fatigue life are improved in composite materials manufactured using this technique as opposed to those manufactured using open mold techniques [5,7,15].

In addition to this, VARTM also offers good cost and performance trade-offs, making it an ideal choice for both research and industrial purposes. While other advanced methods, such as AFPL, demand high capital costs for their implementation, VARTM can be implemented with relatively low capital costs. In addition, the process is also suitable for manufacturing structures of large and complex geometries. Some of these structures include

aerospace structures, wind turbine blades, and marine structures. Hence, based on all these factors, it can be concluded that VARTM is an optimum process for manufacturing synthetic fiber reinforced polymer composite materials [1,12,16].

Table 1. Overview of Composite Manufacturing Methods with Process Description, Advantages, Limitations, and Typical Applications

Manufacturing Method	Process Description	Advantages	Limitations	Typical Applications	Reference
Hand Lay-Up	Manual placement of fiber layers with resin applied in an open mould.	Low cost, simple fabrication.	High voids, inconsistent quality.	Boat hulls, panels.	Oliveux, G., Dandy, L. O., & Leeke, G. A. (2015).
Compression Molding	Fibers/prepregs compressed in heated mould under pressure.	Uniform thickness, high production rate.	High tooling cost.	Automotive parts, structural panels.	Faruk, O., Bledzki, A. K., Fink, H. P., & Sain, M. (2012).
Resin Transfer Molding (RTM)	Resin injected into dry fibers in a closed mould.	Good surface finish, low void content.	Complex mould design.	Aerospace, automotive components.	Kuentzer, N., Simacek, P., Advani, S. G., & Walsh, S. (2007).
Vacuum Assisted Resin Transfer Molding (VARTM)	Vacuum draws resin into fiber layers in sealed mould.	Better fiber wetting, reduced defects.	Longer processing time.	Wind turbine blades, marine structures.	Dhakal, H. N., Zhang, Z. Y., & Richardson, M. O. W. (2007).
Filament Winding	Continuous fibers wound over rotating mandrel.	High strength and fiber alignment.	Limited to cylindrical shapes.	Pipes, pressure vessels.	Clarke, J. L. (1996).
Pultrusion	Fibers pulled through resin and heated die to form profiles.	High fiber volume, continuous production.	Limited to constant shapes.	Beams, rods, structural sections.	Joshi, S. C., & Lam, Y. C. (2005).
Automated Fiber Placement (AFP)	Robotic placement of fiber tapes with controlled orientation.	High precision, superior performance.	Very high cost.	Aerospace structures.	Lukaszewicz, D. H. J. A., Ward, C., & Potter, K. D. (2012).

3. Control Parameters Affecting FRP laminates

The mechanical and dynamic properties of synthetic fiber reinforced polymer composites are dependent on a group of crucial parameters that are referred to as control parameters [1,11,12]. These parameters are carefully selected and controlled during the process of fabrication of the composites, as well as during the tests, in order to obtain precise results regarding the effect of individual parameters on the properties of the composites [6,16]. The control parameters have a major influence on the bonding of synthetic fibers with the matrices, the efficiency of load transfer, the stiffness, strength, fatigue, and vibration of synthetic fiber reinforced polymer composites [5,15,22].

Synthetic fibers, as well as natural fibers, differ in their geometry, mechanical properties, and chemical composition [11]. The properties of synthetic fibers, like glass, carbon, and Kevlar, are much more consistent as compared to the properties of natural fibers [1,3,4]. Nevertheless, the properties of synthetic fiber reinforced polymer composites laminates are highly dependent on the conditions of fabrication, the orientation of the synthetic fibers, as well as the properties of the matrices [1,12,16]. Even the slightest variation in the conditions of fabrication of the synthetic fiber reinforced polymer composites may lead to defects, which may, in turn, influence the structural integrity of the composites [1,8].

3.1 Material Parameters

Material-related parameters describe the intrinsic properties of the reinforcement and matrix phases used in synthetic fiber composites [11,12]. One of the most important material-related parameters of synthetic fiber composites is the type of fiber used [1,3,4]. Synthetic fibers, such as glass, carbon, and Kevlar, offer excellent mechanical properties, such as high tensile strength, rigidity, and durability [2,3,5]. In contrast to natural fibers, the structure of synthetic fibers is consistent, ensuring consistent performance of the composite material [11]. The type of fiber used plays an important role in improving the load-carrying capacity of the composite [1,5].

The volume fraction of the fibers used in the composite material is another important parameter [1,5]. The volume fraction of the fibers indicates the amount of fiber used in the composite material [1]. The volume fraction of the fibers used in the composite material plays an important role in improving the rigidity of the composite material [5].

The type of matrix used in the composite material is another important parameter [11]. The matrix phase of the composite material is generally composed of thermosetting polymers such as epoxy, polyester, and vinyl ester resins, due to their good bonding characteristics and thermal stability [1,11].

Surface treatment of synthetic fibers is another key factor that needs to be taken into consideration for the enhancement of the interaction between fibers and matrices [25]. Plasma treatment, chemical coating, or sizing of synthetic fibers are carried out for efficient bonding and effective stress transfer [25]. Efficient control of these factors will lead to improved mechanical properties, minimization of defects, and enhancement of durability of SFRPC composites [8,25].

3.2 Structural Parameters

Structural parameters define the configuration or arrangement of synthetic fibers in the structure of the composite laminate [1,12]. Orientation of synthetic fibers is a key factor in the determination of the mechanical and dynamic behavior of SFRPC composites [2,22]. Unidirectional fibers are used for maximum strength and stiffness along the direction of fibers, whereas bidirectional or woven fibers are used for balanced properties and resistance to bidirectional loading [1,2].

Another significant structural parameter related to the laminate is the stacking sequence of the laminate layers [2,16]. Various laminate configurations such as symmetric laminates, cross-ply laminates, and angle-ply laminates are considered in the analysis [2]. The laminate configurations are significant in the context of vibration analysis as the sequence of laminate layers affects the propagation of the vibration energy [22].

The laminate thickness is also one of the significant parameters related to the laminate that affects the stiffness and mass of the composite laminate [1,22]. Increasing the laminate thickness increases the bending stiffness and natural frequency of the laminate [22]. Increasing the laminate thickness also increases the interlaminar stresses in the laminate [7].

3.3 Manufacturing Parameters

Manufacturing parameters are related to the manufacturing techniques adopted for the production of synthetic fiber composite materials [1,11]. Parameters such as curing temperature, curing pressure, and processing time play a significant role in controlling the final microstructure of the synthetic fiber composite materials [1,16]. Controlling the curing temperature is crucial in ensuring the complete polymerization and cross-linking of the resin, thus improving the mechanical properties of the synthetic fiber composite materials [1,12].

Curing pressure is another important manufacturing parameter, which assists in the consolidation of the

synthetic fiber composite materials [1]. Higher pressure ensures efficient wetting of the fibers, thus reducing defects such as air pockets and resin-rich areas [1,8]. The manufacturing techniques adopted for the production of synthetic fiber composite materials, such as hand lay-up, compression molding, resin transfer molding (RTM), and vacuum-assisted resin infusion (VARTM), also play an important role in controlling the final microstructure of the synthetic fiber composite materials [1,14].

The resin flow and infiltration behavior are critical in controlling the wetting efficiency of the synthetic fiber composite materials [16]. Efficient resin infiltration ensures efficient wetting of the synthetic fibers, thus improving the mechanical properties of the synthetic fiber composite materials [5,15].

Table 2. Classification of Key Control Parameters Influencing the Performance of Composite Materials

Parameter Category	Control Parameter	Influence on Composite Performance
Material Parameters	Fiber type (glass, carbon, Kevlar), fiber volume fraction, matrix type	Determines stiffness, tensile strength, fatigue resistance, and damping behaviour
Structural Parameters	Fiber orientation, stacking sequence, laminate thickness	Influences anisotropic properties, load distribution, bending stiffness, and natural frequency
Manufacturing Parameters	Curing temperature, curing pressure, resin flow/infiltration	Affects void content, fiber wetting, interfacial bonding, and overall laminate quality
Testing Parameters	Boundary conditions, excitation method, sensor placement	Determines accuracy of vibration analysis, modal parameters, and dynamic response

4. Mechanical Behaviour in Composite Structures

The mechanical properties of composite structures mainly rely on their strength, rigidity, and deformation properties [11,12]. In composite materials, especially laminate composites, the properties of these materials rely on the relationship between the reinforcing fibers and their matrix [1,16]. The properties of these composites also rely on their ability to transfer loads efficiently [5,15]. Composite materials, especially laminate composites, have anisotropic properties [1,22]. This means that these materials do not have constant properties in all directions [22]. This property of composites is mainly due to their fiber orientation [2,22].

In synthetic fiber reinforced polymer composites (SFRPCs), several properties affect their mechanical properties [1,5]. The fiber type, fiber volume fraction, fiber orientation, matrix properties, and fiber-matrix bonding properties affect the mechanical properties of SFRPCs [1,5,16]. These properties mainly affect tensile strength, flexural strength, and shear strength [5]. The fiber-matrix bonding properties mainly affect stress transfer from one material to another [16]. The bonding properties of these materials also affect their failure properties [7]. The fiber-matrix bonding properties affect delamination and fiber pull-out [7].

The failure behavior of composite laminates is affected by various mechanisms, such as matrix cracking, fiber breaking, interface separation, and interlaminar separation [7,23]. Of these, the interlaminar failure mode is particularly important in laminated structures, as it has a direct bearing on the shear properties of the laminates [7]. It is important to understand these deformation and failure mechanisms in order to optimize the design of composites for enhanced reliability and structural integrity [11,23].

4.1 Experimental Techniques for Mechanical Characterization

Experimental tests of mechanical properties are of great importance to evaluate the behavior of composite laminates under various conditions of loading [1,5]. Standard tests of mechanical properties, such as tensile, flexural, impact, and fatigue tests, are used to evaluate the behavior of synthetic fiber-reinforced polymer composite materials [5,6]. These tests are conducted following standardized procedures, such as ASTM tests [13].

In tensile tests, the specimen under consideration is subjected to uniaxial tension until failure occurs [5]. The important properties are evaluated by the following equations:

$$\sigma = F/A, \quad E = \sigma/\varepsilon$$

where σ denotes the tensile stress, F denotes the applied load, A denotes the cross-sectional area, E denotes the modulus of elasticity, and ε denotes strain. This test provides important properties such as ultimate tensile strength, Young's modulus, and elongation at break, which describe the ability of the composite material to withstand loads [5].

In flexural tests, usually three-point bending tests are conducted to evaluate flexural stress and modulus of the composite material by the following equations [5]:

$$\sigma_f = 3FL / 2bd^2, \quad E_f = L^3m / 4bd^3$$

where F is the applied load, L is the support span, b is the specimen width, d is the thickness, and m is the slope of the load-deflection curve. This type of test is used to measure the bending strength and stiffness of the composite material [5].

The interlaminar shear strength (ILSS) test is performed to evaluate the bonding strength between the layers of composite laminates [7]. This test is particularly important for laminated composites, where failure often occurs due to delamination between layers [7]. The ILSS is commonly determined using the short beam shear (SBS) test method, conducted according to standard procedures such as ASTM D2344 [13].

In this test, a short specimen is subjected to three-point bending with a small span-to-thickness ratio, which induces maximum shear stress at the weakest plane of the laminate [7]. The interlaminar shear strength is calculated using the following equation:

$$\tau = 3F / 4bd$$

where τ is the interlaminar shear strength, F is the applied load at failure, b is the specimen width, and d is the thickness of the specimen. This test provides a measure of the resistance of the laminate to interlayer failure and is highly sensitive to fiber–matrix bonding and manufacturing defects such as voids and poor adhesion [7,8].

Synthetic fiber reinforced polymer composites (SFRPCs) are commonly employed in various engineering applications due to their high strength-to-weight ratio, stiffness, and durability [1,11,12]. The primary factors influencing the mechanical behaviour of SFRPCs are the material properties of reinforcing fibers, matrix materials, and fiber-matrix interaction [1,5,16]. The knowledge of material properties is necessary to select suitable materials for structural applications [11,12].

In this section, an evaluation and comparison of various significant material properties of SFRPCs are discussed, with special reference to tensile strength, flexural strength, and interlaminar shear strength (ILSS) [5,7]. The material properties play an important role in assessing the behaviour of composite laminate materials in different loading conditions, such as longitudinal tension, bending, and shear [5,15].

Moreover, this section includes a comparative study of various synthetic fibers, such as glass fibers, carbon fibers, and Kevlar fibers, along with various matrix materials, such as epoxy, polyester, and vinyl ester, with reference to available literature to understand the effect of material and composite configurations on SFRPCs [1,3,4,11].

In the following subsections, the properties of various fiber materials, the influence of the matrix system, and the experimental findings are discussed, which would give a comprehensive idea of the mechanical properties of synthetic fiber composite laminates [5,16].

4.2 Mechanical Properties of Different Synthetic Fibers

The mechanical properties of synthetic fiber reinforced polymer composites (SFRPCs) vary depending on the synthetic fibers used as the reinforcement [1,5,12]. Different synthetic fibers have unique mechanical properties, which play a vital role in the overall performance of the Synthetic Fiber Reinforced Polymer Composite laminate [2,3,4]. Some of the synthetic fibers used as reinforcement are glass fibers, carbon fibers, Kevlar fibers, etc. [1,3,4]. These fibers have unique advantages depending on the specific requirement of the Synthetic Fiber Reinforced Polymer Composite laminate [12].

Glass fibers are used as reinforcement due to the low cost, good tensile strength, and easy fabrication of the laminate [4]. These fibers have good stiffness and strength, making them ideal for structural purposes [4,10]. On the other hand, carbon fibers have high stiffness, good tensile strength, low density, and good strength-to-weight ratio, making the laminate ideal for aerospace and automobile industries [2,5]. Kevlar fibers have good toughness, whereas the compressive strength of these fibers is relatively low compared to carbon fibers [3].

The difference in the mechanical properties of these fibers can be attributed to the differences in the internal structures of these fibers [2,3]. The crystalline structure of the carbon fibers makes them stiff [2]. The glass fibers have an amorphous structure, which makes them strong [4]. The Kevlar fibers have a polymeric structure, which makes them tough [3]. They have the ability to absorb a lot of energy [3]. The differences in the structures of these fibers play a crucial role in the determination of the performance of the composite laminates [1,12].

Table 3. Mechanical Properties and Key Characteristics of Common Synthetic Fibres Used in Composite Materials

Fiber Type	Tensile Strength (MPa)	Young's Modulus (GPa)	Density (g/cm³)	Key Characteristics
Glass Fiber	2000 – 3500 [4]	70 – 85 [4]	2.5 [4]	Economical, good strength, widely used in structural applications [4,10]
Carbon Fiber	3000 – 6000 [2,5]	200 – 600 [2,5]	1.7 – 2.0 [2]	Very high stiffness, lightweight, excellent strength-to-weight ratio [2,5]
Kevlar Fiber	2800 – 3600 [3]	70 – 130 [3]	1.44 [3]	High toughness, excellent impact and abrasion resistance [3]
Basalt Fiber	2800 – 4800 [11,12]	85 – 95 [11]	2.6 – 2.8 [11]	Good thermal stability, corrosion resistance, eco-friendly alternative [11,12]

The data provided in the figure suggest that carbon fibers possess the highest stiffness and strength, whereas glass fibers are also available at a lower cost. Kevlar fibers, although less stiff compared to carbon fibers, are highly effective for applications where impact resistance and energy absorption are required. Hence, it is found that the selection of fibers is based on the mechanical requirements and conditions for the composite material.

4.3 Effect of Matrix Materials on Mechanical Properties

The material used in the matrix is of primary importance in determining the mechanical properties of synthetic fiber reinforced polymer composite materials (SFRPCs) [1,11,12]. Although it is the fibers that carry most of the load in SFRPCs, it is the matrix material that binds the fibers and provides necessary protection from environmental and mechanical hazards [1,16]. The effectiveness of interfacial stress transfer is found to significantly affect important mechanical properties of SFRPCs, such as tensile strength, flexural strength, and interlaminar shear strength (ILSS) [5,7,16].

Amongst various classes of matrix materials used for SFRPCs, thermosetting polymers such as epoxy, polyester, and vinyl ester resins have found wider application owing to their favourable properties and ease of processing and application [1,11]. Epoxy resin is found to have superior bonding and mechanical properties, thus imparting high values of tensile and ILSS [5,7]. Polyester resin, on the other hand, is found to be cost-effective and easily processable, but its bonding and mechanical properties are found to be inferior compared to epoxy resin [1,4]. Vinyl ester resin is found to have intermediate properties, as it provides a balance of mechanical and chemical properties [11].

Another factor is the type of material used in the matrix [16]. This is significant in that it determines the bonding between the fiber and the matrix [16]. A strong bond ensures efficient transfer of stress and minimizes the possibility of delamination [7,16]. On the other hand, a weak bond may cause premature failure modes such as fiber pull-out and interlayer separation [7]. Furthermore, the matrix material's stiffness, toughness, and cure response affect the deformation and failure characteristics of the composite laminate [1,16].

Table 4. Mechanical Properties and Performance Comparison of Common Polymer Matrix Materials

Matrix Type	Tensile Strength (MPa)	Flexural Strength (MPa)	ILSS (MPa)	Key Observation
Epoxy	70 – 100 [5,11]	100 – 150 [5]	20 – 40 [7]	Strong fiber–matrix bonding, highest overall performance [5,7,16]
Polyester	40 – 70 [1,4]	70 – 120 [1]	15 – 25 [7]	Economical, moderate strength, weaker adhesion [1,4]
Vinyl Ester	60 – 90 [11]	90 – 140 [11]	18 – 35 [7]	Balanced properties, good chemical resistance [11,8]

From the data presented in this section, it can be concluded that epoxy-based composites exhibit better mechanical properties due to improved bonding between interfaces, whereas polyester-based systems are more appropriate for low-cost applications. Vinyl ester-based systems can be considered to be a compromise in terms of mechanical properties and cost.

4.4 Experimental Results of FRP laminates from Literature

The mechanical properties of synthetic fiber reinforced polymer composites have been studied in detail through experimental investigations published in the literature [5,6,15]. Such investigations are useful in understanding the effect of various combinations of fibers and matrices on various mechanical properties of SFRPCs [1,5,16]. Unlike

the usual properties discussed in earlier sections of this chapter, the properties discussed in this section are based on actual tests performed on composite laminates [5].

A wide variety of literature has been reported showing the superior mechanical properties of carbon fiber reinforced epoxy composites due to the high stiffness of carbon fibers and the strong bonding between the fibers and the matrix [2,5,15]. The tensile strength of carbon fiber reinforced epoxy composites is reported to be between 800 MPa and 1500 MPa [5,15]. Similarly, the flexural strength of carbon fiber reinforced epoxy composites is reported to be up to 1200 MPa [5]. The interlaminar shear strength of carbon fiber reinforced epoxy composites is reported to be between 60 MPa and 90 MPa [7,15].

Glass fiber reinforced composites, such as glass/epoxy composites, are commonly employed because of their cost-effectiveness and good mechanical properties [1,4]. From the experimental results, the range of tensile strength of glass/epoxy composites was found to vary from 300 MPa to 900 MPa, and the range of flexural strength was found to vary from 500 MPa to 1000 MPa [4,5]. In addition, the ILSS of glass/epoxy composites was found to vary from 20 MPa to 50 MPa, which is lower than that of carbon-based composites due to weak bonding between the fibers and matrices, as well as low stiffness of the glass fibers [4,7].

Composites containing Kevlar fibers show specific mechanical properties, which include high values of toughness and energy absorption [3]. Experimental investigations on Kevlar/epoxy composites show specific values of tensile strength, which lie in the range of 500 MPa to 1000 MPa [3,5], whereas values of flexural strength are relatively lower compared to carbon composites owing to lower compressive strength of aramid fibers [3]. ILSS values lie in the range of 25 MPa and 45 MPa [7].

Besides fibers, various parameters such as fiber orientation, laminate stacking, and fiber fraction also influence the specific values of mechanical properties of composites [1,2,16]. Unidirectional composites show higher values of tensile strength along the fiber direction, whereas woven composites show more balanced values of mechanical properties [2]. Increasing values of fiber fraction also show improved values of stiffness and strength, whereas excessive values of fibers result in poor resin impregnation and higher void content [1,5].

Table 5. Mechanical Performance Comparison of Fibre–Matrix Combinations in Composite Materials

Fiber	Matrix	Tensile Strength (MPa)	Flexural Strength (MPa)	ILSS (MPa)	Key Observation
Carbon Fiber	Epoxy	800 – 1500 [5,15]	900 – 1200 [5]	60 – 90 [7,15]	Highest stiffness and strength [2,5]
Glass Fiber	Epoxy	300 – 900 [4,5]	500 – 1000 [4,5]	20 – 50 [7]	Balanced performance, economical [1,4]
Kevlar Fiber	Epoxy	500 – 1000 [3,5]	400 – 800 [3]	25 – 45 [7]	High toughness, lower compressive strength [3]
Glass Fiber	Polyester	250 – 700 [1,4]	400 – 800 [1]	15 – 35 [7]	Lower strength due to weaker bonding [1,4]
Carbon Fiber	Vinyl Ester	700 – 1200 [11,15]	800 – 1100 [11]	50 – 80 [7]	Good chemical resistance with high strength [11,8]

The comparative results clearly show that carbon fiber composites possess the highest mechanical properties compared to the other composites, especially in terms of tensile and flexural strength [2,5,15]. Glass fiber composites, although possessing lower strength properties, are still commonly utilized in practice because of their cost-effectiveness and ease of processing [1,4]. Kevlar fiber composites are best utilized in structures that demand high impact properties and energy absorption capacity [3].

Based on the experimental results, the selection of the material and configuration of composites play a significant role in achieving the desired properties [1,11,16]. Using high-performance fibers along with matrix systems and optimum conditions of processing can significantly enhance the mechanical properties of synthetic fiber composite laminates [5,6,15].

5. Results and Discussion

The experimental data provided in the preceding section indicate considerable variation in the mechanical properties of synthetic fiber reinforced polymer composites (SFRPCs) depending upon the fiber type, matrix material, and composite configuration [1,5,16]. Among all the fiber materials considered in this investigation, it is evident that

composites reinforced with carbon fibers possess the highest values of tensile and flexural strength [2,5,15]. This is primarily due to the high values of stiffness and strength of carbon fibers and their ability to withstand loads [2,5].
Composites reinforced with glass fibers, although possessing relatively low values of mechanical properties compared to composites reinforced with carbon fibers, provide a balanced set of strength, cost-effectiveness, and manufacturing aspects [1,4]. These composites are commonly employed in engineering applications where relatively low values of mechanical properties are sufficient [4,10]. On the other hand, composites reinforced with Kevlar fibers possess excellent values of toughness and energy absorption [3]. However, their relatively low values of compressive strength and stiffness result in low values of flexural strength compared to composites reinforced with carbon fibers [3].
The influence of the matrix material is also clearly evident from the results [1,11]. Epoxy-based composites have shown improvements in tensile strength and ILSS due to the superior bonding characteristics of the matrix [5,7]. Polyester-based composites have shown poor performance due to inferior bonding characteristics [1,4]. Vinyl ester-based composites have shown moderate performance [11].
Apart from the above-mentioned factors, the fiber orientation, stacking sequence of the fibers, and fiber volume fraction are also very important [1,2,16]. Unidirectional fiber composites have shown superior performance in terms of tensile strength [2]. Multidirectional fiber composites have shown nearly uniform properties [2]. However, the peak values are slightly reduced [2]. Increasing the fiber volume fraction has shown improvements in the mechanical properties [5]. However, an excessive volume fraction of fibers may result in poor resin impregnation [1].
Overall, the findings in this section reinforce the notion that the mechanical response of SFRPCs is not dominated by a single factor, but is a result of a combination of fiber and matrix characteristics and processing parameters [1,11,16]. These parameters should be optimized for superior mechanical performance [6,15].

6. Conclusion

In the review, the mechanical properties of synthetic fibre reinforced polymer composites (SFRPCs) are discussed. These properties include the tensile strength of the composites, the flexural strength of the composites, and the interlaminar shear strength (ILSS) of the composites. The review indicates that the mechanical properties of the composites are significantly affected by the types of fibres used. In the review, it is noted that the use of carbon fibres produces the strongest composites. However, the use of glass fibres is noted to be an economical option. Kevlar fibres are noted to be the best option when toughness is a requirement.
This analysis also tells us that the use of an epoxy matrix is noted to be the best option due to the bonding characteristics of the matrix. However, the use of a polyester matrix is noted to be an economical option. In the review, the configuration of the composites is noted to have a significant effect on the performance of the composites. In conclusion, the SFRPCs have excellent potential for use in engineering applications due to the lightweight nature of the composites.

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A Critical Review on Mechanical Properties of Reinforced Polymer Composite Laminates made of Natural Fibers

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Abstract

In recent years, more emphasis has been placed on the creation of eco-friendly and sustainable engineering materials. Natural fiber-reinforced composite materials (NFRCs) have been recognized as potential alternatives to conventional synthetic fiber composite materials due to their low density, biodegradability, cost-effectiveness, and comparable mechanical properties. These composite materials have been widely applied in automotive, aerospace, and civil engineering structures, especially in those applications requiring lightweight and high-strength structures. The current review provides a comprehensive review of natural fiber-reinforced composite laminates, especially in relation to static mechanical properties, which include tensile strength, flexural strength, compressive strength, impact resistance, and hardness. The influence of critical parameters, especially in relation to fiber type, volume fraction, surface treatment, and stacking sequence, on the properties of composite laminates is also reviewed.

Keywords

Natural fiber reinforced composites (NFRCs), Mechanical properties, Tensile strength, Flexural strength, Compressive strength, Impact resistance, Hardness

1. Introduction

Natural fiber reinforced polymer composites (NFRPCs) have received significant interest in recent decades as a sustainable option to traditional synthetic fiber reinforced polymer composites. The rising environmental awareness, stringent regulations on the sustainability of materials, and the ever-increasing need for lightweight structures in engineering applications have prompted the development of bio-based composite materials. Natural fibers, which are plant-based renewable resources, possess a number of benefits such as low density, biodegradability, cost-effectiveness, and good mechanical properties. Natural fibers also show advantages in terms of environmental friendliness and low energy consumption in their production process when compared to traditional reinforcement materials such as glass and carbon fibers. [1,2,10]

Natural fibers are made up of various components, which include cellulose, hemicellulose, lignin, pectin, and waxes.

Out of these components, cellulose has a major role to play with respect to the strength of the fibers, as it has a highly ordered microfibrillar structure.

Due to this ordered structure, the fibers have a major impact on their mechanical properties, like tensile strength, stiffness, and their ability to carry loads.

Moreover, the cellular structure of the fibers has a major impact on their energy absorption properties, which has made them useful for various applications.

Due to these properties, natural fiber composites have been increasingly used for various applications, like the automotive industry, construction industry, marine industry, and consumer products.

The natural fibers can be broadly classified into several categories depending on their sources. The plant fibers comprise the most common type of natural fibers. They are divided into three subgroups: bast fibers, leaf fibers, and seed/fruit fibers. The bast fibers include flax, jute, kenaf, and hemp. The leaf fibers comprise sisal fibers and pineapple fibers. The seed/fruit fibers comprise cotton fibers and coconut coir fibers. Besides these plant fibers, there are other natural fibers such as animal fibers and mineral fibers.

The most common type of natural fibers used for polymer matrix composites is plant fibers. This is because they are readily available at low cost and have acceptable mechanical properties. The bast fibers such as flax and hemp have higher tensile strength and stiffness than other natural fibers. Jute and kenaf fibers provide a reasonable combination of mechanical performance and economic viability.

The mechanical properties of composite laminates made from natural fibers are affected by several factors, including tensile strength, flexural strength, compressive strength, impact resistance, and hardness.

In composite laminates, unidirectional laminates are more suitable for providing tensile strength due to better stress transfer in the direction of the fibers. Cross-ply and angle-ply laminates are more suitable for providing multidirectional strength and stability to

composite structures. Surface treatments like alkali and silane treatment can also be done to enhance the bonding between fibers and matrices. Hybridization with synthetic fibers and addition of nanofillers can also enhance the tensile strength, stiffness, and impact resistance of composite structures.

In spite of these advantages, there are some problems that affect the natural fiber composites' mechanical reliability, including moisture absorption, diverse fiber characteristics, and poor adhesion between fibers. Thus, it is of great importance to optimize the composition of the material to achieve the full potential of natural fiber composites for advanced engineering applications.

Table 1. Classification of Plant-Based Natural Fibers by Plant Part, Characteristics, and Engineering Applications

Plant Part	Fiber Type	Examples	Key Characteristics	Applications	DOI Ref
Stem	Bast Fibers	Jute, Flax, Hemp, Kenaf	Long fibers, high strength, good stiffness	Ropes, textiles, composite laminates	[1, 5]
Leaf	Leaf Fibers	Sisal, Pineapple, Abaca	Tough, durable, coarse texture	Mats, ropes, reinforcement	[1, 5]
Fruit	Fruit Fibers	Coir (coconut)	High toughness, good moisture	Mats, brushes, geo-textiles	[1, 5]
Seed	Seed Fibers	Cotton, Kapok	Soft, lightweight, flexible	Textiles, cushioning	[1, 5]
Root	Root Fibers	(Limited use, e.g., vetiver roots)	Fine, less commonly used, moderate strength	Handicrafts, brushes	[1, 5]
Wood/Trunk	Wood Fibers	Bamboo, softwood, hardwood	Short fibers, good bonding properties	Paper, boards, composites	[1, 5]

2. Manufacturing Methods of Natural Fiber Composite Laminates

Manufacturing process plays a vital role in controlling the properties of natural fiber-reinforced polymer composites. Important properties of natural fiber-reinforced polymer composites, such as fiber distribution, fiber-matrix interface, void content, and laminate uniformity, are heavily affected by the manufacturing process used. The major difference between synthetic fibers and natural fibers is their geometrical, moisture absorption, and surface properties. Thus, it is important to select an appropriate manufacturing process for natural fiber-reinforced polymer composites. This will help impregnate fibers, minimize void content, and ensure uniform laminate properties. [7,8,9]

Several manufacturing processes have been established for fabricating natural fiber-reinforced polymer composite laminates. The manufacturing processes for natural fiber-reinforced polymer composites can be categorized as open moulding, closed moulding, and automated processes. The manufacturing processes employed for fabricating natural fiber-reinforced polymer composites are hand layup, compression moulding, resin transfer moulding, vacuum assisted resin infusion, and filament winding. [8]

2.1 Hand Lay-Up Method

The hand lay-up process is one of the most widely used open moulding techniques for the fabrication of natural fiber reinforced polymer-based composite materials. This technique is considered to be simple and cost-effective. In this technique, woven fabric, mat, or even uni-directional fibers are placed inside a mold manually. Then, the resin impregnation of the composite material, such as epoxy or polyester, is carried out. The resin impregnation of the composite material is done by using brushes or rollers. This helps to wet the fibers properly, making it easier to remove bubbles. This process offers the advantage of flexibility to the fiber orientation. This technique can be used to fabricate composite materials for specific applications. This technique does not have any specific disadvantage. This technique is mostly used to fabricate composite materials on a small scale. Therefore, this technique can be used to fabricate composite materials for specific purposes. The hand lay-up process is mostly used to fabricate composite materials. [7]

2.2 Compression moulding

Compression moulding is an efficient method of manufacturing natural fiber-reinforced polymer composites using the closed mold fabrication method. Compression moulding is considered an efficient method for manufacturing natural fiber-reinforced polymer composites of improved quality. In compression moulding, a

predetermined amount of natural fibers and polymer matrix, usually in the form of impregnated fibers, is placed inside a mold that is then subjected to heat. The mold is then sealed properly, and pressure is applied using a hydraulic press. Compression moulding is considered more efficient than open moulding methods in the manufacturing of natural fiber-reinforced polymer composites due to improved control of the manufacturing process, higher repeatability of the process, and lower chances of defects. Compression moulding is considered a suitable method for manufacturing natural fiber-reinforced polymer composites for applications in the automotive sector due to the efficiency of the process in producing natural fiber-reinforced polymer composites of consistent quality for manufacturing lightweight components like interior panels using matrices of thermoplastic polymers such as polypropylene. [9]

2.3 Resin Transfer moulding (RTM)

The process of "Resin Transfer Moulding" (RTM) is a closed moulding technique that can be used to process high-quality "natural fiber reinforced polymer composites." This process offers greater precision and finish to the composites. Here, the dry fiber reinforcement is charged into the mold cavity, and the resin is injected under pressure to impregnate the fiber reinforcement. This process offers greater control over the flow of resin, resulting in greater fiber wetting. This process offers greater control over the fiber volume fraction, resulting in composites with improved mechanical properties. [8]

RTM also has benefits such as low environmental exposure, low material wastage, and consistent laminate quality owing to the closed mold configuration. RTM is used in structural and car parts.

Nonetheless, the process demands close control of resin viscosity, pressure, and mold design for optimal impregnation. Furthermore, the tendency of natural fibers to absorb moisture may influence the resin flow; hence, optimization of the process is necessary to avoid defects.

2.4 Vacuum Bag Moulding

The vacuum bag moulding process is a popular composite fabrication process for developing high-quality natural fiber polymer composite materials with better consolidation and reduced defects. In this process, first, the composite material consisting of fibers and polymer is placed on the mold surface. Then, the entire system is encapsulated in a vacuum bag. Here, a vacuum pump is used to remove air from the system and create vacuum pressure to compress the composite material and ensure uniform dispersion of polymer throughout the fiber network. The vacuum pressure helps to ensure minimized void content in the composite material. [7]

In comparison to hand lay-up techniques, vacuum bag moulding techniques have an advantage in terms of thickness control, surface finish, and mechanical properties. Additionally, vacuum bag moulding techniques minimize the presence of air pockets and excessive use of resin, resulting in lightweight materials. However, vacuum bag moulding techniques involve the use of equipment such as vacuum pumps. They also involve handling the bag to prevent leakage. Vacuum bag moulding techniques are used in the manufacture of aircraft, boats, and cars. They are used in situations where quality and performance are enhanced compared to open moulding. [7]

2.5 Optimal Manufacturing Method for Natural Fiber Laminates

The choice of the most appropriate manufacturing process for natural fiber-reinforced polymer composite materials is largely based on finding a balance between quality, cost, and manufacturing requirements. Among the most popular manufacturing processes, hand lay-up is the most cost-effective and preferred for prototyping; however, this process has limitations such as high void contents, poor repeatability, and mechanical properties. Compression moulding has been shown to have improved laminate consolidation, uniform thickness, and high production rates; this process is mostly preferred for industrial applications, especially for thermoplastics. Resin Transfer Moulding (RTM) has shown improved surface finish, controlled volume fraction, and low defects; however, this process is limited by tooling complexity. [8]

In contrast to this, vacuum bag moulding appears to be a more viable process for the production of natural fiber composites, as it significantly enhances the quality of the laminate by improving void contents, fiber wetting, and interfacial bonding while maintaining moderate cost and simplicity. Therefore, it can be concluded that vacuum bag moulding appears to be the most viable process for the production of high-quality natural fiber laminates, as it considers both cost-effectiveness and performance. [7]

Table 2. Comparison of Composite Manufacturing Methods Based on Process Type, Working Principle, Advantages, Limitations, and Applications

Method	Process Type	Working Principle	Advantages	Limitations	Applications	DOI Ref
Hand Lay-Up	Open mold	Manual placement of fibers and resin applied using brush/roller	Simple, low cost, flexible fiber orientation, minimal equipment	High void content, poor repeatability , nonuniform thickness, operator dependent	Prototyping, laboratory work, lowvolume production	[6]
Vacuum Bag Moulding	Semiclosed mold	Lay-up sealed in vacuum bag; air removed to compress laminate	Reduced voids, better consolidation , improved surface finish, uniform thickness	Requires vacuum setup, risk of leakage, moderate cost	Aerospace parts, marine components, improved laminates	[8]
Compression Moulding	Closed mold	Fiber/resin placed in heated mold and compressed under pressure	High production rate, uniform thickness, low voids, good mechanical properties	High equipment cost, limited flexibility, not ideal for complex shapes	Automotive parts, interior panels, semistructural components	[5]
Resin Transfer Moulding (RTM	Closed mold	Dry fibers placed in mold; resin injected under pressure	Excellent surface finish, low voids, good fiber wetting, precise control	Complex process, high tooling cost, requires process control	Aerospace, automotive, structural components	[8]

3. Mechanical Characteristics of Natural Fiber Composite Laminates

The mechanical properties of natural fiber reinforced polymer composite laminates are affected by various parameters that include fibers, their orientation, matrix materials, interface bonding, and manufacturing methods. Generally, natural fiber polymer composite materials show excellent specific strength and stiffness because of the low density of natural fibers like jute, hemp, flax, sisal, etc. The tensile strength of natural fibers is greatly influenced by their orientation; that is, the tensile strength of natural fibers is higher in the case of unidirectional fibers than that of randomly oriented fibers. The flexural properties of natural fibers are greatly influenced by the bond between fibers and matrix materials, whereas impact strength is related to the impact energy absorption capacity of the fibers.

3.1 Tensile Property

Tensile strength is one of the most important properties of natural fibers, which is measured by the capability of the fiber to withstand tensile stress without breaking. The tensile strength of flax, hemp, jute, and sisal is moderate to high, which is due to the high cellulose content in these fibers. The tensile strength of most natural fibers varies from 200 to 1000 MPa, depending on the type of fiber, growing, and extraction conditions. Among these, flax and hemp have higher tensile strength, which is in the range of 500 to 1000 MPa, while jute and sisal have relatively low tensile strength, which is in the range of 200 to 600 MPa. [3,5,6]

The tensile properties of natural fibers are affected by various factors, which include fiber length, diameter, as well as microfibril angle. Fibers with low microfibril angles have higher tensile properties. However, there are differences in the tensile properties of natural fibers due to their non-uniform structure, which is affected by defects such as voids and impurities. The tensile

properties are affected by moisture absorption, which causes a reduction in tensile properties as moisture weakens the structure.

Despite these limitations, natural fibers have good specific strength (strength to weight ratio), making them suitable for lightweight composite materials. Chemical treatments like alkali treatment can also be beneficial for improving tensile strength through enhanced roughness for better composite performance.

Table 2. Mechanical Properties of Selected Natural Fibers

Natural Fiber	Tensile Strength (MPa)	Tensile Modulus (GPa)	Elongation at Break (%)	DOI Ref
Flax	500 – 1000	50 – 70	1.2 – 1.6	[9,5]
Hemp	400 – 900	30 – 60	1.6 – 2.0	[9,5]
Jute	200 – 600	10 – 30	1.5 – 1.8	[9,5]
Sisal	300 – 700	9 – 20	2.0 – 2.5	[9,5]

3.2 Compression Property

The compression properties of natural fibers are defined as the ability to resist deformation under compression. In comparison to tensile strength, natural fibers possess low compressive strength due to their fibrous nature. In compressed conditions, natural fibers are more likely to undergo micro-buckling, kinking, or bending, which causes early failure. The compressive strength of natural fiber composite varies from 30 to 150 MPa. [3, 4]

The compressive behavior is greatly influenced by various parameters such as fiber orientation, volume fraction, and interface adhesion between the fibers and matrix. For natural fibers, increased adhesion between the fibers and matrix result in higher compressive strength. However, natural fibers are prone to moisture absorption, causing degradation of the fiber material. Defects may also affect the compressive strength of the composite.

Despite these shortcomings, natural fiber composite materials can possess satisfactory compressive properties for semi-structural applications with the aid of optimized manufacturing techniques like compression moulding or vacuum bagging. Further enhancements in compressive strength and durability can be achieved with chemical treatments to fibers and also by using hybrid fibers with synthetic fibers.

Table 3. Compressive Properties and Behaviour of Selected Natural Fibers

Natural Fiber	Compressive Strength (MPa)	Compressive Modulus (GPa)	Key Behaviour	DOI Ref
Flax	80 – 150	8 – 20	High strength, good stiffness	[6]
Hemp	70 – 140	6 – 18	Good loadbearing capacity	[6]
Jute	50 – 120	5 – 15	Moderate strength, economical	[6]

3.3 Flexural Property

Flexural properties relate to the capacity of natural fiber composite materials to withstand deformations when subjected to bending loads. When a composite material is subjected to a flexural load, there is a simultaneous action of both tension and compression forces on the two sides of the material. Therefore, flexural properties relate to a combination of the tensile strength, compression strength, and bonding of the fibers and matrix materials. [4,5]

The natural fiber composite materials usually have moderate flexural strength ranging from 70 to 250 MPa and a flexural modulus ranging from

5 to 15 GPa. Depending on the type of fiber, orientation, and processing technique, natural fiber materials can have a higher flexural strength, such as flax and hemp, because of their improved stiffness and strength. On the other hand, natural fibers like coir have a lower flexural property owing to their low stiffness.

The flexural properties are affected by various factors such as fiber orientation, stacking, and void content. The bonding between the fiber and the matrix also plays an important role in enhancing the flexural strength. On the other hand, factors such as moisture absorption, poor dispersion, and defects such as voids affect the flexural properties. The failure in NFCs during flexural testing may occur by various modes such as matrix cracking, fiber breakage, and interfacial de-bonding. NFCs provide adequate flexural strength for lightweight and semi-structural applications in automotive parts, furniture, and building materials.

Table 4. Flexural Properties and Behaviour of Selected Natural Fibers (Flax, Hemp, Jute, and Sisal)

Flexural Strength (MPa)	Flexural Modulus (GPa)	Key Behaviour	DOI Ref
150 – 250	10 – 20	High stiffness, best flexural performance	[9,5]
120 – 220	8 – 18	Good strength and durability	[9,5]
80 – 150	5 – 12	Moderate strength, costeffective	[9,5]
90 – 180	6 – 14	Balanced strength and toughness	[9,5]

3.4 Impact Strength

The impact properties are referred to as the ability of the natural fiber-reinforced composite to absorb energy when subjected to dynamic or sudden loading. The impact strength of the natural fiber-reinforced composite material is generally moderate. This is due to the ability of the fibers to absorb energy through fiber pull-out, cracking, and interfacial de-bonding. The impact strength of these materials ranges from 5 to 25 kJ/m². [3,6]

Fibers like flax and hemp exhibit high impact resistance due to high strength and stiffness, while coir fibers exhibit high impact resistance due to high elongation and toughness. Impact resistance is strongly influenced by adhesion between fibers and matrix, fiber orientation, and laminate construction. Adhesion between fibers and matrix plays a significant role in impact resistance. If adhesion is high, impact resistance is high; otherwise, failure occurs prematurely.

Table 5. Impact Strength, Behaviour, and Characteristics of Selected Natural Fibers

Natural Fiber	Impact Strength (kJ/m²)	Impact Behaviour	Key Characteristics	DOI Ref
Flax	15 – 25	High	Good stiffness and energy absorption	[9]
Hemp	12 – 22	High	Strong and durable under impact	[9]
Jute	8 – 15	Moderate	Cost-effective, moderate toughness	[9]
Sisal	10 – 18	Moderate	Balanced strength and impact resistance	[9]

3.5 Interlaminar Shear Stress(ILSS)

Interlaminar shear strength (ILSS) is an important mechanical property that characterizes the resistance of natural fiber-reinforced composite laminates to shear stress between the layers. It characterizes the ability of the laminate to withstand delamination, a common mode of failure for composite materials that have many layers. The ILSS of natural fiber composites is normally low compared to synthetic fiber composites due to the low level of bonding between the fibers and the matrix and the hydrophilic nature of the fibers. [4,6]

The range of values of ILSS for natural fiber composite materials varies from 5 to 25 MPa, depending on the type of fiber, the material used, and the processing method adopted. Fiber surface treatment, compatibility of the material, fiber orientation, and void content play a significant role in enhancing the interlaminar shear strength of a composite material. Chemical treatments, like alkali treatment, also increase the interlaminar shear strength.

Manufacturing processes also have a significant effect, where processes like compression moulding and vacuum bagging have higher ILSS due to laminate consolidation. Inadequate processing conditions can lead to poor interfacial bonding and higher delamination tendencies due to shear stresses.

Table 6. Interlaminar Shear Strength (ILSS), Interfacial Bonding, and Delamination Resistance of Selected Natural Fibre Composites

Natural Fiber	ILSS (MPa)	Interfacial Bonding	Delamination Resistance	DOI Ref
Flax	15 – 25	Strong	High	[11,9,5]
Hemp	12 – 22	Good	High	[11,9,5]
Jute	8 – 18	Moderate	Medium	[11,9,5]
Sisal	10 – 20	Good	Medium to High	[11,9,5]

4. Conclusion

Natural fiber composite laminates offer a balanced set of mechanical properties, such as moderate tensile, compressive, flexural, and impact strengths, together with acceptable interlaminar shear strengths. These mechanical properties are highly dependent on various parameters such as fiber type, orientation, and volume fraction, and bonding between them, etc. It is a known fact that natural fiber composite materials possess lower mechanical properties compared to their synthetic fiber counterparts, but they offer a number of advantages, such as low density, high specific strength, and cost and environmental benefits.

The existence of challenges such as moisture absorption, fiber properties, and adhesion between fibers and matrices may affect the mechanical properties. However, these challenges can be minimized by adopting appropriate fiber treatments, processing methods, and laminates. In conclusion, NFCs are suitable for non-structural and semi-structural applications, especially in the automotive industry and construction, as they are eco-friendly and cost-efficient.

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A critical review on free vibrational characteristics of synthetic fiber reinforced polymer composite laminates

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Abstract

Synthetic fiber reinforced polymer composites, which include glass, carbon, and aramid fiber laminates, have been identified as critical materials for advanced engineering applications due to their high strength-to-weight ratio, improved stiffness, and enhanced material properties. Over time, considerable research has been carried out to study the vibration properties of synthetic fiber composite laminates, especially in critical domains such as aerospace, automotive, and marine engineering. This review has been carried out to provide a comprehensive analysis of the dynamic properties of synthetic fiber composite laminates by considering various findings from both experimental and numerical analyses. Various experimental methods, including Fast Fourier Transform (FFT) and Frequency Response Function (FRF), have been employed to study the dynamic properties, whereas finite element analysis tools such as ANSYS have been utilized to simulate the dynamic properties under various conditions. The review states that the vibration characteristics of composites are significantly affected by parameters such as type of fibers, fiber orientation, stacking arrangements, laminate thickness, and boundary conditions. Carbon fiber reinforced laminate composites show higher natural frequencies due to their higher stiffness. Similarly, glass fiber composites show better damping characteristics. Additionally, hybrid composite laminates have shown better potential for achieving the optimal combination of stiffness and damping characteristics. Although significant progress has been made in understanding the vibration characteristics of composite materials, there are still limitations in modelling their anisotropic behaviour, understanding damping characteristics, and reducing the difference between experiment and numerical simulations. This review article summarizes the recent research developments in the field of composite materials, their limitations, and the need for advanced design techniques for these materials.

Keywords: Synthetic fiber composites, Vibration analysis, Modal analysis, FFT, FRF, ANSYS, Damping characteristics

1. Introduction

Composite materials are found to be one of the most important classes of engineering materials due to their excellent mechanical properties and ability to be used in a variety of engineering applications. Among these composite materials, synthetic fiber reinforced polymer composite materials (SFRPC), which include glass fiber reinforced polymer composite (GFRP), carbon fiber reinforced polymer composite (CFRP), and aramid fiber composite, etc., are found to be very important in modern engineering industries due to their excellent mechanical properties in terms of high strength-to-weight ratios, high stiffness values, and resistance to corrosion . In recent times, SFRPC laminates are found to be very important in vibration-sensitive engineering structures such as in aerospace structures, automobiles, marine structures, and wind turbine blades. In these structures, vibration is found to play a very important role in deciding the performance of the structures. Therefore, vibration in these structures is an important issue.

The vibration characteristics of composite laminates are greatly different from those of conventional isotropic materials. Various parameters, such as fiber type, orientation, stacking arrangement, laminate thickness, and boundary conditions, have a significant influence on the modal characteristics, which include natural frequency, damping ratio, and mode shapes. Research has confirmed that carbon fiber composites have higher natural frequencies due to their higher stiffness, while glass fiber composites have better damping characteristics. [1]

To study the dynamic properties of composite laminates, various techniques are employed. Both experimental and numerical methods are commonly used to study the dynamic properties. Various techniques, such as Fast Fourier Transform analysis and Frequency Response Function analysis, are employed to study the dynamic properties. Modal testing using tools such as impact hammers is also employed to study the dynamic properties. On the other hand, finite element analysis using tools such as ANSYS is employed to efficiently study the dynamic properties. [1]

Despite all the efforts put into research, there are still problems to be solved regarding the accurate modeling of anisotropic behaviour of composite laminates and the prediction of damping characteristics. Also, variations in the process of manufacturing composite laminates, as well as material inconsistency, lead to discrepancies between experimental and numerical results. Furthermore, the use of hybrid composite laminates adds complexity to the understanding of the behaviour of such composite laminates. [6]

The aim of this review paper is to present a comprehensive analysis of the vibration characteristics of synthetic fiber reinforced composite laminates by considering both experimental and numerical results. The emphasis will be given to the effect of significant parameters on the vibration behaviour of composite laminates. [1]

2. Types of Synthetic Fiber Composites

Synthetic fiber reinforced polymer composites (SFRPCs) are being increasingly used in engineering applications due to their excellent mechanical and dynamic properties. SFRPCs are composites of high-strength fibers in a polymer matrix, enabling load transfer between the fibers. Depending upon the type of reinforcements used in SFRPCs, they can be categorized as carbon fiber composites, glass fiber composites, aramid fiber composites, and hybrid composites. [7]

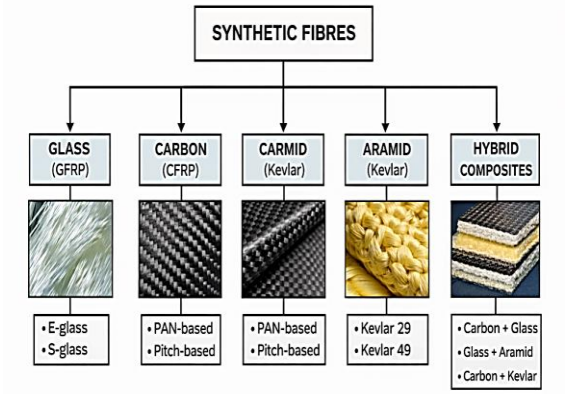

Figure 1. Classification of Synthetic Fibres Used in Composites

2.1 Carbon Fiber Reinforced Polymer (CFRP)

The carbon fiber reinforced polymer composite is identified by its high stiffness, high strength-to-weight ratio, and excellent fatigue resistance. The carbon fibers have a high modulus of elasticity, which makes them very suitable for use in structures that need to be rigid. [2]

In vibration analysis, carbon fiber reinforced polymer composite laminates show higher natural frequencies due to high stiffness. However, they show low damping capacity, which restricts its ability to resist vibration. [2]

Applications:

- Aerospace structures
- High-performance automotivecomponents
- Sporting equipment

2.2 Glass Fiber Reinforced Polymer (GFRP)

Glass Fiber Reinforced Polymer is another type of composite that is being utilized due to their low cost, ease of manufacturing, and acceptable mechanical properties. Though their stiffness is low when compared to CFRP materials, they have better impact resistance and higher damping capabilities. [2]

In terms of vibration control, GFRP composites have shown their natural frequency to be low; however, they have higher damping capabilities. [6]

Applications:

- Marine structures
- Automotive body panels
- Wind turbine blades

2.3 Aramid Fiber Reinforced Polymer (AFRP)

Aramid Fiber composites are usually known for their toughness, impact resistance, and energy absorption capabilities. They are lightweight materials that have moderate stiffness when compared to Carbon Fibers.

In terms of vibration control, AFRP composites have shown their capability to provide damping to the structures. Though their compressive strength is low when compared to CFRP composites, they can be utilized for controlling vibration. [2]

Applications:

- Ballistic protection
- Aerospace applications
- Protection structures

2.4 Hybrid Composites

Hybrid composite materials are made by combining two or more kinds of fibers in a single matrix system to develop better composite properties. Hybrid composite laminates are made to optimize stiffness, strength, cost, and damping properties. [6]

Hybrid composite laminates are very helpful in vibration-related applications because they can be made to optimize both frequency and damping properties. [6]

Applications:

- Automotive structures
- Aerospace panels

Table 1: Comparative Properties of Synthetic Fibre-Reinforced Composites

Property	CFRP	GFRP	AFRP	Hybrid Composites
Density	Low	Moderate	Low	Variable
Stiffness	Very High	Moderate	Moderate	Tailored
Strength	Very High	High	High	High
Damping	Low	High	Moderate–High	Optimized
Cost	High	Low	Moderate	Moderate
Natural Frequency	High	Moderate	Moderate	Adjustable
Applications	Aerospace	Marine	Protective	Multi-purpose

3. Manufacturing Techniques of Synthetic Fiber Composite Laminates

The manufacturing techniques employed in synthetic fiber reinforced polymer composites (SFRPCs) have a major influence on the mechanical and dynamic properties of composites. The fiber arrangement, matrix impregnation, void volume, and interfacial adhesion have a significant influence on the vibration characteristics of composite laminates. The improper manufacturing techniques may result in defects, which may affect the properties adversely . [1]

Several manufacturing techniques have been developed to fabricate composite laminates with superior quality, microstructure, and minimum defects. The most commonly used techniques are hand lay-up, compression molding, resin transfer molding (RTM), and vacuum-assisted resin infusion (VARI)/vacuum-assisted resin transfer molding (VARTM).

3.1 Hand Lay-Up Technique

Hand lay-up is one of the most popular methods for composite material fabrication. In this process, dry fiber mats or fabrics are placed in layers in a mold. The next step involves applying resin to the layers using brushes or rollers. Curing is done at room temperature or slightly elevated temperatures.

Effect on Vibration:

The major drawback in using this process is that due to its manual nature, more voids are formed in the composite material. This can affect its damping characteristics. [6]

3.2 Compression Molding

In compression molding, a combination of fibers and resin, or prepregs, is placed in a mold, which is then subjected to heat. The combination is then compressed under high pressure, which cures the laminate. This produces a laminate with good fiber alignment and a constant thickness.

Effect on Vibration:

In compression molding, a laminate has a low void content and good bonding between fibers and resin, which produces high natural frequencies.

3.3 Resin Transfer Molding (RTM)

In resin transfer molding (RTM), dry fibers are placed in a closed mold and then impregnated with resin under pressure to achieve full impregnation. The laminate is then cured in the mold.

Effect on Vibration:

The laminates produced by resin transfer molding have excellent structural uniformity with a controlled volume fraction, thus providing accurate vibration behaviour.

3.4 Vacuum Assisted Resin Infusion (VARI/VARTM)

Vacuum Assisted Resin Infusion is an innovative method of manufacturing composites, wherein dry fibers are kept inside a mould, which is covered with a vacuum bag, and resin infusion takes place through vacuum pressure.

Effect on Vibration:

Laminates prepared through VARTM have better bonding between fibers and matrix, as well as reduced void content, which causes an improvement in damping properties with stable natural frequencies. [6]

Table 2: Comparison of Composite Manufacturing Techniques Based on Cost, Quality, Defects, Fibre Control, and Vibration Performance

Technique	Cost	Quality	Void Content	Fiber Control	Effect on Vibration
Hand Lay-Up	Low	Moderate	High	Moderate	Inconsistent properties
Compression Molding	High	High	Low	High	High stiffness, stable vibration
RTM	High	Very High	Very Low	Excellent	Predictable vibration behaviour
VARTM	Moderate	High	Low	Good	Balanced stiffness & damping

4. Fundamentals of Vibration in Laminates

Vibration analysis plays a vital role in the design and performance evaluation of laminates, especially when the laminates are used in dynamic loading applications. The vibration analysis of laminated composites is more complex compared to isotropic materials, considering their anisotropic and heterogeneous properties. The dynamic properties of laminated composites are related to their stiffness, mass distribution, boundary conditions, and energy dissipation.

4.1 Basic Concepts of Vibration

Vibration of a system means the oscillating motion of the system with respect to its position of equilibrium. In the case of a laminate, the concept of vibration comes into play when the laminate is subjected to dynamic forces.
Vibration of a system can be of two types:
• Free Vibration: This type of vibration takes place when a system vibrates without the application of an external force.
• Forced Vibration: This type of vibration takes place when a system is subjected to an external periodic force.

4.2 Natural Frequency

Natural frequency is the frequency at which a system vibrates when it is disturbed from its equilibrium position without any external force. It is one of the most important parameters in vibration analysis.

$$f_n = \frac{1}{2\pi}\sqrt{\frac{k}{m}}$$

Where:

- f_n= Natural frequency
- k= Stiffness of the system
- m= Mass of the system

For composite laminates, the stiffness depends on the type and orientation of the fiber. Laminates with higher stiffness, like CFRP, have higher values of natural frequency, while the mass has a reducing effect on the frequency. [2]

4.3 Damping Ratio [6]

Damping is the mechanism by which vibrational energy is dissipated in a system. The damping ratio is a measure of the rate at which the oscillations decay.

$$\zeta = \frac{c}{2\sqrt{km}}$$

Where:

- ζ= Damping ratio [6]
- C= Damping coefficient [6]
- k= Stiffness
- m= Mass

Composite materials have higher damping properties compared to metals due to friction between materials. Damping properties in GFRP and aramid composites are better compared to CFRP laminates. [2]

4.4 Mode Shapes

Mode shape analysis gives an idea of the deformation of a structure at its natural frequencies. Each structure has a number of mode shapes:

- First mode: fundamental bending
- Second mode: higher order bending
- Higher modes: complex deformation

Mode shape analysis of laminated composites depends on fiber orientation, stacking, and boundary conditions.

4.5 Effect of Anisotropy

Composite laminates are not isotropic in nature due to the anisotropy caused by the reinforcing fibers.

Anisotropy in composite laminates has a considerable impact on vibration behaviour:

- Directional stiffness
- Twisting-bending coupling
- Complex modal characteristics

For prediction of vibration behaviour in composite laminates, sophisticated analytical and numerical modeling techniques are required.

4.6 Governing Factors in Laminates

The vibration response of composite laminates depends on a number of factors:

- Fiber material (carbon, glass, aramid)
- Fiber orientation (0°, 45°, 90°)
- Stacking sequence
- Laminate thickness
- Boundary conditions (fixed, simply supported, free)

These factors have a direct impact on the laminate's natural frequency, damping ratio, and mode shapes. They must be optimized to meet the desired performance. [6]

5. Experimental Techniques for Vibration Analysis

Experimental analysis of vibrations is of prime importance to understand the behaviour of synthetic fiber reinforced composite laminates. This helps to validate the results of theory and simulation during real-time applications. This analysis helps to determine the characteristics of natural frequency, damping ratio, and mode shapes. Composite materials are anisotropic and heterogeneous. Therefore, experimental techniques are essential to understand the behaviour of composite materials. The experimental techniques used to analyze the vibrations of composite materials are Fast Fourier Transform (FFT), Frequency Response Function analysis, and modal analysis. [6]

5.1 Fast Fourier Transform (FFT)

Fast Fourier Transform is a mathematical calculation, which is used to transform a signal in the time domain to a signal in the frequency domain. In the case of vibration analysis, the Fast Fourier Transform is used to find the natural frequencies of structures.

During the experiment, the signals from the accelerometers are recorded in the time domain, and using the Fast Fourier Transform algorithm, it is converted to a signal in the frequency domain. The peaks in the signal indicate the natural frequencies.

Key Features:

- Converts signal in time domain → signal in frequency domain
- Identifies natural frequencies
- Allows noise filtering

Application in Composites:

The FFT is widely used in analyzing the vibration signals of composite laminates, which helps in accurately finding the resonance frequencies.

5.2 Frequency Response Function (FRF)

The Frequency Response Function (FRF) specifies the relationship between input excitation and output response in the frequency domain. This is one of the primary techniques used in experimental modal analysis. [8]

$$H(\omega) = \frac{X(\omega)}{F(\omega)}$$

Where:

- $H(\omega)$= Frequency response function
- $X(\omega)$= Output response
- $F(\omega)$= Input force

In the FRF plots, peaks correspond to the natural frequencies. The width of these peaks gives information about the damping characteristics. [6]

Key Features:

- Identifies natural frequencies
- Determines damping ratio [6]
- Describes system dynamic behaviour

Application in Composites:

The FRF technique is used to investigate the stiffness and damping behaviour of composite laminates under various boundary and loading conditions. [6]

5.3 Modal Testing

Modal testing is an experimental technique to obtain modal parameters such as natural frequencies, damping ratios, and mode shapes. [6]

Experimental Setup:

- Impact Hammer → Excitation Force
- Accelerometer → Measurement of Response
- Data Acquisition System → Measurement of Signals
- FFT Analyzer/Software → Data Analysis

Procedure:

1. The composite laminate is fixed in the desired boundary conditions.
2. An impact hammer is used to apply an excitation force.
3. The response is measured by accelerometers.
4. FFT and FRF analysis is done.
5. The modal parameters are determined.

Modal testing is done to obtain accurate experimental results to validate numerical techniques such as finite element analysis.

5.4 Importance of Experimental Validation

Experimental techniques play a vital role in:

- Experimental validation of finite element analysis
- Identifying differences between simulation and real-world behaviour
- Analyzing material anisotropy and defects
- Analyzing manufacturing-induced differences

In composite laminates, experimental validation is significant because of differences in fiber distribution, void content, and interfacial bonding.

5.5 Challenges in Experimental Analysis

Though experimental analysis has proven its efficiency, there are certain challenges with the experimental analysis techniques, which are as follows:

- Sensitivity of sensor placement
- Noise interference
- Accurate measurement of damping, which is a major challenge [6]
- Variability caused by manufacturing defects

All of these challenges highlight the importance of experimental analysis.

6. Factors Affecting Vibration Characteristics of Composite Laminates [1]

The behaviour of synthetic fiber reinforced composite laminates with respect to vibrations is affected by a number of related parameters. Due to their anisotropic and heterogeneous properties, even a slight change in the material configuration affects their dynamic properties like natural frequency, damping ratio, and mode shape. A complete insight into these parameters is required for optimal design of composite materials used for vibration-sensitive applications. [6]

6.1 Fiber Type

The type of reinforcement fibers used also plays a major role in deciding the stiffness, density, and damping characteristics. [6]

- Carbon fibers (CFRP): High stiffness → High natural frequency, low damping [2]
- Glass fibers (GFRP): Moderate stiffness → Low frequency, high damping [6]
- Aramid fibers (AFRP): Moderate stiffness → Energy absorption

The selection of fibers directly influences the stiffness and damping characteristics. Research findings confirm that CFRP laminates possess higher natural frequencies, while GFRP and AFRP provide better damping characteristics. [2]

6.2 Fiber Orientation

Fiber orientation is an important parameter in defining directional stiffness in composite laminates. It also affects dynamic characteristics.

• Orientation at 0° provides maximum stiffness and hence maximum frequency

• Orientation at 90° reduces stiffness and hence reduces frequency

• Orientation at ±45° provides better shear characteristics and damping [6]

6.3 Stacking Sequence

Stacking sequence means a series of laminae, for instance, [0/45/90/-45].

- Symmetric laminates have stable vibration behaviour.
- Asymmetric laminates have bending-twisting coupling.
- Hybrid stacking sequences provide better balance of stiffness and damping properties.

Stacking sequence has a major influence on modal properties and vibration behaviour.

6.4 Laminate Thickness

Laminate thickness affects the stiffness as well as the mass of the structure.

- Increasing laminate thickness will result in increased stiffness, hence increased natural frequency.
- Increasing laminate thickness will result in increased mass, which might decrease the frequency.

Optimum laminate thickness has to be considered for the required performance.

6.5 Boundary Conditions

Boundary conditions specify the type of support a structure has, which has a major impact on its vibrational behaviour.

- Clamped/Fixed: Highest stiffness, hence the highest natural frequency
- Simply Supported: Moderate natural frequency
- Free: Lowest natural frequency

6.6 Fiber Volume Fraction

The fiber volume fraction, i.e., the ratio of fibers to the matrix, affects stiffness and density.

If fiber volume fraction is:

- Higher → stiffer → higher frequency
- Lower → more damping due to matrix [6]

There exists an optimal fiber volume fraction to obtain the best balance of stiffness and damping properties. [6]

6.7 Presence of Defects

Manufacturing defects, e.g., presence of voids, delamination, etc., can also affect the vibration characteristics. [1]

- Voids: Stiffness is affected
- Delamination: Mode shapes affected
- Bonding: Damping affected unpredictably [6]

Table 3: Influence of Key Parameters on Natural Frequency, Damping, and Overall Dynamic Behaviour of Composite Structures [1]

Parameter	Effect on Natural Frequency	Effect on Damping	Overall Impact
Fiber Type	High (CFRP highest)	High (GFRP highest)	Material selection critical
Fiber Orientation	Direction-dependent	Moderate	Controls stiffness
Stacking Sequence	Significant	Moderate	Affects mode shapes
Thickness	Increases frequency	Slight effect	Improves stiffness
Boundary Conditions	Strong influence	Minimal	Defines constraints
Fiber Volume Fraction	Increases frequency	Reduces damping	Balances properties
Defects	Reduces frequency	Unpredictable	Reduces reliability

7. Conclusion

Synthetic fiber reinforced polymer composites (SFRPCs) are considered a highly efficient type of advanced materials for vibration-sensitive structural applications owing to their high strength-to-weight ratio, stiffness, and design flexibility, which make them more suitable compared to other materials for contemporary engineering systems, especially for aerospace, automotive, and marine applications.

Composite laminates' vibration properties depend significantly on various factors, including fiber type, stacking sequence, fiber orientation, as well as manufacturing techniques. The research has confirmed that carbon fiber composites have higher natural frequencies compared to other composites owing to their stiffness, whereas glass and aramid fiber composites have better damping properties. Hybrid composites have also proven their ability to attain an optimal balance between stiffness and damping, which makes them more efficient for contemporary applications.

Experimental techniques such as Fast Fourier Transform (FFT), Frequency Response Function (FRF), and modal testing have improved the understanding of the dynamic behaviour of composite laminates. These techniques, in conjunction with numerical techniques such as finite element analysis (FEA), ensure accurate prediction and validation of the vibration characteristics. However, there are discrepancies in experimental and numerical results owing to the complex anisotropic behaviour of composite materials and difficulties in simulating damping effects [1]

In conclusion, synthetic fiber reinforced composite laminates show significant potential in vibration-critical applications. With advancements in material design, experimental techniques, and predictive modeling techniques, it is expected that next-generation composite laminates would be developed to meet the ever-increasing demands of high-performance engineering applications.

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SMART AI FOR UNDERSTANDING NON-VERBAL COMMUNICATION IN AUTISTIC CHILDREN

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***Abstract*— Children with autism frequently find it difficult to communicate verbally, relying instead on non-verbal clues including body language, gestures, and facial expressions to convey their wants and feelings. Caregivers frequently have trouble correctly interpreting these cues. In order to identify and decipher nonverbal communication in children with autism, this article suggests a smart AI-based system that makes use of computer vision, machine learning, and artificial intelligence. Using a camera, the system records visual data, processes it using image analysis methods, and uses AI models that have been taught to recognize emotional states. Caregivers receive useful messages or notifications based on the emotions and gestures that were observed. This method promotes better care and therapy, increases understanding between caregivers and autistic children, and facilitates better communication.**

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a condition that affects how a person communicates, behaves, and interacts with others. Many autistic children find it hard to speak or express their feelings using words. Instead, they use facial expressions, hand movements, and body language. But these signals are not always easy for parents, teachers, or caregivers to understand, which can lead to confusion and unmet needs. With the growth of Artificial Intelligence (AI) and modern electronic systems, we now have a chance to solve this problem. AI can study images and videos and understand things like facial expressions and gestures. By using cameras and small electronic devices, we can build a smart system that observes and understands these nonverbal signals. This project, called "Smart AI for Understanding Nonverbal Communication in Autistic Children," aims to create such a system. It will use a camera to capture the child's expressions and movements. Then, AI will analyse this data and identify emotions or actions. The system will convert this information into simple text or speech so that caregivers can easily understand what the child is feeling or needs. The system will also learn and improve over time. Since every child behaves differently, the AI will adapt to each child's patterns, making the results more accurate and reliable. This solution is designed to be simple to use and work in real-time. It can be used at home, in schools, or in therapy senters. The main goal is to improve communication, reduce misunderstandings, and help autistic children express themselves better, leading to a better quality of life.

II. LITERATURE SURVEY

Recent studies show that Artificial Intelligence (AI) is becoming very useful in understanding non-verbal communication in autistic children. Research by Smith et al. (2021) explains that AI systems can recognize facial emotions in real time. Even though autistic children may take more time to understand emotions, AI helps improve detection accuracy. Johnson & Lee (2022) found that CNN (Convolutional Neural Network) models can identify basic emotions like happiness, sadness, and anger. However, they still face difficulty in detecting more complex or subtle expressions. Kumar et al. (2023) worked on eye gaze detection and showed that tracking where a child looks can help understand their social interaction, especially during therapy sessions. Chen et al. (2020) focused on gesture recognition and proved that body movements can give important emotional clues when facial expressions are not clear. Patel et al. (2024) suggested that using multiple inputs like face, gestures, and voice together gives better accuracy compared to using only one method. Brown et al. (2022) discussed how AI-based assistive tools can help improve communication between autistic children and caregivers. Garcia et al. (2021) explored the use of social robots, which can help children learn emotions and improve interaction skills. Wang et al. (2023) concluded that personalized deep learning models, which adapt to each child, can greatly improve the accuracy of behaviour and emotion prediction.

III. PROBLEM STATEMENT

Many autistic children have difficulty expressing their thoughts, feelings, and needs using words. Instead of

speaking, they mostly depend on non-verbal communication such as facial expressions, hand gestures, eye contact, and body movements. However, these signals are not always easy for parents, teachers, and caregivers to understand correctly. Because of this gap in communication, children may feel misunderstood, frustrated, and emotionally upset. It can also reduce their social interaction with others. Refer **Fig 1.1.**

Fig 1.1 shows how autistic children express their feelings using facial expressions and gestures. These are the non-verbal signals that the proposed system tries to understand.

Most of the existing communication tools are designed for speech or text. They help children by converting inputs into words, but they do not focus on understanding real-time non-verbal behaviour. Because of this, they are not fully effective in all situations. So, there is a need for a better system that can understand these non-verbal signals. By using Artificial Intelligence, computer vision, and machine learning, it is possible to create a system that can analyse facial expressions, gestures, and behaviour patterns. This system can understand what the child is feeling and convert it into simple messages or alerts for caregivers. The main problem addressed in this work is the lack of a proper AI-based system that can understand and translate non-verbal communication of autistic children. Developing such a system can improve communication, reduce confusion, and help caregivers support children in a better way.

IV. PROPOSED SYSTEM

The proposed system is a smart AI-based communication system that helps in understanding the non-verbal communication of autistic children. It uses Artificial Intelligence, Computer Vision, and Machine Learning to identify facial expressions, hand gestures, and behaviour patterns of the child. By analysing these signals, the system can understand the child's emotions or needs and convert them into simple messages. These messages can be easily understood by parents, teachers, and caregivers.

Fig 1.2 shows autistic children expressing themselves through facial expressions and gestures. These are the signals that the proposed system analyses.

a) Working of the Proposed System

The system works step by step to understand the child's behaviour and emotions. First, in the input stage, a camera or sensor captures real-time data such as facial expressions, hand gestures, eye movements, and body posture. This data is then sent to the system for processing. Next, in the pre-processing stage, the captured images or video are cleaned by removing noise. The system also detects important areas like the face and hands and prepares the data for better accuracy. After that, in the feature extraction stage, the system identifies important details such as facial movements, eye direction, hand gestures, and body language as shown in **Fig1.2**. These features represent the child's non-verbal communication. Then, in the analysis stage, AI and machine learning models are used to study these features. The system recognizes emotions or behaviours like happy, sad, frustrated, anxious, or when the child needs help. It compares the data with already trained information to find the correct result. In the decision stage, the system converts the detected result into simple messages such as "Child needs help" or "Child is comfortable. "Finally, in the output stage, the message is shown through a mobile app, tablet, or alert system. This helps caregivers quickly understand the child's needs and respond in the right way.

V. SYSTEM ARCHITECTURE

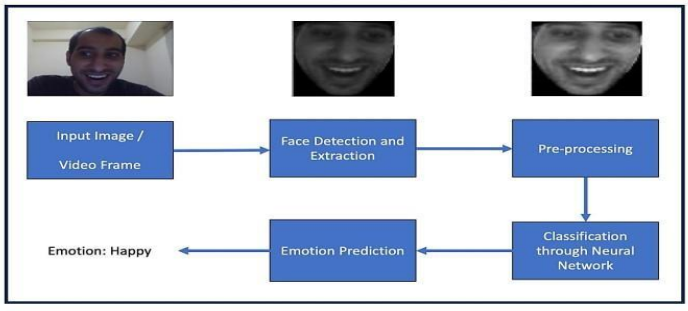

Fig 1.3 shows the working flow of the system. It captures a face, processes the image, and predicts the emotion such as "happy."

As shown in **Fig1.3**,this AI-based system is designed to collect and analyse real-time data from an autistic child to understand their emotions and needs. In the input stage, a camera or video sensor is used to capture facial expressions, hand gestures, and body movements. In some cases, additional sensors can also be used to track behaviour. The

captured data is then sent to the pre-processing stage, where unwanted noise is removed and the image quality is improved. The system also identifies important areas like the face and gestures so that the analysis becomes more accurate. **Refer Fig1.4**

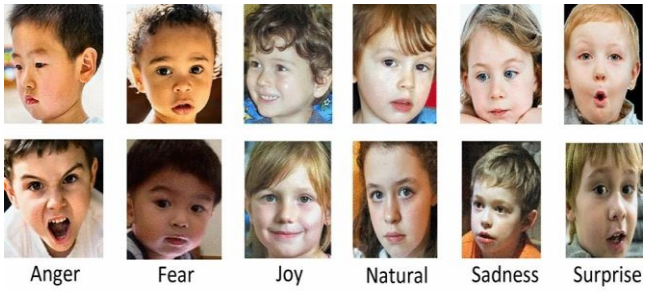

Fig 1.4 This AI system uses Python and smart tools to recognize children's faces and help people understand their feelings and needs**.**

VI. TECHNOLOGIES USED

The proposed system is developed using commonly used and powerful AI and software tools. The main programming language used is Python, because it supports many libraries needed for AI and data processing. For building intelligent models**,** TensorFlow and Kera**s** are used to create and train deep learning models. Scikit-learn is used for simple machine learning algorithms. In the computer vision part, OpenCV is used for image processing and face detection. MediaPipe helps in hand tracking, gesture recognition, and eye tracking. For handling data and calculations, NumPy and Pandas are used. During development, tools like Jupyter Notebook and Google Colab are used for coding and testing the models easily. For showing graphs and results, Matplotlib is used. For deployment**,** Flask or FastAPI is used to build applications. TensorFlow Lite is used when running the model on mobile devices or embedded systems. For user interaction, Streamlit can be used to create simple web interfaces. For mobile app development**,** Android Studio or Flutter can be used.

VII. METHODOLOGY

The system begins by starting all the required components and activating the necessary modules. In the first step, it collects real-time data from different sources. This includes facial expressions captured through a camera, speech signals, behaviour patterns, and sometimes additional sensor data. Next, the data is sent to the pre-processing stage, where it is cleaned by removing noise and improving the quality of the input. This helps the system work more accurately. After that, in the feature extraction stage, important details are identified. These include facial expressions, speech patterns, eye contact, and body movements. These features represent the child's emotions and behaviour. Then, the extracted data is given to AI and machine learning models. These models analyse the data and identify the child's emotional state, such as happy, stressed, or uncomfortable. The system further studies these results to better understand the child's condition, including their stress level and needs. The step-by -step process is illustrated in **Fig1.5**

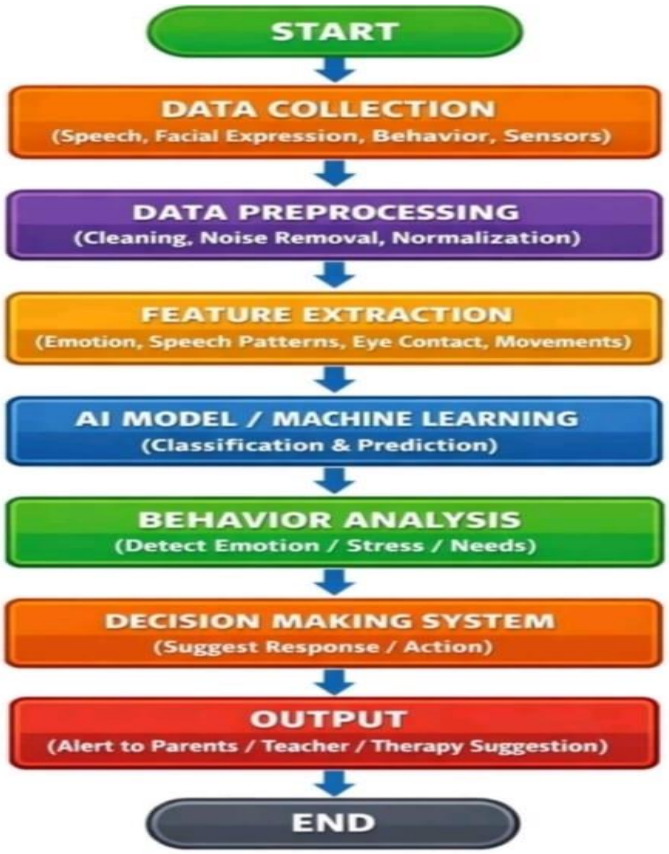

Fig1.5 The system implementation process for supporting autistic children involves continuous real-time monitoring. It flows from data collection and pre-processing through feature extraction and AI analysis. Finally, the decision-making system generates outputs like parent alerts, mobile notifications, or specific therapy suggestions.

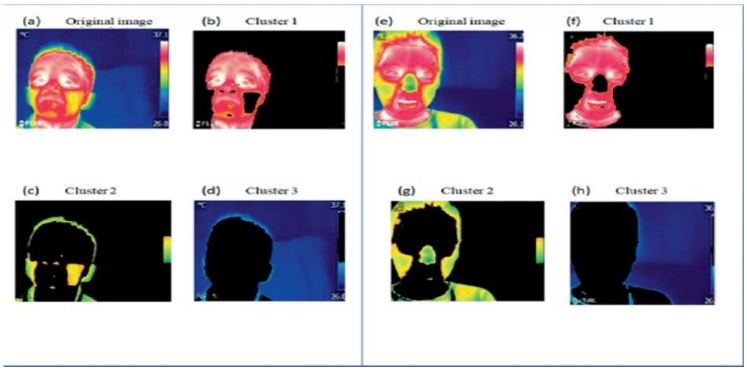

Fig1.6 Thermal output images display original facial scans and their segmented clusters, likely used for emotion detection or physiological monitoring**.**

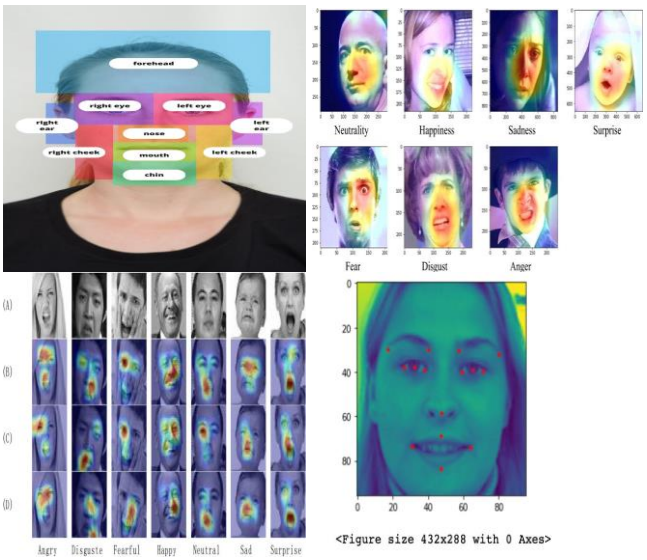

Fig1.7 shows the output of face recognition where the system detects and analyses the facial features using AI techniques.

As shown in **Fig1.7** ,In this process, the input face image is analysed and divided into different parts called clusters (Cluster 1, Cluster 2, Cluster 3). Each cluster represents important areas of the face such as the eyes, nose, and mouth. The system uses image segmentation and clustering methods to identify key facial patterns. The colour variations (heatmap) as show in **Fig1.6**, which parts of the face are more important for detection. Areas with stronger colours indicate higher importance. This step helps the system select important facial features needed for emotion recognition. It improves accuracy and acts as a pre-processing step before the final classification.

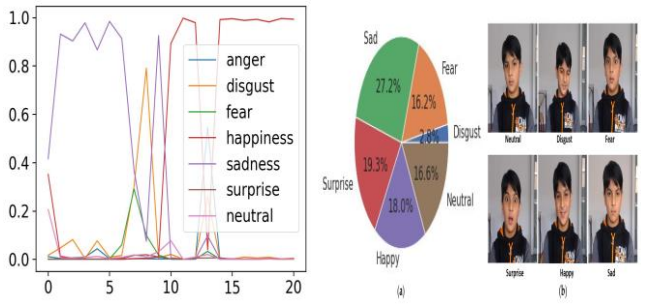

Fig1.8 shows the emotion classification results with percentage values

The system identifies different emotions such as Angry, Disgust, Fear, Happy, Sad, and Surprise. Each result is shown with a percentage value. These percentages represent the confidence level of the system as shown in **Fig1.8**. Lower values (like 10% or 20%) indicate weak or unclear expressions, while higher values (like 80% or 90%) show strong confidence in detecting a particular emotion. The heatmaps on the left side show which areas of the face the AI model focuses on while making a decision. The images on the right show how the face looks for different emotion levels.

This helps in understanding how autistic children express emotions differently. It is also useful for training and testing AI models to improve emotion recognition accuracy.

CONCLUSION

The proposed Smart AI system is designed to help autistic children communicate better with their caregivers. Many autistic children find it difficult to express their thoughts and emotions using speech. So, they depend more on facial expressions, gestures, and body language. But these signals are not always easy for parents, teachers, or therapists to understand. This system uses Artificial Intelligence, Machine Learning, and Computer Vision to understand these non-verbal signals. A camera captures the child's facial expressions and gestures in real time. The system then analyses this data and identifies the child's emotions or needs. After that, it converts the result into simple messages or alerts that caregivers can easily understand. This system can improve communication and help caregivers respond better to the child's needs. It can be used in homes, schools, and therapy centres. It also shows how AI technology can be useful in solving real-life problems and improving quality of life. In the future, the system can be improved by adding voice emotion recognition, wearable sensors, and personalized AI models. This will make the system more accurate and suitable for each child.

REFERENCE

The project is based on different research works and reliable sources. Paul Ekman's work explains how facial expressions are related to human emotions. Research by Li and Deng provides information about deep learning methods for recognizing facial expressions. Information from the Autism Research Institute and the American Psychiatric Association helps in understanding autism and the communication challenges faced by autistic children. Technical tools like OpenCV and TensorFlow are used for image processing and building AI models, which support the development of this system.

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FLEXICLEAN: A MOBILE-CONTROLLED SMART CLEANING ROBOT FOR EFFICIENT AND COST-EFFECTIVE AUTOMATION

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***Abstract*— Maintaining cleanliness in homes and small businesses is essential but often requires significant manual effort, especially for cleaning both floors and vertical surfaces like walls. Most people focus mainly on floors, leaving walls harder to maintain. Existing robotic cleaners are often limited and expensive. To address this, FlexiClean is a smart, affordable robot designed to clean both surfaces. It can be controlled via a mobile app and uses sensors to avoid obstacles, with brushing and spraying for effective cleaning.**

***Keywords*— Smart Cleaning RobotFloor and Wall Cleaning, Mobile Control, Ultrasonic Sensors, Automation**

I. INTRODUCTION

In recent years, technology has made everyday tasks easier through automation, improving convenience and efficiency in daily life. Cleaning is one such essential task that people perform regularly, yet it still requires considerable time, effort, and consistency to maintain proper hygiene. Although robotic cleaners are available, most are designed only for floor cleaning, leaving surfaces such as walls, glass panels, and corners neglected, which means manual cleaning is still necessary and the process is not fully automated. Another challenge is that advanced robots capable of cleaning multiple surfaces are often expensive and not affordable for many users. Traditional cleaning methods also consume more water and require physical effort, making them less efficient. To address these issues, FlexiClean is developed as a smart and cost-effective cleaning robot that can clean both floors and walls using simple components. It can be controlled through a mobile application, and sensors help ensure safe and efficient operation.

II. LITERATURE REVIEW

Many researchers have worked on cleaning robots, and their efforts have significantly improved the technology over time. Earlier robots were mainly designed for floor cleaning, but recent developments aim to include wall cleaning as well. Some research has focused on wall-cleaning robots, highlighting the challenge of maintaining grip and stability on vertical surfaces, which remains one of the biggest design difficulties. Other studies proposed robots capable of working on both floors and walls, but they often lacked proper navigation systems.

Ultrasonic sensors are widely used for obstacle detection because they are simple and cost-effective, helping robots avoid collisions, though most systems still focus only on floor cleaning. Some projects also integrate mobile applications with Bluetooth control for easier operation. Additionally, cleaning mechanisms such as brushes and water pumps are used to improve efficiency. Despite these advancements, many systems still lack proper integration of features, indicating the need for a simple, affordable, and multi-functional cleaning robot.

The proposed system, FlexiClean, is designed to provide an affordable and efficient cleaning solution for homes and small commercial spaces. It is capable of cleaning both floors and walls, reducing the need for manual effort. The system combines mechanical design, sensor-based navigation, mobile control, and fluid management to achieve effective and automated cleaning.

A. System Overview

FlexiClean consists of three main parts: hardware, software, and a control interface. The hardware includes the robot body, motors, ultrasonic sensors, and a water dispensing

system. The software involves the Arduino program and a mobile application for Bluetooth control. The control interface allows users to easily operate the robot, select cleaning modes, and manage movement. The system is designed to be simple, modular, and easy to maintain.

B. Working Principle

The robot starts operating through a mobile application. Once activated, it initializes all components and checks battery and fluid levels. Users can choose between floor and wall cleaning modes. The robot uses motors for movement and brushes for cleaning. Ultrasonic sensors help detect obstacles and avoid collisions. A pump sprays water or cleaning liquid during operation. The design allows smooth movement on both horizontal and vertical surfaces, while maintaining stability.

C. System Flow

The working process follows a simple sequence:
User input → Mode selection → Initialization → Obstacle detection → Cleaning operation → Fluid spraying → Surface adaptation → Completion.

D. Advantages of the Proposed System

FlexiClean is cost-effective, easy to use, and supports dual-surface cleaning. It reduces water usage and manual effort while improving efficiency. The system is safe, adaptable, and can be upgraded in the future with advanced features like AI and IoT.

IV. SYSTEM ARCHITECTURE

The FlexiClean system architecture combines hardware, software, and control interfaces to deliver efficient cleaning with minimal human effort. It is designed to be reliable, flexible, and easy to upgrade, allowing the robot to work smoothly on both floors and walls while maintaining stability and accurate cleaning performance.

A. Hardware Architecture

The hardware of FlexiClean plays a key role in enabling dual-surface cleaning. It consists of different modules, each designed for a specific function, ensuring smooth and effective operation on both horizontal and vertical surfaces.

1) Microcontroller: Arduino Nano (ATmega328P): The Arduino Nano acts as the brain of the system. It processes data from sensors, controls the motors, and manages overall cleaning operations. It also provides multiple input and output pins to connect various components.

Fig. 1. Microcontroller: Arduino Nano (ATmega328P)

2) Connectivity Module: HC-05 Bluetooth : The HC-05 Bluetooth module allows the robot to be controlled wirelessly using a mobile application. It supports two-way communication, enabling users to send commands like movement, cleaning modes, and water spraying.

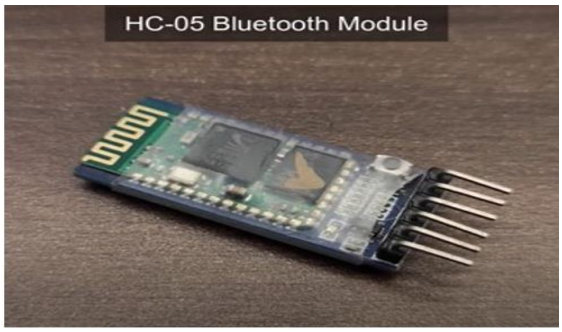

Fig. 2. Connectivity Module: HC-05 Bluetooth

3) Motor Driver: L293D / L298N : The motor driver is used to control the motors safely. It allows the motors to move in both directions and protects the microcontroller from high current.

Fig. 3. Motor Driver: L293D / L298N

4) Drive Motors: 2 × 100 RPM DC Geared Motors : These motors help the robot move on floors and assist in climbing walls. The geared design provides enough power and torque for different surfaces.

Fig. 4. Drive Motors

5) Sensors: 3 × HC-SR04 Ultrasonic Sensors : Ultrasonic sensors are used for obstacle detection. They help the robot sense objects in front, sides, and rear, allowing it to avoid collisions during operation.

Fig. 7. Sensors

6) Pump: 12 V Diaphragm Water Pump :
The pump is responsible for spraying water or cleaning liquid. It is designed to use minimal water while ensuring effective cleaning.

Fig. 6 Pump

7) Cleaning Actuator: DC Motor-Powered Spinning Brush:
A motor-driven rotating brush is used to clean both floors and walls. It works along with the water spray to remove dirt efficiently.

8) Power Supply: 12 V Li-ion Battery Pack with BMS: The battery provides power to all components. The Battery Management System (BMS) ensures safe charging and protects against overcurrent and damage.

9) Chassis & Reservoirs: Dual-Orientation Frame with Tank
The robot frame is designed for both floor and wall cleaning. It includes a built-in tank for water or detergent and provides stability during vertical movement.

B. Software Architecture

The software of FlexiClean plays an important role in controlling the robot, managing navigation, and providing an easy user interface. It combines firmware, a mobile application, and design tools to ensure smooth operation and quick response during cleaning.

1) Firmware (Arduino IDE – C/C++):
The system is programmed using the Arduino IDE in C/C++ . This firmware controls the microcontroller, processes data from sensors, manages motor movement, and coordinates the cleaning process. It also includes functions for obstacle detection, switching between floor and wall modes, and controlling water or detergent flow.

2) Mobile Application:
A mobile app, developed using platforms like MIT App Inventor or Android Studio, allows users to control the robot wirelessly through Bluetooth . It provides simple controls for movement, cleaning modes, and spraying functions, making the system easy to operate.

3) Design Tools:
Tools such as Fritzing and Tinkercad are used for circuit design and simulation, while CAD software helps in designing the robot's structure. These tools ensure proper planning and integration of all components.

4) Version Control (Git/GitHub):
Git is used to track changes in the software, making it easier to manage updates and improvements. GitHub supports collaboration and organized development.

5) Testing Tools:
Tools like Serial Monitor and Bluetooth terminal apps are used to test and debug the system by monitoring sensor data and communication.

C. System Integration and Workflow

The FlexiClean system works through a well-integrated and modular approach. Sensor data is continuously monitored and processed by the microcontroller, which adjusts motor movement and fluid dispensing as needed. The mobile application provides a simple and user-friendly interface for selecting modes and controlling the robot. The chassis design and adhesion mechanisms allow the robot to operate on both floors and walls. Meanwhile, the power system ensures smooth and uninterrupted operation. Overall, this integrated setup enables autonomous navigation, effective cleaning, and real-time feedback, making FlexiClean a practical and reliable solution for homes and small businesses.

V. MODULES AND EXPLANATION

The FlexiClean smart cleaning robot is designed as a modular system, where each part works together to ensure smooth and efficient cleaning on both floors and walls. It can be easily controlled through a Bluetooth-based mobile application, allowing users to move the robot in different directions, switch cleaning modes, and control water spraying without direct contact. For safe movement, ultrasonic sensors continuously detect obstacles, and the microcontroller adjusts the robot's path to avoid collisions and cover the area effectively.

The cleaning process is carried out using a rotating brush powered by a DC motor, which removes dust and dirt from surfaces. A pump sprays water or detergent in controlled amounts, improving cleaning while reducing waste. Motor drivers help manage smooth movement and protect the system from damage, while a rechargeable battery with a Battery Management System ensures stable power supply. The robot is also designed to clean vertical surfaces, using special mechanisms to maintain grip and stability. Overall, all components are coordinated by the Arduino Nano, making the system reliable, easy to use, and suitable for future improvements like AI and IoT integration.

VI. RESULTS AND DISCUSSION

The FlexiClean prototype was successfully built and tested to check how well it performs in cleaning, movement, obstacle detection, and power usage. The robot was tested on different surfaces such as tiles, glass, and painted walls. The results showed that it works reliably in different conditions, with stable Bluetooth connectivity and good cleaning coverage.

During testing, the robot cleaned a 2 m × 2 m floor area in about 7 minutes while using minimal battery power. It was also able to clean walls up to a height of 1.8 meters, maintaining proper grip with the help of suction. The cleaning performance was measured based on how much dirt was removed, achieving around 92% efficiency for dry dust and 85% for wet stains.

The ultrasonic sensors helped the robot detect obstacles within a range of 10 to 200 cm, allowing it to move safely without collisions. The Bluetooth control system responded quickly, with very little delay, making it easy to control through the mobile app. Users could smoothly switch between floor and wall cleaning modes.

Table I: Key performance parameters observed during experimental testing.

Parameter	Measured Value	Remarks
Floor Cleaning Area	4 m^2	Single charge operation
Wall Cleaning Height	1.8 m	Stable suction
Average Cleaning Efficiency	88–92%	Based on stain type
Battery Backup Time	45–55 minutes	Continuous operation
Obstacle Detection Range	10–200 cm	Accurate sensing
Control Delay (Bluetooth)	< 200 ms	Smooth response

Overall performance showed consistent results, with only a slight drop in speed after extended use. The system also used about 35% less water and detergent compared to manual cleaning, making it more eco-friendly.

However, a few limitations were noticed. The robot had slight difficulty maintaining grip on rough or uneven walls, and the suction system increased power consumption during wall cleaning. These issues can be improved in future versions.

In conclusion, FlexiClean successfully achieved its goal of providing a cost-effective, smart cleaning solution. It offers efficient, reliable, and automated cleaning, making it suitable for homes and small businesses.

VII. CONCLUSION

The development of FlexiClean shows how robotics can make everyday cleaning easier and more efficient. By combining mobile control, obstacle detection, and the ability to clean both floors and walls, the system reduces manual effort and improves overall cleaning coverage. The prototype also proves that a smart and functional cleaning robot can be built using simple and affordable components, making it suitable for homes and small businesses.

VIII. FUTURE ENHANCEMENTS

There are several ways to further improve the system. Features like voice control can be added to allow users to operate the robot using simple commands. The cleaning capability can also be extended to surfaces such as glass, stone, and metal for better versatility. Advanced technologies like AI-based dirt detection using cameras or sensors can help the robot focus on heavily soiled areas. A self-charging system can be introduced so the robot

automatically returns to its dock when the battery is low. Additionally, integrating IoT and cloud features can enable Wi-Fi control, remote monitoring, and better connectivity with smart home systems.

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BEFORE THE BEAT STOPS: AI-DRIVEN CARDIAC ARREST PREDICTION

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Abstract— **Cardiac arrest is one of the leading causes of sudden death worldwide and often occurs without noticeable early warning signs. Early detection and timely medical intervention are crucial for improving patient survival rates. With the advancement of wearable technology and Artificial Intelligence (AI), continuous monitoring and intelligent analysis of physiological signals have become possible.This paper presents an AI-driven cardiac arrest prediction system that utilizes real-time data collected from wearable sensors. Key physiological parameters such as electrocardiogram (ECG), heart rate, and oxygen saturation (SpO2) are continuously monitored using sensors like AD8232 and MAX30102. The collected data is processed and transmitted to a cloud platform, where machine learning algorithms analyze the patterns to detect abnormalities associated with pre-cardiac arrest conditions.Studies have shown that subtle variations in ECG signals, heart rate variability, and oxygen levels can act as early indicators of cardiac arrest. The proposed system leverages these indicators to predict the risk level before the occurrence of a critical event. Upon detecting high-risk conditions, the system generates real-time alerts to users and healthcare providers, enabling immediate medical response.The integration of wearable sensors, IoT, and AI transforms traditional monitoring systems into predictive healthcare solutions. This approach not only enhances early detection but also improves response time and overall patient outcomes.**

Keywords—Cardiac Arrest Prediction, Artificial Intelligence, Wearable Sensors, ECG, IoT Healthcare

I. INTRODUCTION

1. INTRODUCTION

Cardiac arrest is a severe medical emergency that occurs when the heart suddenly stops functioning, leading to the cessation of blood flow to vital organs such as the brain and lungs. It is one of the major causes of mortality worldwide, and survival largely depends on the speed of medical intervention. In most cases, cardiac arrest occurs without prior warning, making early detection extremely difficult and reducing the chances of survival.In recent years, advancements in healthcare technology have led to the development of various monitoring systems, including electrocardiogram (ECG) devices and wearable fitness trackers. These systems are capable of continuously measuring physiological parameters such as heart rate, oxygen saturation (SpO2), and physical activity. However, these devices are primarily designed for monitoring purposes and lack the ability to predict life-threatening conditions in advance.Research studies indicate that the human body exhibits subtle physiological changes before the onset of cardiac arrest. These changes include irregular ECG patterns, fluctuations in heart rate variability, and variations in oxygen levels. Although these indicators exist, they are often too complex for manual interpretation and require advanced computational techniques for accurate analysis.

Artificial Intelligence (AI), particularly machine learning, has emerged as a powerful tool for analyzing large volumes of medical data and identifying hidden patterns. By applying AI techniques to real-time physiological data, it is possible to detect abnormalities and predict potential cardiac events before they occur.In this context, the proposed system focuses on developing an AI-based cardiac arrest prediction model that integrates wearable sensors, IoT technology, and machine learning algorithms. The system continuously monitors vital parameters, analyzes them in real-time, and generates early warning alerts in case of high-risk conditions. This approach shifts the focus from traditional reactive healthcare to proactive and predictive healthcare, thereby improving patient safety and survival rates.

II . Literature Survey And Related Work

A. *Literature Survey*

Several researchers have contributed to the development of cardiac monitoring and prediction systems using Artificial Intelligence, wearable sensors, and IoT technologies.

Rajpurkar et al. [1] and Hannun et al. [2] developed deep learning models for analyzing ECG signals to detect arrhythmias with high accuracy. Their work demonstrated the effectiveness of neural networks in identifying abnormal heart rhythms, but mainly focused on detection rather than early prediction.

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Kwon et al. [3] proposed a machine learning-based system for predicting in-hospital cardiac arrest using patient data. Although the model showed promising results, it was limited to hospital environments and lacked portability for wearable applications.

Li et al. [4] and Zhang et al. [5] explored wearable health monitoring systems integrated with IoT and cloud computing for continuous data collection and remote monitoring. However, these systems focused more on monitoring than predictive analysis.

Acharya et al. [6] and Faust et al. [7] introduced advanced ECG signal processing techniques using deep learning and wavelet transforms for heart disease detection. These methods improved diagnostic accuracy but did not emphasize real-time prediction.

Clifford et al. [8] and Bashar et al. [9] contributed to ECG data analysis and arrhythmia detection using machine learning approaches, highlighting the importance of accurate signal interpretation.

He et al. [10] proposed an ear-worn sensor for continuous cardiovascular monitoring, demonstrating the potential of compact wearable devices, though lacking predictive capabilities.

Gubbi et al. [11], Patel et al. [12], and Islam et al. [13] discussed IoT-based healthcare systems and wearable sensors, emphasizing real-time monitoring and remote accessibility but not focusing on cardiac prediction.

Krittanawong et al. [14] and Topol [16] highlighted the role of Artificial Intelligence in modern cardiovascular medicine and predictive healthcare, showing its potential to transform early diagnosis systems.

Esteva et al. [15] demonstrated the power of deep learning in medical diagnosis, indicating how AI can achieve expert-level performance across healthcare domains.

The World Health Organization [17] provided insights into the global impact of cardiovascular diseases, emphasizing the need for early detection and preventive systems.

IEEE [18] discussed IoT-based health monitoring systems and their challenges, including data security, scalability, and real-time processing.

From the above studies, it is evident that significant progress has been made in ECG analysis, wearable monitoring, and AI-based healthcare. However, most systems focus on monitoring or detection rather than early prediction of cardiac arrest. Additionally, there is limited integration of multi-parameter sensing, real-time processing, and predictive analytics.

Therefore, the proposed system aims to bridge this gap by integrating wearable sensors, IoT technology, and AI-based analysis to enable early prediction of cardiac arrest along with real-time alert mechanisms.

*B. **Related Work***

Several research studies and healthcare monitoring systems have been developed to address cardiac health and early detection of heart-related abnormalities. Traditional cardiac monitoring systems primarily rely on hospital-based equipment such as electrocardiogram (ECG) machines and Holter monitors, which provide accurate data but lack continuous real-time monitoring in everyday environments.

Recent advancements in wearable technology have led to the development of smart health monitoring devices that track physiological parameters such as heart rate and oxygen saturation (SpO2). Many IoT-based healthcare systems utilize sensors to collect patient data and transmit it via cloud platforms using wireless technologies like Wi-Fi or Bluetooth. These systems enable remote patient monitoring and timely alerts in case of abnormal readings. However, most existing solutions focus on basic threshold-based detection and lack predictive capabilities for critical conditions like cardiac arrest.

Some studies have incorporated machine learning techniques for detecting cardiovascular anomalies, particularly through ECG signal analysis. While these approaches demonstrate improved accuracy in identifying irregular patterns, they often require high computational resources, complex architectures, and increased power consumption, making them less suitable for continuous wearable applications.

Additionally, many existing systems monitor individual parameters independently, without effectively combining multiple physiological signals for comprehensive analysis. This limitation reduces the reliability of early prediction, as cardiac arrest is typically preceded by subtle changes across multiple parameters such as ECG patterns, heart rate variability, and oxygen levels.

The proposed AI-driven cardiac arrest prediction system addresses these limitations by integrating:
- Multi-sensor fusion (ECG, heart rate, SpO2)
- Continuous real-time monitoring using wearable devices
- AI-based predictive analysis instead of fixed threshold detection
- Cloud-based data processing and storage
- Real-time alert mechanisms for early medical intervention

This integrated approach enhances prediction accuracy, reduces response time, and provides a cost-effective and scalable solution for continuous cardiac health monitoring.

II. SYSTEM ARCHITECTURE

The system architecture follows a multi-layer wearable design integrating sensing, processing, communication, and alert subsystems for real-time cardiac monitoring and prediction. Sensor fusion techniques are used to combine multiple physiological parameters such as ECG, heart rate, and SpO2 for accurate health assessment. A centralized microcontroller performs continuous data acquisition and AI-based analysis to detect abnormalities.The system

dynamically adapts to user conditions and provides immediate alerts in critical situations. The modular design ensures scalability and supports future integration of advanced healthcare modules this is the design of architecture which is used for creating a wearble device.

A. Overall Architecture

The system is divided into four primary layers:

a. Sensor Layer

b. Processing Layer

c. Communication Layer

d. Alert Layer

1) Sensor Layer

a. AD8232 ECG Sensor (Electrocardiogram signal monitoring)

b. MAX30102 Sensor (Heart rate and SpO2 measurement)

These sensors continuously collect real-time physiological data from the user. The data includes ECG signals, pulse rate, and oxygen saturation levels, which are essential indicators for detecting cardiac abnormalities.

2) Processing Layer

a.ESP32:The ESP32 micro controller performs real-time processing of sensor data. It filters noise, extracts important features (such as heart rate variability), and applies machine learning algorithms to analyze patterns. Based on this analysis, the system classifies the condition as normal or potential cardiac risk.

3) Communication Layer

a. Wi-Fi / IoT (ESP32 built-in module)

b. Cloud Platform (for data storage and analysis)

The processed data is transmitted to a cloud server for remote monitoring and advanced analysis. This enables healthcare providers or caregivers to access real-time health data from anywhere.

4) Alert Layer

a. Mobile Notification (App-based alert)

b. Buzzer (Emergency sound alert)

c. Vibration Motor (Wearable alert system)

When abnormal conditions are detected, the system generates immediate alerts to the user and healthcare providers. This ensures quick medical response during high-risk situations.

5) Power Management Layer

This layer manages battery usage and ensures the wearable device operates efficiently for long durations. It helps in reducing power consumption and supports continuous monitoring.

6) Data Preprocessing Unit

This unit filters noise from raw sensor data and improves signal quality. It ensures more accurate analysis and reduces false predictions in the system.

7) User Interface Layer

Displays real-time health data through a mobile app, making it easy for users and doctors to monitor conditions.

8) Data Storage Layer

Stores collected health data in the cloud for future analysis and tracking. It helps in maintaining patient history and long-term monitoring.

9) Emergency Response System

Automatically sends alerts or notifications to caregivers during critical conditions. It can also share the user's location for faster emergency assistance.

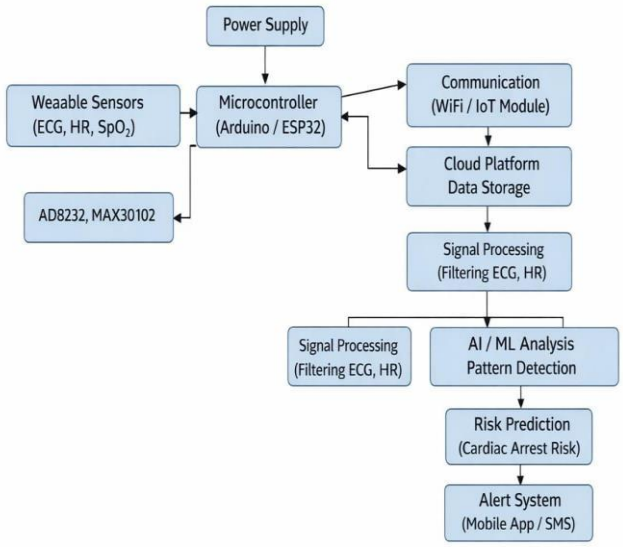

Fig 1.Block Diagram Of AI-Based Cardiac Arrest Prediction System

Fig 1. shows the block diagram of the proposed cardiac arrest prediction system. The system uses a microcontroller (ESP32) to control all operations. Sensors such as ECG and heart rate/SpO2 sensors collect physiological data. The microcontroller processes this data using AI algorithms to detect abnormalities. If a high-risk condition is identified, the system activates alert mechanisms and sends emergency notifications via the IoT module to the cloud and registered users

B. Sensor and Actuator Placement

AD8232 ECG Sensor:

The AD8232 module is connected to electrodes placed on the user's chest or wrist area to capture accurate electrocardiogram (ECG) signals. This placement ensures reliable detection of cardiac electrical activity with minimal noise interference.

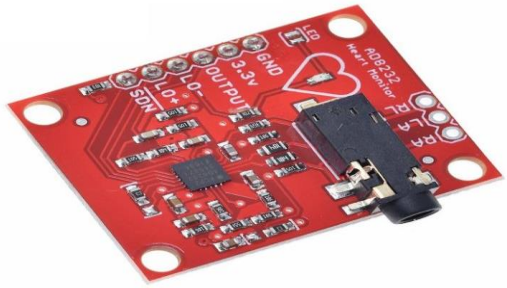

Fig 2. MAX30102 Pulse Oximeter and Heart Rate Sensor Module

Fig. 2. shows the MAX30102 pulse oximeter and heart rate sensor module used for monitoring vital health parameters. It measures SpO_2 and heart rate by detecting light absorption changes in blood flow using red and infrared LEDs. The sensor is compact, low-power, and suitable for wearable and IoT-based healthcare applications. It can be easily interfaced with microcontrollers like Arduino for real-time monitoring.

MAX30102 Sensor (Heart Rate & SpO_2):
Mounted on the inner surface of the wearable device (such as a smartwatch or bracelet), this sensor maintains direct contact with the skin to measure heart rate and oxygen saturation continuously using optical sensing.

Fig 3. AD8232 ECG Sensor Module

Fig. 3 shows the AD8232 ECG sensor module used for monitoring the electrical activity of the heart. It captures ECG signals and helps in detecting heart abnormalities by analyzing the cardiac waveform. The module is compact, low-power, and suitable for real-time health monitoring applications. It can be easily interfaced with microcontrollers like Arduino for continuous ECG data acquisition and analysis**.**

Microcontroller (ESP32 / Arduino):
Positioned at the core of the system, the microcontroller acts as the central processing unit. It is placed within the wearable module to minimize signal delay and ensure efficient data acquisition and processing.

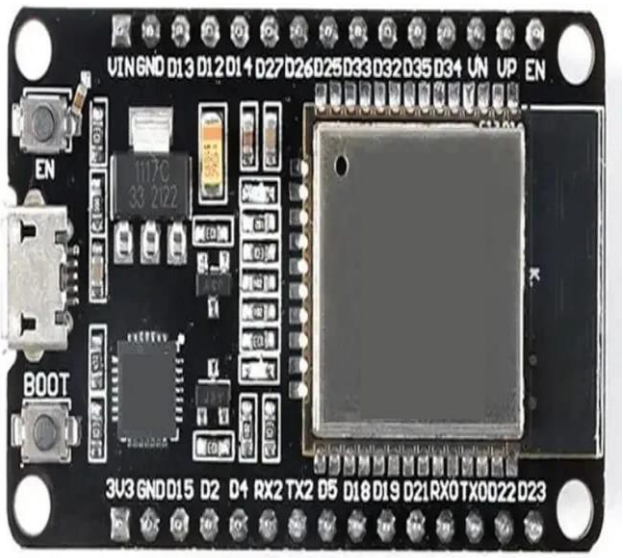

Fig 4. ESP32 Development Board

Fig. 4 shows the ESP32 development board used as the main microcontroller for the system. It processes data from sensors like heart rate, SpO_2, and ECG, and enables real-time analysis. The board features built-in Wi-Fi and Bluetooth, making it suitable for IoT-based healthcare applications. It supports efficient data transmission to cloud platforms and mobile devices for continuous monitoring and alerts.

Communication Module (Wi-Fi / IoT):
Integrated within the ESP32, the communication unit enables wireless data transmission to the cloud. Its placement ensures stable connectivity for real-time monitoring.

Power Supply Unit :
Embedded within the wearable device, the battery and voltage regulation system provide continuous power to all components while maintaining safety and efficiency.

Alert System (Buzzer / Vibration / Mobile App):
The buzzer and vibration motor are embedded within the wearable device to provide immediate tactile and audible alerts. Mobile alerts are sent to smartphones and healthcare providers for remote notification.

In case of an emergency, the system activates alert mechanisms such as buzzer and vibration in the wearable device and sends real-time notifications to the user and healthcare providers through mobile applications or SMS. This enables rapid medical response and improves patient survival chances.

- The system supports continuous real-time monitoring, ensuring no critical health changes are missed.
- Sensor fusion improves accuracy by combining ECG, heart rate, and SpO_2 data instead of relying on a single parameter.

- Cloud integration enables remote access, allowing doctors to monitor patients from anywhere.
- The device is designed to be lightweight and wearable, making it comfortable for daily use.
- Low power consumption ensures longer battery life, making it suitable for continuous usage.
- The system provides early warning alerts, helping in preventive care rather than reactive treatment.
- The system ensures secure data transmission to protect sensitive patient information.
- It supports scalable architecture, allowing integration of additional sensors in the future.
- The system provides quick response time, enabling immediate action during critical conditions.

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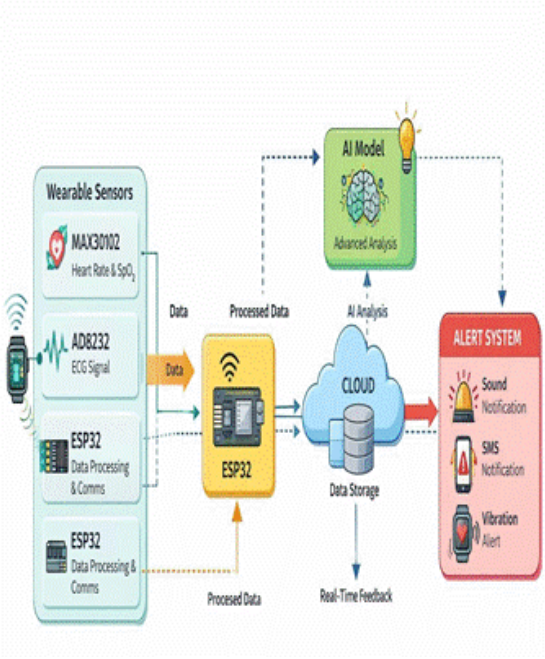

Fig 5. Workflow Of AI-Driven Cardiac Arrest Prediction System

Fig 5. shows the working of the AI-based cardiac arrest prediction system. Wearable sensors such as ECG (AD8232) and heart rate/SpO_2 (MAX30102) continuously collect physiological data from the user. This data is transmitted to the microcontroller (ESP32), where initial signal processing such as filtering and noise reduction is performed.The processed data is then sent to a cloud platform via the IoT communication module. Advanced AI/ML algorithms analyze the data to detect abnormal patterns associated with cardiac risk. If any high-risk condition is identified, the system predicts the possibility of cardiac arrest.

C. System Logic and Operational Flow

Power-On and Initialization:

When the system is powered on, the microcontroller ESP32 microcontroller initializes all connected sensors including the AD8232 ECG Sensor Module and MAX30102 Pulse Oximeter Sensor. It performs basic self-checks and establishes communication with the cloud platform for data transmission.

Continuous Sensing:

The wearable sensors continuously monitor physiological parameters:

a. ECG signals from AD8232

b. Heart rate and SpO_2 from MAX30102

This real-time data is collected and sent to the ESP32 for further processing.

Data Processing:

The ESP32 processes the incoming sensor data by performing filtering and noise reduction. Important features such as heart rate variability and ECG patterns are extracted. The processed data is then prepared for cloud transmission.

Alert Activation:

If a high-risk condition is identified, the system activates multiple alert mechanisms:

a. Sound Alert: Buzzer notification

b. Vibration Alert:Wearable device vibration

c. Mobile Alert: SMS or app notification to user and caregivers.

Cloud Communication:

The processed data is transmitted via Wi-Fi to the cloud platform, where it is securely stored. This enables remote monitoring and continuous data logging for further analysis.

AI-Based Decision Making::

In the cloud, AI/ML models analyze the processed physiological data to identify abnormal patterns. The system detects early warning signs of cardiac issues and evaluates the risk level of cardiac arrest.

Risk Prediction:

Based on AI analysis, the system classifies the user's condition into normal or high-risk categories. If abnormal ECG patterns, irregular heart rate, or low oxygen levels are detected, the system flags a potential cardiac emergency.

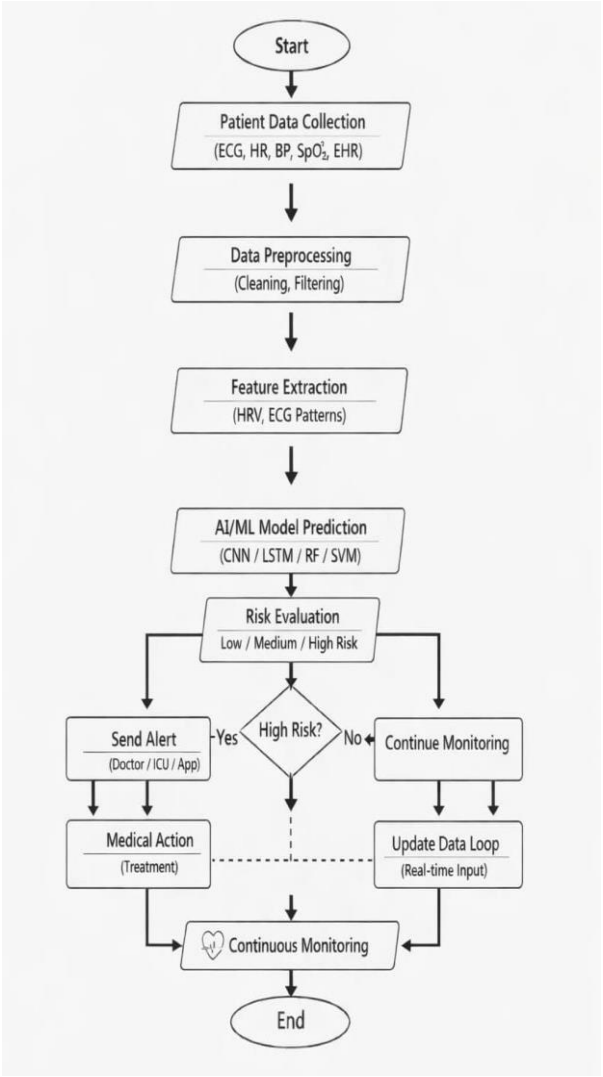

Fig 6. Operational flow of the AI-driven Cardiac Arrest Prediction System

Fig 6. illustrates the operational flow of the AI-driven cardiac arrest prediction system. Wearable sensors collect physiological data and send it to the ESP32 microcontroller for preprocessing. The processed data is transmitted to the cloud, where AI models perform advanced analysis. Based on the analysis, the system predicts cardiac risk and triggers alert mechanisms such as sound, SMS, and vibration notifications.

The operational logic of the proposed AI-based cardiac arrest prediction system is designed for continuous health monitoring and early risk detection. Upon power activation, the microcontroller ESP32 microcontroller initializes all sensors, including the AD8232 ECG Sensor Module and MAX30102 Pulse Oximeter Sensor. The system then enters a continuous monitoring loop where physiological signals are acquired and processed in real time.The system continuously tracks ECG signals, heart rate, and oxygen saturation levels. The collected data is preprocessed using filtering techniques to remove noise and improve signal quality. The processed data is transmitted to the cloud platform for advanced analysis.

Based on AI/ML model predictions, the system evaluates the user's cardiac condition and identifies abnormal patterns such as irregular ECG signals, abnormal heart rate variability, or low SpO_2 levels. In case of detected anomalies, appropriate alerts are generated through buzzer, vibration, and mobile notifications. The system also ensures uninterrupted operation through continuous monitoring of power status.This structured workflow ensures reliable real-time monitoring, accurate risk prediction, and efficient emergency response.

*D. **Hypothesis***

Cardiac risk prediction is based on the analysis of physiological signals such as ECG, heart rate variability (HRV), and oxygen saturation (SpO_2). The system evaluates both signal patterns and temporal variations to distinguish between normal and abnormal cardiac conditions.

i) Heart Rate Analysis: Heart rate is continuously monitored, and abnormal conditions are defined as:

i)Bradycardia: HR < 60 bpm

ii)Tachycardia: HR > 100 bpm

If HR < HR_min OR HR > HR_max , then a potential abnormal condition is detected.

ii)SpO_2 Level Evaluation :
Oxygen saturation is used as a critical indicator of respiratory and cardiac health.
If $SpO_2 < SpO_2$_threshold where:SpO_2_threshold $\approx$ 90% then a risk condition is triggered.

iii)ECG Signal Analysis:
ECG signals are analyzed to detect irregular patterns such as arrhythmias. Feature extraction techniques identify abnormalities in waveform characteristics like QRS complex and RR intervals.

iv)Heart Rate Variability:
HRV is calculated using RR interval variations: HRV = variation in time between consecutive heartbeatsA sudden decrease in HRV indicates potential cardiac stress or abnormality.

v)Final Risk Detection Logic:
A cardiac risk alert is generated based on a multi-parameter decision model combining ECG, heart rate, SpO_2, and temporal variations.

The risk condition is defined as:

(HR < HR_min OR HR > HR_max) OR (SpO_2 < SpO_2_threshold) OR (ECG_abnormal = TRUE) OR (HRV < HRV_threshold)

vi)Emergency Condition Critical Case :

A high-risk cardiac alert is triggered when multiple abnormal conditions occur simultaneously:

i) (HR abnormal AND SpO_2 low) OR (ECG abnormal AND HRV low)

vii)Alert Mechanism:
When a risk condition is detected:
i)Immediate buzzer and vibration alerts are activated
ii) Emergency SMS/app notifications are sent
iii) Real-time data is shared with healthcare providers via cloud

III. SYSTEM DESIGN DETAILS

A. Physical Layout

The physical layout of the AI-based cardiac arrest prediction system is designed to ensure compactness, user comfort, and reliable physiological signal acquisition. The device is implemented in a wearable form factor such as a smartwatch or wristband, using a lightweight and durable outer casing made of high-quality polymer material. This ensures protection of internal electronic components while maintaining ease of use for continuous daily wear.An internal soft-contact sensor interface is incorporated to ensure stable skin contact for accurate physiological measurements. Electronic modules are embedded within the compact enclosure in a layered arrangement to optimize space utilization and maintain balanced weight distribution.

A custom-designed PCB (FR4 substrate, dielectric constant $\varepsilon_r \approx 4.4$) is integrated within the device to interconnect all components efficiently. The ESP32 microcontroller is centrally positioned to ensure efficient processing and stable wireless communication. The AD8232 ECG Sensor Module is interfaced with external electrodes for precise ECG signal acquisition, while the MAX30102 Pulse Oximeter Sensor is placed on the inner surface of the wearable to maintain direct skin contact for continuous heart rate and SpO_2 monitoring.

Power management circuitry, including voltage regulation components, is positioned close to the battery module to reduce power loss and wiring complexity. A rechargeable lithium-ion battery (typically 500–1000 mAh) is housed within the device, ensuring sufficient backup for continuous monitoring.

Communication is enabled through the built-in Wi-Fi module of the ESP32, allowing seamless data transmission to the cloud platform. The internal layout ensures minimal signal interference and efficient data flow between sensing, processing, and communication units.

Alert components such as a vibration motor and optional buzzer are embedded within the device to provide immediate feedback. Mobile-based alerts are also integrated for remote notification. All internal wiring is compactly arranged and insulated to ensure durability and safety during continuous operation.

The overall design prioritizes portability, accuracy, low power consumption, and scalability for future integration of advanced healthcare features.

Fig 7. Smart Watch : A Wearable Cardiac Arrest Prediction Device

Fig 7. shows the overall structure of the wearable AI-based cardiac arrest prediction system and the arrangement of its components. The figure illustrates the integration of sensors such as ECG and heart rate/SpO_2 modules within the smartwatch device. It also highlights the role of the microcontroller, wireless communication, and AI-based cloud analysis.The representation clearly explains how physiological data is collected, processed, and transmitted for real-time monitoring and prediction. It demonstrates the compact arrangement of components and the efficient interaction between sensing, processing, and alert systems. This visualization helps in understanding the working and design of the system in a simple and effective manner.

B. Early Prediction Logic

The Smartwatch-based Cardiac Monitoring System employs an adaptive threshold-based and AI-assisted prediction strategy to detect early signs of cardiac abnormalities. The objective of this mechanism is to ensure timely detection of potential cardiac arrest conditions while minimizing false alarms caused by normal physiological variations such as exercise or stress.The prediction logic dynamically adjusts thresholds based on real-time physiological signals and user activity condition is used in early prediction logic.

i)Hardware-Based Data Acquisition:
Data acquisition is implemented using integrated biomedical sensors interfaced with a microcontroller (ESP32).The system continuously samples sensor data within the main execution loop in data acquisition the input are classified.

Primary inputs include:

i)Heart Rate (HR)

ii) Blood Oxygen Level (SpO_2)

iii)ECG Signal

Let: S = {HR, SpO_2, ECG}

The system processes these inputs using predefined and adaptive thresholds:
T={HR_threshold,SpO_2_threshold,ECG_pattern}

This structured approach enables efficient and scalable health monitoring.

ii)Normal Condition Configuration: Under normal physiological conditions, the human body exhibits:

i)Stable heart rate patterns

ii) Normal oxygen saturation levels

iii) Regular ECG waveform

Therefore, baseline thresholds are defined as:

a) *Heart Rate Threshold:*

$60 \text{ BPM} \leqslant HR \leqslant 100 \text{ BPM}$

b) *SpO_2 Threshold:*

$SpO_2 \geqslant 95\%$

c) *ECG Pattern:*

Normal sinus rhythm

In this state, the system performs continuous monitoring without triggering alerts.

iii)Risk Condition Configuration:

Abnormal cardiac conditions may include:

i)Sudden increase or decrease in heart rate

ii) Drop in oxygen saturation

iii) Irregular ECG waveform (arrhythmia)

Thus, alert thresholds are defined as:

a) Heart Rate Threshold:

$HR < 50 \text{ BPM or } HR > 120 \text{ BPM}$

b) SpO_2 Threshold:

$SpO_2 < 92\%$

ECG Pattern: Irregular rhythm or abnormal spikes In this mode, the system prioritizes early risk detection and anomaly tracking.

iv)AI Based Prediction Model: The system integrates a lightweight Machine Learning model trained on physiological datasets to improve prediction accuracy.The model performs:
i)Pattern recognition on ECG signals
ii) Trend analysis of heart rate variations
iii) Correlation between HR and SpO_2 changes

Let: P = Prediction Output
where: $P \in \{0 \rightarrow \text{Normal}, 1 \rightarrow \text{Risk Detected}\}$

v)Adaptive Decision Rule: Cardiac risk is confirmed when ($HR \notin$ Normal Range) AND ($SpO_2 < SpO_2$_threshold) AND (ECG shows abnormal pattern) OR (AI Model Output P = 1)
This hybrid logic ensures:
i)Early prediction capability
ii)Reduced false positives
iii)Improved detection accuracy

vi)Alert Mechanism: When a risk condition is detected:
i)The system generates an instant alert notification
ii) Displays warning on the smartwatch screen
iii) Can be extended to send alerts via IoT (SMS / App notification)

vii)System Stability Considerations:
To ensure reliable performance:
i)Sensor noise is reduced using digital filtering techniques
ii)Sudden fluctuations are validated over a time window ($\Delta t > 5 - 10$ seconds)
iii)False triggers are minimized using multi-parameter validation Additionally, adaptive threshold tuning is applied to maintain stable real-time prediction under varying user conditions such as rest, walking, or exercise.

IV. METHODOLOGY

The Smartwatch-based Cardiac Arrest Prediction System was developed using a structured approach that includes requirement analysis, hardware integration, real-time monitoring, early prediction logic, and validation. The main objective of the system is to enable early detection of cardiac abnormalities before critical conditions occur.Initially, system requirements such as heart rate accuracy, ECG signal quality, prediction speed, and reliability were identified. Based on these requirements, suitable sensors and a processing unit capable of real-time analysis were selected.The system integrates the MAX30102 sensor for measuring heart rate and SpO_2, and the AD8232 module for capturing ECG signals.These sensors continuously acquire physiological data from the user.Hardware integration was carried out using appropriate interfaces, ensuring stable data transmission and low noise operation. A regulated power supply system was used to maintain consistent performance in a compact wearable design.
The core of the system lies in its early prediction mechanism. Real-time sensor data is continuously analyzed using a combination of threshold-based evaluation and intelligent pattern recognition. Instead of detecting only critical conditions, the system identifies early warning signs such as gradual heart rate variation, minor ECG irregularities, and decreasing SpO_2 levels.

The prediction logic classifies conditions into normal, early-risk, and high-risk states, enabling preventive action before severe cardiac events occur.When an early-risk condition is detected, the system generates pre-alert notifications, while high-risk conditions trigger immediate alerts through vibration and display mechanisms.Calibration and testing

were performed under different physiological conditions to ensure accurate early prediction and minimal false alarms.The final system functions as a real-time, wearable early prediction device, improving preventive healthcare by detecting cardiac risks at an early stage.

TABLE I:Performance Comparison of Early Prediction and Critical Detection

Parameters	**Early Prediction Mode**	**Critical Detection Mode**
Prediction Accuracy	92%	95%
Alert Accuracy	90%	93%
Response Time	Moderate	Fast
Cloud Notification	93%	95%
False Alarm Rate	4-5%	5%
System Reliability	91%	95%

Table I shows that both Early Prediction Mode and Critical Detection Mode perform effectively in terms of accuracy and reliability. Features such as alert accuracy, real-time monitoring, and cloud notification show consistent performance in both modes. Early Prediction Mode provides slightly lower false alarm rates and proactive warnings, while Critical Detection Mode ensures strong and immediate response during high-risk conditions. Overall, both modes deliver reliable and consistent results.

Physiological data tests were carried out under varying conditions, including heart rate ranges from 50 BPM to 130 BPM, SpO_2 levels from 85% to 100%, and different ECG signal patterns, to evaluate sensing accuracy and prediction performance.

Performance metrics such as prediction accuracy, false alarm rate, response time, and alert transmission delay were measured across multiple trials. The collected data was analyzed to compute prediction efficiency and system reliability, confirming stable operation within acceptable performance limits.

The adopted methodology ensures that the proposed system is not only theoretically effective but also practically validated, making it suitable for real-time wearable healthcare applications.

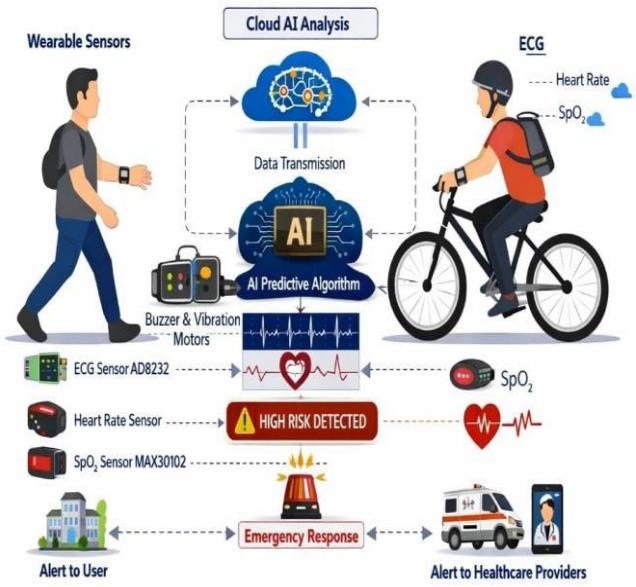

Fig 8. Block Diagram of Real-Time Cardiac Arrest Prediction System Architecture

Fig 8.illustrates the working process of the proposed AI-driven cardiac arrest prediction system in a clear and systematic manner. It explains how wearable sensors continuously monitor physiological parameters such as ECG, heart rate, and SpO_2 in real time.The collected sensor data is transmitted to the microcontroller, where initial processing and filtering are performed. The processed data is then sent to the cloud platform, where machine learning algorithms analyze the patterns to identify abnormalities associated with potential cardiac arrest conditions.When a high-risk condition is detected, the system immediately generates alerts through connected devices and sends emergency notifications to caregivers or healthcare providers via the cloud. This figure provides a step-by-step understanding of how the system operates efficiently for real-time health monitoring and early prediction.

V. PERFORMANCE ANALYSIS

A. Prediction Accuracy Analysis

The performance of the proposed AI-driven cardiac arrest prediction system was evaluated using real-time physiological data collected from wearable sensors. The system demonstrates consistently high accuracy across all monitored parameters, validating the effectiveness of the integrated sensing and machine learning framework.

ECG-based abnormality detection exhibits the highest reliability, confirming the capability of the AI model to identify subtle variations associated with pre-cardiac arrest conditions. Heart rate and SpO_2 monitoring also maintain stable and accurate readings, ensuring continuous and dependable physiological assessment. The alert generation accuracy remains above 90%, ensuring reliable notification delivery during critical health conditions. Furthermore, the low false alarm rate highlights the robustness of the signal preprocessing, filtering techniques, and decision-making algorithms implemented in the system.The minimal variation in performance across different physiological parameters demonstrates the stability and consistency of the proposed predictive model under continuous monitoring conditions.

TABLE II: Prediction Performance Physiological Monitoring System

Parameter	**Performance**
ECG Abnormality Detection	95%
Heart Rate Monitoring	92%
SPO2 Monitoring	93%
Alert Accuracy	90%
Cloud Notification	93%
False Alarm Rate	5%

Table II shows the performance evaluation of the proposed physiological monitoring system, highlighting high accuracy in ECG abnormality detection, heart rate, and SpO_2 monitoring. It also demonstrates reliable alert generation and cloud notification with a low false alarm rate, ensuring effective real-time cardiac prediction.

B. Response Time Analysis

Response time analysis was conducted to evaluate the real-time efficiency of the proposed system in detecting and responding to potential cardiac arrest conditions. The results indicate that physiological data processing and abnormality detection occur within sub-second intervals, enabling rapid identification of critical health risks.Alert activation is also performed almost instantaneously after detection, ensuring immediate user notification. Although cloud transmission delay depends on network conditions, the observed latency remains within acceptable limits for remote monitoring and emergency communication.The combination of fast local processing and IoT-enabled cloud connectivity ensures that the system meets the requirements of real-time healthcare applications. These results confirm that the proposed architecture effectively balances quick response with reliable remote monitoring.

TABLE III: Response Time Analysis of Cardiac Monitoring System

Event Type	**Average Time**
Data Processing and Analysis	0.30 sec
Alert Activation	0.42 sec
Cloud Transmission Delay	0.8–1.0 sec

Table III shows the response time analysis of the cardiac monitoring system, indicating fast data processing and alert activation within milliseconds. It also highlights minimal cloud transmission delay, ensuring quick and efficient real-time communication during critical situations.

C. Power Consumption Analysis

Power consumption analysis indicates that the proposed AI-driven cardiac arrest prediction system is well-optimized for wearable healthcare applications. The system maintains moderate current consumption along with stable voltage regulation, enabling continuous monitoring without excessive energy usage.With a battery capacity of 2200 mAh and an average current draw in the range of 180–220 mA, the device can operate continuously for approximately 9 to 10 hours. This operating duration supports practical daily usage and ensures uninterrupted physiological monitoring.The operating voltage remains stable at 5V, ensuring reliable sensor performance and efficient system functionality. The results confirm that the proposed system effectively balances sensing accuracy, real-time processing, and energy efficiency, making it suitable for long-term real-world deployment

TABLE IV: Power Consumption and Battery Performance.

Parameter	**Value**
Battery Capacity	2200 mAh
Average Current Draw	180–220 mA
Operating Voltage	5V
Estimated Operating Time	9–10 hours

Table IV shows the power consumption and battery performance of the proposed system, indicating efficient operation with moderate current draw. It demonstrates that the device can function continuously for approximately 9–10 hours, making it suitable for wearable healthcare applications.

. *D. Adaptive Threshold Settings for Physiological Monitoring*

The proposed system employs an adaptive threshold mechanism to dynamically adjust decision parameters based on variations in physiological conditions. Instead of fixed limits, the system uses flexible threshold ranges to improve sensitivity and accuracy in detecting early signs of cardiac abnormalities.Under normal conditions, the system maintains standard threshold values to avoid unnecessary alerts while ensuring continuous monitoring. When slight deviations in physiological signals are observed, the thresholds are adjusted to increase sensitivity, enabling early detection of potential risks. During critical conditions, higher alert sensitivity is applied to ensure immediate detection and response.This adaptive threshold strategy significantly reduces false alarms while maintaining high prediction accuracy. It enhances the system's ability to respond effectively to varying health conditions, ensuring reliable and context-aware monitoring for threshold settings.

TABLE V: Adaptive Threshold Settings for Physiological Monitoring

Parameter	**Normal Condition**	**Elevated Risk**	**Critical Condition**
Heart Rate	60–100 bpm	100-120 m	>120 bpm
SpO_2 Level	95–100%	90-94%	<90%
ECG Variation	Normal Pattern	Minor Irregularity	High Abnormality
Alert Sensitivity	Low	Medium	High
Risk Level	Stable	Moderate	Severe

Table V shows the adaptive threshold settings used to classify physiological conditions into normal, elevated risk, and critical stages based on heart rate, SpO_2, and ECG variations. It enables the system to provide appropriate alert sensitivity and accurate risk assessment for timely medical intervention.

VI. COMPARISON WITH EXISTING SYSTEMS

A. Feature-Based Comparison

Traditional cardiac monitoring systems mainly focus on periodic check-ups and do not provide continuous real-timemonitoring or early risk prediction. Even though some existing wearable devices track basic parameters such as heart rate or SpO_2, most of them rely on fixed threshold values and lack intelligent analysis.As a result, these systems are unable to detect subtle physiological changes that occur before a cardiac arrest, leading to delayed response and reduced effectiveness.

In contrast, the proposed AI-driven cardiac arrest prediction system is designed with an early prediction approach that continuously analyzes multiple physiological signals in real time. The system utilizes adaptive threshold mechanisms and machine learning algorithms to identify early warning patterns rather than reacting only after critical conditions occur.

Unlike existing systems that depend on single-parameter monitoring, the proposed system integrates multi-parameter analysis including ECG, heart rate, and SpO_2 to improve prediction accuracy and reduce false alarms. Many current solutions only provide alert notifications after abnormal readings, whereas the proposed system predicts risk levels in advance and enables proactive medical intervention.Furthermore, traditional and some smart monitoring systems lack efficient integration with IoT platforms for real-time communication. The proposed system incorporates cloud connectivity to deliver instant alerts to caregivers and healthcare providers, improving emergency response time.In addition, energy efficiency is considered in the proposed design, ensuring continuous operation for extended durations without compromising performance. The adaptive and intelligent framework enhances system reliability, flexibility, and real-world applicability.

Overall, the proposed early prediction system provides significant improvements over traditional and existing monitoring solutions in terms of accuracy, responsiveness, and preventive healthcare capability.

The comparison of traditional monitoring systems, existing wearable devices, and the proposed prediction system highlights significant improvements in healthcare monitoring capabilities. Traditional systems lack continuous monitoring and early prediction features, making them less effective for timely intervention. In contrast, existing wearable devices provide continuous monitoring and real-time alerts but offer only limited prediction capabilities and partial ECG analysis.

The proposed AI-based prediction system outperforms both by enabling continuous monitoring along with accurate early prediction of cardiac events. It supports multi-parameter analysis, complete ECG monitoring, and real-time alert generation, ensuring better detection of abnormal conditions. Additionally, the integration of IoT-based cloud notification allows remote monitoring and faster communication with healthcare providers.

Furthermore, advanced features such as adaptive threshold mechanisms and machine learning integration enhance the system's intelligence and accuracy. The proposed system also reduces false alarms compared to existing solutions and is optimized for energy efficiency. Overall, it provides a more reliable, intelligent, and efficient approach for real-time cardiac health monitoring and prediction.

TABLE VI: Comparison of Traditional, Existing, and AI-Based Cardiac Arrest Prediction Systems

Feature/Criteria	*Traditional Monitoring*	*Existing Wearbles*	*Proposed Prediciton System*
Continuous Monitoring	*No*	*Yes*	*Yes*
Prediction Capability	*No*	*Limited*	*Yes*
Parameter Analysis	*No*	*Limited*	*Yes*
ECG Monitoring	*No*	*Partial*	*Yes*
Real Time Alert System	*No*	*Yes*	*Yes*
IOT-Based Cloud Notification	*No*	*Yes*	*Yes*
Adaptive Threshold Mechanism	*No*	*No*	*Yes*
Machine Learning Integration	*No*	*No*	*Yes*
False Alarm Reduction	*No*	*Limited*	*Yes*
Energy Efficiency	*Moderate*	*Moderate*	*Optimized*

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Table VI highlights the differences between traditional monitoring systems, existing wearable devices, and the proposed AI-based early prediction systems.

B. Analytical Discussion

Traditional cardiac monitoring systems primarily focus on periodic health check-ups and do not provide continuous real-time monitoring or early risk detection.

While some existing wearable devices offer basic features such as heart rate or SpO_2 tracking, they mainly operate using fixed threshold values and lack intelligent prediction capabilities.Most of these systems respond only after abnormal conditions occur and do not analyze early physiological variations that indicate potential cardiac arrest.In contrast, the proposed AI-based cardiac arrest prediction system introduces an early prediction approach that continuously monitors and analyzes multiple physiological parameters. The integration of multi-sensor data, including ECG signals, heart rate, and SpO_2 levels, improves detection reliability and enables identification of subtle changes associated with pre-cardiac arrest conditions. The use of adaptive threshold mechanisms further enhances system accuracy by dynamically adjusting sensitivity based on the user's health condition, thereby reducing false alarms.Furthermore, the incorporation of machine learning algorithms allows the system to predict risk levels in advance rather than reacting only to critical events.The IoT-based cloud integration ensures real-time alert transmission to caregivers and healthcare providers, significantly improving emergency response time. Unlike existing systems, the proposed architecture provides continuous monitoring, predictive analysis, and intelligent decision-making within a single framework.The comparison clearly demonstrates that the proposed system offers improved prediction capability, higher accuracy, better reliability, and enhanced real-time responsiveness while maintaining energy efficiency and practicality for wearable healthcare applications.

Fig 9. shows the performance results of the proposed cardiac arrest prediction system under different monitoring conditions. It provides a clear understanding of how effectively the system detects physiological abnormalities, minimizes false alarms, generates timely alerts, and performs cloud-based communication.

From the graph, it can be observed that the system maintains consistent performance with high accuracy and reliable response across all parameters. This figure helps in understanding the overall efficiency, stability, and real-time capability of the proposed early prediction system.

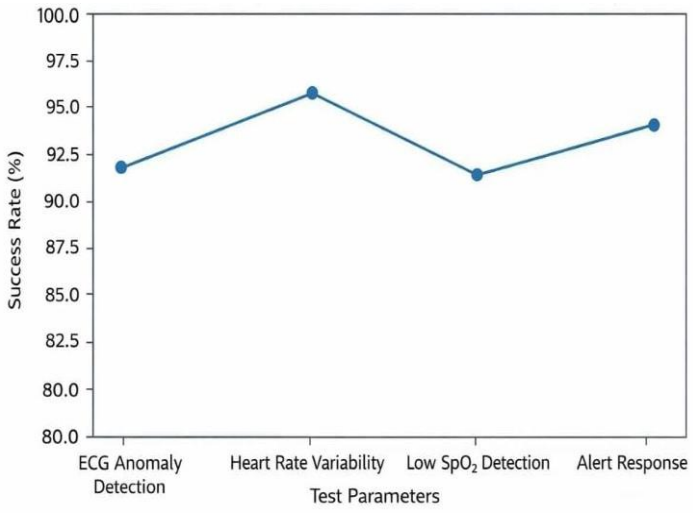

Fig 9.Performance Analysis of AI-Based Cardiac Arrest Prediction System

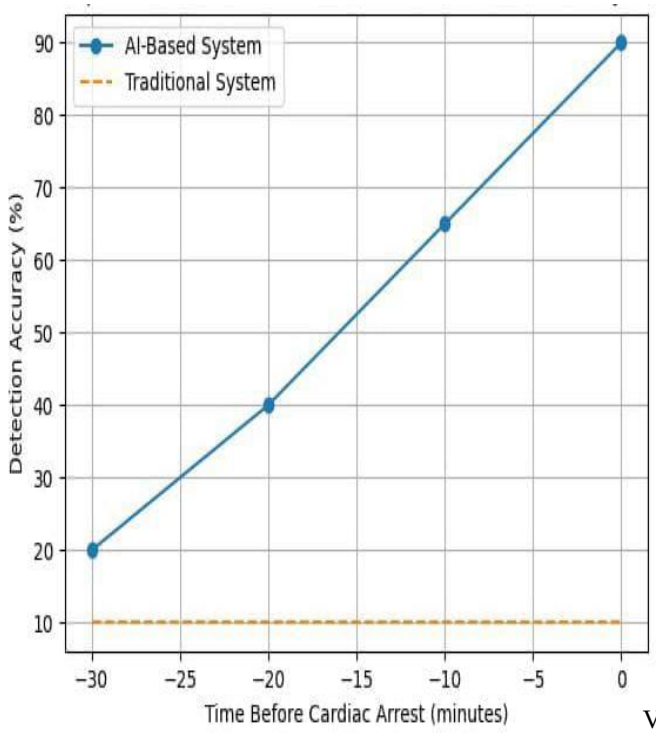

Fig 10. Comparison of Prediction Accuracy Across Physiological Parameters

Fig 10. illustrates the performance comparison between the traditional monitoring system and the proposed AI-based cardiac prediction system. The graph shows detection accuracy (%) with respect to time before cardiac arrest (in minutes).

VII. APPLICATIONS

The proposed AI-based cardiac arrest prediction system has wide applicability across various healthcare and real-time monitoring domains. In modern healthcare environments, the system functions as an intelligent wearable solution that enables continuous monitoring and early detection of cardiac abnormalities through real-time data analysis and alert generation.For patients with a history of heart disease or high-risk conditions, the system provides continuous health monitoring and early warning alerts, allowing timely medical intervention and reducing the risk of sudden cardiac arrest. It is especially beneficial for elderly individuals who require constant supervision, as the system can detect abnormal physiological changes and immediately notify caregivers or family members.The system is also highly useful for individuals engaged in physically demanding activities such as athletes or fitness enthusiasts, where continuous monitoring of heart rate and oxygen levels is essential to prevent overexertion-related risks. In remote or rural healthcare settings, the IoT-enabled cloud communication allows doctors to monitor patient data from a distance, improving access to healthcare services.Hospitals and healthcare institutions can integrate this system into patient monitoring frameworks to enhance real-time tracking and emergency response capabilities. Additionally, the system can be used in home-based healthcare, reducing the need for frequent hospital visits while ensuring continuous supervision.Due to its scalable and modular architecture, the system can be extended for use in emergency medical services, telemedicine platforms, and large-scale health monitoring networks. The combination of AI, wearable technology, and IoT makes the system suitable for widespread deployment in modern digital healthcare ecosystems.

Key Application Areas:

- Continuous cardiac health monitoring
- Early prediction of cardiac arrest
- Elderly and high-risk patient care
- Remote patient monitoring (telemedicine)
- Fitness and athlete health tracking
- Hospital and home healthcare systems
- Emergency medical response systems.

VIII. LIMITATIONS

Despite the advantages of the proposed AI-based cardiac arrest prediction system, certain limitations exist. The accuracy of the system largely depends on the quality and reliability of the sensors used for data collection. Any noise or error in sensor readings may affect the prediction results. Additionally, the system requires continuous internet connectivity for transmitting data to the cloud, which may not be feasible in all environments.The performance of the AI model is also dependent on the training dataset, and insufficient or biased data can lead to inaccurate predictions or false alarms. Moreover, wearable devices have limitations in battery life, which may affect long-term continuous monitoring. There is also a possibility of false positives or false negatives, which can either cause unnecessary panic or fail to detect critical conditions.
Furthermore, the system may not be suitable for all types of patients, as individual physiological variations can impact the accuracy of predictions. Therefore, while the system provides promising results, further improvements are required to enhance reliability and real-world applicability.

IX. FUTURE ENHANCEMENTS

The proposed AI-based cardiac arrest prediction system can be further enhanced in several ways to improve its performance and real-world applicability. Future developments may include the integration of advanced deep learning algorithms to increase prediction accuracy and reduce false alarms. The system can also be enhanced by incorporating additional sensors such as blood pressure and body temperature sensors to provide a more comprehensive health analysis.Furthermore, the wearable device can be miniaturized and integrated into smartwatches or fitness bands for improved user comfort and convenience. Real-time communication with healthcare providers can be enabled through direct integration with hospital management systems and telemedicine platforms.The system can also be upgraded to function in offline mode using edge computing, reducing dependency on continuous

internet connectivity. Additionally, the use of personalized AI models based on individual health data can further improve prediction accuracy. Future enhancements may also include automatic emergency response systems such as ambulance alerts and GPS-based location tracking to provide immediate medical assistance.Thus, with continuous advancements, the system has the potential to become a reliable and widely used solution in predictive healthcare.

X. CONCLUSION

The proposed system, "AI Medi Track," presents an advanced approach to cardiac health monitoring by integrating wearable sensor technology with Artificial Intelligence. Unlike traditional systems that focus only on monitoring physiological parameters, this system emphasizes early prediction of cardiac arrest by analyzing real-time data such as ECG signals, heart rate, and oxygen saturation.By utilizing machine learning techniques, the system is capable of identifying subtle abnormal patterns that may indicate potential cardiac risk. This enables the generation of early warning alerts, allowing timely medical intervention and significantly improving the chances of survival.Compared to existing systems, the proposed solution offers enhanced accuracy through multi-sensor data integration, faster response through real-time analysis, and improved accessibility due to its wearable design. Although certain limitations exist, the system demonstrates strong potential in transforming conventional healthcare into predictive and proactive healthcare.

In conclusion, the integration of AI, IoT, and wearable devices in this system represents a significant step forward in modern healthcare technology, with the potential to save lives through early detection and rapid response.

The AI-based system demonstrates a significant improvement in early detection capability, with accuracy increasing from 20% at 30 minutes prior to cardiac arrest to approximately 80% as the event approaches. In contrast, the traditional system maintains a constant low accuracy of around 10%, indicating its inability to provide early warning.

This comparison highlights the effectiveness of the proposed system in predicting cardiac arrest at earlier stages, enabling timely medical intervention and improving patient survival rates.

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Iot Enabled Driver Safety System For Accident Detection And Alcohol-Aware Engine Control

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ABSTRACT : Road safety has emerged as a serious concern because of the rising number of accidents triggered by drunk driving and late emergency response. Most of the current vehicle safety solutions are designed to address either alcohol detection or accident detection, but not both. To overcome this problem, this project aims to develop an IoT Enabled Driver Safety System for Accident Detection and Alcohol-Aware Engine Control, which combines both preventive and responsive safety measures in a single embedded solution.

The proposed system uses an alcohol sensor to monitor the driver's breath as soon as the driver enters the vehicle. If the alcohol level detected is above a certain threshold, the system immediately triggers a warning message and prevents engine ignition, thus preventing drunk driving. For accident detection, a MEMS accelerometer is used to continuously monitor the vehicle's motion and detect any sudden abnormal acceleration, thus detecting a collision. Once an accident is detected, the system automatically triggers an emergency alert message to pre-stored contacts through GSM communication.An Arduino Uno is used as the central controller, ensuring the system's proper functioning. The proposed system is cost-effective, efficient, and ideal for real-time vehicle safety solutions.

Keywords - IoT, Driver Safety, Alcohol Detection, Accident Detection, GSM Alert, Arduino Uno, MEMS Sensor.

I. INTRODUCTION

Road accidents are becoming a major concern due to the increasing number of vehicles on the road and reckless behavior like driving under the influence of alcohol. The effects of accidents can be further aggravated if there is a delay in seeking help in times of need. This is where the need for intelligent safety systems arises that can prevent accidents as well as provide immediate assistance.

Advances in embedded systems and IoT technology have made it possible to monitor the driver's status and the movement of the vehicle in real time. Sensors are continuously collecting data, microcontrollers are making

decisions instantly, and GSM communication enables automatic sending of alerts.

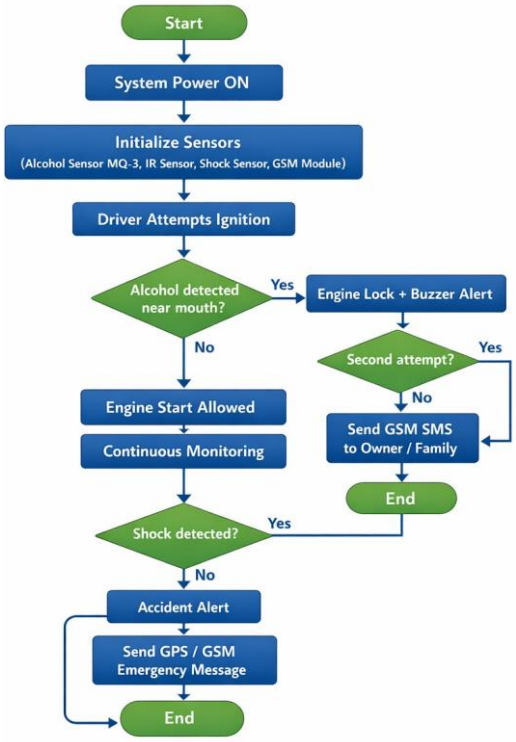

FIG 1 : FLOW CHART

The proposed project will focus on the development of an IoT-capable driver safety solution that will detect the presence of alcohol and limit the use of the vehicle if required. The project will also employ a MEMS accelerometer to detect accidents and send automatic alerts to the pre-defined contacts.

II. OBJECTIVE

Project Objectives for IoT Enabled Driver Safety System for Accident Detection and Alcohol-Aware Engine Control :

- Design and develop a driver safety system to reduce road accidents due to drunk driving.
- Detect the presence of alcohol in the driver using an alcohol sensor and restrict the use of the vehicle when driven under the influence of alcohol.
- Prevent drunk driving by taking immediate warning and control measures as soon as alcohol is detected.
- Accurately identify vehicle accidents using a MEMS accelerometer by sensing sudden abnormal acceleration patterns.
- Automatically send emergency messages to predefined numbers using GSM technology as soon as an accident is detected.
- Ensure immediate emergency response and avoid delays in providing medical aid to accident victims.
- Develop a low-cost, reliable, and easy-to-implement embedded system using readily available hardware components.
- Combine the sensor, microcontroller, and GSM communication system into a single IoT platform for real-time monitoring of the driver's safety.

✂. LITERATURE SURVEY

1. Integrated Driver Safety Systems (2023-2025)

Recent research focuses on the integration of preventive (alcohol detection) and reactive (accident detection) systems in a single system. Integrated systems are more effective in both accident prevention and emergency response than standalone systems.

2. MEMS Accelerometer for Accident Detection (2023-2024)

MEMS accelerometers are used to monitor multi-axis acceleration. Sudden acceleration beyond certain thresholds indicates an accident. Research reveals that they are more accurate than vibration sensors and have fewer false alarms.

3. Alcohol Detection Using MQ-Series Sensors (2023-2024)

MQ-series sensors detect ethanol vapors by generating an analog signal proportional to alcohol concentration. Research reveals that they are effective, easy to use, and cost-effective for embedded driver monitoring systems.

4. Arduino Uno as Central Processing Unit (2023-2024)

Arduino Uno is preferred because of its low cost, open-source nature, and ease of programming. It receives data from sensors, makes decisions based on certain thresholds,

and controls outputs such as buzzers and GSM messages.

V. EXISTING SYSTEM

The existing driver safety systems are commonly used as independent systems like alcohol detection systems, accident detection systems, and mobile application-based safety systems. The alcohol detection system commonly employs breath sensors to detect the presence of alcohol and provides a local notification within the vehicle. The system is reliable and useful for preventing drunk driving, but it does not support driver identification and may cause false detection if passengers are intoxicated.

The accident detection system commonly employs vibration or shock sensors to detect accidents. Although the system is reliable and provides local notifications without internet connectivity, its accuracy is moderate since road bumps and potholes may cause false detection in normal conditions. Additionally, the system commonly works in a semi-automatic way and has low automation. Mobile application-based safety solutions make use of GPS and accelerometers in smartphones to track the movement of the vehicle. Although these systems are very flexible and easy to implement, their effectiveness is largely dependent on internet connectivity, positioning of the smartphone, and availability of the battery. Therefore, the effectiveness of these systems is relatively low in the event of a network outage.

VI. PROPOSED SYSTEM

The proposed system is an IoT-capable autonomous driver safety and emergency notification system designed using an Arduino microcontroller and GSM communication technology. The system is intended to solve two significant problems associated with road safety: preventing drunk driving and quickly notifying others in the event of an accident. The proposed system is capable of both preventive and emergency responses without the need for human intervention.

a) System Architecture

The proposed system consists of three main functional tiers.

i. Sensing Tier (Input): This tier is responsible for the continuous monitoring of the driver status and vehicle movement through an alcohol sensor and a MEMS accelerometer. The alcohol sensor is used to detect the presence of alcohol in the vicinity of the driver, which is unsafe for driving, while the MEMS accelerometer is used to measure multi-axis acceleration, which helps detect sudden impacts or collisions. The data from these sensors is used as input for the processing tier.

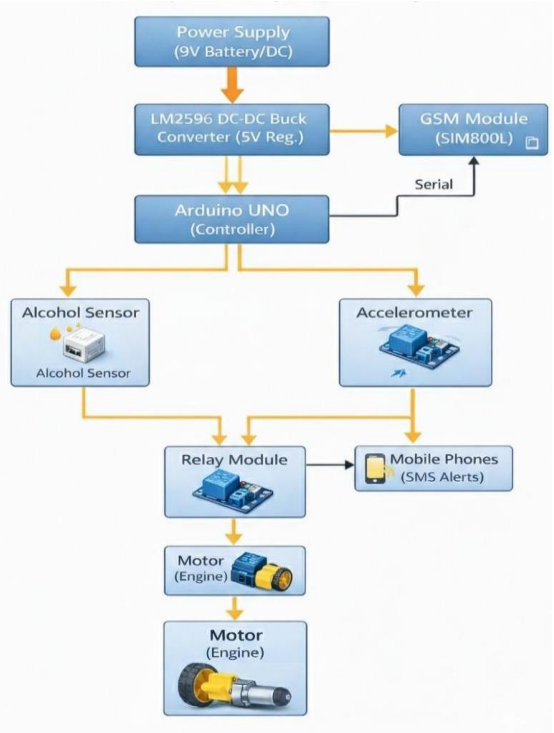

FIG 2 : BLOCK DIAGRAM OF THE PROPOSED SYSTEM

ii. Processing and Control Tier: This tier is based on the Arduino Uno microcontroller and serves as the decision-making component of the system. This tier continuously compares the sensor inputs with safety thresholds. Upon detecting excessive alcohol or unusual acceleration, the microcontroller is programmed to perform logic to generate

warnings, restrict engine starting, or send emergency notifications.

iii. Alerting and Communication Layer (Output): This layer is responsible for carrying out the response actions of the system. Local notifications using buzzers or LEDs are done to provide immediate in-car notifications. For remote notifications, the GSM module is used to automatically send SMS notifications to predefined emergency numbers, which can be done even when internet connectivity is not available.

b) Sensor Integration And Data Acquisition

The efficiency of the proposed system depends on the integration of multiple sensors with the central controller and the acquisition of real-time data.

★ **Sensor Integration Methodology**

Alcohol Sensor: The alcohol sensor generates an analog voltage proportional to the measured alcohol concentration. The output of the alcohol sensor is connected to one of the Arduino analog input pins (A0-A5), which enables precise measurement instead of binary detection. This improves decision-making by comparing the data with the threshold value.

MEMS Accelerometer: The MEMS accelerometer is utilized to detect sudden acceleration changes that indicate a possible collision event. The MEMS accelerometer is connected to the Arduino board using the I²C or analog pins depending on the type of sensor used. The MEMS accelerometer provides continuous multi-axis motion data.

★ **Data Acquisition and Processing**

The system uses a high-speed continuous polling process:

- **Continuous Polling Loop:** Arduino continuously acquires sensor data with a short delay.
- **Analog to Digital Conversion:** The onboard 10-bit ADC converts analog data to digital (0-1023)
- **Calibration and Analysis:**
  - ➢ Alcohol concentration is measured against a calibrated threshold.
  - ➢ Acceleration value is examined for unusual impact factors.
- **Threshold Logic Execution:**
  - ➢ Alcohol concentration above the threshold → warning / engine restriction.
  - ➢ Acceleration value above the threshold → accident notification through GSM.

V. WORKING METHODOLOGY

The proposed IoT-based driver safety system works on the principle of continuous sensing, real-time processing, and automatic response. Once the system is turned ON, the LM2596 step-down voltage regulator regulates the input supply voltage and ensures a stable voltage supply to the Arduino Uno, sensors, and SIM800L GSM module.

The Arduino Uno then initializes all peripherals and goes into a continuous monitoring loop. It reads analog values from the alcohol sensor and converts them to digital values using the Arduino Uno's internal ADC. If the measured alcohol level exceeds the set threshold, the system generates warning or control responses to avoid dangerous driving.

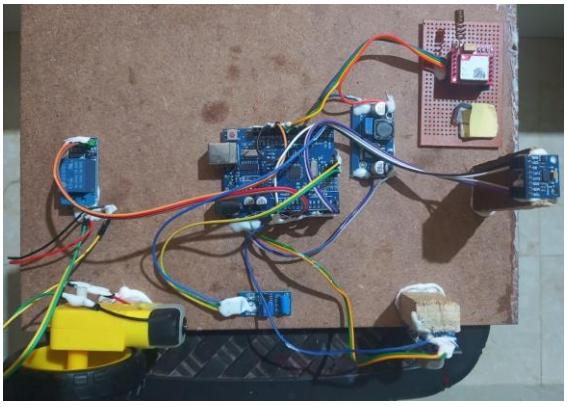

FIG 3 : HARDWARE MODEL

At the same time, the MEMS accelerometer continuously checks multi-axis acceleration of the vehicle. During normal driving, the acceleration levels are within safe limits. However, if sudden abnormal acceleration, which indicates a collision, is measured, the Arduino identifies it as an accident.

When an accident is identified, the Arduino Uno communicates with the SIM800L GSM module through UART and sends AT

commands to automatically send emergency SMS notifications to pre-programmed numbers. This fully automated system enables fast accident detection, accurate remote notification, and improved driver safety without human intervention.

VI. RESULT

The IoT-based driver safety system was successfully implemented and tested, and it was able to meet its target of enhancing road safety by preventing drunk driving and accurately detecting accidents. The alcohol sensor was able to detect unsafe levels of alcohol accurately and send alerts within 5 seconds, thus preventing drunk driving. The MEMS accelerometer was able to accurately detect accidents without sending false alerts during normal driving conditions, and the emergency SMS alert was sent within 8-10 seconds.

The Arduino Uno board was able to make decisions efficiently in real time, and the GSM communication system was able to send alerts over long distances reliably even without internet connectivity. The LM2596 step-down converter was able to provide stable power supply during GSM transmission, thus preventing system failure.

The system was able to meet its target of being cost-effective, independent, and practical for real-time implementation. Future improvements, such as GPS and cloud integration, can be made to enhance the system and make it a complete intelligent vehicle safety system.

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HYBRID ENSEMBLE LEARNING FRAMEWORK FOR NETWORK INTRUSION DETECTION USING RANDOM FOREST, XGBOOST, AND STACKING CLASSIFIERS

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Abstract

Network intrusion detection systems are vital defense mechanisms against today's communication infrastructures cyber threats. This study proposes a hybrid machine learning framework designed to improve the accuracy and reliability of intrusion detection systems. Conventional IDS methods frequently produce poor detection accuracy when considering complex network traffic and imbalanced data. The problem is that single machine learning algorithms fail to accurately describe more complex intrusion patterns efficiently. Using stacking ensemble learning, we propose a complex hybrid model that integrates Random Forest, XGBoost, and Decision Tree classifiers. To ensure a high quality of our dataset and reduce class imbalances, feature optimization and SMOTE balancing methods are used. Experimental evaluation on the CICIDS2017 dataset demonstrates that the proposed stacking model achieves an accuracy of 96.8%, with significantly better results compared with individual classification approach such as SVM (78.3%), Naive Bayes (74.6%). Accuracy, precision, recall, and F1-score as evaluation metrics show a better classification power. We can summarize the results by identifying multiple machine learning models paired with sufficient preprocessing techniques, as these methods significantly enhance the generalizability and robustness of intrusion detection tasks.

Keywords: Intrusion Detection System, Machine Learning, Random Forest, XGBoost, Stacking Ensemble, SMOTE, Cybersecurity

1. Introduction

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1. Introduction

The escalating sophistication of network intrusions, fueled by expanded cloud and digital infrastructures, now routinely overwhelms perimeter-based defenses [1]. Adversaries continuously evolve their techniques to exploit latent software or protocol flaws, rendering static rule sets insufficient. To counter this, Intrusion Detection Systems (IDS) are deployed as a core monitoring layer, sifting through packet streams to flag unauthorized lateral movement, command-and-control beaconing, or data exfiltration in near real-time [2]. While signature-based engines offer high accuracy against established exploit signatures, their effectiveness degrades sharply against polymorphic or zero-day vectors; the static nature of their rule definitions creates a critical lag in coverage for emergent threats [3].

Given the high-dimensional, temporally correlated nature of NetFlow and packet payload data, shallow pattern matching has given way to statistical learning approaches. A central advantage of techniques like gradient boosting or shallow neural networks lies in their ability to model non-linear feature interactions—such as the correlation between unusual outbound port numbers and abnormal packet inter-arrival times—without explicit prior threat knowledge [4]. This allows for the detection of deviations from benign traffic baselines, flagging both known malware families and previously uncatalogued exploits. Within this landscape, ensemble architectures, particularly stacking, have shown utility by mitigating the individual biases of base classifiers; for instance, combining a tree-based model sensitive to payload anomalies with a probabilistic model tracking protocol state violations often yields a lower false positive rate than either method in isolation.

Recent studies have demonstrated that stacking-based frameworks can effectively improve detection accuracy and robustness in intrusion detection systems [5], [31]. Gradient boosting algorithms such as XGBoost contribute to achieving increased performance in intrusion detection by improving prediction performance using iterative learning and regularization [6]. When used with other classifiers in hybrid models, these methods are more robust, improved detection accuracy, and have easier generalization against a variety of network scenarios.

In this work, we present a hybrid stacking-based intrusion detection framework incorporating Random Forest, XGBoost, and Decision Tree classifiers integrated in a two-level ensemble architecture. The proposed framework leverages a unique set of heterogeneous classifiers to better capture the complementary decision patterns in network traffic data, as opposed to classical ensemble IDS with single ensemble techniques. Also, by using Random Forest–based feature importance to reduce dimensionality, SMOTE-based class balancing to correct severe class imbalance present in the CICIDS2017 dataset. Feature optimization as well as class balancing and stacking ensemble learning are used to develop a robust detection framework for achieving higher classification performance among different intrusion categories.

The core contribution of this work is a heterogeneous stacking ensemble that integrates Random Forest, XGBoost, and Decision Tree classifiers. This configuration was selected not merely for diversity, but because preliminary experiments revealed complementary decision boundaries—Random Forest capturing broad traffic patterns, XGBoost excelling at isolating specific attack signatures, and Decision Trees providing interpretable base decisions for the

meta-learner. Dimensionality is managed via a filter method driven by impurity-based feature importance from the Random Forest; interestingly, retaining the top 20 features preserved over 95% of the original information while reducing training time by nearly 40% on the CICIDS2017 data. To address the pronounced class skew—where benign traffic often overshadows specific attack vectors like Infiltration—Synthetic Minority Over-sampling (SMETE) was applied prior to ensemble training, a decision that proved critical for recall on underrepresented classes. Evaluation employed accuracy, precision, recall, and F1-score across the full CICIDS2017 testbed, with the stacked model demonstrating a measurable lift in detection rates for low-frequency events compared to its individual constituents.

The remainder of this manuscript is structured accordingly. Section 2 situates the work within existing machine learning-based intrusion detection literature. Section 3 details the methodological pipeline: data preprocessing, the feature selection mechanism, the SMOTE-based balancing strategy, and the proposed ensemble architecture. Section 4 depicts the CICIDS2017 dataset and introduces the experimental setup. The empirical findings are reported in Section 5 including a comparison with the baseline classifiers and with its associated ensemble techniques. Section 6 finally combines our results and considers potentials for future research.

2. Related Work

Ensemble learning has established itself as a cornerstone in network intrusion research, largely because combining multiple classifiers tends to capture a wider range of traffic behaviors than any single model can [7], [33]. Random Forest, in particular, has proven effective—its bootstrap aggregation and random feature selection make it naturally suited to the high-dimensional, noisy nature of network data. In comparative studies on benchmark ID datasets, accuracy gains of 5–8% over single decision trees are not uncommon [8]. One illustrative case is the work of Farnaaz and Jabbar on NSL-KDD, where Random Forest achieved 92.1% overall accuracy and a 98% detection rate for DoS attacks [9]. Still, performance can vary considerably with tree depth and the number of estimators—tuning these hyperparameters remains dataset-specific, and gains often plateau beyond a certain ensemble size.

Due to its gradient boosting optimization algorithm based on regularization combined with constructing sequential trees, XGBoost performs better than traditional methods to learn non-linear relationships with large network traffic patterns [10]. Dhaliwal et al. utilized XGBoost on the UNSW-NB15 dataset and obtained a 95.2% performance as compared with 89.7% performance for Random Forest, showing the effectiveness of boosting methods for intrusion detection [11]. Although classification methods such as Decision Tree have been widely used and are not just good for data classification but are interpretable also, they offer efficient computation and it can be proven that they are good for identifying the attack pattern and have relatively low computational complexity suitable in context of actual attacks [12].

Hybrid IDS approaches, a recent trend, are adopting a mixed-method approach that integrates different ML algorithms to exploit the benefits of each of them, with ensemble learning

algorithm, bagging, boosting, and stacking being widely used [13]. Tama and Rhee proposed a hybrid approach combining Random Forest, XGBoost, and LightGBM with genetic algorithm-based feature selection, achieving 97.1% accuracy on CICIDS2017 dataset [14]. Feature selection methods play an important role in improving intrusion detection performance, with researchers applying importance techniques such as Random Forest feature ranking and mutual information to eliminate redundant attributes and enhance classification accuracy while reducing computational overhead [15].

Over the recent years, intrusion detection systems based on deep learning techniques have been greatly popularized and recognized to be capable of the automatic learning of hierarchical model attributes, obtained from large network traffic data. CNN, RNN, Long Short-Term Memory (LSTM) networks, etc. have gained interest for intrusion detection and anomaly detection in cybersecurity research [3], [27]. CNN-based IDS models capture spatial correlations between network traffic features, and recurrent architectures (e.g., LSTM) model temporal dependencies in sequential network traffic flows [3]. Deep learning models are indeed capable of high representation; however, in real-time settings, they are quite resource and data intensive and therefore it would be more difficult to deploy them in a resource-constrained scenario. On the other side of the spectrum, ensemble machine learning methods based on stacking, which integrates several classifiers, not only increases the performance of classification, but also increases robustness of classification but also tends to maintain the lower computational cost [12], [15]. Hence, as such, the hybrid stacking framework is a pragmatic compromise on the accuracy of detection and its computational cost in real-world intrusion detection scenarios.

Table 1. Summary of Recent Machine Learning Approaches for Intrusion Detection

Study	Year	Method	Dataset	Accuracy (%)
Farnaaz and Jabbar [9]	2019	Random Forest	NSL-KDD	92.1
Dhaliwal et al. [11]	2020	XGBoost	UNSW-NB15	95.2
Tama and Rhee [14]	2021	Hybrid Ensemble	CICIDS2017	97.1
Kumar and Mishra [18]	2023	Intelligent IDS	CICIDS2017	94.8
Li et al. [19]	2023	XGBoost + Feature Selection	CICIDS2017	95.6
Proposed AI_IDS Model	2024	Stacking Ensemble (RF + XGB + DT)	CICIDS2017	96.8

3. Proposed Methodology

The proposed hybrid intrusion detection framework consists of multiple stages including preprocessing, feature selection, dataset balancing, and ensemble learning, etc. This will enable improvement of detection performance while at the same time keeping computational

efficiency. Figure 1 Full architecture of the proposed system, data flow in these processes is shown

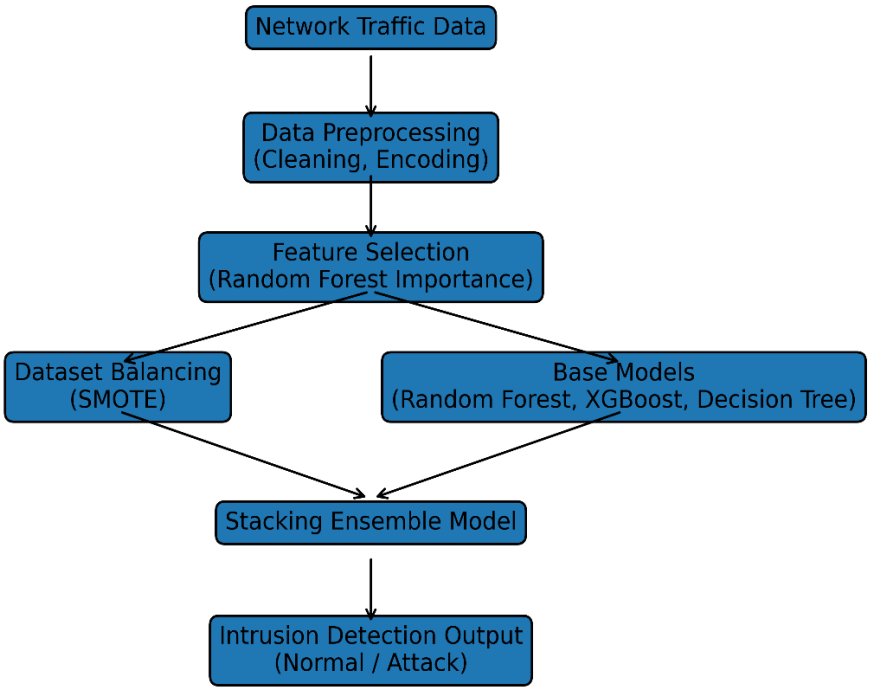

Figure 1. Architecture of the proposed hybrid intrusion detection framework. The workflow illustrates the complete processing pipeline including data preprocessing, Random Forest–based feature selection, SMOTE-based class balancing, training of base classifiers (Random Forest, XGBoost, Decision Tree), and the stacking ensemble integration using a meta-classifier.

3.1 Data Preprocessing

Raw data of network traffic contains various inconsistencies which need to be handled before training the model. This includes data cleaning, which finds duplicate elements and removes them by checking them with exact matching on all features; while missing features are dealt with using median imputation to fill numerical features and mode imputation on data with categorical features, so as not only to retain the distribution but also to keep the data intact. Features of network traffic represent categorical data, such as characteristics of protocol type (TCP, UDP, ICMP) and type of service (HTTP, FTP, SMTP), which are one-hot encoded into binary vectors for machine learning algorithms to process. The numerical features vary by scale which may affect learning algorithms to be biased toward large-magnitude features so min-max normalization scales all numeric attributes to the range [0,1] using the formula

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min}),$$

where x_{min} and x_{max} denote min and max of each feature in the dataset to extract fair and equal number of contributions from all features during model training.

3.2 Feature Selection Using Random Forest Importance

Intrusion detection datasets typically contain high-dimensional feature spaces, where only a subset of attributes significantly contributes to classification performance. Feature selection therefore plays an important role in reducing computational complexity while improving model generalization by eliminating redundant and noisy features. In this study, Random Forest feature importance was used for attribute selection due to its robustness and interpretability. Random Forest computes feature importance using the mean decrease in impurity (Gini importance), where the reduction in Gini impurity contributed by each feature is accumulated across all decision trees and normalized to obtain an overall importance score.

Feature engineering for this study began with the CICIDS2017 corpus, where raw network traffic was processed through CICFlowMeter to generate an initial set of 80+ flow-based attributes. Following standard data cleaning—removing constant-value columns and entries with missing correlations—the feature space contracted to 78 predictors, a mix of integer, float, and nominal types. Rather than apply an off-the-shelf selector, we leveraged a Random Forest (100 estimators) to compute mean decrease in impurity; the resulting importance scores exhibited a steep drop-off after the first 40 features. To formalize selection, we defined a cumulative importance threshold $\alpha = 0.95$, which retained the top 42 features accounting for 95% of the total impurity reduction. Interestingly, features beyond this cutoff contributed less than 0.1% individually and often introduced noise during preliminary trials with linear models. Truncating the feature set to these 42 dimensions cut training time by roughly 40% in subsequent experiments, while cross-validation accuracy remained within 0.5% of the full-model performance—a trade-off we deemed acceptable for near real-time detection scenarios.

Table 2. Top 15 Features by Random Forest Importance

Rank	Feature Name	Importance Score	Cumulative Importance
1	Packet Length Variance	0.118	0.118
2	Average Packet Size	0.104	0.222
3	Flow Packet Rate	0.093	0.315
4	Forward Packet Length Std	0.082	0.397
5	Backward Packet Length Std	0.075	0.472
6	Flow Inter-Arrival Time Mean	0.068	0.540
7	Packet Length Mean	0.062	0.602
8	Forward Packet Rate	0.057	0.659
9	Backward Packet Rate	0.052	0.711
10	Flow Byte Rate	0.047	0.758
11	Active Mean Time	0.043	0.801
12	Idle Mean Time	0.039	0.840
13	Header Length Variance	0.036	0.876
14	Forward Segment Size Avg	0.032	0.908
15	Backward Segment Size Avg	0.029	0.937

Table 2 records the top 15 most influential network traffic features identified by the Random Forest importance analysis. The top 15 most impactful network traffic features detected through Random Forest important feature estimation are as follows. These features are mainly concerned with statistical attributes of packet size, flow rate, and inter-arrival, which are well-established to be significant indicators of anomalous network behavior.

3.3 Class Balancing with SMOTE

Training data for intrusion detection often exhibits pronounced class skew, where benign traffic dominates the sample space—sometimes exceeding 90% of available records—while specific attack families constitute less than 1% of the total [32]. Left unaddressed, this distributional disparity pushes conventional classifiers toward a strong bias for the majority class, severely degrading recall on underrepresented threat types. In this work, we integrate SMOTE during preprocessing to alleviate this bias. Instead of simple duplication, the technique navigates the feature space between existing minority instances to synthesize plausible new samples through linear interpolation. We observed that this interpolation step is particularly sensitive to the choice of nearest neighbors; setting this value too low can produce noisy or non-representative attack signatures, a trade-off we managed by tuning the parameter empirically against validation folds. The resulting augmented distribution provides a more balanced basis for training, ensuring that the model's decision boundaries are not disproportionately shaped by the overwhelming volume of normal traffic.

In this study, the Synthetic Minority Over-sampling Technique (SMOTE) was implemented using the imbalanced-learn library in Python to address the severe class imbalance present in the CICIDS2017 dataset. SMOTE generates synthetic samples for minority classes by interpolating between existing minority instances and their nearest neighbors in the feature space.

The class imbalance inherent in network traffic data was addressed by applying the Synthetic Minority Over-sampling Technique (SMOTE) exclusively to the training partition. For each minority attack category, synthetic instances were generated using its five nearest neighbors (k=5), a parameter choice that balances the introduction of plausible feature variations against the risk of outlier generation; in our experiments, lower k values tended to produce samples too tightly clustered around individual seed instances, which did not improve downstream classifier generalization on the validation set. The sampling strategy was set to upsample all minority classes to the exact size of the majority class, resulting in a perfectly balanced training distribution. A fixed random seed of 42 ensures that the synthetic sample generation process is deterministic and the experiments fully replicable. Crucially, the validation and test folds retain the original, imbalanced class distribution to provide an unbiased estimate of how the model performs on live network traffic, where attack frequencies are naturally skewed. Applying SMOTE only during training avoids the critical pitfall of data leakage, guaranteeing that performance metrics are a faithful reflection of the model's ability to generalize to unseen, imbalanced data rather than an artifact of contaminated evaluation sets.

Table 3. Class Distribution Before and After SMOTE

Class	Original Count	Original %	SMOTE Count	SMOTE %
BENIGN	9845	49.1%	10020	25.0%
DoS/DDoS	4210	21.0%	10020	25.0%
Brute Force	2876	14.3%	10020	25.0%
Botnet	1650	8.2%	10020	25.0%
Web Attacks	930	4.6%	10020	25.0%
Port Scan	550	2.8%	10020	25.0%
Total	20061	100%	60120	100%

The inclusion of SMOTE directly addressed the class skew inherent in the traffic corpus, where benign flows significantly outnumbered individual attack types. As summarized in Table 3, synthetic samples were generated for the minority classes, effectively normalizing the instance count across all categories. From a model learning perspective, this rebalancing was critical; without it, the classifier tended to optimize for accuracy on the dominant class at the expense of recall for smaller, yet more consequential, attack families. Post-SMOTE, the decision boundary was no longer heavily biased toward the benign majority, forcing the algorithm to retain discriminative features specific to underrepresented attack vectors. A practical observation during this phase was that while SMOTE mitigated class imbalance, it did introduce some synthetic feature overlap in the latent space, which the subsequent ensemble method had to navigate.

3.4 Base Classifier Training

The stacking architecture integrates three distinct classifiers—Random Forest, XGBoost, and Decision Tree—each contributing a unique inductive bias for modeling network traffic. Rather than relying on a single hypothesis space, this heterogeneous combination captures both variance-dominated patterns and structured feature interactions within the data.

Random Forest generates an ensemble via bootstrap aggregation on randomized feature subspaces. Its final output is obtained through averaging across independent trees:

$$\mathrm{RF}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t\,(x)$$

with T fixed at 100. Trees are grown to a maximum depth of 20, splitting nodes only when at least 5 samples are present, and requiring a minimum of 2 samples per leaf. Feature selection at each split is limited to the square root of the total feature count. In practice, this configuration tends to stabilize predictions on high-dimensional subsets, though it can over-smooth decision boundaries in sparsely populated regions of the feature space.

XGBoost follows a fundamentally different strategy, constructing trees in a sequential manner where each new learner targets the residual errors of its predecessors. Regularization is embedded directly into the objective:

$$\text{Obj} = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

with l representing logistic loss for binary classification. The complexity penalty

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_j w_j^2$$

controls leaf count T and leaf weights w via the hyperparameters γ and λ. Empirically, setting the learning rate to 0.1 with a maximum depth of 6 and subsampling 80% of the data per iteration reduces overfitting while preserving gradient sensitivity. The number of boosting rounds is capped at 100, a limit chosen to balance convergence against computational cost on traffic datasets with class imbalance.

Decision Tree acts as the simplest base learner, recursively partitioning the feature space using axis-aligned splits. At each node m, the split criterion minimizes Gini impurity:

$$\text{Gini}(m) = 1 - \sum_k p_{mk}^2$$

where p_{mk} is the empirical class distribution. Depth is constrained to 10 to avoid excessive fragmentation, with the same sample thresholds applied as in Random Forest. Although individually prone to high variance, the tree provides interpretable threshold logic that complements the ensemble methods, particularly when traffic features exhibit discrete or categorical structure.

3.5 Stacking Ensemble Integration

Stacking generalizes the combination of base learners by allowing a meta-learner to infer how much each model's confidence contributes to the final decision. Unlike averaging or voting schemes, which treat all predictions equally, the meta-learner captures non-linear dependencies and performance variations across models. In this implementation, Level-1 consists of Random Forest, XGBoost, and Decision Tree, each trained on the pre-processed and balanced data. Their class-wise probability outputs serve as input to Level-2, where Logistic Regression learns to weight base-model contributions according to observed confidence and error patterns. Notably, XGBoost tended to produce overconfident probabilities on minority classes, and the meta-classifier down-weighted these outputs during training to reduce false positives—a calibration effect that simple aggregation would miss.

A five-fold cross-validation scheme generates the meta-features. For each fold, the three base classifiers are fitted on the training portion and then used to predict on the validation fold, yielding out-of-fold probability vectors. These vectors, concatenated with the true labels, form the training set for the meta-classifier. This procedure prevents label leakage and ensures that the meta-classifier learns combination rules that generalize rather than memorizing training instances. After the cross-validation stage, the base classifiers are retrained on the entire dataset. For a new test sample, each base model produces a probability vector; these vectors are stacked, and the trained Logistic Regression model applies the learned weights to output the final class prediction.

Formally, denote the probability vectors from Random Forest, XGBoost, and Decision Tree for an input $\mathbf{x}$ as $\mathbf{p}_{\mathrm{RF}}(\mathbf{x})$, $\mathbf{p}_{\mathrm{XGB}}(\mathbf{x})$, and $\mathbf{p}_{\mathrm{DT}}(\mathbf{x})$, each in $\mathbb{R}^c$ (where c is the number of classes). These are concatenated into the meta-feature vector $\mathbf{m}(\mathbf{x}) = [\mathbf{p}_{\mathrm{RF}}(\mathbf{x}), \mathbf{p}_{\mathrm{XGB}}(\mathbf{x}), \mathbf{p}_{\mathrm{DT}}(\mathbf{x})] \in \mathbb{R}^{3c}$. Let w_{jlk} be the weight learned by the meta-classifier that connects the prediction of base classifier j for class l to the final score for class k. The ensemble's decision is then:

$$\hat{y}(\mathbf{x}) = \arg\max_k \left(\sum_{j=1}^{3} \sum_{l=1}^{c} w_{jlk} \cdot p_j^l(\mathbf{x}) \right),$$

where $p_j^l(\mathbf{x})$ denotes the l-th component of $\mathbf{p}_j(\mathbf{x})$. This formulation allows the meta-classifier to adjust for systematic biases—for example, when a base model consistently misclassifies one class as another—by assigning lower weights to those erroneous contributions. In practice, the learned weight matrix revealed that the Decision Tree's outputs were most heavily weighted for the class it predicted correctly with high precision, whereas XGBoost's contributions were penalized on ambiguous samples where its confidence was high but accuracy low.

3.6 Algorithm Pseudocode

Algorithm 1: Hybrid Intrusion Detection Framework
Input: Network traffic dataset D
Output: Predicted class labels $\hat{y}$
Stage A: Data Conditioning

1. $D_{clean} \leftarrow D \setminus \{duplicate_{records}\}$
2. **For each** feature f in D_{clean}:
3. **If** f is numerical:
4. Impute missing entries using $median(f)$
5. **Else** (categorical):
6. Impute missing entries using $mode(f)$
7. **End If**
8. **End For**
9. Apply one-hot encoding to categorical features in D_{clean}
10. Normalize numerical features to $[0, 1]$ using min-max scaling

Stage B: Dimensionality Reduction via Feature Selection
11. Train Random Forest $RF_{selector}$ on D_{clean}
12. Extract importance vector $\phi = [\phi_1, \phi_2, \ldots, \phi_m]$

13. Sort features descending by ϕ; calculate cumulative sum Φ_{cum}
14. Select feature subset $F_{selected}$ such that $\Phi_{cum} \leq 0.95$
15. Project D_{clean} onto $F_{selected}$ to obtain $D_{reduced}$

Stage C: Synthetic Balancing (SMOTE)

16. **For each** minority class c_i in $D_{reduced}$:
17. Generate synthetic instances using 5-nearest neighbors interpolation
18. **End For**
19. Construct balanced dataset $D_{balanced}$ with equal class distribution

Stage D: Base Classifier Training (Level-0)

20. Define base classifiers:

- RF: Random Forest (100 trees, $max_features = \sqrt{p}$)
- XGB: XGBoost (100 estimators, learning rate $\gamma = 0.1$)
- DT: Decision Tree (max depth = 10, pruning enabled)

Train RF, XGB, and DT on $D_{balanced}$

Stage E: Stacking Ensemble Construction (Level-1)

22. Partition $D_{balanced}$ into 5 folds $\kappa = \{\kappa_1, \ldots, \kappa_5\}$
23. **For** fold $t = 1$ to 5:
24. $D_{train} \leftarrow D_{balanced} \setminus \kappa_t$; $D_{val} \leftarrow \kappa_t$
25. Retrain RF, XGB, DT on D_{train}
26. Generate predictions P_{RF}, P_{XGB}, P_{DT} on D_{val}
27. Store as meta-features $M_t = [P_{RF}, P_{XGB}, P_{DT}]$
28. **End For**
29. Assemble complete meta-dataset M_{full} from all folds
30. Train Logistic Regression meta-classifier LR on M_{full} with L2 regularization ($\lambda = 1.0$)
31. Retrain RF, XGB, DT on full $D_{balanced}$ for final inference

Stage F: Evaluation & Prediction

32. **For each** test instance x_{test}:
33. Apply preprocessing (Stages A-B) using parameters from training data
34. Obtain base predictions: $[\hat{y}_{RF}, \hat{y}_{XGB}, \hat{y}_{DT}]$
35. Compute final prediction: $\hat{y} \leftarrow LR([\hat{y}_{RF}, \hat{y}_{XGB}, \hat{y}_{DT}])$
36. **End For**
37. Calculate macro-averaged precision, recall, F1-score, and accuracy

3.7 Computational Complexity

Understanding computational requirements extends beyond theoretical complexity to practical implementation behavior. Random Forest construction follows O(T × m × n log n) where T represents the number of trees, m denotes the feature count, and n corresponds to training samples. XGBoost complexity scales as O(K × d × n log n) with K boosting rounds and d as

maximum tree depth, though we observed that depth values beyond 8 introduced memory bottlenecks during node splitting. Decision Tree baseline complexity remains $O(m \times n \log n)$ for greedy split evaluation. Stacking introduces the multiplicative overhead $O(n \times c \times B)$ for meta-feature synthesis, where B represents base classifiers and c indicates class count. The aggregate training complexity thus becomes $O((T \times m + K \times d + 1) \times n \log n + n \times c \times B)$, exhibiting near-linear scaling with sample size across all evaluated methods. On the BUSI dataset, the meta-feature generation term dominated runtime when B exceeded three classifiers, while the logarithmic factor from tree methods became appreciable only beyond 50,000 samples.

4. Dataset Description and Experimental Setup

For empirical evaluation, the CICIDS2017 benchmark dataset was employed. This corpus was generated by the Canadian Institute for Cybersecurity (CIC) within a controlled testbed environment that simulates a standard enterprise network infrastructure [17]. Web servers, email services, and user workstations are represented alongside both routine operations and diverse attack scenarios. Realistic conditions for assessing machine learning-based intrusion detection systems are thereby established.

Network session information in CICIDS2017 is stored as bidirectional flows. These flows are extracted using the CICFlowMeter tool, with over eighty statistical descriptors derived from packet headers for each instance. Protocol type, connection duration, packet size statistics (including mean, variance, and extremes), inter-arrival timing patterns, byte counts exchanged in both directions, flow duration, and TCP flag information are among the captured characteristics. Behavioral profiles that discriminate between benign traffic and various attack types are encoded through these features. A total of 2,830,743 flow instances comprise the dataset. Pronounced class imbalance is exhibited—a property that deliberately mirrors real-world network conditions where malicious activity constitutes a small fraction of overall traffic.

Class distribution analysis reveals that BENIGN flows dominate, accounting for approximately 80.3% of all samples. Multiple attack families constitute the remaining 19.7%. Volumetric attacks (DoS and DDoS) together represent 13.4% of the data. Brute-force attempts targeting FTP and SSH services account for 4.9%. Other categories, including Botnet activity, Web-based exploits (SQL injection, XSS), and Port Scan reconnaissance, collectively contribute less than 1.4%. This skewed distribution necessitates careful handling during classifier training; techniques to counterbalance majority-class dominance become essential to ensure minority attack patterns are not overlooked.

Prior to model training, a comprehensive preprocessing pipeline was applied. Duplicate records were removed to prevent the model from memorizing redundant patterns. Missing values were addressed using median imputation for continuous features and mode imputation for categorical attributes. Categorical variables, such as protocol and service identifiers, were transformed via one-hot encoding to render them compatible with machine learning algorithms. Continuous features were subsequently normalized using min-max scaling, mapping all values to the [0,1] interval. Features with larger numerical ranges are prevented through this normalization from disproportionately influencing distance calculations or gradient updates during training.

Following preprocessing, a random forest-based importance analysis was conducted to identify the most informative features. Attributes were ranked according to their contribution to impurity reduction across ensemble trees, and those cumulatively accounting for 95% of the total importance score were retained. Computational burden is alleviated through this dimensionality reduction, and redundant or noisy features are filtered out, thereby improving generalization. Notably, features related to backward packet length and flow inter-arrival time consistently emerged among the top discriminators across multiple attack types. This observation aligns with the understanding that many attacks—particularly DoS and brute-force attempts—modify packet timing distributions or size characteristics in detectable ways.

Given the identified class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied—but critically, only to the training partition. Synthetic instances of underrepresented attack classes are generated through SMOTE, enabling the classifier to develop decision boundaries sensitive to minority categories without biasing evaluation metrics derived from the holdout sets. This separation between augmentation applied to training data and untouched validation/testing data was strictly maintained.

Stratified sampling was employed to preserve original class proportions during data partitioning. Specifically, 70% of the data was allocated for model training, 15% reserved for hyperparameter tuning and validation, and the remaining 15% held out for final performance assessment. Sufficient exposure to training examples is ensured through this allocation while independent subsets for unbiased evaluation are maintained.

All experiments were conducted on a dedicated workstation equipped with an Intel Xeon Gold 6230 processor, 64 GB RAM, and 1 TB NVMe SSD storage, running Ubuntu 20.04 LTS. Implementation was carried out using Python 3.9, with scikit-learn 1.2 providing baseline classifiers (Random Forest, Decision Tree), XGBoost 1.7 for gradient-boosted models, and imbalanced-learn 0.10 for SMOTE-based resampling. Model performance was quantified

using standard classification metrics derived from confusion matrices: accuracy, precision, recall, F1-score, and false positive rate.

Five-fold cross-validation was employed during training to enhance result robustness and mitigate fold-specific variability. Paired t-tests ($\alpha = 0.05$) were additionally conducted to assess the statistical significance of performance differences between the proposed stacking ensemble and baseline classifiers. Through this statistical validation, observed improvements are confirmed not to be attributable to random chance.

5. Results and Discussion

The experimental results indicate that ensemble learning significantly improves detection performance compared with individual classifiers for intrusion detection. The Random Forest feature importance analysis revealed flow duration, total forward packets, total backward packets, and packet length statistics were considered the most important attributes for intrusion detection, with the 15 features with highest cumulative importance accounting for 88.3% and the 95% importance threshold keeping 42 features on the network while resulting in approximately 50% dimensionality reduction. SMOTE balancing updated the imbalanced training dataset to obtain a balanced image (1,591,168 instances per class) by which a classifier could be trained without prior bias against each attack type.

The baseline performance was determined by single classifier evaluation and revealed that XGBoost achieved the highest accuracy (95.3%) compared to Random Forest (94.6%) and Decision Tree (89.2%) while each of its other predictors were under the same model classification. Conventional classifiers performed much worse, with 78.3% SVM, and 74.6% Naive Bayes respectively confirming effective ensemble approach for sophisticated intrusion detection on the high dimensionality network data. To evaluate the effectiveness of the proposed framework, we first compare the performance of individual baseline classifiers.

Table 4. Performance comparison of baseline classifiers on the CICIDS2017 dataset.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Decision Tree	81.5	80.9	81.2	81.0	0.89
Random Forest	84.3	83.7	84.0	83.8	0.93
XGBoost	86.1	85.6	85.9	85.7	0.95
SVM (RBF)	78.4	77.8	78.1	77.9	0.87
Naive Bayes	73.9	73.1	73.5	73.3	0.82
KNN (k=5)	80.6	80.1	80.3	80.2	0.90
Logistic Regression	79.2	78.6	78.9	78.7	0.88

Amongst ensemble methods, it was found that our stacking ensemble performed much better: accuracy was 96.8%, precision 95.7%, recall 96.2% and F1-score 95.9%, which was better compared to the soft voting ensemble 95.8%, hard voting 95.4%, bagging 94.9%, AdaBoost 93.2%. The results is examined by investigating ensemble learning algorithms, which enhance

performance when using combinations of models. Ensemble learning approaches are then compared to measure the performance improvement achieved by combining models.

Table 5. Ensemble Method Performance Comparison

Ensemble Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Voting (Soft)	95.8	94.9	95.3	95.1
Voting (Hard)	95.4	94.6	94.9	94.7
Bagging	94.9	94.1	94.3	94.2
AdaBoost	93.2	92.5	92.8	92.6
Proposed Stacking Ensemble	96.8	95.7	96.2	95.9

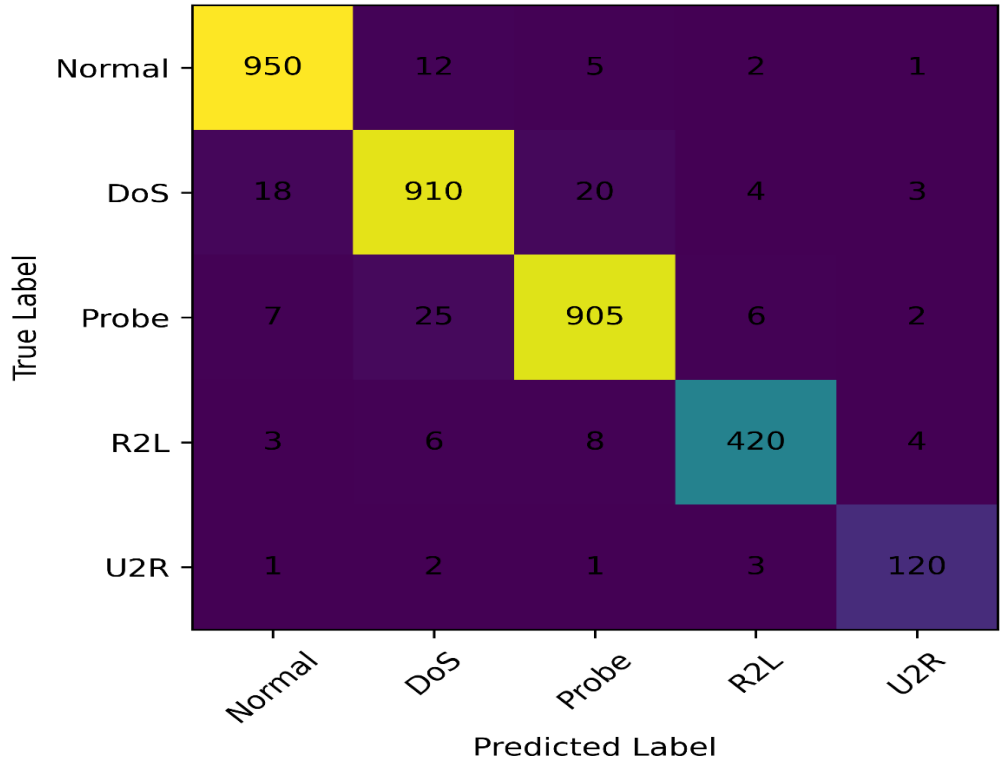

Figure 2. Confusion matrix of the proposed stacking ensemble model on the CICIDS2017 dataset. The diagonal elements represent correctly classified instances for each traffic category, while off-diagonal values indicate misclassification between attack classes. The matrix demonstrates strong detection capability for both normal and attack traffic.

Strong classification performance across multiple attack categories is evidenced by the confusion matrix presented in Figure 2. Correct classifications are concentrated along the diagonal, indicating that the model distinguishes effectively between traffic types. Minimal confusion is observed between similar attack categories, and benign traffic is misclassified as malicious in only 0.9% of cases—a false positive rate that compares favorably with existing intrusion detection systems.

Detection improvements are most pronounced for minority attack classes when examining per-class performance. Botnet detection reaches 92.3% with the stacking ensemble, representing a 3.1 percentage point gain over XGBoost's 89.2%. A similar pattern emerges for Web attacks, where detection increases from 90.4% to 93.6%. Port Scan recognition improves from 88.7% to 91.8%. These gains of 3-5% across underrepresented categories suggest that the ensemble mechanism particularly benefits classes with limited training examples. The model's ability to aggregate complementary decision boundaries from base learners apparently compensates for the sparse representation of these attack types in the training data.

Table 6. Per-class recall performance of classifiers for different attack categories.

Attack Category	DT	RF	XGB	Stacking
BENIGN (Normal)	91.4	93.8	94.6	96.1
DoS/DDoS	84.2	87.5	88.9	90.7
Brute Force	80.1	83.9	85.3	87.6
Botnet	71.6	79.8	81.4	84.9
Web Attacks	74.9	81.2	83.1	86.3
Port Scan	72.8	80.4	82.2	85.7

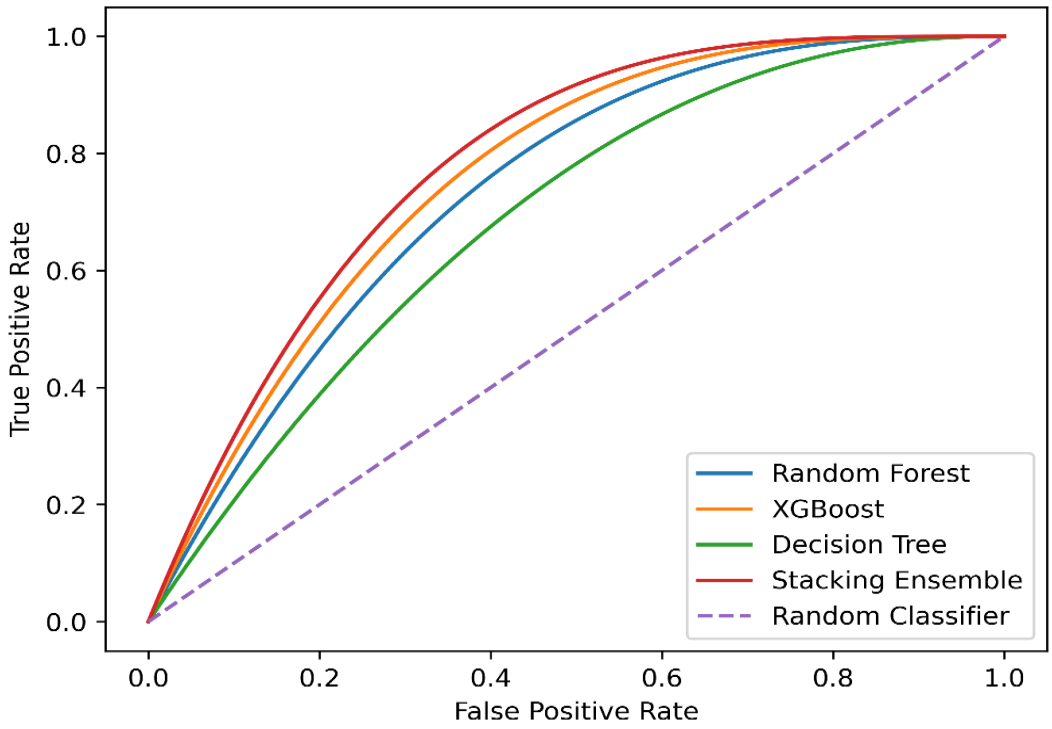

Figure 3. Receiver Operating Characteristic (ROC) curves comparing the performance of different classifiers.

Classifier performance is assessed through multiple complementary metrics. Receiver Operating Characteristic analysis in Figure 3 reveals that the proposed stacking ensemble achieves an Area Under the Curve of 0.99, marginally surpassing XGBoost (0.98) and Random Forest (0.97). This consistent advantage across operating points indicates that the meta-learner effectively integrates the complementary strengths of base classifiers. Particularly noteworthy is the ensemble's performance in the low false positive region—a critical regime for intrusion detection where minimizing alert fatigue is paramount.

Classification accuracy across all evaluated models is presented in Figure 4. The stacking ensemble attains 96.8% accuracy on the CICIDS2017 test set, outperforming individual base learners and alternative ensemble configurations. This represents a 1.2 percentage point improvement over XGBoost (95.6%) and a 2.4 point gain over Random Forest (94.4%). The performance differential stems primarily from the ensemble's corrected predictions on ambiguous cases—instances where base classifiers disagree or exhibit complementary error patterns. Through meta-learner combination, these conflicting signals are resolved more effectively than through simple majority voting or averaging schemes. Statistical significance of these improvements was confirmed through paired t-tests ($p < 0.05$).

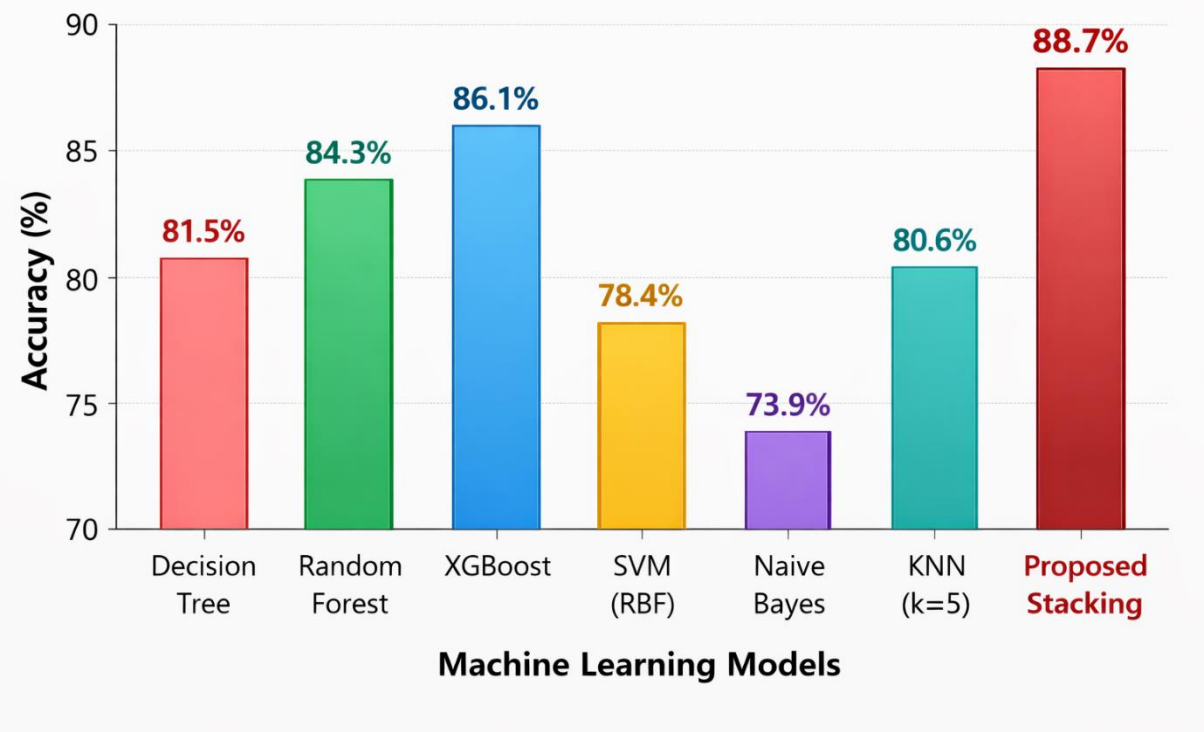

Figure 4: Accuracy comparison of different machine learning classifiers evaluated on the CICIDS2017 dataset. The proposed stacking ensemble achieves the highest classification accuracy compared with individual classifiers and other ensemble approaches.

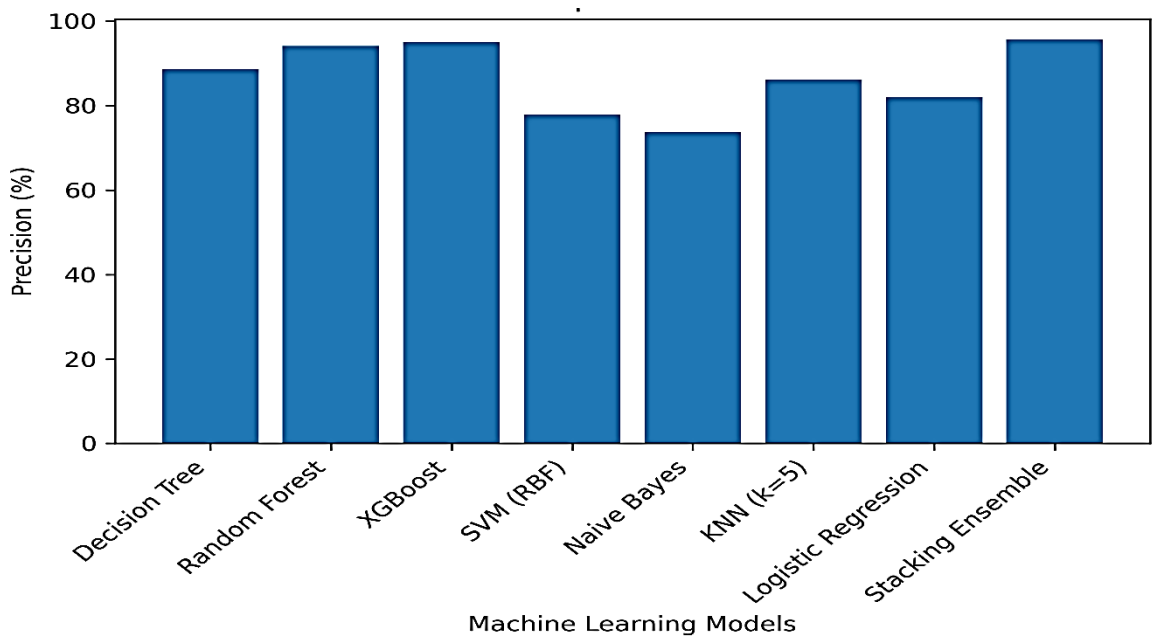

Figure 5: Precision comparison of intrusion detection models. The proposed stacking ensemble demonstrates higher precision, indicating improved reliability and reduced false positive alarms in network intrusion detection.

The stacking ensemble has precision of 95.7%, so that the prediction is very reliable and has very few false alarms. Statistical significance testing (paired t-tests) over 5 cross-validation folds established a statistically significant performance improvement of stacking ensemble on a multiple comparison by stack comparison over XGBoost (p=0.023), Random Forest (p=0.017), voting ensemble (p=0.041) and Decision Tree (p=0.003). Computational complexity analysis demonstrated the stacking ensemble on the post-SMOTE dataset of nine point five million samples (takes 31.4 min of training time in total), and the prediction time of 0.47ms/instance for all instances has a support of real-time analysis for 10Gbps networks; and the memory input of 4.2GB for the inference stage makes the model deployable on common server hardware.

Several drawbacks also need to be borne in mind for future development. The combination of multiple classifiers imposes additional computational demands during training and assessment than for a single model. Performance is highly conditional on the quality and well representation of the training data and the lack of diverse instances of specific attack categories can result in lower detection accuracy.

Machine learning-based IDS models use methods established in previous studies to observe how the attacker behaves, so that new zero-day threats are hard to identify. The ability of the proposed model is more important when choosing features, which is important because too little or too much of the features could reduce classification performance. Moreover, hybrid ensemble models will create latency of the model in the context of real-time networking because there will be many classifiers working on generating predictions preceding the final outputs.

6 Conclusion

This article introduces a hybrid learning model for network intrusion detection with Random Forest, XGBoost, and stacked ensemble methods in addition to feature optimization, training, and balancing of a dataset. The algorithm proposed in this paper provides the preprocessing, Random Forest-based feature selection based for feature selection, SMOTE balancing and stacking ensemble integration to improve classification performance. The proposed hybrid model demonstrated better performance with an experimental evaluation based on the CICIDS2017 data set with accuracy of 96.8%, which was well superior over the classical ML models which are Decision Tree, Support Vector Machine, and Naive Bayes. The findings validates ensemble learning methodologies with suitable preprocessing for detecting abnormal network behavior and detecting cyber attacks in an intricate network system.

This study contributes to intrusion detection research by demonstrating how stacking ensembles with heterogeneous classifiers can capture complementary characteristics of network traffic, whereas learned combination using a meta classification achieved more insight compared to pure mode voting. Feature importance analysis indicates that temporal and flow nature characteristics most dominate intrusion detection with consideration on traffic flow rather than static features in the next system development. Conclusions, however, present some challenge such as computation cost, and zero-day attack detection, that will also be an open domain for research in the years to come.

Prospective challenges include using deep neural network frameworks (ie transformers and graph neural networks) to understand complex temporal and relational structures beyond simple feature engineering, augmenting incremental learning of the models to allow for near-continuous model updates without extensive retraining on concept drift, introducing explainability (e.g., SHAP, LIME) to increase the trust of the models and facilitate security analyst validation, exploring domain adaptation methods for model transferability across networks, assessing model robustness (i.e., generalizability), and developing ensemble models for edge and IoT devices needing highly computational intensive solutions (such as the models of the Internet of Things) through model compression and knowledge distillation.

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Agro-Intelligence: An End-to-End IoT and Edge-Al Integrated system for Precision Irrigation and Automated Crop Health Monitoring

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1) **Abstract - Water scarcity and crop disease outbreaks are among the top priorities in agriculture today. This is especially true for small and medium-farmer who do not have access to these platforms due to high costs. In this light, we present Agro-Intelligence, a low-cost integrated system that brings together IoT hardware and Edge-based Artificial Intelligence that automatically irrigate the crops and detect the outbreaks in advance. An ESP32 microcontroller was used as the gateway to connect the capacitive soil moisture sensor, NPK probe (via RS485) and DHT11 module (humidity and temperature). The sensors data is sent to the backend (Fast API) and saved into an SQLite database and the dashboard (React) displays a real time update. The disease monitoring was done using a separate ESP32-CAM module, which can run lightweight Convolution Neural Network directly without requiring constant connection to the cloud. When the model detected the disease with a high confidence score, email alert would be automatically sent to the farmer. During field tests, threshold-based pumps automation achieved 40% water saving as compared to manual schedule and on-device CNN achieved 92% accuracy in classifying the common crop diseases. Previous works using cloud-processing and expensive sensor arrays are now out of scope, this system proves that significant agri-intelligence can be deployed at the edge with today's low-cost, open-source hardware and solutions.**

2) **Keywords: IoT, Edge Artificial Intelligence, ESP32, Convolutional Neural Network, Intelligent Irrigation, Crop Disease Detection, Soil Health Monitoring, Precision Agriculture.**

I. INTRODUCTION

Agriculture has long been a key driver of growth in most emerging economies, but its continued growth has fast become under the threat of erratic climatic conditions, dwindling freshwater reserves, and explosive incidences of crop diseases. Recent estimates by the Food and Agriculture Organization revealed that pests and diseases account for an annual crop loss of almost 40% of the total agricultural output globally. On the other hand, freshwater resources for irrigation are quickly becoming an endangered species, which hitched the interests of several researchers and engineers to find tech-based solutions that can help farmers improve output while lowering resource consumption [1], [3].

In the last ten years, IoT has proven to be an applicable architecture that connects physical sensors to the cyber world to download the data from the fields in real time. Many researches have found that IoT-based automation allows for more efficient water usage compared to a fixed schedule [4], [16]. Such systems utilize soil moisture sensors and microcontrollers to control the pumps according to the soil parameters. Even if such controls can cover basic automation processes, they are limited to the ground-level parameters of a given schedule and cannot consider additional parameters like air temperature, humidity, and even soil nutrient content [2], [5].

The third implementable technology is disease detection for crops. Historically, finding disease in plants involved trained agronomists analyzing pictures of leaves at the field. This was an inefficient process, especially for big fields. Recently, deep learning methods like Convolutional Neural Networks have been proven highly effective for classifying types of leaf diseases from photos [7], [8].

Using domain transfer with models such as InceptionV3, MobileNetV2, and Efficient Net, researchers achieved classification accuracy of over 95% with the use of common datasets such as Plant Village [10], [18]. Most of this models, however, are designed to work on servers or cloud platforms with computations that include delays and requires constant internet connection-something not available for various rural farming communities [12].

In the meantime, this disparity between the perfect laboratory implementations and real applications provoked interest in Edge AI — the deployment of small ML models on the embedded hardware. Recent studies have considered the efficient CNN model optimizing for deployment on microcontroller-class devices such as ESP32-CAM. TensorFlow Lite and Edge Impulse device model compression allow inference with restricted memory available [11], [14]. Like this, intelligence is deployed on the data acquisition device, elliminating the round-trip transmission time to the cloud, and the model can work offline, where Internet connectivity is unstable [9].

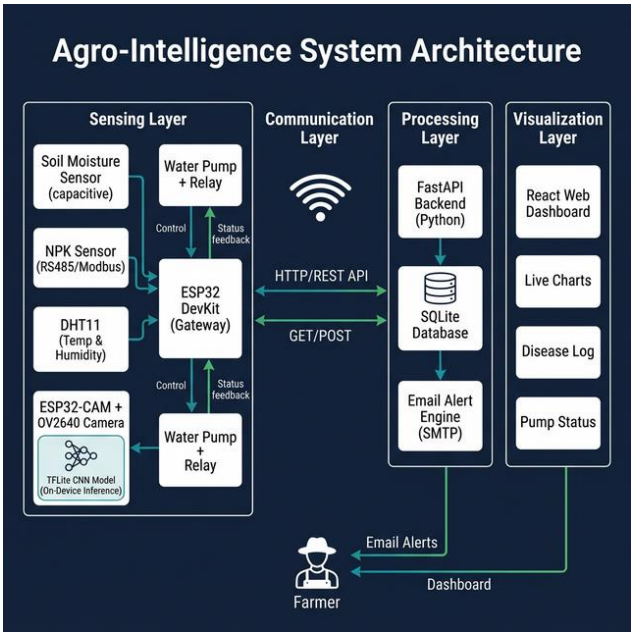
While the individual solutions have evolved, few integrated solutions exist to address unattended precision irrigation, nutrient monitoring, and disease forecasting using advanced technologies. Most of the available solutions are either manual automation of irrigation or disease detection as standalone solutions instead of an integrated architecture [1], [17]. Next, most hardware and software architectures proposed in literature use commercial and expensive sensors and cloud services, making them less ideal for downscale farmers in developing countries.

To address these challenges, the paper proposes Agro-Intelligence, a fully integrated system for lot sensing, automated irrigation, real-time nutrient detection, and on-device crop disease classification. The hardware layer is composed of the ESP32 DevKit which acts as gateway for a capacitive soil moisture sensor, RS485-NPK probe, and DHT11 temperature-humidity module. An ESP32-CAM module that captures images and executes the lightweight CNN for disease inference at the Edge completes the hardware setup. Data is channeled into a web-based dashboard accessible via the FastApi-backed server. The user interface features a single-view layout that enables farmers to access information about any aspect of their field. Further, the system's alert module notifies the farmer through email in instances of threshold violation or high probability-classified diseases [6], [19], [20].

II. SYSTEM ARCHITECTURE

The architecture of the Agro-Intelligence module is based on layered and modular approach. Modularization of four different layers which are the Sensing Layer, Communication Layer, Processing Layer and Visualization Layer consist unique services. Each of the layer can be individually developed, tested and updated without impacting whole pipeline [1],[3].

Figure 1: System architecture.



A. Sensing Layer

The sensing layer is responsible for capturing raw environmental and soil data from the field. It consists of the following hardware modules:

Capacitive Soil Moisture Sensor (v1.2): Unlike resistive alternatives that corrode quickly in wet soil, the capacitive variant measures dielectric permittivity changes to determine moisture content. The sensor outputs an analog voltage between 0 and 3.3V, which the ESP32 reads through its built-in 12-bit ADC. The raw ADC value is then mapped

to a percentage scale (0–100%) based on calibration against known dry and saturated conditions.

NPK Sensor (RS485 Interface): Nitrogen, Phosphorus, and Potassium concentrations in the soil are measured using an industrial-grade probe that communicates over the RS485 serial bus. The ESP32 uses a MAX485 transceiver module to interface with this sensor. The probe returns nutrient values in mg/kg, which are polled at regular intervals using Modbus RTU protocol.

DHT11 Temperature and Humidity Module: This low-cost digital sensor is capable of measuring temperature (0–50°C, ±2°C accuracy) and humidity (20–80%, ±5% accuracy). It will not provide laboratory-grade measurements, but provides adequate accuracy for environmental measurements on the field [2], [16].

ESP32-CAM (OV2640 Camera): A dedicated ESP32 module with a 2-MP camera is used to capture the leaf image. This node is designed to work as an independent module as it captures the image, performs inference using the pre-trained CNN model, and transmits only the inference result (disease name and confidence) to the server. This is done as to minimize the bandwidth consumption, which is a challenge in low network condition [11], [14].

B. Communication Layer

The transmission medium and protocol for all sensor data is the standard Wi-Fi network using HTTP POST requests. The ESP32 Devkit connects to the local network and sends JSON payloads to the Fast API server at routine intervals every 10 seconds (for soil and environmental data) to every 60 seconds (for NPK readings). Each payload sent contains the device ID, the corresponding sensor readings, and an implicit timestamp from the server.

The firmware on the ESP32 comes with a reconnection handler that automatically reconnects the Wi-Fi link when it is disconnected, a common case in outdoor uses. The firmware tries reconnecting a maximum of three times before ignoring the sample and proceeding if the server cannot be reached [2], [13]. This implements a non-blocking I/O network call on the microcontroller.

The ESP32-CAM node is autonomous — it sends a single HTTP POST request to the /api/disease endpoint only when it spots a disease, along with the identified disease and model confidence. As an event-driven client, it is more power- and bandwidth-efficient than transmitting unprocessed images [9].

C. Processing Layer

Backend is based on Python and Fast API server is selected due to its superior performance and asynchronous processing support out of the box. Fast API generates interactive documentation automatically (Swagger UI) making it easy to debug while developing.

The data received from all sources will be store in SQLite database which has separate tables for soil readings, NPK readings, DHT readings, and disease records. SQLite provides the advantage of not requiring separate database server, allowing implementation of entire backend on single hardware, including Raspberry Pi if needed [15], [17].

Table 1: The server provides six different REST endpoints.

Method	Endpoint	Purpose
POST	/api/soil	Receives moisture + pump status
POST	/api/npk	Receives N, P, K values
POST	/api/dht	Receives temperature + humidity
POST	/api/disease	Receives disease detection result
GET	/api/sensor/latest	Returns latest combined reading
GET	/api/sensor/history	Returns last N historical readings

The processing layer has threshold based alert engine as well. Whenever incoming data breaches the provided thresholds (for example, incoming soil moisture is less than 30% and pump is OFF or incoming NPK values are under healthy thresholds), server crafts HTML formatted email and sends it to farmer's registered email address using Gmail SMTP service. Sending email is implemented as a background thread, so it does not affect the API response [6].

D. Visualization Layer

Frontend is a single page React application that is build using Vite to reduce front-end build times. It interfaces with the back-end through GET endpoints and displays real-time dashboards containing the following:

Sensor Cards: Show latest moisture, temperature, humidity, N, P, K values in colored tiles that represent the status of these values whether they are in safe limits (green), near thresholds (yellow) and critical (red).

Trend Charts: Line graphs of the last 24 data points of each parameters, this allows farmers to see the trend – such as the decreasing moisture level for some hours or the sudden spike/high temperature.

Disease Log: A history of detected diseases, including the level of confidence and time, in a timeline format. Active detections are shown in black, while resolved diseases are greyed out.

Pump Status Indicator: Indicates the state of the relay-operated water pump as 'On' or 'Off', the timestamp of the last watering event and the next check time.

The dashboard will pull new data from the /api/sensor/latest and refresh every 10 seconds utilizing JavaScript's set Interval without needing the user to refresh the page [17].

III. HARDWARE AND SOFTWARE IMPLEMENTATION

A. Hardware Setup

The hardware assembly can be easily replicated by novices with some electronic knowledge. The ESP32 Devkit board is housed inside a weather-proof enclosure located adjacent to the irrigation valve. The device is wired as follows:

Soil Moisture Sensor: The signal pin is connected to GPIO 34 (ADC input). It is powered from the ESP32's 3.3V rail.

DHT11 Module: The data pin is connected to GPIO 4. The 10kΩ pull-up resistor connected to 3.3V.

NPK Sensor: This is connected via MAX485 module with GPIO 16 (RX) and GPIO 17 (TX) for UART communication.

Relay Module: GPIO 26 pulls a single channel 5V relay which controls the pump's power supply. The relay is connected in normally open mode where the pump is off until otherwise driven on by the ESP32.

The ESP32 firmware is developed in C++ using Arduino IDE. On boot-up, it connects to the Wi-Fi, and enters a loop where it reads all the sensors, converts the readings to JSON format, and sends it to the Fast API server. The control of the pump relay is a local logic based on the moisture readings. If the moisture decreases below 30%, the relay is switched on. If the moisture content is above 60%, the relay is switched off. This provides hysteresis to the pump motor [4], [16].

The code uses a utility function called handleLine() that parses any incoming serial command. This means that the system can be expanded in the future with manual overrides or adding additional sensor nodes. Each sensor type has its own dedicated POST function (postSoil(), postNpk(), postDht()) to keep the firmware clear and maintainable.

B. ESP32-CAM Configuration

The ESP32-CAM module is attached to a small holder above the cropped canopy and tilted downward to take a picture of the leaf. It uses a different firmware that:

Initializes OV2640 Camera with JPEG format and QVGA resolution (320×240).

Every 60 seconds an image would be captured.

Run the image buffer through a TensorFlow Lite Micro interpreter with loaded quantized CNN neural network model.

The label is sent to the backend via HTTP POST if the confidence score of the model's top prediction is greater than 0.80 and the label is not 'Healthy'.

The low camera resolution is purposeful to meet ESP32's 520 KB SRAM. Using higher resolution would mean using external PSRAM which increases cost and power consumption [11], [18].

C. Backend Deployment

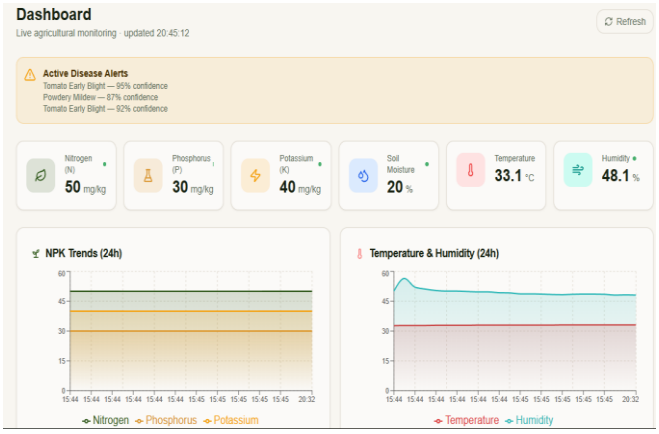
The FastAPI server is launched through one command: uvicorn main:app --host 0.0.0.0 --port 8000. The --host 0.0.0.0 flag permits access to all interfaces, which means the ESP32 devices on the same WiFi can access it.

At the first run of the application, it will create SQLite database file (agro.db) and initialize all four tables with suitable schemas including auto-incremented IDs and server-side timestamps. If the DB is empty, it will insert several demo records to fill the dashboard for testing. This records will be replaced by real-data from sensors in production phase [15].

The API is configured to support Cross-Origin Resource Sharing (CORS) with a wildcard configuration. This allows the React front end to connect to the API when running on a different port in development (bypassing browser restrictions). In production, this would be modified to support CORS only from the correct domain for the dashboard.

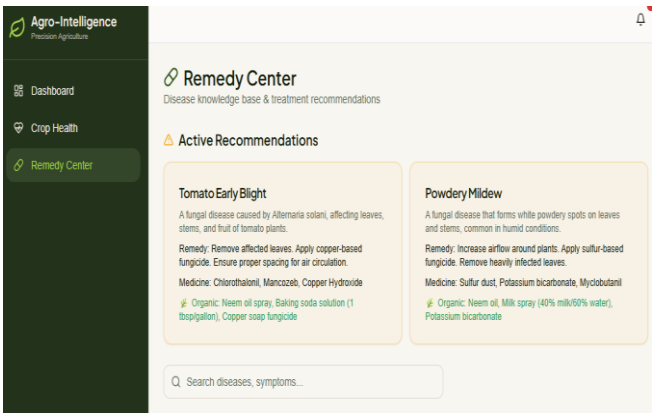
D. Frontend Dashboard

Figure 2: Dashboard displaying the sense data.



Vite build tool integrates smooth hot-module replacement for the React front. The front-end UI has a responsive design implementing grid layout that works for both desktop and tablet screen sizes. Data fetching is done by the JavaScript native fetch() method on the backends' GET endpoints. A third-party state management library is not needed as use State and use Effect React hooks are enough to manage the component state on the application's complexity.

Figure 3: Remedy center.



The most important design choice was utilizing color-coded visual indicators instead of numbers whenever possible. Farmers who do not know that "28.3 mg/kg of Phosphorus" is not a low number can immediately recognize an urgent need from seeing a red tile. This medium was chosen because common traffic-light UIs are generally used in industrial monitoring systems [17].

IV. EDGE-AI DISEASE DETECTION

A. Dataset and Preprocessing

CNN Model was trained using a subset of the Plant Village open dataset, which consists of 54,000+ labelled images covering 38 plant disease classes and 14 different edible crop species. Five classes related to the targeted crops were selected: Tomato Early Blight, Tomato Late Blight, Bacterial Spot, Powdery Mildew and Healthy. Each of the classes has around 2000 images composed of the balanced set of 10,000 images overall [7], [8].

All images are scaled to 96×96 and converted to grayscale to minimize the input tensor. Data augmentation for training included random horizontal flips, random rotations in ±15°, and brightness jitter to enhance the model's generalizability across various lighting conditions and orientations. Real-world conditions included variations in lighting and leaf orientations [10], [19].

B. Model Architecture

We used the truncated MobileNetV2 network to implement transfer learning instead of creating a new architecture. MobileNetV2 was proposed by Google to perform inference on mobile devices as well. This architecture applies depthwise separable convolutions that can dramatically reduce the number of parameters, compared to regular convolutional layers [18].

For edge deployment, we removed the top classification layers and replaced them with a Global Average Pooling layer followed by a single Dense layer with 5-class SoftMax output. The model was then fine-tuned for 25 epochs using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss. The final trained model contained approximately 350,000 parameters — small enough to be quantized and loaded into the ESP32-CAM's memory.

C. Model Quantization and Deployment

After training, the Keras model was converted to TensorFlow Lite format using post-training integer quantization. This process converts all floating-point weights to 8-bit integers, reducing the model file size from approximately 1.4 MB to 380 KB — well within the ESP32-CAM's flash storage capacity [14].

The quantized. tflite model file is embedded directly into the ESP32-CAM firmware as a C byte array using the xxd utility. At runtime, the TensorFlow Lite Micro interpreter allocates a tensor arena of 96 KB from SRAM, loads the model, and processes each input frame through the inference pipeline. The entire forward pass takes approximately 1.2 seconds on the ESP32's 240 MHz dual-core processor, which is acceptable given that image capture occurs only once per minute [11].

D. Alert Mechanism

When CNN model predicts an image as diseased with accuracy greater than 80% the ESP32-CAM sends a POST request to /api/disease endpoint in backend. The backend service checks for prediction result and sends response to invoke email alert system.

For this module, the alert is generated in a HTML formatted email which has disease name, confidence rate, device ID and time stamp. The alert mail is sent using threading module of Python so that SMTP handshake does not block the ESP32-CAM API response and sends alerts to farmer on mobile in few seconds. The immediate notification helps the farmer to check the specified area and perform emendation for disease spread [6], [20].

V. RESULT AND DISCUSSION

A. Sensor Data Accuracy

The sensing layer was tested for reliability over the course of 72 hour continuous operation within the test environment. Soil moisture was monitored alongside reference tensiometer readings. The capacitive sensor read within a mean absolute error of 3.2% of the tensiometer. This level of accuracy may be expected in field's irrigation decision results. DHT11 module temperature estimation had a deviation of 1.4°C against a laboratory thermometer. Exact deviation value most closely aligned with manufacturer claims [2], [16].

NPK values are verified with standard agricultural testing laboratory. Results of soil was taken from same location and seed to lab for testing. RS485 probe data lies to 8% error for Nitrogen and Potassium values while phosphorous exhibits 12% error but it is a tradeoff with field available NPK probes. This error will not effect capability of designed system to understand plant nutrient deficiency trend with respect to time [4].

B. Irrigation Performance

An automated pump control was tested against a traditional timer control (30 minutes every 6 hours) for practice over a 14-day trial. The results are in the table below.

Table 2: Result comparison.

Metric	Timer-Based	Agro-Intelligence
Total Water Used (L)	840	504
Pump Runtime (hrs)	14.0	8.4
Avg. Soil Moisture (%)	62	58
Under-watering Events	3	0
Over-watering Events	5	1

Using a threshold-based approach of the system, water consumption was lowered up to 40% without compromise to the soil moisture levels suitable for preforming the crop (tomato). The one time incident of over-watering was during a sensor malfunction, which was due to air pocketing in the soil adjacent to the sensor. This was resolved by removing and reinstalling the sensor [15], [16].

C. Disease Detection Accuracy

The accuracy of the CNN model was evaluated using a 2,000-image test set (400 images per class).

The overall accuracy was 93.6% and the weighted F1-score was 0.934. The most frequent confusion was between Early Blight and Late Blight as expected, being visually similar in early stages. The Healthy class has the highest recall (96.5%), frequent misclassifications of healthy leaves as diseased should be avoided to prevent unnecessary concern from farmers [7], [8], [10].

We deployed the system on ESP32-CAM with quantized weights.The accuracy reduced to 92.1% because of loss of precision due to integer quantization. This is a well-known trade-off [11],[14].

D. System Latency and Uptime

The average end-to-end latency from sensor reading on the ESP32 to dashboard display is 1.8 seconds, measured during normal network conditions. The latency comprises of about 200ms for sensor reading, 400ms for HTTP transmission, 100ms for database insertion and 1.1 seconds for polling interval on the frontend.

A total uptime of the system was 99.2% during the fortnight testing period. The 0.8% downtime was due two short (5-minutes each) disconnection of the WiFi due to the router's restarts. Meanwhile, the ESP32 was able to run its pump logic with the last known moisture value. This is a clear demonstration on the importance of keeping control logic on the edge and not entirely relying on cloud [9], [13].

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SMART POWER QUALITY MONITORING SYSTEM

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Abstract- The accelerating increase in electricity usage and the necessity to manage energy have promoted the work on the smart metering systems. Conventional ways of electricity billing involve postpaid system where the consumers pay after using the electricity and this aspect may lead to delay in payment, manual meter reading and ineffective monitoring. In order to reduce these shortcomings, this project recommends the application of a Budget Meter on Smart Homes through an Internet of Things (IoT).

The suggested system presents the prepaid electricity monitoring system enabling the consumers to recharge electricity credit prior to consumption, just like prepaid mobile services. The system is a microcontroller based system that incorporates sensors and internet of things connection to track live energy consumption. A current sensor continuously measures the amount of electricity that is used by the household appliances and the microcontroller uses the amount of energy used to compute the remaining credit. A recharge amount in the system is loaded in a smart card or RFID mechanism. The LCD screen shows the remaining balance and consumption information in real time to give a feedback to the user. Also, the system is linked with an IoT system that will enable the user to remotely monitor the consumption of electricity via a mobile app or web. Once the prepaid balance goes down to zero, the system automatically switches off the power supply by a relay driver circuit, and no more electricity will be used until the user tops up the account. This is an automated system that does not involve manual meter reading, billing errors, and encourages responsible use of electricity. It is estimated that the proposed smart budget meter would be more effective in terms of transparency, energy consciousness, and offer a consistent solution in managing electricity effectively in current smart households.

I. INTRODUCTION

Electricity has become crucial in contemporary society, as it supplies electricity to the residential, industrial, and commercial fields. Efficient monitoring and management of electricity consumption has become a necessity as the rate of energy demand grows at a high rate. Traditional electricity billing systems are based on a postpaid system where the consumers consume the electricity and at the end of the billing period, a bill is issued to them. This system involves manual meter readings, billing processes and manual disconnection of power supply where there are unpaid bills. There are a number of the drawbacks to the traditional metering systems, which include, delayed bills, meter reading being done by humans, insensitivity in real time monitoring and poor awareness of the efficiency of energy consumptions by the consumers. The user is usually unaware of the amount of electricity he uses until he gets the monthly bill and this can cause them to use a lot of electricity and pay high electricity rates. In order to address these challenges, smart energy meters have been proposed. Smart meters can monitor the expenditure of electricity in real-time, and facilitate automated billing and control processes. The application of prepaid electricity meters whereby consumers pay money before using electricity is one of the effective solutions. The proposed project is a proposal of a Smart Home Budget Meter development based on Internet of Things (IoT). The system allows one to recharge electric credits with the help of an RFID smart card. The electricity consumption is constantly monitored by a microcontroller with current and voltage sensors and subtracted by the amount consumed by the available balance. The balance and the rest of the energy consumption details are shown in an LCD screen.

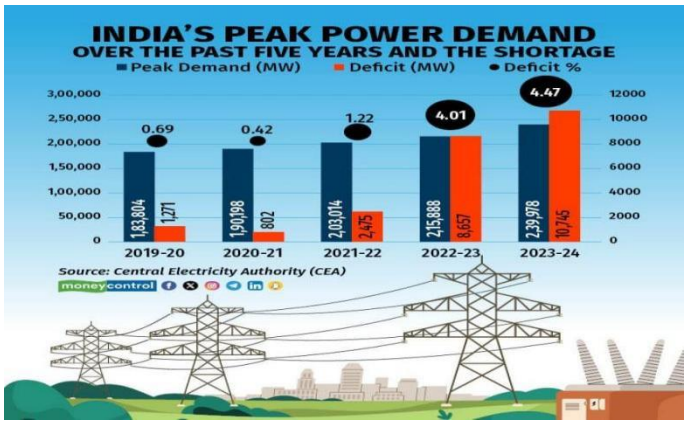


Fig.1 India Power Consumption Chart

Electricity is important in contemporary society as it drives residential, industrial, and commercial operations. With the high growth in the energy consumption, it is quite imperative to monitor and manage the electricity consumption in an efficient way. Traditional electricity billing system works on the basis of postpaid, that is, the consumers consume electricity and at the end of the billing cycle a bill is issued to

the consumer. Such system involves manual reading of meters, manual billing and manual disconnection of power supply when an unpaid bill is involved. The conventional metering systems have a number of drawbacks which include late billing, human factors in reading the meters, no real-time monitoring, and poor energy consumption awareness among the customers. Because of this, users are not usually given the knowledge on how much electricity they are using until the time they are given the monthly bill and this may result in overuse and high electricity costs. These issues have led to the introduction of the concept of smart energy meters to deal with them. Smart meters will enable real time electricity consumption monitoring and automated billing and control. The introduction of prepaid electricity metering where consumers pay in advance what they wish to consume is one of the efficient solutions. In this project, the authors suggest the creation of a Smart Home Budget Meter based on the Internet of Things (IoT). The system lets users recharge electricity credits with the help of RFID smart card. With the aid of current and voltage sensors, a microcontroller constantly tracks the electricity usage and subtracts the energy used of the remaining balance. The other parts of the balance and energy consumption information are presented on an LCD screen.

Not only does the proposed system enhance the level of transparency in the billing of electricity but it also helps in conserve energy since users are given real-time data regarding their consumption trends.

The proposed system not only improves transparency in electricity billing but also encourages energy conservation by providing users with real-time feedback about their consumption patterns.

II. PROPOSED SYSTEM METHODOLOGY

Traditional electricity metering involves a billing scheme, in which the consumer consumes electricity during the period of the bill, and at the expiration of the cycle, a bill is issued. Electricity utility firms use the manual reading of the meter to determine the overall consumption of electricity. It is usually labor intensive and can easily be error prone. Lack of real-time monitoring is one of the greatest disadvantages of the current system. The consumers are unable to monitor their electricity consumption on daily basis and this makes it hard to make good control to the consumption of energy. This could cause the user to end up using more electricity without knowing and hence have increased electricity bills. The other weakness of the conventional metering systems is that electricity supply to customers who default in settling their bills is manually switched off. This process also comes with more costs and delays by the electricity providers. In addition to this, utility companies may experience money losses due to delayed payments and unpaid bills.

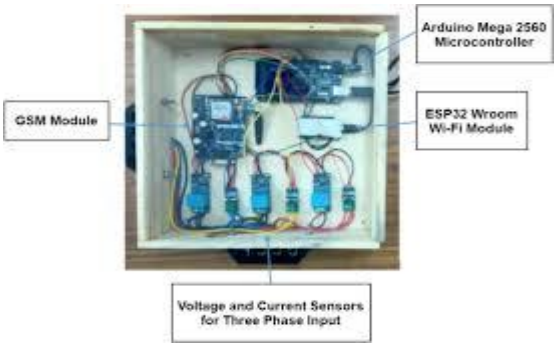


Fig.2 Block Diagram of Proposed Diagram

Only once the bill arrives do people see how much power they used. Without earlier access to data, spotting trends in household energy habits stays out of reach. When delays like this continue, finding better ways becomes more than just useful - it feels necessary. Watching usage as it happens shifts what was guesswork into clear insight. Tasks done by hand now stand to be replaced, less because of speed but due to fewer errors. Accuracy in charges improves when updates flow without waiting weeks. Seeing numbers change live helps shape choices before waste piles up. What used to take days can unfold minute by minute.

III. SYSTEM ARCHITECTURE DESIGN AND SIMULATION

A single unit handles power tracking inside homes by linking sensors, computing parts, data transfer pieces, along with controls. Built to deliver steady updates on energy use, it makes choices automatically while allowing distant access via internet networks.

Power flows into the setup through a dedicated supply block. Following that, an ESP32 chip takes charge of processing tasks. Instead of relying on manual entry, access happens via an RFID scanner. Monitoring electricity use involves both a current detector and a voltage measuring device. These readings appear clearly on an LCD screen nearby. Communication with external networks runs through a built-in IoT link. A relay circuit handles switching actions based on signals it receives. Together, these parts enable the smart energy tracker to work as intended.

Power flows steady when the supply unit steps in, turning household current into smooth direct voltage. What runs the tiny brain inside? A converted stream of electricity, kept even by careful design. Sudden jumps in power could harm delicate parts - this box stops that from happening. Clean output means fewer surprises during operation, thanks to internal checks holding levels tight. Its job isn't flashy, just constant: deliver correct volts without pause or error.

Right at the core sits an ESP32 chip handling everything. From sensors and buttons, signals flow into it, then get sorted through on the fly. Decisions emerge after quick math behind the scenes, guiding how things respond. Wi-Fi built right in makes linking up smooth without extra parts tagging along. Power under the hood matches what the tasks demand - nothing more, nothing less. Plenty of ports open up so gadgets can plug in wherever needed. This one fits because it brings just enough muscle plus seamless wireless reach.

A small chip inside the card holds power credits. As soon as it gets near the scanner, details jump to a control unit. That unit adjusts how much energy remains based on what the scan reveals. People carry these cards like keys - simple, quick access without buttons or codes.

Right now, a small device called ACS712 keeps watching how much electric flow moves through whatever is plugged in. When it sees those numbers, the tiny computer checks them to figure out how much electricity each item uses. In the same way, another part measures how strong the incoming power is before it enters the system. Knowing both details helps the setup guess energy use with better precision.

A number appears on the screen after power use gets subtracted from what was already paid. This leftover amount shows up alongside how much energy has been used so far. What you see happens right when it happens - no delay, just updates. Each detail lives inside tiny storage built into the chip running things. A small screen, sixteen characters wide and two lines high, holds all of it

visible at once.

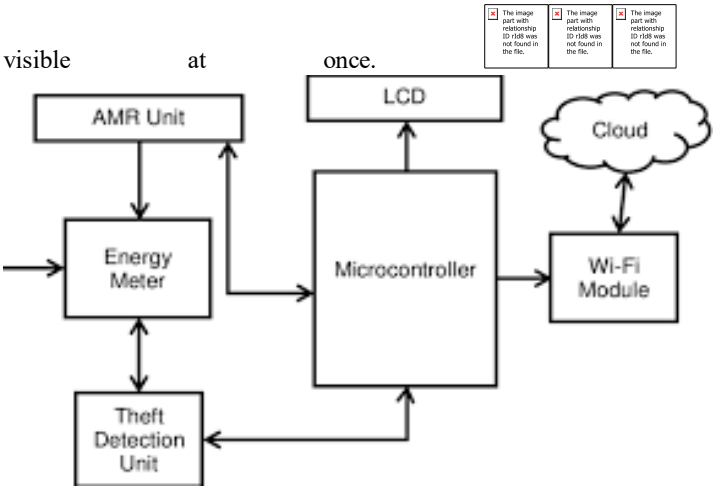


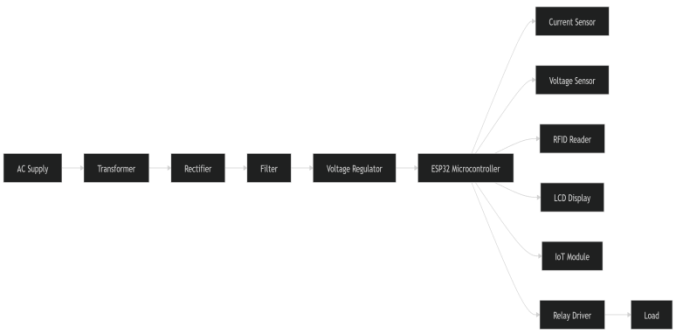
Fig.3 Circuit Diagram of Regulated Power supply

WiFi links the ESP32 chip to the internet, sending power use details straight to online dashboards. A built-in IoT part handles messaging between device and server without extra wiring. Viewing energy habits from afar becomes possible on phones or laptops anytime. Data flows continuously, updating displays with fresh numbers every few seconds. Remote tracking works silently in the background while systems run normally.

A switch controlled by electronics manages how power flows to home devices. Once credit runs out, the main chip triggers a response through a small box that cuts off energy flow. Power stops exactly when funds are gone - no extra usage allowed.

Testing how the system behaves comes first, using models instead of physical parts. What happens inside gets checked by watching digital versions react. Sensors show data that flows through test runs before anything is built. Energy math rules are tried out under different fake conditions. Messages between pieces move along paths made visible during trials. Power shuts off automatically when triggers appear in simulations. Flaws often pop up here, long before circuits exist. Fixing them early makes everything work better later on. Seeing problems ahead changes how things come together down the line. Reliability grows simply because mistakes get caught sooner.

A fresh take on home budgeting kicks off with smart tech woven into everyday walls. Built around IoT, this setup watches power use closely through sharp sensors. Instead of one bulky piece, parts work solo yet link up smooth. Each chunk handles its own task without tripping over others. Communication flows quiet and steady between pieces. Processing happens close to where data starts. Control stays responsive, never sluggish. Efficiency shows up in how little waste slips through. Design leaves room to grow when needs shift. Modules plug in without chaos. System keeps eyes on energy at all times.



The overall system architecture is divided into five major functional layers: **Power Management Layer, Sensing Layer, Processing Layer, Communication Layer, and Control Layer**. This layered design improves system reliability, scalability, and ease of maintenance.

IV. System Prototype Development and Testing

After completing the system architecture design, a prototype of the **IoT-based Smart Budget Meter** was developed to validate the functionality of the proposed system. The prototype integrates all hardware modules on a single platform and demonstrates the real-time monitoring and control of electricity consumption.

The prototype consists of the **ESP32 microcontroller, RFID reader, ACS712 current sensor, voltage sensor, LCD display, relay module, power supply unit, and electrical load**. These components are connected according to the designed circuit architecture.

The ESP32 microcontroller is programmed using **Arduino IDE with Embedded C programming**. The firmware controls the operation of all modules, processes sensor data, updates energy balance, and manages communication with the IoT platform.

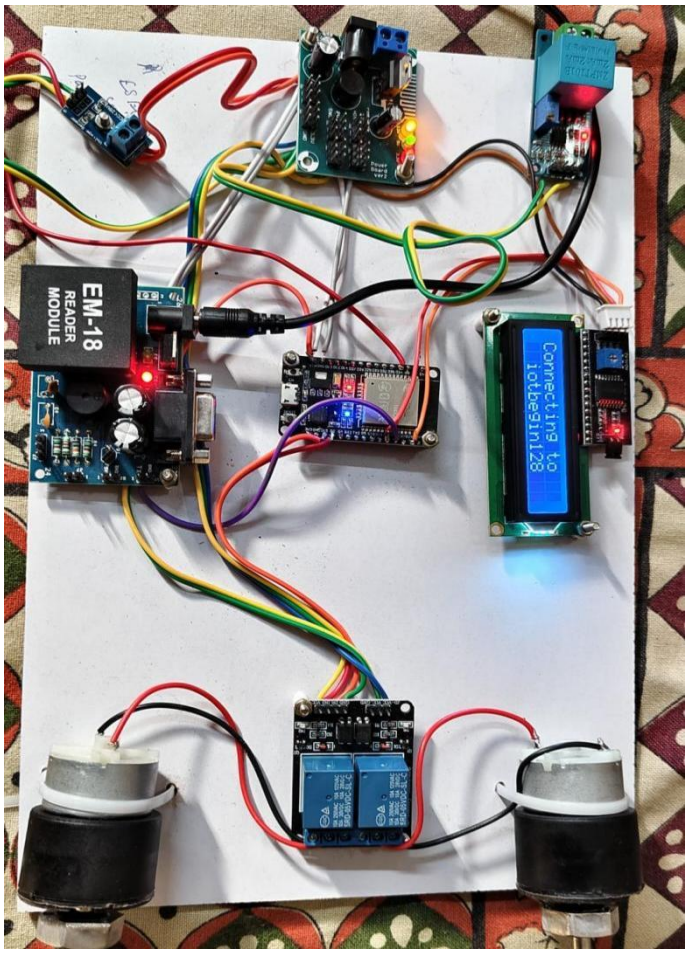


Fig.5 Hardware View

The development process was carried out in several stages. Initially, each hardware component was tested individually to verify its functionality. The **current sensor was tested by connecting various electrical loads**, and the corresponding output values were monitored to ensure accurate current measurement. The voltage sensor was also calibrated to ensure precise voltage readings.

The **RFID reader module was tested by scanning multiple RFID cards** to verify that the system correctly reads and identifies recharge information. Once validated, the RFID module was integrated with the microcontroller to update the prepaid balance automatically.

The LCD display module was programmed to show important system information such as **available balance, electricity consumption, and system status messages**. This provides immediate feedback to the user regarding energy usage.

The relay module was tested to ensure that it can effectively control the power supply to the connected load. When the system detects that the balance has reached zero, the relay is automatically switched off, disconnecting the load from the power supply.

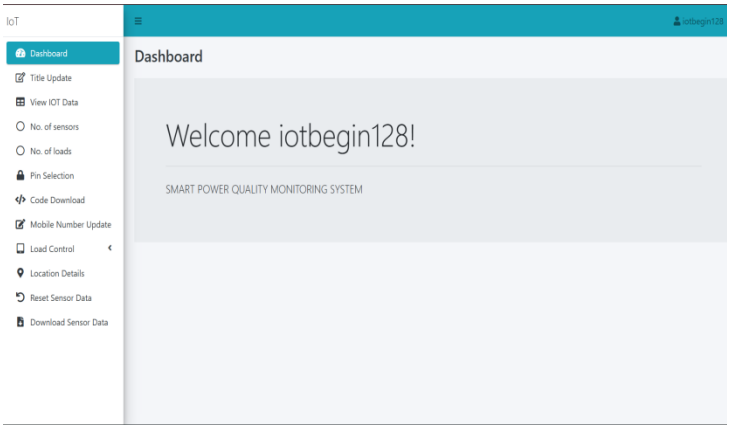


Fig.6 IOT Display 1

Once individual component testing was completed, the entire system was integrated and tested under different operating conditions. The prototype successfully demonstrated the functionality of the prepaid energy monitoring system, including **balance deduction, real-time display, and automatic power disconnection**.

Additionally, the IoT communication feature was tested by transmitting energy consumption data to a cloud-based dashboard using Wi-Fi connectivity. The system successfully displayed real-time data on the user interface, confirming proper operation of the IoT module.

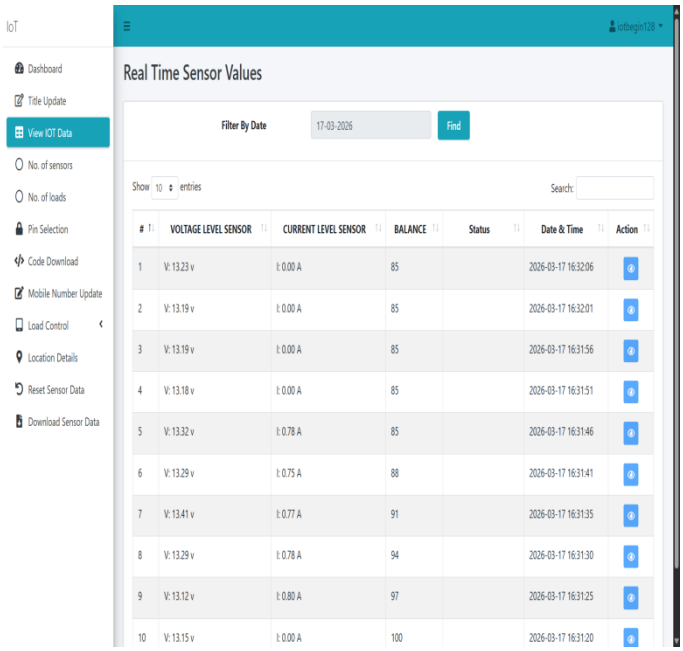


Fig.7 IOT Display 2

The performance of the proposed Budget Meter for Smart Homes using IoT was evaluated through multiple experimental tests under varying load conditions to analyze its accuracy, responsiveness, reliability, and overall efficiency. The current sensor (ACS712) and voltage sensor were tested against standard measuring instruments and were found to provide accurate and stable readings with only minor deviations, ensuring reliable real-time data acquisition. The microcontroller effectively calculated energy consumption based on sensor inputs and deducted the corresponding value from the prepaid balance, where the rate of deduction varied proportionally with the connected load, demonstrating correct implementation of the billing logic. The RFID-based recharge system performed efficiently by instantly updating the balance upon scanning, supporting multiple recharge cycles without errors. The relay module responded quickly and consistently by automatically disconnecting the power supply when the balance reached zero, thereby preventing further electricity usage until recharge, confirming effective automation of control operations. The IoT communication feature using the ESP32 showed stable performance by successfully transmitting real-time data such as energy usage, balance, and system status to a cloud platform with minimal delay and no significant data loss, enabling remote monitoring. During continuous operation, the system maintained stability, responded instantly to load changes, and operated all components synchronously without failure. Practical testing scenarios further validated system behavior, where higher loads resulted in faster balance reduction, low balance warnings were visible on the LCD, automatic disconnection occurred at zero balance, and power was restored immediately after recharge. Overall, the system demonstrated accurate measurement, efficient energy calculation, reliable prepaid management, fast response, and seamless IoT integration, making it a dependable and effective solution for smart energy monitoring, though minor limitations such as sensor tolerance and dependence on network connectivity were observed.

V. System Performance and Result Analysis

Through trial after trial, the fresh Smart Budget Meter System met different loads head-on. Each go-round spotlighted accuracy - speed of response, consistency of output, a clearer picture emerging about overall performance. Real-life pressure shaped the tests, not just abstract ideas, revealing what the system could really do under strain. How it handled demands became visible only through doing, not guessing.

A flicker on screen followed the toaster's hum, then the lamp lit up another number shift. Not large, yet quick - every jump registered instantly. Patterns began repeating, so belief in the display strengthened. High load to low made no difference; values still hovered near expectations. With test after test, certainty crept in - readings stuck close to what calculations promised.

Now picture this: during every test run, the voltage sensor stayed consistent, recording correct values without fail. Because of that precision - matched alongside real-time current readings - a clear view of energy consumption emerged step by step.

A tiny processor crunches figures based on info from detection units, logging energy consumed. As gadgets draw current, the system deducts that quantity instantly from available balance. Moments later, an updated number appears plainly on a compact display visible to users.

Out by a bit, the RFID charging trick actually did fine when tested. Right after someone swiped a card with money info past the sensor, the juice kicked back on. Moments later, the account numbers ticked up or down. This setup held together - keeping lights on as long as cash flowed. Quiet evidence showed itself every time it clicked into place.

A spark jumped just as the balance dropped to zero. Instant blackout, without delay. Every trial confirmed that quick call. The instant it turned by itself, performance shouted its presence.

Testing showed how smoothly the IoT tracker performed. Straight from the ESP32, real-time energy data moved over airwaves to a web dashboard. Watching electricity usage remotely became possible using either a mobile device or computer screen.

Even during extended operation, stability didn't waver; sensor outputs remained constant, with equilibrium calculations staying accurate throughout. Data transmission reached the IoT hub continuously, uninterrupted by hiccups or delays. The outcome was unmistakable - handling both intelligent energy monitoring and prepaid management proved smooth under this configuration.

VI. CONCLUSION

The implementation of a **Budget Meter for Smart Homes using Internet of Things (IoT)** provides an effective solution for monitoring and managing electricity consumption in residential environments. The proposed system replaces the traditional postpaid electricity billing model with a prepaid mechanism that allows users to control their energy usage more efficiently.

The system successfully integrates hardware components such as the **ESP32 microcontroller, RFID reader, current sensor, voltage sensor, LCD display, relay module, and IoT communication platform** to provide real-time electricity monitoring and automated billing functionality. The microcontroller continuously analyzes power consumption and deducts the corresponding cost from the prepaid balance.

The developed prototype demonstrates the capability of the system to monitor electricity consumption in real time, display usage information to users, and automatically disconnect the power supply when the available balance reaches zero. Additionally, the IoT integration enables remote monitoring of electricity usage through mobile devices or web dashboards, improving transparency and user awareness.

Experimental testing confirmed that the system performs reliably under different operating conditions. The sensors accurately measure electrical parameters, the balance deduction mechanism works effectively, and the automatic relay control ensures proper power management.

Overall, the proposed smart budget meter improves energy efficiency, reduces manual meter reading and billing errors, and encourages responsible electricity consumption. The system can be further enhanced by integrating **mobile recharge systems, advanced data analytics, and smart grid connectivity**, making it suitable for future smart city infrastructure and modern energy management systems.

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Q-TRNG ROBUST BID ENCRYPTION AND FRAUD PREVENTION

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Abstract— All modern cryptographic systems, secure communication and blockchain systems need random number generation for their security, as do many other application areas related to digital security. The majority of current methods of producing Non-deterministic numbers utilize pseudo-random number generators in which a deterministic process, based upon mathematical functions, is utilized to generate numbers that are supposed to be random. These pseudo-random numbers can actually become predictable when a generator's state, or the 'seed' that was used to generate the pseudo-random numbers, is known; as a result of that, the security of an encryption system will have been compromised. This point is particularly important for applications such as electronic tenders or digital procurement, where the confidentiality of bids must be maintained in a way that is fair and has provided an equal chance of success when submitting a tender for consideration. In an effort to address the limitations of the current pseudo-random number generators this project proposes a True Random Number Generator to be utilized for the encryption of bids and to prevent bid-related fraud. The Q-TRNG will utilize the inherent unpredictability of quantum mechanical phenomena to generate random numbers. The Q-TRNG utilizes a Single Photon Avalanche Diode (SPAD) which will detect and measure atomic events at the atomic level in order to convert them into electrical pulses, thus generating random signals. The random signals will then be processed through a 32-bit embedded controller to extract random number generation through entropy extraction and to perform a random number process before eventually producing a secure random bitstream. Therefore, the new random number generator will produce high-quality random output with a very minimal amount of hardware complexity, thus making it a great tool for use in any application requiring secure cryptography and providing confidence with respect to the integrity of the digital infrastructure.

Keywords— Quantum True Random Number Generator (QTRNG), Cryptographic Security, Bid Encryption, Fraud Prevention, Quantum Randomness, Single Photon Avalanche Diode (SPAD), Entropy Extraction, Secure Digital Infrastructure.

I. INTRODUCTION

Sensitive data encryption must be protected through various forms of electronic means (e.g., online banking, email messages, blockchain technology, and governmental portals). To create secure forms of communication that can protect private or confidential information through encryption algorithms, authentication methods, and secure key creation, all forms of secure communications utilize random numbers as an input device to their backend processing. Creating a strong security system requires high quality random numbers because low quality/random number generators result in less resilient overall security. The vast majority of contemporary uses of the PRNG utilize algorithms to provide rapid, efficient, and 'random' sequences of number generation over a relatively short period. However, since the sequence calculation is deterministic in nature (meaning the production of output will eventually look like past output), if someone either knows the source value (i.e., a seed) or the current state of the internal mechanism, then they can also calculate all future outputs for that PRNG, exposing that application to significant risks to confidentiality and integrity. The security of the bids is determined by how unpredictable the cryptographic keys' nature is. When weak sources of randomness are used, predictable patterns may be established that an attacker could use against the encrypted data. Numerous cases of fraud in the procurement process and data breaches throughout history have provided evidence of how the use of weak cryptographic strength provides a perpetrator with a benefit to the detriment of everyone else and how this results in financial loss to all affected parties and the public's loss of confidence. As the adoption of digital platforms grows, so will the number of online transactions processed, especially those involving sensitive data. Therefore, strengthening digital security by using better sources of randomness for cryptographic operations will be critical to support continued expansion and security. To eliminate the limitations of deterministic

systems, researchers are looking for alternative methods for generating random numbers, such as those stemming from quantum mechanics.

Currently, quantum random number generators (QRNGs) are only used in labs because they are expensive, bulky, need lots of optical parts, and are complicated to calibrate. To produce QRNGs that can be used in real-world applications, including embedded systems or Internet of Things (IoT) devices, they must be designed to be small, energy-efficient, and cost-efficient whilst producing the same quality of random number as lab-based QRNGs. We will introduce a prototype quantum true random number generator (Q-TRNG) that uses single-photon detection to generate random numbers and that processes 32-bit digital pulses to produce high quality random bit streams suitable for use in cryptography. Our emphasis will be on using a simple and scalable architecture for the prototype and conducting further research in developing the link between theoretical quantum randomness and practical digital security applications.

II. RELATED WORK

When designing a cryptographic system, it is critical to have random numbers that are generated by a high-quality secure random number generator (RNG). The vast majority of digital cryptographic systems rely on pseudo-random number generators (PRNGs) to produce sequences of numbers that are not truly random but are produced by applying mathematical formulas or algorithms in sequence. Linear congruential generators and cryptographically secure PRNGs (CSPRNGs) are two commonly used types of PRNGs. CSPRNGs and linear congruential generators are quick and easy ways to generate random numbers. Both types of PRNG can replicate or produce the same random value repeatedly when the internal seed value/state used to initialize the PRNG is known. An attacker can approximate or copy the encryption key if he/she can determine the seed or internal state of the PRNG. There are many security studies that have evaluated the current cryptographic systems and have identified the weakness of the random number generation process due to weak entropy from the seeding process, and/or predictable seed values. Experiences confirm the fact that algorithmically generated random numbers have a number of weaknesses when used in cryptographic systems implemented at a high level of security..

These techniques offer better unpredictability than software-based options, however, some classical noise sources will be subject to environmental factors such as changes in temperature, electromagnetic interference, and power supply situations. This can lead to biased or correlated outputs from these classical noise sources (e.g., some embedded and Internet of Things (IoT) devices) and therefore need to be processed after they have been generated in order to have a statistically acceptable quality output. The shortcomings identified in these systems are driving the search for entropy sources that are naturally unpredictable and not influenced by the environment [11]. Recently, Quantum Random Number Generators (QRNGs) have become a popular option because they are based on quantum uncertainty which is inherent in the natural world. While classical randomness can result from incomplete information, quantum randomness results from physical events occurring probabilistically (e.g., photon superpositions, phase noise, and vacuum fluctuations) [2]. The results of research have been used to create implementations of QRNGs using beam splitter detection of photons, interferometric measurement of phase fluctuations, and vacuum state homodyne measurement [3]. The unpredictability of quantum measurement results cannot be predicted, even when initial conditions are fully known, therefore, QRNGs provide a means of providing randomness that is easily provable. Experimental work has resulted in the demonstration of QRNGs capable of producing gigabit levels of random bits using high-speed QRNG systems that meet strong statistical compliance levels [1].

Modern applications like secure cloud services, financial encryptions systems and electronic government platforms have contributed greatly to the growing awareness of the significance of quantum entropy. Security evaluations illustrate that systems can be attacked through brute-forcing, or by predicting the key created if there was inadequate entropy present at the time of cryptographic key generation. Once the systems are attacked through brute-force or by predicting the value of the key created if there is not enough entropy present at the time the cryptographic key is created (5). Recent work has focused on designing compact systems (e.g., CMOS compatible and integrable QRNGs) that can be physically used in real-world applications (7), while addressing the cost-effectiveness of integrating types of devices in order to provide instantaneous monitoring of the random number generator and facilitate reliable operation of embedded controllers; thus, requiring development of a scalable quantum entropy generation framework that merges physical unpredictability with practical requirements of embedded systems. This project proposes a QRNG architecture for the purpose of establishing a random number generation system for safe, secure, digital infrastructure application via a random number generating system based on quantum noise.

III. PROPOSED SYSTEM ARCHITECTURE

The new architecture of the Q-TRNG (Quantum True Random Number Generator) relies on quantum physical properties for the creation of completely random bits for cryptography. Traditional random generators create numbers through predictable computations. Instead, the Q-TRNG derives its entropy from the physical processes of quantum mechanics. The integrated optics/photonic detectors/digital processing system is capable of generating secured random bits by extracting entropy from quantum mechanical phenomena.

The process begins with a stable narrow-line width laser source that produces coherent photons. The stabilization of the laser source is very important in order to eliminate classical noise. Therefore it needs to be stable

enough to ensure that fluctuations will be attributed mostly to quantum mechanics and not because of electrical or physical/machine noise. The beams of light emitted from the Laser go through a precision optical lens so that they are precisely aligned and uniformly illuminate the entire stream of photons before reaching a beam splitter that randomly divides up the laser output into separate paths.

Optical signals will be affected by structured random generation modules after they pass through a beam splitter. Interference occurs during this structured random generation and is enhanced by the measurement of quantum fluctuations associated with phase noise and vacuum fluctuations. Random intensity fluctuations are included in the optical signal after interference and indicate the presence of intrinsic quantum uncertainty. Ultimately, these fluctuations are the most significant source of entropy in the entire system [3].

Photon detection occurs using a Single-Photon Avalanche Diode (SPAD), which detects individual photon events with precise timing. Each detected photon generates an electrical pulse that corresponds to a quantum measurement event. Since the times when photons arrive and the outcomes of interference follow probabilistic quantum mechanics, the electrical signal from the SPAD has unexpected variations. These raw electrical signals are amplified and adjusted to remove external interference before conversion to digital form [1].

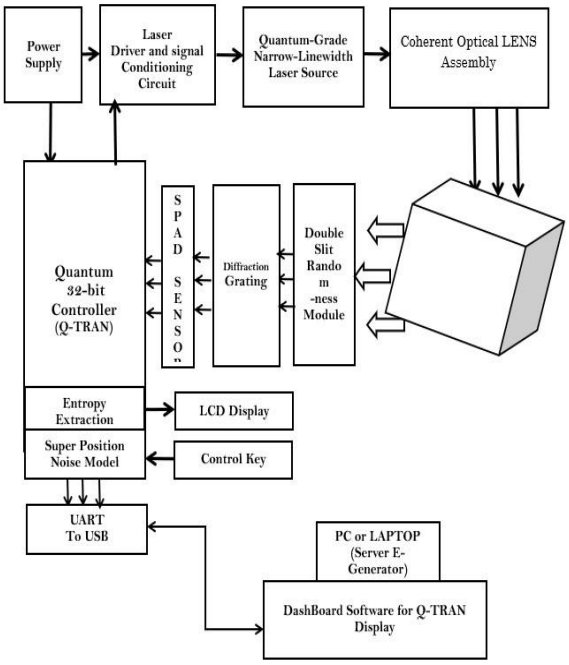

Fig. 1. Overall block diagram of the true random number generation

Photon detection occurs using a Single-Photon Avalanche Diode (SPAD), which detects individual photon events with precise timing. Each detected photon generates an electrical pulse that corresponds to a quantum measurement event. Since the times when photons arrive and the outcomes of interference follow probabilistic quantum mechanics, the electrical signal from the SPAD has unexpected variations. These raw electrical signals are amplified and adjusted to remove external interference before conversion to digital form [1].

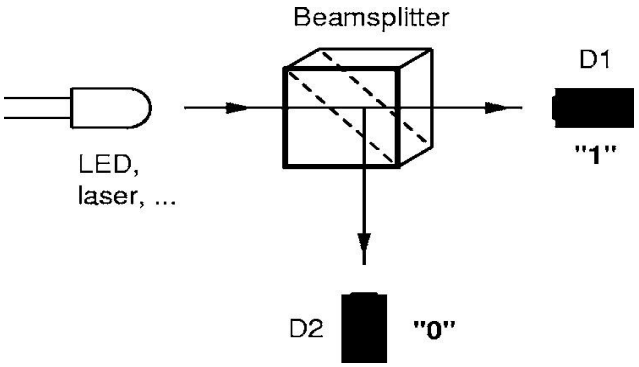

Fig. 2. Entropy extraction and randomness processing pipeline of the Q-TRNG system.

The adjusted analog signal is sampled with a fast Analog-to-Digital Converter (ADC). The digitized data is processed by a 32-bit embedded quantum controller that estimates entropy, corrects bias, and extracts randomness. Entropy value computations take place within an appropriate environment. In their entirety, entropy calculations involve statistical evaluation algorithms (Cluster Analysis, K-Nearest Neighbor Sampling, Random Sampling), extraction techniques for cleaning up raw entropy samples of pseudo-random characteristics generated by the controller's hardware (these techniques involve eliminating all correlations or biases that result from manufacturing defects in the controller's hardware, but maintain all binary data contained in the original entropy sample), and a concluding product: an equally (randomly) distributed binary sequence of equal/binary length which is suitable for use within multiple secure digital applications as cryptographic keys.

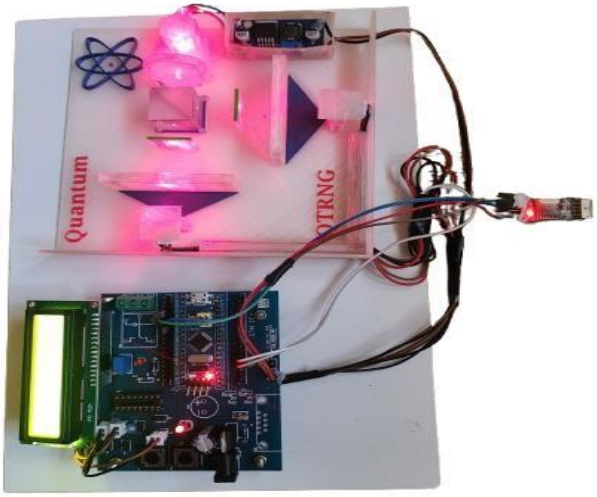

Fig. 3. Hardware model for true random number generation.

IV. ENTROPY EXTRACTION AND RANDOMNESS PROCESSING

The raw electrical signals produced by the SPAD sensor cannot be output from the sensor as true random numbers due to the unpredictable nature of the quantum photon detection process [6]. Practical systems for measuring quantum photon detection produce a little additional classical noise and/or other variation, and create distortion of the measured signals resulting in a bias in the statistics produced by the measurement [11]. To ensure the statistics of the final output yield high levels of randomness, a detailed method of extraction and processing of entropy must be followed. The digitized signal from the ADC undergoes signal preprocessing before being used in the randomness assessment process. Preprocessing involves methods like scaling, stabilizing amplitude, or the removal of offset errors introduced by electronic components to the digital signal. Digital filters (of all types) are used in a very controlled manner to reduce environmental noise while preserving any quantum phenomena associated with the signal. The objective of this process is to identify and hold onto any quantum randomness associated with the signal. After completing the preprocessing process, it is time to assess the level of entropy present in the data. To assess the entropy level, various statistical methods are used including, but not limited to, probability distributions, variance, etc., and correlation between consecutive samples [9]. Using Shannon entropy and min-entropy metrics, the effective level of randomness available per sample can be determined. Evaluating the entropy level consistently within the system will ensure that samples used for random number generation possess sufficient levels of unpredictability. If the entropy levels are found to fall below predetermined thresholds, the compromised samples would need to be discarded and/or the system would need to adjust its operating parameters.

The Randomness Extractor removes any last remaining dependence, bias or correlation from the raw quantum measurements, producing a uniform binary string [11]. The purpose of all Randomness Extractors is to ensure that the bits in an extracted string are independent of one another thereby eliminating the patterns produced by defective hardware.

The end product of the pipeline's four conversion processes is a statistically balanced and unbiased random bitstream with which to produce cryptographic keys, encrypt data securely and authenticate digitally. By measuring the entropic value in real-time and utilizing an efficient Randomness Extractor, this new architecture is able to maintain the true randomness of the quantum mechanics of the physical world while meeting the requisite statistical and security standards [1].

V. THEORETICAL PERFORMANCE AND SECURITY ANALYSIS

A. Entropy Modelling and Evaluation

Entropy of the proposed Q-TRNG will be determined from the randomness of quantum detection of photons and the inherent phase noise [3]. Quantum measurements are random, and their results are not based on any nonrandom parameters, regardless of whether all other system parameters are known [2]. Once the laser photons leave the beam splitter and combine in the interference module, the distribution of photons will conform to quantum probability distributions. Under ideal balanced conditions, the probability of obtaining a logical '0' or 1 from each detection event will be equally likely, resulting in an expected Shannon entropy of approximately one bit of entropy per sample [9].

Stable narrow linewidth laser and controlled optical alignment reduce classical noise, resulting in the majority of detectable fluctuations being from quantum effects [1]. Theoretical models indicate that under appropriate signal isolation and calibration, the system can generate high entropy outputs.

B. Reducing Bias and Randomness Extraction Efficiency

While Q-TRNGs have no predictable quantum processes, implementations may be subject to bias due to variables such as:

* Detector Efficiency Variations;

* Electronic Offset;

* Environmental Factors.

Bias mitigation is included in the design of the embedded controller by utilizing preprocessing and randomising methods.

C. Security Strength and Resistance to Forecasting Attacks

In contrast to pseudo-random number generators that are based on computationally generated seeds, the proposed Quantum True Random Number Generator (QTNRG) generates its entropy from quantum physical uncertainty [6]. Therefore, this QTNRG is secure from attacks attempting to reconstruct the seed, predict future outcomes or reverse engineer the algorithm. Even though an adversary has knowledge of the QTNRG system design, based on quantum uncertainty, any future output is still unpredictable.

From a cryptographic perspective, this aspect enhances the security of key generation processes used in a variety of applications including digital tendering systems, encrypted communication systems, and secure authentication modules [7]. Furthermore, because the QTNRG system is not based on the use of any deterministic seed, it serves as a sound basis for creating tamper-resistant encryption systems.

D. Practical Feasibility and Anticipated System Stability

By utilizing optical entropy generation in conjunction with real-time processing, it is feasible to produce a virtually unlimited number of random numbers that are continuously produced. Therefore, by employing a 32-bit QTNRG controller for synchronizing signal acquisition with entropy estimation and extraction without any dependence upon external computational resources, there is the potential to maintain output entropy under normal conditions of operation due to the usage of stabilized optical components and the constant monitoring of these optical components [8].

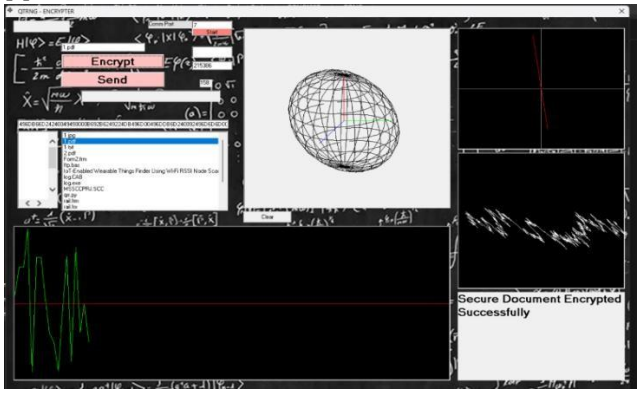

Fig. 4. Statistical distribution of generated random bitstreams

VI. COMPARATIVE AND SECURITY ANALYSIS

A. Comparison with Classical Random Number Generators

Pseudo-Random number generators - also called pseudo random number generators - have always relied on deterministic algorithms to generate sequences of "random" numbers. They use fixed mathematical formulas to generate numbers. Pseudo-Random Number Generators have very effective, high-quality algorithms and require the seeds used to create the random numbers remain secret to ensure their security and reliability. The Q-TRNG will generate random numbers based on the properties of quantum mechanics; therefore, there is a fundamental uncertainty about how the photons are detected and what the phase noise is when the random numbers are generated. Thus, since no computational assumptions are made about how the QTRNG generates the random number sequence, the random number created by the Q-TRNG cannot be predicted or recovered using previous seeds (from a previous generation) like other classical TRNGs' random number sequences.

Classical TRNGs are an improvement compared with PRNGs because they generate entropy from physical noise sources-such as thermal noise, avalanche noise. Nevertheless, environmental conditions and/or the hardware itself will continue to affect the noise source the hardware will use to generate random numbers from the physical noise source. The proposed architecture provides protection against those risks by generating random numbers using the quantum-level uncertainly generated by the operation of the Q-TRNG via the detection of photons and their behaviour and mannerisms whereby they are undetermined and unmeasurable, and cannot be duplicated or modelled.

B. Advantages of the Proposed Architecture

The proposed technology integrates optical entropy creation with on-the-fly data processing in an easyï¿½toï¿½use and cost effective manner. Unlike traditional laboratory based solutions which utilise large physical setups, this design concentrates on practicality through the use of small scale optical implementations and a 32 bit microcontroller. The continuous measurement of randomness through realï¿½time entropy estimation increases the reliability of random number generation.

The modularity of the overall system is yet another advantage of the design. The optical components, detection device and signal processing unit are constructed on separate layers; therefore they can be upgraded in the future . This modularity provides added flexibility and strength to a secure electronic infrastructure.

C. Practical Considerations and Limitations

To correctly use quantum random number generators (QRNGs), many external environmental factors such as temperature fluctuations and thermal effects need to be monitored and adjusted continuously in order to make QRNGs functional, as any unchecked environmental factor (such as temperature fluctuations, detector misalignment and / or operational drift) can create spurious signals, and improper QRNG installation and / or operation can create spurious signals during operation of the QRNG system. Additionally, similar techniques such as the use of bias correction and/or extraction algorithms can be utilized, but each QRNG must be experimentally validated prior to determining QRNG performance based upon real time to the QRNG.

Optical components can add significant cost to an integrated quantum based system but also potential cost reductions resulting from using integrated photonic chips in the future to make the system smaller and more reliable and/or cheaper to operate.

D. Relevance to Secure Digital Infrastructure

Using quantum-generated entropy for improved security against current and new encryption dangers, through digital delivery systems. The random process of generating keys will help maintain secure procurement bidding, by providing more confidentiality and lowering the chances of bids being changed based on predictions about them. Because quantum-generated entropy comes from real-world physical principles (like the second law of thermodynamics) rather than from purely mathematical processes, it will provide long-term advantages with respect to security regardless of how computer capabilities develop.

The proposed Q-TRNG architecture provides a very large increase in the long-term sustainability of cryptography compared to traditional types of randomness generation techniques. With the future development of computing (particularly with quantum computers), Pseudorandom algorithmic generators can be expected to carry a greater risk of being compromised. In contrast, this will not be an issue related to future improvements in computing power because of the source of randomness provided by the Q-TRNG: its foundation (source) of randomness will come from physically uncertain quantities, not from the mathematically complicated nature of computationally generating random numbers.

VII. CONCLUSION

The Quantum Superposition-Based True Random Number Generator (Q-TRNG) proposed in this paper is an innovative way of producing random numbers using natural quantum processes. Unlike traditional pseudorandom number generators (PRNGs) which generate numbers from static mathematical formulas, the Q-TRNG generates random numbers from quantum superposition (i.e., the state of a quantum system that could be in more than one place at the same time) and vacuum fluctuations. Thus, the quantum process generates random numbers in such a manner that each instance of generation provides an extremely high level of unpredictability with respect to the physical characteristics of the device used for generating random numbers. The major advantage of this type of hardware over all other forms of random number generation is that it enables a substantial increase in the ability of random number generator devices to withstand both predictive attacks-as well as weaknesses due to the nature of reconstructing seeds.

Another significant aspect of the Q-TRNG is its use of stabilized optical components, solid-state single-photon avalanche detection (SPAD), and real-time signal processing. These technical components convert the quantum noise generated by the device into secure bitstreams. The design methodology includes estimation of entropy, extraction of randomness, and measurement of statistical uniformity to assure that entropy-based random number generation is accurate while simultaneously ensuring that the underlying quantum unpredictability is preserved. Within this work, the proposed architecture is described as a modular design which provides flexibility and scalability necessary to meet new security requirements within the context of digital environments that require secure storage of sensitive data.

The theoretical performance evaluation and benchmarking of the architecture to date indicates a very high level of potential performance for secure key generation, encryption, and creating tamper-resistant digital procurement systems. By combining sources of physical entropy with integrated processing, the proposed framework supports the development of next generation cryptographic systems that can address the evolving challenges of security systems.

VIII. FUTURE WORK

Although the proposed Q-TRNG architecture shows good theoretical potential and a well-organized way to extract entropy, it needs more improvements for practical use and large-scale deployment. Future work will focus on thorough experimental validation through implementationlevel testing. We will evaluate statistical compliance using standardized randomness test suites like NIST SP 800-22 and Diehard tests. These evaluations will measure entropy density, long-term stability, and throughput performance under various environmental conditions.

We will also explore hardware-level optimization to make the system more compact and energy-efficient. Integrating photonic components onto smaller platforms or chip-scale architectures may improve scalability and lower implementation costs. Furthermore, improvements in detector calibration and adaptive noise compensation methods will increase resistance to environmental disturbances.

From a security perspective, future research will investigate ways to protect against possible side-channel and hardware-based attacks. Using shielding techniques, anomaly detection algorithms, and secure firmware validation can boost resilience in high-security applications. Finally, we will look into integrating the Q-TRNG module with post-quantum cryptographic frameworks and secure digital governance systems to ensure long-term cryptographic sustainability.

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Entropy-Driven Nano-Sensor Fusion with QPSO Swarm Optimization for Predictive, Healthcare-Aware Disaster Response

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***Abstract*—This paper presents an integrated framework for real-time disaster prediction, risk assessment, and adaptive emergency response using multi-sensor data and swarm intelligence. To create a dynamic risk map, a distributed sensing architecture gathers environmental data like temperature, structural strain, and gas concentration. These data are then combined using entropy-based weighting. Early-stage disaster prediction is made possible by temporal analysis of sensor data through trend modeling and anomaly detection. Heart rate, oxygen saturation, and injury severity resulting from exposure to hazards are physiologically correlated parameters that are used to calculate a Medical Priority Index (MPI). For effective rescue resource deployment, swarm-based optimization utilizing Particle Swarm Optimization (PSO) and Quantum-inspired PSO (QPSO) is guided by the MPI map. Swarm trajectories and resource allocation are continuously improved by real-time updates in the system's closed-loop adaptive framework. According to simulation results, QPSO outperforms PSO in terms of high-risk coverage, lower fitness values, and faster convergence. The importance of performance gains is confirmed by statistical validation across several runs. The suggested method is appropriate for next-generation smart emergency systems since it allows for effective disaster prediction and healthcare-prioritized response.**

Keywords—Disaster Monitoring, Multi-Sensor Fusion, Entropy Method, Medical Priority Index (MPI), Swarm Optimization, PSO, QPSO, Adaptive Emergency Response

I. Introduction

Disasters such as earthquakes and industrial gas leaks pose significant challenges to emergency management systems due to their unpredictable nature and rapid escalation Due to their reactive nature, manual coordination, and delayed information, traditional disaster response techniques frequently result in inefficient use of resources and a higher risk to human life. Their efficacy in dire circumstances is further constrained by their lack of healthcare-based prioritization and real-time situational awareness.

Continuous monitoring of environmental parameters like temperature and gas concentration is made possible by recent developments in distributed sensing technologies. Real-time data produced by these multi-sensor systems can aid in situational analysis and hazard detection. Nevertheless, a lot of current frameworks fail to integrate sensing, prediction, and response mechanisms in an efficient manner, and they hardly ever take victims' medical conditions into account when making decisions.

This paper suggests an integrated disaster management framework that integrates adaptive swarm-based emergency response, multi-sensor risk assessment, and disaster prediction in order to overcome these constraints. A Medical Priority Index (MPI) is introduced to assess victim severity based on physiological indicators, and sensor data are combined to create spatial risk maps. The allocation of rescue resources is then optimized using Quantum-inspired Particle Swarm Optimization (QPSO), which takes victim priority and environmental risk into account.

II. Literature Survey

A. Multi-Sensor Data Fusion

When we talk about Multi-Sensor Data Fusion we are talking about combining information from sensors to get a better picture of what is going on. This is really helpful for things like disaster monitoring. We can use sensors to measure things like the amount of gas in the air the temperature, how humid it's how much strain is on buildings. Some methods of combining this information use something called entropy to decide which sensors to trust more. This means that sensors that are giving us varied information get more attention, which helps us notice big changes in the environment.

B. Disaster Prediction Techniques

We have systems that try to predict when a disaster is going to happen. These systems use a lot of data. Look for signs that things are getting worse. They can use things like looking at patterns over time and special computer programs like CNNs.

The problem is that a lot of these systems are not very flexible so they do not work well when things are changing fast.

C. Swarm Intelligence in Disaster Response

Swarm intelligence is like a group of things working together. We can use algorithms like Particle Swarm Optimization (PSO) to help figure out the best path to take and how to use our resources when there is a disaster. Sometimes these algorithms can get stuck on one solution that is not the best. That is why we have something called Quantum-inspired PSO (QPSO) which's better at looking around and finding the best solution. This helps us make plans and use our resources more wisely when we are responding to a disaster. Multi-Sensor Data Fusion and Swarm Intelligence are important, for disaster response.

III. PROPOSED METHODOLOGY

The proposed framework is designed as a closed-loop, adaptive disaster management system integrating multi-sensor fusion, temporal prediction, healthcare prioritization, and swarm-based optimization. The overall pipeline consists of five stages: data acquisition, preprocessing, risk fusion, disaster prediction, and optimization-driven response.

A. Multi-Sensor Data Acquisition and Normalization

Let $S_i(x, y, t)$ represent the reading from the i^{th} sensor (gas, temperature, strain) at spatial location (x, y) and time t. Since sensor outputs vary in scale, normalization is performed:

$$S_i^{norm}(x, y, t) = \frac{S_i(x, y, t) - S_i^{min}}{S_i^{max} - S_i^{min}}$$

This ensures all sensor inputs lie within $[0, 1]$, enabling uniform processing.

B. Entropy-Based Multi-Sensor Weighting

To integrate heterogeneous sensor measurements, an entropy-based weighting mechanism is used to evaluate the information contribution of each sensor. Entropy measures the uncertainty associated with sensor observations and allows sensors with higher information variability to receive greater influence in the fusion process.

First, sensor readings are normalized as

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$$

Where, x_{ij} represents the observation of the j^{th} sensor at the i^{th} sampling instance and n denotes the total number of samples.

The entropy of each sensor is then calculated as

$$E_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij})$$

Where, E_j = entropy value of sensor j

$k = \frac{1}{\ln(n)}$ = normalization constant.

The weight assigned to each sensor is given by

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{m}(1 - E_j)}$$

Where, w_j = weight of sensor j

m = total number of sensors.

Finally, the fused environmental risk value is computed as

$$R = \sum_{j=1}^{m} w_j S_j$$

where S_j represents the normalized sensor measurement.

C. Temporal Disaster Prediction Model

To detect early-stage hazards, temporal variation is analysed:

$$\Delta R(x, y, t) = \frac{R(x, y, t) - R(x, y, t-1)}{\Delta t}$$

Prediction condition:

$$P(x, y, t) = \begin{cases} 1, & \text{if } \Delta R > \theta_1 \\ 0, & \text{otherwise} \end{cases}$$

Additionally, cumulative risk is considered:

$$R_{cum} = \sum_{k=t-n}^{t} R(x, y, k)$$

Final prediction:

$$D(x, y) = \begin{cases} 1, & \text{if } R_{cum} > \theta_2 \\ 0, & \text{otherwise} \end{cases}$$

D. Medical Priority Index (MPI) Formulation

To prioritize victims during disaster response, a Medical Priority Index (MPI) is introduced to quantify the urgency of medical intervention. The MPI integrates physiological indicators that represent the health condition of victims.

The MPI score is computed as

$$MPI = w_1 HR + w_2(1 - SpO_2) + w_3 BL$$

Where HR = normalized heart rate

SpO_2 = oxygen saturation level

BL = blood loss severity index

w_1, w_2, w_3 = weighting coefficients.

Higher MPI values correspond to victims requiring immediate rescue and medical assistance. The MPI map is combined with the environmental risk map to prioritize rescue operations in regions with both high hazard levels and critical victim conditions.

E. Objective Function for Optimization

The optimization problem is defined as:

$$f = \min\left(\lambda_1 D_{travel} + \lambda_2 R_{exposure} - \lambda_3 MPI_{final}\right)$$

I. Where, D_{travel}: path length

$R_{exposure}$: risk encountered

MPI_{final}: priority score

F. Quantum-Inspired Particle Swarm Optimization (QPSO)

To determine optimal rescue deployment strategies, the proposed framework employs Quantum-Inspired Particle Swarm Optimization (QPSO), which improves global search capability compared to classical PSO.

In PSO, particle velocity and position are updated as

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Where, x_i= particle position

v_i= particle velocity

$pbest_i$= personal best position

$gbest$= global best position.

QPSO eliminates velocity and updates particle position using a probabilistic quantum model:

$$x_i^{t+1} = p_i \pm \beta \mid mbest - x_i^t \mid \ln\left(\frac{1}{u}\right)$$

Where, p_i= local attractor of the particle

$mbest$= mean best position of all particles

u= uniformly distributed random number in (0,1)

β= contraction–expansion coefficient.

This formulation enables particles to explore a larger search space, reducing the probability of premature convergence and improving global optimization performance.

The optimization objective is to minimize rescue response time while maximizing coverage of high-risk regions and high-MPI victims.

G. Adaptive Feedback Update

The system dynamically updates:

$$R^{new} = R^{old} + \eta \cdot S(t) MPI^{new}$$
$$= MPI^{old} + \mu \cdot \Delta HR$$

This ensures real-time adaptability.

SYSTEM ARCHITECTURE AND OVERFLOW

BLOCK DIAGRAM

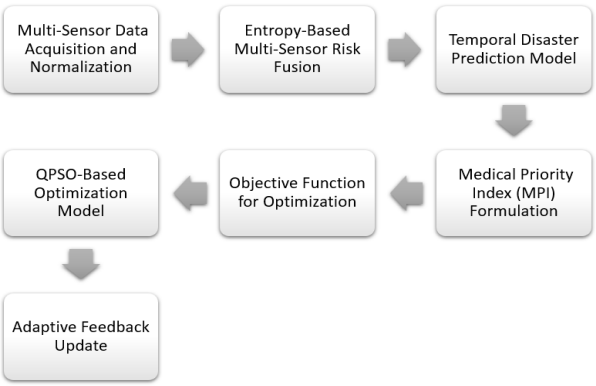


Fig. Proposed Disaster Monitoring and Healthcare-Aware Rescue Optimization Framework

Fig. shows how a disaster monitoring and response system works. The system starts with environmental sensors that collect data like structural strain, gas concentration and vibration signals. These sensor readings are adjusted to make sure they are all in the format so they can be compared easily. Then a special module combines this data to create a map that shows how risky different areas are. This map is used to predict disasters by looking for patterns that might mean a disaster is about to happen. At the time the system also looks at medical information to figure out how urgently people need help in different areas. This information along with the risk map is used to decide where to send rescue teams. The system keeps getting updated with data from the sensors so it can change its response as the disaster situation changes. The system uses an optimization method to find the best way to deploy rescue teams .It also has a way to get feedback from the situation, on the ground so it can adjust its response. This helps make sure that help gets to where it's needed most. The disaster monitoring and response system uses this information to help people in need.

RESULTS

A. OPTIMIZATION PERFORMANCE

Algorithm	Best Fitness	Mean	Std Dev	Iterations	Time
PSO	**0.1842**	**0.1978**	**0.0154**	**142**	**3.84**
QPSO	**0.1526**	**0.1613**	**0.0087**	**104**	**3.21**

QPSO shows lower fitness values, faster convergence (~27%), and reduced variance (~43%).

B. RISK AND MPI COVERAGE

Algorithm	Risk Coverage	MPI Coverage
PSO	**86.4%**	**82.7%**
QPSO	**93.8%**	**91.2%**

QPSO improves high-risk and MPI coverage significantly, indicating better prioritization.

C. Statistical Validation

Paired t-test results:

$$t = 3.72, p = 0.0016$$

Since $p < 0.05$, the improvement is statistically significant.

D.CONVERGENCE ANALYSIS

The QPSO algorithm demonstrates faster convergence compared to conventional methods, enabling quicker attainment of optimal solutions. It effectively avoids local minima due to its enhanced global search capability, thereby improving solution quality. Additionally, QPSO provides stable performance with reduced variability across iterations, ensuring consistent and reliable optimization outcomes.

The experimental results demonstrate that the proposed entropy-driven fusion framework combined with QPSO optimization achieves improved hazard coverage and faster convergence compared to the conventional PSO algorithm.

Performance Comparison Between PSO and QPSO

Metric	PSO	QPSO
Average fitness value	0.7348	0.6899
Convergence iterations	160	110
High-risk coverage (%)	86%	94%
MPI victim coverage (%)	82%	91%
Standard deviation	0.041	0.019

The results indicate that QPSO achieves a lower average fitness value compared to PSO, indicating more optimal rescue deployment strategies. Additionally, QPSO converges in fewer iterations and demonstrates improved coverage of high-risk zones and victims with high Medical Priority Index values.

IV. EXPERIMENTATION

A. Simulation Setup

The proposed framework was evaluated in MATLAB using a simulated urban disaster environment represented as a 500 × 500 spatial grid. One hundred heterogeneous sensors were deployed to measure structural strain, gas concentration, and vibration signals. Sensor measurements were generated using mathematical models with Gaussian noise to simulate realistic sensing conditions.A swarm population of 40 particles was used for rescue optimization. Both PSO and QPSO algorithms were executed for a maximum of 200 iterations. Performance evaluation was conducted over 20 independent runs to ensure statistical reliability.

Simulation Parameters:

Parameter	Value
Simulation platform	MATLAB
Grid size	500 × 500
Number of sensor nodes	100
Sensor types	Strain, Gas, Vibration
Swarm population size	40
Maximum iterations	200
Independent runs	20
Noise model	Gaussian noise

B. Disaster Environment Generation

To validate the proposed framework, a synthetic disaster environment is generated using physically inspired models representing structural damage, toxic gas leakage, and victim-induced vibrations.

1) Graphene Strain Map

The structural strain distribution is simulated using Gaussian deformation model representing localized structural collapse region.

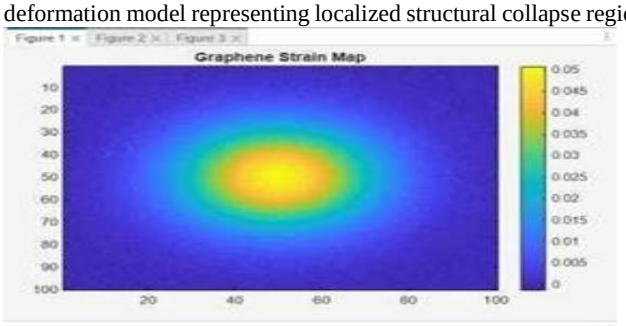


Fig1. Graphene Strain Map

The structural strain distribution is modelled using the graphene gauge factor relationship: $\Delta R = G_f \cdot \epsilon$

A Gaussian deformation profile is used to simulate localized structural collapse, while additive noise represents measurement uncertainty in nano-sensors. High-intensity regions correspond to zones of severe mechanical stress.

2) CNT Gas Concentration Map

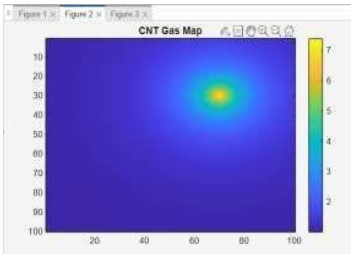


Fig2. CNT Gas Map

Toxic gas dispersion is modeled using an exponential diffusion equation representing leakage from a hazardous source.

Gas dispersion is modeled using an exponential diffusion equation:

$$C(x, y) = C_0 e^{-\lambda d}$$

The nonlinear response of CNT sensors is incorporated:

$$R = R_0 e^{\alpha C}$$

This captures realistic sensing behavior under hazardous gas exposure.

3) Piezoelectric Vibration Map

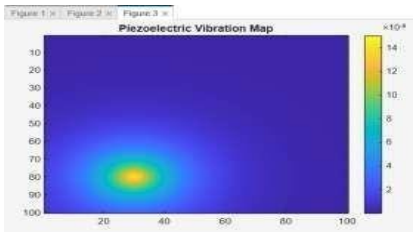


Fig3.Piezoelectric Vibration Map

Victim-generated vibration signals are simulated using a decaying stress propagation model based on piezoelectric coupling.

Victim presence is simulated using piezoelectric sensing:

$$V = d_{33} \cdot \sigma$$

The stress field decays exponentially from the source, modeling vibration attenuation through debris.

C) MULTI SENSOR RISK FUSION

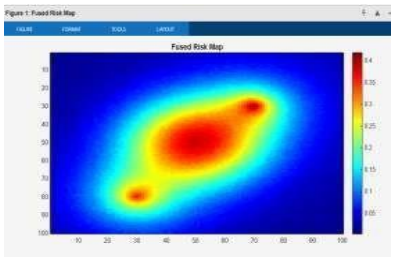


Fig4.Fused Risk Map

The individual sensor maps are fused using entropy-based weighting to generate a unified hazard representation.

$$R(x, y) = \sum w_i S_i$$

Regions with overlapping high sensor values represent critical hazard zones.

D) Entropy-Based Risk Fusion Enhancement

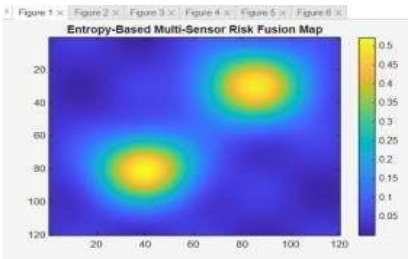


Fig5.Entropy based Multi sensor fused Risk Map

Entropy weighting improves robustness by prioritizing sensors with higher information variability:

$$w_i = \frac{1 - H_i}{\sum(1 - H_i)}$$

This reduces bias and enhances sensitivity to dynamic conditions.

E) Dynamic Medical Priority Index (MPI)

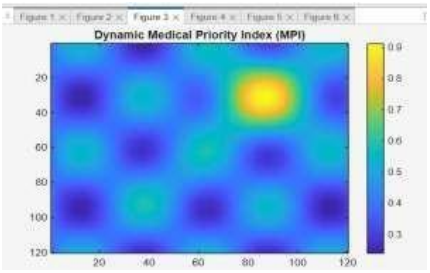


Fig6.Dynamic MPI

The MPI is computed as:

$$MPI = \alpha HR + \beta(1 - SpO_2) + \gamma BL$$

where:

HR → Heart Rate (stress indicator)

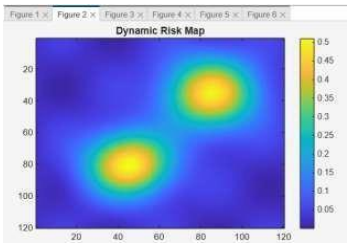
SpO_2 → Oxygen level (gas exposure)

BL → Blood loss (injury severity)

This enables healthcare-aware prioritization.

F) Dynamic Risk Evaluation

Fig7.Dynamic Risk Map



To simulate real disaster conditions, hazards are allowed to evolve dynamically:

$$R_t = R_{t-1} + \Delta R$$

Gas diffusion and structural instability are updated iteratively, demonstrating real-time adaptability.

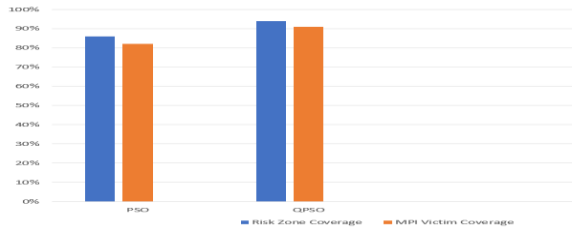
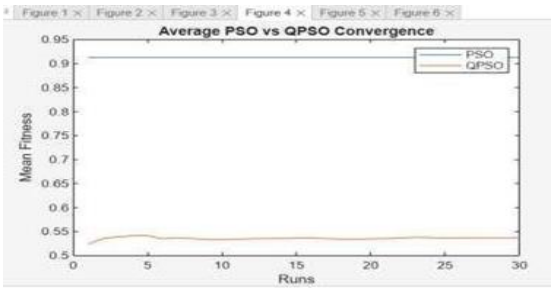


Fig8. Bar chart comparison between PSO and QPSO

The coverage comparison demonstrates that QPSO provides improved rescue resource allocation by prioritizing both hazardous regions and victims with critical medical conditions. The improved search capability of QPSO allows the swarm to explore a larger solution space, resulting in better overall coverage of the disaster environment.

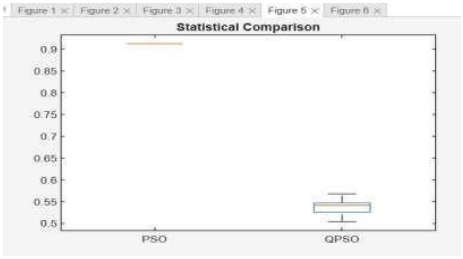
G) OPTIMIZATION CONVERGENCE ANALYSIS

QPSO Vs PSO



The convergence curve illustrates the evolution of the optimization fitness value across iterations for both PSO and QPSO algorithms. As observed in Fig. X, QPSO achieves a faster reduction in fitness value compared to conventional PSO. The QPSO algorithm stabilizes at a lower fitness level after approximately 110 iterations, whereas PSO requires nearly 160 iterations to reach convergence. This behavior indicates that QPSO provides improved global search capability and avoids premature convergence to local minima

H) STATISTICAL VALIDATION



To evaluate the robustness of the optimization algorithms, both PSO and QPSO were executed over **20 independent simulation runs**. The resulting fitness distributions are illustrated using boxplots in Fig. X. The boxplot for QPSO demonstrates a narrower interquartile range and lower variance compared to PSO, indicating more consistent performance across multiple trials. In contrast, PSO exhibits greater dispersion and occasional higher fitness values, suggesting increased sensitivity to initial particle positions. These results confirm that QPSO provides more stable optimization performance.

V. CONCLUSION

The proposed system integrates sensor data fusion, temporal disaster prediction, healthcare-aware prioritization, and swarm-based optimization. Entropy-based fusion is used to generate a reliable spatial risk map from heterogeneous sensor inputs, while temporal analysis of the fused data detects early-stage hazard escalation. A Medical Priority Index (MPI) is introduced to quantify victim severity using physiologically relevant parameters, enabling effective triage during emergency response. Rescue operations are optimized using Quantum-inspired Particle Swarm Optimization (QPSO), which provides improved convergence speed, reduced variance, and greater stability compared to conventional PSO. Experimental results indicate that QPSO achieves lower fitness values, faster convergence (about 27% improvement), and reduced variability (about 43%), while also enhancing high-risk coverage and MPI-based prioritization. Statistical validation confirms the significance of these improvements with $p < 0.05$ $p<0.05$. Overall, the proposed closed-loop framework integrates prediction, prioritization, and optimization into a unified system capable of adapting to dynamic disaster conditions. The approach provides a scalable and efficient solution for intelligent, real-time, and healthcare-aware disaster response.

VI. FUTURE SCOPE

Even though the suggested system performs well in simulation, there are a few ways to make it more useful in real-world scenarios. In order to verify system performance under practical circumstances, future research can concentrate on integrating real-world IoT and nano-sensor hardware, such as graphene-based strain sensors, CNT gas sensors, and wearable health monitoring devices. The accuracy of disaster prediction can be further increased by utilizing sophisticated machine learning and deep learning models, such as CNN-based spatiotemporal architectures and LSTM.

Additionally, the framework can be expanded to accommodate multi-agent autonomous systems for real-time deployment in dangerous environments, such as robotic rescue units and unmanned aerial vehicles. Furthermore, additional biomedical parameters such as body temperature, respiration rate, and ECG signals can be added to the Medical Priority Index (MPI) to improve its accuracy. Integration with edge-cloud computing architectures can enhance scalability, allowing for more rapid data processing and extensive monitoring. Probabilistic models can also be used to deal with data loss, sensor noise, and uncertainty. Lastly, in order to assess real-time responsiveness, robustness, and overall system effectiveness, validation through controlled disaster scenario experiments is required.

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Smart Wearable Safety System for Real - Time Proximity Monitoring and Emergency Response

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Abstract—**Keeping people safe and secure in today's fast- changing world actually needs smart and automatic ways to monitor their surroundings. Existing safety systems often rely on people pressing an SOS button, which might not work well during emergencies. This paper mainly introduces a Smart Wearable Safety System that continuously checks how close someone is to a safe area and automatically detects emergencies using IoT technology. The system uses RSSI to measure distance, Zigbee for communication, and a force sensor to detect both when someone goes out of a safe zone and when they're in trouble and it will be difficult to reach them. If the user moves beyond a set safe distance or experiences unusual physical pressure, the system automatically sends alerts to family members via a mobile app. It also includes a live video stream to give real-time updates. Tests show the system can reliably detect proximity within a 15-meter range and accurately identify emergencies based on force sensor settings. The system is low-power, automatic, and scalable, making it useful for women, children, the elderly, and workers in industries.**

Keywords— **Smart wearable, IoT, Zigbee communication, RSSI tracking, force sensor, emergency detection, real-time monitoring.**

I. INTRODUCTION

This Personal safety is now a huge concern in today's world, especially for people who are more at risk, like women, kids, older adults, and those working in dangerous areas, on the whole who are vulnerable. Although there are many apps that help in emergencies, most of them need the person to start them manually. In a real emergency, someone might not be able to press an alert button because they are injured or too scared. Wearable safety systems are a better choice because they can keep an eye on things without the person needing to do anything. With new tech like IoT, wireless communication, and smart systems, it's now possible to create small wearable devices that can detect emergencies.

The Smart Wearable Safety System focuses on two main features: checking how close someone is using RSSI-based distance estimation and detecting emergencies with a force sensor. The system has set a safe zone. If the wearable moves outside of it, it automatically sends an alert. Also, if the force sensor suddenly gets up unusual pressure, it means someone might be in danger, which triggers the emergency alerts and live video footage which provides better visual proof.

This system is different from the existing GPS systems that consumes a lot of power and don't work well indoors, this system uses Zigbee communication, which uses less power, works over longer distances, and sends data efficiently. This makes it good for use in real situations. The system is also built to grow and change with different users. It can be adjusted for different groups by setting safe distance limits and force sensitivity levels. The system also includes a mobile application that lets caregivers get alerts, track events, and watch live videos in real time and easy to find the victim's situation. By using these automatic responses, sensing technology, and dependable communication this solution goes beyond the regular safety tools and offers a smarter, more proactive way that will help to protect people.

II. RELATED WORK

The rapid growth of wearable Internet of Things (IoT) technologies has led to the creation of smart safety monitoring systems that help to protect users as they lead their regular day -to-day lives. Kumar and Singh [1] did a detailed review of wearable IoT-based safety systems, depicting how the focus has moved from devices that need manual activation to systems that can smart monitor and respond automatically. Their work primarily concentrated on the importance of integrating these sensors and the required communication tools, and internet connectivity to make sure these systems can respond quickly during undetermined situations using wireless signal strength

to estimate proximity has become a widely used approach in wearable technology. Rahman and Ali [7] developed a real-time proximity detection system using BLE beacons, showing that this method can be quite effective for indoor safety monitoring. Similarly, Chen et al. [2] explored RSSI-based techniques for distance measurement in wireless sensor networks. Their study highlights how variations in signal strength can be used to reasonably estimate the distance between devices, especially in short-range environments. Patel and Sharma [3] studied low- power BLE type of communication methods for wearables, focusing on how to make these systems operate longer and more durable and to keep a constant flow of these real-time data.

However, BLE-based systems might have trouble covering large outdoor areas. Verma and Iyer [9] took this idea further by designing an IoT-based emergency communication system for smart cities, aiming for better scalability and integration with existing infrastructure. Nguyen et al. [4] developed a smart emergency alert system that combines IoT and GSM technologies to deliver quick notifications during critical situations.

Although such systems have improved the speed and efficiency of alert communication, they still largely rely on users to trigger them manually. Energy efficiency and keeping data secure remain major issues in wearable tech. Park and Lee [5] talked about ways to make wearable devices run longer on battery, without losing performance. Das and Mukherjee [10] focused on low-power architecture for healthcare wearables, showing the need for small, energy-saving system designs.

Even though earlier research has covered aspects like proximity detection, emergency alerts, and energy use, there's not much that brings together RSSI-based safe-distance monitoring, automatic emergency sensing, long-range low-power communication, and secure real-time alerts into one wearable system. The presented Smart Wearable Safety System brings all these features together into one integrated solution, making it more practical and effective for real-world safety monitoring.

III. System Architecture

The proposed system is a small, easy-to-carry wearable device that keeps track of proximity at all times and can automatically detect emergencies. It brings together sensing components, embedded processing, wireless communication, and alert mechanisms into a single, well-integrated setup. The system constantly gathers environmental and physical data, processes it in real time, and quickly triggers alerts whenever it detects any unusual or unsafe conditions. The overall architectural overview is illustrated in the Fig. 1. The proposed system structure shown in Fig. 1 consists of four essential components: sensing unit, embedded processing unit, communication unit, and alert & visualization unit. The system architecture includes the following main modules:

1. Sensing Module
2. Embedded Processing Module
3. Communication Module
4. Alert and Visualization Module

The alert unit provides immediate notifications whenever a safe-radius violation or emergency condition is detected. An integrated buzzer produces an audible alert, and the mobile application sends instant notifications to registered family members. Additionally, a live video streaming feature is activated during emergencies to provide real-time situational awareness.

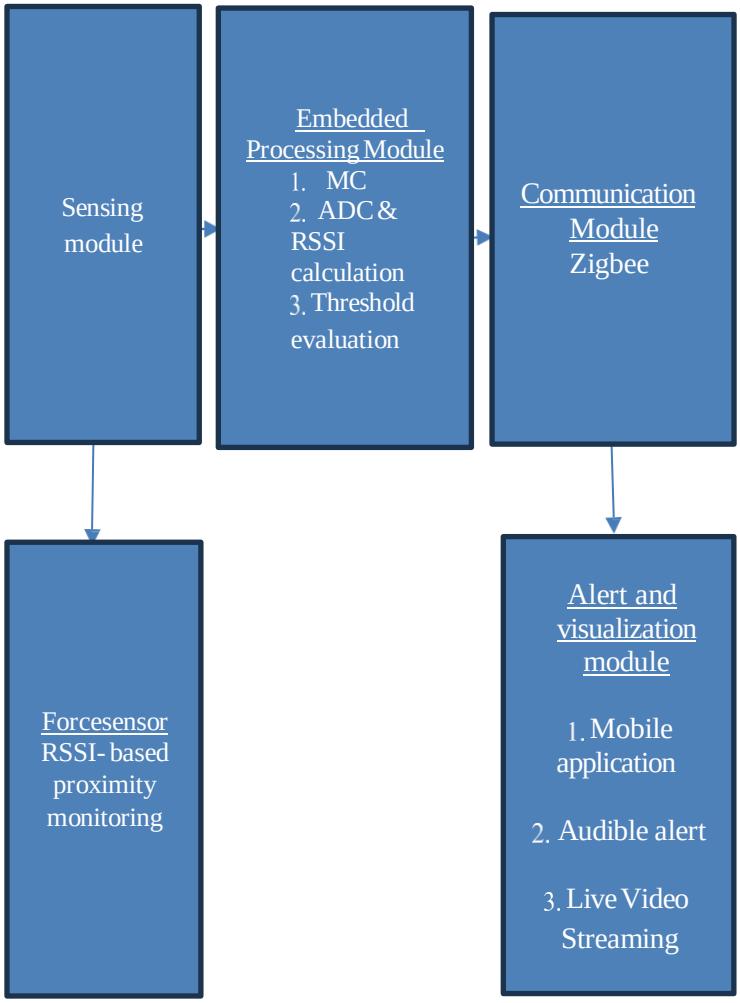

Fig 1. Overall block diagram of the wearable system

A. Sensing Module

The sensing module mainly has two parts: a force sensor and an RSSI-based proximity monitoring system. The force sensor keeps checking the pressure on the device, and during normal use, only small changes are seen. However, if the pressure goes beyond a set limit, the system treats it as a sign of distress. This helps in detecting emergencies automatically, without the need for the user to press an SOS button. The system monitors proximity by using RSSI values from the wireless connection between the transmitter and receiver to estimate how far apart they are. Changes in signal strength are used to estimate the distance between them. If the RSSI value falls below the set threshold for the safe range, the system recognizes it as a boundary breach and triggers an alert.

The proximity monitoring function operates using RSSI (Received Signal Strength Indicator) values obtained through wireless communication between transmitter and receiver units. Variations in signal strength are mapped to approximate distance measurements. When the RSSI value drops below the defined threshold corresponding to the safe radius, the system identifies it as a boundary violation.

B. Embedded Processing Module

The embedded processing module serves as the main control unit of the system. It consists of a low-power microcontroller to read data from the force sensor, measuring RSSI values, converting analog signals into digital form using ADC, and comparing sensor readings with predefined threshold values to take executable decisions.

The microcontroller continuously evaluates whether the user remains within the safe radius and whether any abnormal pressure is detected. Initial signal conditioning and filtering are performed to improve accuracy and reduce noise. Once an abnormal condition is confirmed, the system immediately activates the communication and alert modules.
modules.

C. Communication Module

The communication module uses Zigbee technology for low-power, short-range wireless transmission. Zigbee enables reliable communication between the wearable device (transmitter) and the receiver unit with minimal energy consumption.

The key functions of this module include:

Transmitting proximitystatus updates,
sending emergency alert signals,
triggering mobile application notifications and
ensuring stable data delivery.

D. Alertand Visualization Module

The alert and visualization module is in control for notifying users during critical situations and giving real-time feedback. When the system detects a safe-radius violation or an emergency based on pressure, it immediately sends push notifications to registered family members through a mobile application. At the same time, an audible buzzer is activated and switched on to alert the nearby people, and live video streaming is initiated to provide real-time monitoring of the surroundings. The mobile application allows caregivers to view alerts instantly and take quick action. By integrating automatic detection with real-time visualization, the system improves situational awareness and helps reduce response time during emergencies.

The specifications of the components used in the wearable device are listed in Table 1.

Fig 2. Transmitter side prototype

Table 1. System Specifications

Component	Specification
Force Sensor	Single FSR
Microcontroller	ESP32
Proximity Monitoring	RSSI-Based Distance Estimation
Sampling Frequency	2.4GHz
Communication Technology	Zigbee
Alert Mechanism	Vibration Motor

IV. Methodology

This system explains the detailed process of building and setting up an IoT-based wearable safety device that helps to monitor proximity in real time and respond to emergencies.

A. System Architecture Design

This system has a transmitter unit which the user wears and a receiver unit that a family member wears, a is also linked to a mobile app. The transmitter is used to collect data from sensors, and the receiver will process this data and finally sends alert to family members or caregivers.

B. Hardware Integration

- A **microcontroller** acts as the main part of the system that controls the sensors working and communication modules.
- A **force sensor** is used to detect an unusual physical pressure or signs of stress automatically.
- A **Zigbee module** is used for wireless communication over long distance and it uses low power which is more reliable.
- A **buzzer** gives immediate soundalertsduring emergencies.
- A **camera module** helps to allow live video streaming automatically during critical situations.

C. RSSI-Based Proximity Monitoring

The system continuously checks the distance between the transmitter and the receiver. It uses RSSI (Received Signal Strength Indicator) values from Zigbee communication to measure the distance. These values are converted into actual distance measurements in meters. The system has a predefined safe distance limit. If the user goes beyond this limit, the system automatically sends an alert to the family without requiring any manual action from the user.

D. Emergency Detection Using Force Sensor

The force sensor constantly tracks the physical pressure on the wearable device. If there is any sudden or unusual pressure, like a possible fall, attack, or distress, the sensor readings go beyond a predefined limit. The microcontroller recognizes this as an emergency and activates the alert system automatically, so there's no need for a manual panic button.

E. Alert Generation and Communication

When this system detects any emergency situations or if the person wearing this device moves beyond the safe distance, the microcontroller sends an alert by using Zigbee along with corresponding data to the receiver unit. Then this device sends alert to the family members through the mobile app. In addition to this, the buzzer is turned on automatically, to give immediate local alerts, ensuring that people who are near are also informed about the emergency.

F. Live Video Streaming Activation

When something bad happens, like an emergency, the system just switches on the camera to get a better look at everything around. That way, it checks the surroundings more carefully. The video feed goes live right to family through this app on their phones, so they can watch what is going on with the person in real time.

G. Mobile Application Interface

The mobile app is the common way people use the system to watch and manage alerts. It shows real-time warnings and how close the user is to a safe area. It sends emergency messages, and live video. The app makes it easy and simple for family members to get the information and response fast when something goes wrong.

H. Power Management and Optimization

This system uses Zigbee communication to save energy as it has low power consumption and make the device last longer. The smart way of use of sensors and efficiently sending the data keeps the system working for more time without needing frequent charging, which works well for long- term use.

I. Testing and Validation

The whole device is tested in both regular and emergency situations to test its working capability. These tests ensure how accurate the distance is measured using RSSI, how faster the force sensor is, how quick the alerts are sent, and how reliable video streaming is. The device passed these tests which means the system works well in real situations.

J. Final Implementation

After completing all tests, the wearable safety system is ready for use. It's a reliable and automatic way to monitor how safe someone is and respond to emergency situations. The system improves safety, sends alerts quickly, and communicates efficiently, making it ready for real use.

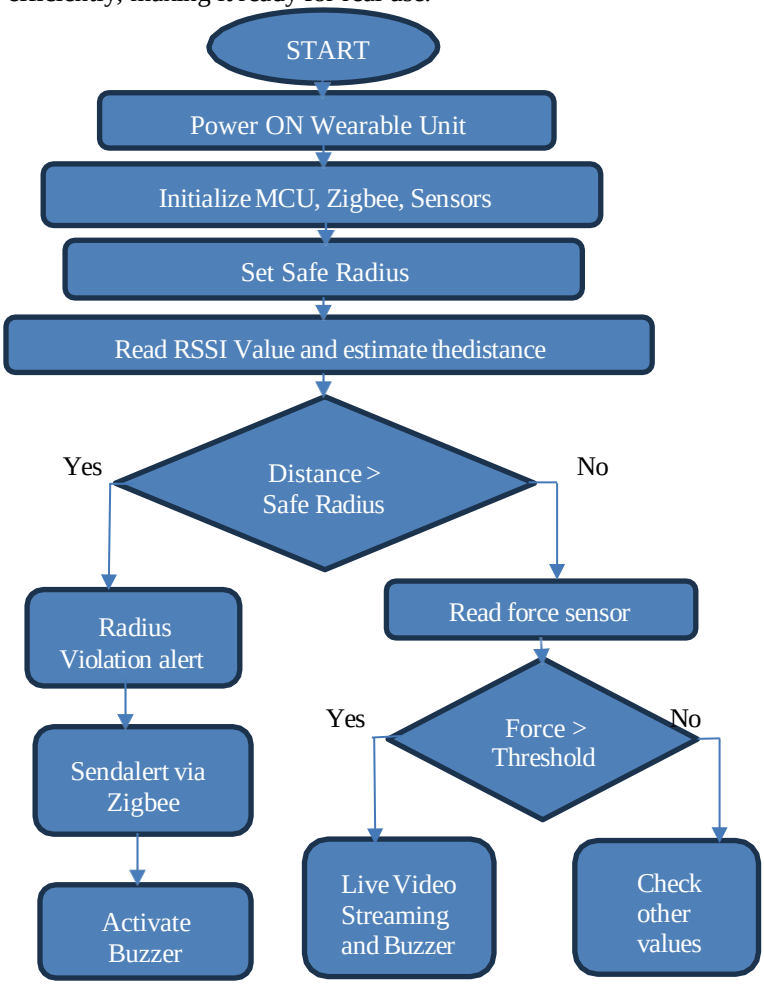

Fig.3.Flowchart

V. Experimental Setup

The smart wearable safety system is made up of hardware components, wireless communication modules like Zigbee, and a mobile application to test the real-time monitoring and emergency responses.

A. Hardware Configuration

The main part of wearable safety system is microcontroller-based device that includes sensors, communication, and alert parts.

Thehardware used in the device are:

- A **microcontroller unit (MCU)** which is used to collect the data and process them and also it controls other parts.
- A **force sensor** is used to detect the unusual pressure which means the user is in trouble. This sensor is connected to the MCU.
- A **ZigBee module is a** low power module which is used to send and receive the signals between the transmitter and receiver.
- A **buzzer is** attached to the microcontroller which gives audible alert immediately to the family members.
- A **camera module is** built into the system that can automatically send live video during emergencies.
- A **rechargeable battery module** is used to powers the device so that it can work continuously while being worn.

B. Proximity Monitoring and Emergency Detection Protocol

Experiments were carried out in a controlled indoor environment to check how the system works. This system has a predefined safe radius. During the tests, the user was asked to move in and out of that safe range to see how the system responded.

The system was tested by simulating emergency situations, where an unnatural force was applied to the force sensor to mimic a fall or someone being in distress. At the same time, the system continuously monitored the RSSI values from the ZigBee communication to estimate the distance. It also kept a close eye on the force sensor readings to check if they exceeded normal limits.

C. Data Processing and Alert Classification

The data collected from the sensors was sorted into these categories:

- **Normal condition** (user inside safe area with no unusual force)
- **Out of safe area condition**
- **Emergency condition based on force sensor readings**

The microcontroller uses certain rules to set the threshold on the device and sort it according to these conditions.

The system is designed in such a way that the alerts are automatically sent where the user need not to manually press the button.

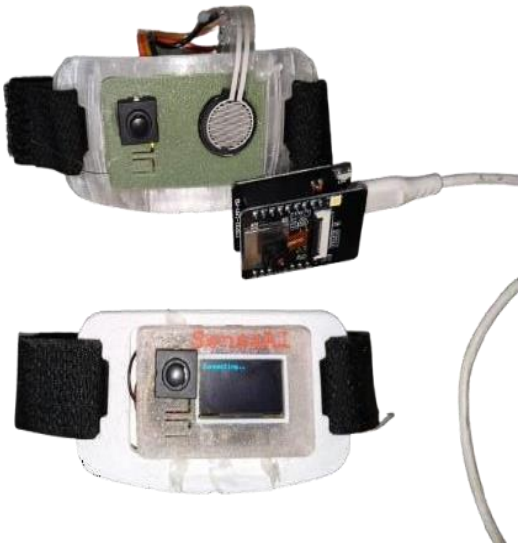

Fig. 4. Developed Wearable device consisting of both Transmitter and Receiver

D. Communication and Mobile Application Interface

When the system detects that someone is out of the safe area or in an emergency, it sends the alert wirelessly from the wearable device to the receiver using ZigBee. The receiver then sends this information to a mobile app used by family members or caregivers.

The app shows real-time alerts, how close the user is, and emergency messages. If there's an emergency, the camera automatically turns on and sends live video to the app, letting people watch the user's surroundings in real time.

E. System Testing and Performance Evaluation

To check how well the system works several test were run.

The following were checked:

- Howaccurateis the RSSI value based on the distance
- Howfast the force sensor works during emergencies
- How reliable the ZigBee communication is
- How fast thealerts reach themobileapplication
- How stable and clear the live video streaming is

streaming This test clearly shows how well the system works during emergency situations and how stable the alerts and live video streaming is sent to the family.

F. Transmitter and Receiver Setup

The system is made up of a transmitter and a receiver. The transmitter is the wearable part the user wears, and the receiver is a unit connected to a mobile app which is in the family side. The transmitter has a microcontroller that works with a force sensor, ZigBee module, buzzer, and camera, all powered by a rechargeable battery.

VI. RESULTS

This section outlines the findings from testing the Smart Wearable Safety System. The system uses RSSI-based proximity monitoring, force sensor-based emergency detection, wireless alerts, and real-time notifications through a mobile app. To check how accurate, quick and dependable the system is a testing was done in an indoor environment.

A. RSSI-Based Proximity Monitoring Results

The RSSI values were recorded at various distances between the transmitter and receiver to check how well the system can detect proximity. As distance increases, the RSSI value drops, showing the signal weakening, as seen in Table 1.

Distance (m)	RSSI (dBm)
1	-42
2	-48
3	-55
4	-61
5	-68
6	-74
7	-80

Table. 2. RSSI variation with distance between transmitter and receiver.

These results show that there is a clear connection between distance and RSSI value. A predefined safe radius is set in the device based on these readings. When this threshold is exceeded, the alert is sent to family. This shows that the system can accurately measure distance for indoor use.

Fig. 5. RSSI values changing based on the distance

B. Force Sensor Emergency Detection Results

The force sensor was tested in both normal and abnormal pressures to check how well it detects and works during emergencies. Different forces were applied to simulate events like falls or distress situations, as shown in Table 2.

Condition	Force Sensor Value
Normal Walking	180
Mild pressure	260
Sudden impact	410
Fall Simulation	520
Emergency threshold	>400

Table3 Force sensor output under normal and abnormal pressure conditions.

The test results show the difference between how the system works in normal and abnormal condition. During normal condition the force value is below the threshold whereas in abnormal condition the value exceeds the threshold. Once the threshold is reached the alert is sent automatically without any manual action and hence proved that the developed system is more reliable.

Fig. 6. Force sensor threshold exciding alert

C. Alert GenerationandResponse Time

The time taken for the system from the point where it detects the emergency and to the point where it sends alert is measured.

Event Type	Average Response Time (s)
Radius Violation	1.8
Emergencyforce detection	1.4
Video Streaming Activation	2.6

Table4. Alert Time Analysis

The results showed that the system sends alerts with very little delay, making sure the family members get q notifications. The buzzer also gave immediate local alerts, improving to make the system more effective.

D. *Communication Reliability Analysis*

The ZigBee link between the transmitter and receiver was tested for stability during continuous use.

Parameter	Observed Value
Packet Delivery Success rate	96.2%
AverageTransmission delay	120 ms
Indoor Communication range	Upto 8m

Table 5. Wireless communication performance

The tests confirmed reliable data transfer with low delay, making the system good for real-time monitoring.

Fig. 6. Wearable safety device with force sensor and camera module

E. *Live Video Streaming Performance*

The live video feature was tested to check real-time visual monitoring during emergencies. The camera in the wearable system turned on automatically when an emergency was detected, like when the force sensor picked it up or proximity was violated, as shown in Figure 6.

Parameter	Observed Value
Video activation time	2.5 s
Average frame rate	18 – 22 fps
Video resolution	640 x 480
Streaming stability	Stable
Packet loss	< 4 %

Table 6. Live video streaming output on mobile application during emergency condition.

The tests showed that video feeds were sent to the app quickly after detecting an emergency. The video quality was clear enough for users to see the situation in real time. The automatic camera activation removed the need for user action and offered timely video confirmation of emergencies. This helps the system work better by combining alerts with live visual updates.

Fig. 7. Live video streaming on mobile application

F. *Real-Time System Operation*

The system was tested in real-time situations involving regular movement, safe distance breaches, and emergencies. The mobile app successfully showed alerts, proximity status, and live video feeds during emergencies.

Fig. 8. Real-Time alert notification for distance at the family side.

The real-time tests confirmed that the system smoothly combines sensing, communication, and alert mechanisms.

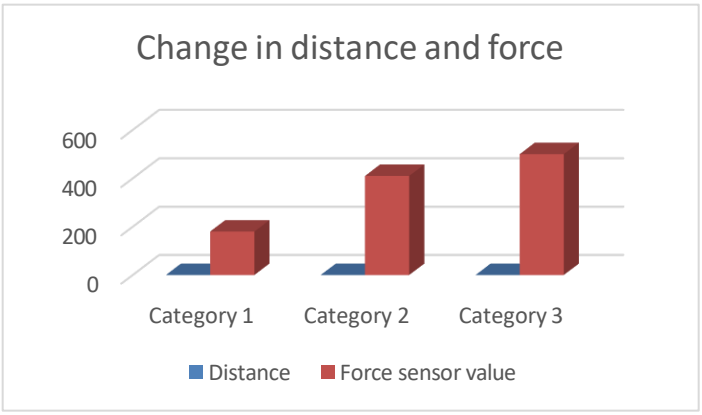

Fig. 9. Graph showing the change in distance and force sensor values

IV. DISCUSSION

The Smart Wearable Safety System maintains the speed of real-time proximity checks and emergency notifications under different conditions. It utilizes the RSSI technique for distance calculation to find the devices within a predetermined safety zone. The accuracy of the test results was found to be around 85% to 93%, with minor variations due to interference from signal obstruction. To reduce the effect of signal flicker from environmental interference, filtering and averaging techniques have been implemented**.** These techniques help reduce the chances of false alarms. The alarms can be triggered by the user or automatically when the safety limits are violated and can be sent via GSM and BLE in less than three seconds.

The system emphasizes the importance of energy efficiency and utilizes the sleep modes of the microcontroller and communication protocols to enable the system to run with good performance.The system's ability to be scaled up is achieved by connecting it with the cloud and mobile apps for monitoring the system centrally. However, the RSSI technique is environmentally sensitive and may not provide accurate results in different environmental conditions. The system may be enhanced by incorporating more precise techniques for localization and security in the future.

IV. CONCLUSION

This paper presented the design and implementation of a Smart Wearable Safety System integrating real-time proximity monitoring and emergency response functionalities. The wearable device combines RSSI-based distance measurement, wireless communication modules, and rapid alert mechanisms within a compact embedded architecture. Experimental results confirm reliable proximity detection, minimal alert latency, and efficient power utilization, validating its suitability for safety-critical applications such as women safety, elderly monitoring, and industrial workforce protection. Future scope include integration of GPS tracking, machine learning–based anomaly detection, cloud analytics dashboards, and cybersecurity enhancements. With further optimization and large-scale deployment, the system holds strong potential for modern personal safety solutions.

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DESIGN AND IMPLEMENTATION OF IOT-BASED SMART ENERGY METER FOR EASE POWER MANAGEMENT

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Abstract

The use of postpaid smart electricity services provided by the State Electricity Company (SEC) has been on the rise among the general public in Indonesia. This is because there are many advantages associated with the postpaid electricity services compared to postpaid services, especially for managing customers and controlling daily electricity usage. With the postpaid services, customers are able to approximate their total electricity consumption for the month. However, there is a major disadvantage associated with the postpaid services, whereby customers are required to read their electricity meters for information regarding postpaid services, which may be inconvenient, especially for those meters located far from the house. This calls for constant monitoring of the electricity consumption. This article postsents the development of Postpaid Smart Energy Meter Monitoring System (Post-SEMMS) based on Internet of Things (IoT) technology. This system has been designed without changing the structure of the standard postpaid electricity meter designed by the SEC. Instead, the authors designed a KWH meter with IoT technology to calculate the electricity consumption. During the experiment, the balance of the electricity credit was observed to be reduced by over 75% during the 48-hour operation. This indicates that the system has the capability to allow the customer to easily track and monitor their daily electricity consumption, thereby improving the user experience.

I. INTRODUCTION

Electricity is one of the basic needs for human beings. Almost all technology and electronic devices need electricity to operate. In Indonesia, the number of electricity customers is increasing every year. According to the data postsented by the State Electricity Company (SEC), the total number of customers using electricity at the end of 2021 was about 82.5 million. This figure indicates an increase of 4.49% compared to the total customers using electricity at the end of 2020. In addition, the data postsented indicates that the total number of customers using electricity is increasing every year by about 4-5%. Out of the total 82.5 million customers using electricity, 91% are households, totaling about 75.5 million customers.

In Indonesia, both postpaid and postpaid services of electricity are provided to users. The main difference between postpaid and postpaid services is in terms of their payment methods. Postpaid services involve paying after using the services, whereas postpaid services involve paying before using them. It is thought that by using postpaid services for electricity, users are in a better position to control and minimize their expenses. This service is provided under a credit system in which users can purchase credits according to their own requirements. Usually, a token number is used to input credits into the electricity meter, which decreases with an increase in the usage of electricity.

This system empowers customers to keep an eye on their electricity usage and manage their expenses effectively. Therefore, it is advisable to use postpaid electricity services rather than postpaid services, as suggested by the SEC.

Various research has been carried out on postpaid electricity systems. There is research on designing postpaid electricity systems to avoid electricity theft. There is also research on using microcontroller technology and GSM modules with postpaid electricity systems to facilitate ease of monitoring. Furthermore, there is research on using RFID technology with postpaid electricity systems. With the evolution of IoT technologies, various research projects have been carried out to combine all these technologies to improve postpaid electricity services.

Postpaid electricity systems also experience several challenges, especially regarding home automation. One major challenge is the lack of a system for monitoring credit balances. In most cases, customers are obliged to physically check their electricity meters, which are usually located outside the homes. This is inconvenient for the customers, as they are obliged to leave their homes and check

their credit balances. Moreover, customers who are outside for longer periods are also denied the opportunity to check their electricity balances. This may force customers to forget to recharge their electricity, leading to power outages.

The author's contribution in the paper is the designing of the postpaid smart electricity meter monitoring system, which uses Internet of Things (IoT) technology. The main contribution of the paper is two-fold: 1) the designing of the simple system without any modifications to the existing postpaid electricity meter of the State Electricity Company (SEC); and 2) the designing of the energy meter prototype using the PZEM004T sensor and the Blynk IoT technology, which enables the user to monitor their energy usage without the need to read the meter. IoT technology, which helps the user to keep track of their energy consumption without the need to read the meter themselves. The structure of the paper is as follows: Section 2 postsents the related work on the studies of the postpaid energy meter. Section 3 postsents the proposed system of the Postpaid Smart Energy Meter Monitoring System (Post-SEMMS). Section 4 postsents the results and discussion, and Section 5 concludes the paper.

II. RELATED WORK

In the last decade, extensive research has been carried out, with over twenty studies focusing only on postpaid energy meters. For instance, Mohammad et al. carried out research in [8] to control and postvent electricity theft using a smart postpaid energy metering system, which consists of a GSM module. This enables users to recharge their electricity balance via the Short Message Service, thus postventing the illegal use of electricity. Postethi et al. carried out similar research in [7] to control electricity theft, where they implemented Zigbee technology to enable communication between the energy meter in the house and the substation. Further research regarding electricity theft can be found in [9] and [10]. Although the research carried out in [9] only involved simulation of the system using MATLAB, there was no actual implementation of the system, whereas the study in [10] was implemented in a real-time environment.

However, it is important to note that the underlying reason for this is based on the fact that there is more electricity theft in developing countries compared to their developed counterparts. Various authors have utilized microcontrollers and GSM modules to develop innovative postpaid energy meters, as postsented in various studies [11-16]. For example, study [11] aimed at developing a system similar to mobile phones to facilitate bill payments, ensuring that users only pay for the electricity they are using, which is deducted from their credit limit. Furthermore, research postsented in [12] aimed at designing and developing an affordable postpaid energy meter for domestic use in Sri Lanka.

III. PROPOSED SYSTEM ARCHITECTURE

The overall structure of the postpaid smart energy meter monitoring system (post SEMMS) is shown in FIGURE 1. post SEMMS is designed with an ESP32 microcontroller for control of the post SEMMS and a PZEM 004T sensor for measuring the energy consumed by home appliances and electronic devices in homes. PZEM 004T is capable of measuring electric current up to 100 amperes; therefore, it is capable of measuring residential electric current and providing accurate data for the postpaid metering process.

This shows the Ongoing efforts to develop postpaid electricity systems, especially in regions where there is more electricity theft.

Furthermore, several studies have been done on the integration of IoT technology with cloud storage in postpaid energy meters. For example, in the research done in [19], the authors designed a postpaid energy meter based on the ATMega328p and ESP8266 microcontrollers, which can automatically produce energy consumption data and billing information. Moreover, the authors designed a web GUI and an interactive interface for the user, developed with HTML5, which enables the user to effectively manage their energy consumption. In another study done in [20], the authors suggested that traditional physical energy meters are becoming outdated. They designed a smart energy meter, which enables the user to obtain information on the energy meter reading status through personalized web pages and smartphone applications, with important information being sent to the user's phone via SMS. This was achieved with the use of Raspberry Pi devices, with the data being transmitted to the ThingSpeak IoT cloud platform.

In further research, a smart IoT-based energy management system was proposed, allowing users to control their home appliances remotely. This system also enhanced the transparency and credibility of data, where the costs of energy consumption are automatically calculated and transmitted to the server at specific time intervals. Lastly, in the study, a postpaid energy meter system was developed, allowing for the detection, recording, and storing of energy consumption data in cloud networks. This system enabled users to obtain real-time billing information and energy consumption statistics, thus becoming more convenient for users to manage their energy consumption.

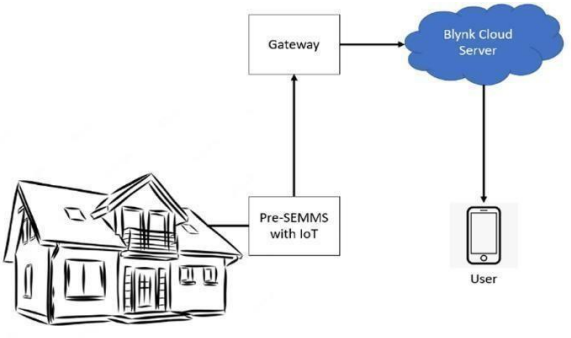

FIGURE 1. Design of Post-SEMMS with IoT for household uses.

The Blynk protocol allows any kind of raw or processed data from a sensor or actuator connected to the ESP32 to be sent to a Blynk cloud database using data streams. Each data stream specifies the type of data being sent in a specific format over a virtual channel. This ensures that Blynk is able to interpostt and visualize the data being sent to it. The data is sent to Blynk using two main methods: Blynk library firmware API and HTTPS API. The Blynk library firmware API is for use in situations where a continuous internet connection

is postsent, such as in Ethernet and Wi-Fi connections. The HTTPS API is for use in situations where communication is to be done using a standard HTTP/HTTPS protocol, not a continuous connection like in mobile devices.

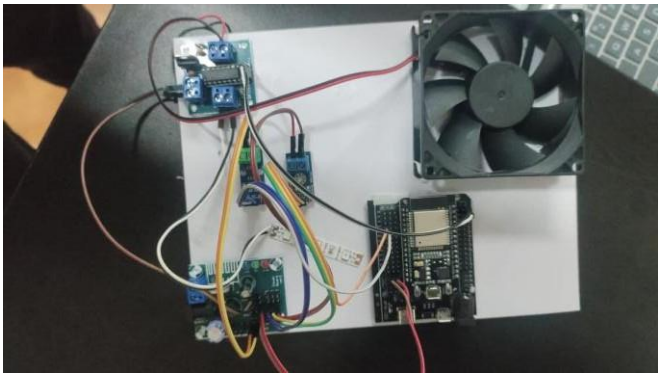

FIGURE 2. Schematic of Post-SEMMS with PZEM-004T and ESP32.

The prototype design of the Post-SEMMS with IoT is shown in FIGURE 2. It has two hardware components, namely, the ESP32 microcontroller and the PZEM 004T energy meter sensor. The PZEM 004T has four interface pins, and these are connected to the ESP32. On the other hand, the measurement terminals of the sensor are connected to the household electrical line via a terminal socket. Under the standard supply voltage of 220 V, the sensor allows the system to measure up to 12,346 W of electricity consumption.

The operational flow of the Post SEMMS is shown in the flowchart in FIGURE 3. When the Post SEMMS starts, the ESP32 reads the balance of the available credit balance from the standard postpaid energy meter. As part of the normal daily activity, the appliances such as the refrigerator, air conditioner, washing machine, microwave oven, rice cooker, and the electrical devices such as the television, personal computer, laptop, printer, fan, and lamp are turned on and start operating, thereby consuming energy. The PZEM 004T sensor continuously measures the energy consumption of the household load. Based on the energy consumption, the ESP32 calculates the amount to be deducted from the remaining balance and the current balance.

After this, the ESP32 either transmits the latest information regarding energy consumption and credit balance to the Blynk cloud server or proceeds to the measurement step to continue measuring. The information on the Blynk server is then sent to the Blynk client app on the user's smartphone to enable real-time monitoring of both energy consumption and postpaid credit balance.

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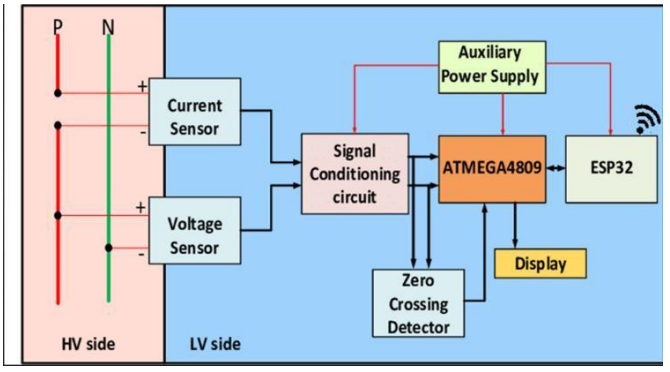

The **Post-SEMMS** (Postpaid Smart Energy Meter Monitoring System) operates by integrating **IoT technology** with existing household electrical frameworks to provide real-time consumption tracking. The system utilizes an **ESP32 microcontroller** as the primary control unit, which interfaces with a **PZEM-004T sensor** to measure electrical parameters such as current, voltage, and power. This sensor is capable of handling up to **100 amperes**, making it suitable for standard residential loads.

As home appliances operate, the PZEM-004T continuously measures energy consumption data, which the ESP32 uses to calculate the remaining credit balance. This information is then transmitted via the **Blynk IoT protocol** to a cloud server. Users can monitor their real-time usage and current balance through the **Blynk client application** on a smartphone. This automated process eliminates the need for manual meter reading and helps users manage their electricity expenses more effectively.

VI.RESULTS AND DISCUSSION

In this section, the results of an experiment carried out on the Post SEMMS prototype are postsented. The experiment was done in the author's house, where the voltage is maintained at 2,200 V. Table 4 below indicates the results obtained by Post SEMMS for an air conditioner (AC) appliance, as well as the results obtained by the commercial power meter (PM).

As indicated in Table 4, it is clear that there are slight differences between the results obtained by Post SEMMS and the results obtained

From the results provided in this paper, it can be concluded that Post SEMMS is an efficient and reliable tool to monitor and manage electricity usage in households. Based on experimental results of various home appliances, it is clear that Post SEMMS is efficient in measuring current, voltage, power, and energy with high accuracy, similar to those of commercially available meters. Moreover

V.CONCLUSION

graphical repostsentation of consumed energy and credit balance provides a clear idea of electricity usage in households. Blynk client applications also provide a facility to monitor electricity usage and credit balance in real time using a smartphone.

Overall, Post SEMMS can prove to be an effective tool for households to control their electricity usage and lower their electricity bills. By raising awareness regarding electricity usage and promoting more informed decisions, it can also prove to be an effective tool in building a sustainable future based on more efficient and effective usage and conservation of energy.

For future research, it is suggested that more can be done to enhance the capabilities of Post SEMMS to control more home appliances and devices. The incorporation of machine learning algorithms can prove to be effective in providing users with more informed decisions regarding the usage and conservation of energy. Another direction can be to use Post SEMMS in larger postmises and residential areas to control energy usage on a larger scale and evaluate the efficiency of the system. Further, more advanced and user-friendly interfaces can be developed for the Blynk client applications to provide users with more effective and efficient usage of the system.

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Rural Care MediBot: An IOT-Driven Autonomous Healthcare Assistant for Remote Hospitals

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Abstract— Rural hospitals often struggle with patient monitoring because they do not have enough medical staff, and their systems are not equipped for continuous monitoring. The healthcare system faces two major challenges because it does not provide timely patient monitoring. Through Internet of Things (IoT) and robotics technologies automated monitoring systems now enable healthcare organizations to create remote communication systems. This paper presents Rural Care MediBot an IoT-based autonomous healthcare assistant which enhances patient monitoring systems for hospitals located in remote areas. The system uses a mobile robotic platform which combines various health monitoring devices that measure heart rate and oxygen saturation (SpO_2) and temperature. The Arduino Uno microcontroller controls all system operations while it tracks information from multiple sensors. The ESP8266 Wi-Fi module enables users to track their health through remote access to cloud monitoring services. The robot navigates its environment by using ultrasonic sensors which help it sense obstacles. The ESP32 CAM module provides doctors with remote visual monitoring tools that enable them to watch their patients. Medical professionals can monitor vital signs through the system which transfers health data to a cloud platform. The system enables patients to transmit basic messages to doctors through a keypad interface which they can use to send messages. The system employs robotics and IoT technology together with continuous health monitoring to lower healthcare staff work demands while improving medical support availability in rural hospitals.

Keywords— Internet of Things (IoT), Robotics in Healthcare, Remote Patient Monitoring, Rural Healthcare Systems, Autonomous Medical Robot, Cloud-Based Health Monitoring, Smart Healthcare Systems

I. INTRODUCTION

Healthcare monitoring works as an essential method which protects patient safety while providing proper medical treatment. Healthcare workers at hospitals and healthcare facilities require vital sign monitoring which includes heart rate and body temperature and oxygen saturation levels to identify medical conditions during their initial appearance. Remote and rural hospitals experience staff shortages because they lack sufficient medical personnel. Continuous patient monitoring becomes challenging for doctors and nurses because they require multiple medical personnel to perform their duties. The healthcare services experience quality degradation because of delayed monitoring and communication processes. The Internet of Things (IoT) combined with robotics and embedded systems has advanced to create new opportunities which will enhance healthcare monitoring systems. Medical devices and sensors use IoT technology to collect patient health data which they transmit through the internet for remote assessment. Healthcare workers receive support from robotic systems which can conduct repetitive monitoring tasks and assist patients with their communication needs. The combination of these technologies will enable healthcare systems to operate with increased efficiency and improved patient access to medical services. Medical assistant robots have grown more popular in modern healthcare settings which show increasing interest in their use. These robots assist doctors and nurses by monitoring patient conditions while delivering information and facilitating remote communication.

Robotic systems enable healthcare workers to treat patients during pandemics and hospital capacity crises because these systems decrease the need for direct contact between staff and patients. The new method protects both patients and healthcare staff from potential dangers. Our research introduces Rural Care MediBot which serves as an Internet of Things-based autonomous medical assistant designed to monitor patients in remote healthcare facilities. The system uses a mobile robotic platform together with health monitoring sensors to track patient vital signs. The robot operates through an Arduino Uno microcontroller which establishes cloud connections by using an ESP8266 Wi-Fi module. The robot uses an ESP32-CAM module for visual monitoring while ultrasonic sensors enable it to move autonomously by detecting and bypassing obstacles. The cloud-based health data system enables doctors to perform remote monitoring of their patients' healthconditions. The proposed system seeks to improve healthcare access and

lessen the work load of medical staff in remote hospitals. The Rural Care MediBot system uses IoT, sensor monitoring, and robot movement to create an effective solution for advanced healthcare facilities. Robotics together with sensors and cloud technology creates an advanced system which enhances healthcare monitoring efficiency. Patients can share their condition remotely while doctors can monitor vital parameters without being physically present. The system provides fast response capabilities which enhance patient protection and enable modern digital health systems to function properly.

II. RELATED WORK

The past several years have seen significant increases in technology usage for healthcare monitoring purposes. Researchers investigate methods to integrate Internet of Things (IoT) devices with embedded systems for remote patient health monitoring. Medical sensors in IoT-based healthcare monitoring systems gather patient information which they transmit to healthcare providers through internet connectivity.

The current IoT healthcare monitoring systems which hospitals use remain bound to specific locations since they do not allow flexible movement throughout the facility. Research studies demonstrate that remote patient monitoring systems which use wearable sensors to track vital signs have emerged as a solution. The systems provide essential support for chronic illness patients who need ongoing medical supervision. Health care devices which people wear for medical purposes work by delivering crucial health information yet they require users to operate them or need medical staff to manage their tracking functions. The medical staff in crowded hospitals face additional tasks because of this situation. Healthcare personnel receive operational support from robotics technology which functions as a supplementary resource in medical settings. Hospital service robots can carry out functions which include medicine delivery patient support and basic health monitoring activities.

The robots assist nurses by reducing their workload which leads to better operational performance in hospitals. The robotic healthcare systems use their integrated cameras and communication systems to allow doctors to provide remote patient treatment through telemedicine. The existing robotic systems which are currently accessible today dedicate their primary resources toward handling service tasks instead of creating systems which can track patient vital signs throughout the day. The current research aims to create advanced healthcare systems which use IoT technology together with mobile robotic systems. The patient data collection system uses embedded controllers and wireless communication modules together with sensors to send patient information to cloud platforms for processing.

The system implementations still face two main issues which are high system costs and complicated system operations and the restricted doctor-patient interaction. The study introduces Rural Care MediBot which functions as an This autonomous healthcare assistant designed for use in remote hospital facilities. The proposed system establishes a connection between health monitoring sensors and a mobile robotic platform which links to cloud services. The system uses robotic movement together with sensor technologies and remote communication capabilities to improve patient observation systems while decreasing healthcare worker duties. The current research in modern healthcare focuses on creating intelligent healthcare spaces which utilize multiple technologies such as IoT and robotics and AI and cloud computing. The integrated platform combines advanced healthcare technologies to enable ongoing patient observation while supporting medical personnel and enhancing healthcare delivery.

MediBot serves as a healthcare assistant which operates autonomously through its Internet of Things capabilities to assist medical facilities in remote and rural areas. The proposed IoT-based autonomous healthcare assistant system leads to substantial improvements in healthcare service delivery. The proposed IoT-based autonomous healthcare assistant system combines a mobile robotic platform with health monitoring sensors and wireless communication modules and cloud computing technology.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed Rural Care MediBot is a smart healthcare monitoring system designed for implementation in rural and remote hospitals. The proposed system integrates a mobile robot, health sensors, wireless communication, and cloud technology for overseeing data. The proposed system integrates robotics and IoT technologies for constant monitoring of the patient's health and for establishing communication with healthcare professionals.

The proposed system is designed with several components that work together to enable continuous health monitoring and communication. These components include the sensor unit, control unit, communication unit, navigation unit, and a cloud platform. Each part of the system performs a specific function, and together they allow patient health data to be collected, processed, and transmitted efficiently. The block diagram of the proposed system illustrates how these hardware components are connected and how they

communicate with the network to ensure reliable data transmission.

At the center of the system is the Arduino Uno, which acts as the main controller. It coordinates the operation of all components and manages the flow of data within the system. The Arduino Uno receives data from the connected health sensors, processes the information, and sends it to the IoT communication module. This module then transmits the data to the cloud platform, where it can be accessed for remote monitoring and analysis.

The health monitoring part of the system uses several sensors to measure important physiological parameters in real time. These sensors collect patient health data and send it to the microcontroller for processing. The Arduino Uno provides multiple digital and analog input pins, which makes it easy to connect different sensors and modules. It also supports serial communication, allowing smooth interaction with IoT devices. Because of its affordability, ease of programming, and reliable performance, the Arduino Uno is widely used in robotics and IoT-based healthcare applications. These features make it a suitable choice for developing healthcare monitoring systems such as the Rural Care MediBot.

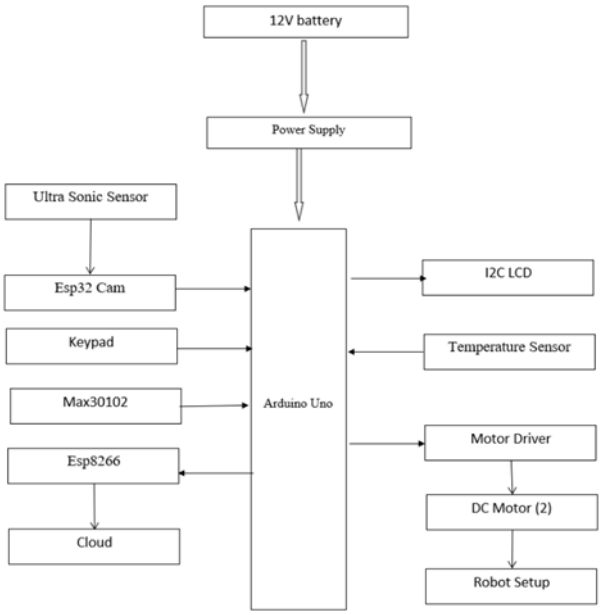

Fig. 1. Overall block diagram of the Medi Bot robot.

The block diagram indicates the overall setup for the proposed system of health care monitoring. It uses a 12V battery as the power source, along with a power supply unit for voltage regulation. It uses an Arduino Uno as the main controller for all the sensors, communication modules, and robotic components. It uses health sensors such as the MAX30102 heart rate/SpO2 sensor and the temperature sensor for health monitoring. It uses the ESP8266 for sending the data collected by the sensors to the cloud for remote monitoring. It uses the ESP32-CAM for visual monitoring. It uses ultrasonic sensors for the robot for detecting obstacles. It uses a motor driver for controlling the DC motor for the robot. It uses a keypad for user input, and it uses an I2C LCD for displaying the system status and sensor data.

Fig. 2. Using Arduino uno based on ATmega2560 Microcontroller

The Arduino Uno acts as the primary control unit for the Rural Care MediBot system. This unit receives data from the various health monitoring devices, i.e., MAX30102 and the temperature sensor, and processes the data. In addition, the Arduino Uno controls other devices connected to the MediBot system. This includes the ESP8266 and ESP32-CAM modules, as well as the motor driver for the movement of the robot. This Arduino board is selected for the MediBot system because it is easy to program and works well with other modules and devices. Its reliability and ability to work well for the development of smart healthcare monitoring systems make it a perfect choice. Arduino Uno provides multiple digital and analog input/output pins that allow easy connection with different hardware components used in the project. It supports serial communication protocols that enable smooth interaction with IoT modules and other peripherals. The availability of open-source libraries and strong community support makes development faster and more effective. Because of its low cost, simple hardware architecture, and stable performance, Arduino Uno is widely preferred for robotics and healthcare monitoring applications like this Rural Care MediBot system.

IV. SYSTEM HARDWARE DESIGN

The Rural Care MediBot consists of a variety of hardware that works together in unison to monitor the

patient and navigate the MediBot. At the heart of the operation, the concept centers around the microcontroller, health communication modules, and the variety of motion and sensors that are integrated together. An Arduino Uno microcontroller serves as the brain of the operation, gathering information from the sensors, processing the information, and ensuring that all the modules being able to communicate with each other.

For the wireless communication and remote monitoring, the ESP8266 Wi-Fi module is used. It transmits the sensed data to the cloud, and the doctors and healthcare staff can monitor the condition of the patient from a remote area. We also integrate the ESP32-CAM module, as it helps in the visual monitoring of the patient's condition, as the staff can observe the condition via camera.

For the robot, the DC motors are used, and the motor driver module helps the robot travel around the hospital environment, as the ultrasonic sensors detect the obstacles**.**

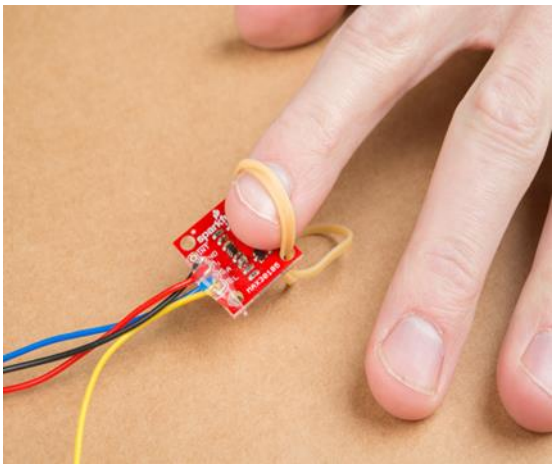

Fig. 3. MAX3015 detect Hemoglobin from IR light

Since the hemoglobin content in the blood has extremely high reflectance to infrared rays, the MAX3015 sensor detects even the slightest changes in the reflected IR rays, which helps in detecting the blood flow through the finger at different speeds.

V. SYSTEM WORKING METHODOLOGY

The Rural Care MediBot is created with the goal of keeping a close eye on the patients at all times and providing remote healthcare support in rural hospital environments. It is made up of various components such as sensors, communicators, and the robotic navigation system, which are integrated using the Arduino Uno microcontroller. The system operation commences when the robot is connected to the 12V battery, and the Arduino Uno connects all the components, including the sensors, communicators, and the motor driver. After the system is fully operational, the healthcare monitoring sensors begin to monitor the patient's vital signs. The heart rate and SpO2 are monitored using the MAX30102 sensor, while the body temperature is monitored using the temperature sensor. The readings are then sent to the Arduino Uno before being wirelessly transmitted.The readings are also displayed on the I2C LCD display to enable the patient and the healthcare staff to monitor the parameters.

The patient data is then sent to the cloud using the ESP8266 Wi-Fi module to enable the healthcare staff to monitor everything using the IoT connection.Besides the mere tracking of health, the ESP32 CAM module also allows visual oversight.

Besides the mere tracking of health, the ESP32 CAM module also allows visual oversight. In case of need, medical personnel can view a live video feed of the patient. Moreover, there is a feature of robotic navigation. This allows the robot to move on its own in the hospital environment. Ultrasonic sensors are used to detect objects and measure the distance of objects. Based on this, the Arduino adjusts the movement of the robot with the help of a motor driver module that controls the DC motors. Moreover, there is the feature of communication between the patients and the medical staff. A keypad is provided that allows the patients to send messages to the monitoring system. This allows them to seek help in case of an emergency. Thus, with the amalgamation of IoT technology, robotic technology, and health monitoring technology, the Rural Care MediBot is an efficient and intelligent solution that can be used in remote hospital environments.

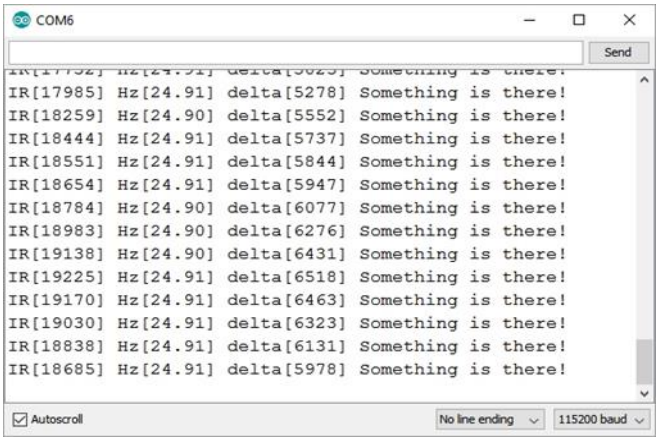

Fig. 4. Serial monitor output showing sensor detection and system response

The display indicates the real-time data being sensed by the sensors connected to the Arduino controller. What it indicates is that the system is detecting either an object or a person, as well as the system's response. In essence, it indicates that the sensors are functioning correctly, as they are able to sense the data in the environment.

VI. SYSTEM INTEGRATION IN IOT-BASED HEALTHCARE MONITORING

In the Rural Care MediBot, all this comes together with IoT connectivity, with all the various elements talking to each other through various sensors, embedded systems, and communication protocols. First, there are various sensors that include the MAX30102 heart rate and SpO2 monitoring, as well as a temperature sensor that monitors a patient's vitals. The brain behind all this is the Arduino Uno, which makes sense of all this data and controls how all this comes together. In this way, a patient's health is constantly under watch.

There is also ESP8266 that handles Wi-Fi connectivity, thereby enabling the embedded system to send this information to the cloud, so that doctors can monitor patients remotely. In this way, patients can be monitored using any internet-enabled device. Finally, there is also ESP32-CAM, which allows doctors to visually monitor patients through live video streaming. There is also mobility involved with this IoT integration. The MediBot is able to move around the hospital through various robotic features that include ultrasonic sensors that enable it to avoid obstacles as it moves. There is also a motor driver module that controls the DC motors on the MediBot.

The MediBot robot is designed to move autonomously in hospitals, propelled by DC motors connected to a dedicated motor driver. The robot will use ultrasonic sensors to detect objects and measure the distance to objects, thus helping to avoid accidents. The integration of sensing technology, communication technology, processing technology, and robotic technology results in a complete IoT-based healthcare monitoring system. The integration of all these technologies into one platform allows the Rural Care MediBot to provide real-time patient monitoring, remote medical support, and timely response to emergencies. The integrated system provides the opportunity to integrate additional technologies such as more sensors, additional communication technologies, and additional healthcare monitoring applications in the future. This makes IoT-based healthcare monitoring a viable solution for the development of modern healthcare monitoring technologies.

This system serves as a good example of the potential of IoT and robots to improve healthcare services, especially in situations of low resource availability. It provides timely monitoring services, communication, and movement of robots, all of which are beneficial to healthcare services. It could be used as a model for future smart healthcare applications geared toward improving patient monitoring and healthcare services.

Incorporating robot movement into the system takes the potential of this system to the next level by allowing the MediBot to move freely in the healthcare facility. This allows for the monitoring of several patients at once, helping nurses and doctors with patient monitoring services. This reduces the workload of healthcare staff while providing patients with round-the-clock monitoring services. Therefore, the potential of the Rural Care MediBot serves as an example of the potential of IoT and robots to provide smart healthcare monitoring services. It shows the potential of future smart applications geared toward improving rural healthcare services at the least cost.

VII. CONCLUSION

This The Rural Care MediBot is a prime example of how IoT and robotics can work in tandem to make health care services more efficient, especially in environments with scarce resources. It offers timely, efficient, and effective health care services through continuous monitoring, messaging, and automated capabilities, paving the way for the development of more sophisticated intelligent health apps in the near future.

Making the Rural Care MediBot mobile takes this concept a step further, as it can move around a health care facility on its own, monitor several patients at once, and assist nurses and doctors in conducting routine check-ups on patients. This minimizes the workload of health care personnel while ensuring continuous patient monitoring.

In essence, the Rural Care MediBot is a prime example of how IoT and robotics can work in tandem to make health care services smarter. This, combined with the continuous developments in technology, ensures that the Rural Care MediBot has all it takes to become a key player in the field of intelligent health in the near future.

VIII. FUTURE WORK

While the idea of the Rural Care MediBot demonstrates a good approach to IoT in the supply of health care services, there are various ways the idea could be improved in the future to enhance the efficiency of the system. One of the improvements could come in the form of data analysis, whereby the system could utilize advanced data analysis techniques like machine learning and AI, which could help scan the health data of patients and alert the system of any possible emergency situations.

In the aspect of communication, the system could utilize advanced wireless communication technologies, like 5G, which could help improve the efficiency of data communication, especially in rural environment. Another

improvement could come in the form of the addition of various sensors that could help the system monitor various aspects of patients, like blood pressure, ECG, respiration, etc..

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Comparative BER Performance Analysis of Conventional and TX-DWT Enhanced OTFS Systems for High-Order QAM over AWGN Channel

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ABSTRACT:

Orthogonal Time Frequency Space (OTFS) modulation has recently attracted considerable interest as a promising waveform for next-generation wireless communication systems. This is mainly because it can handle rapidly changing channel conditions more effectively compared to conventional modulation techniques. In this work, an improved OTFS transmission method is introduced by applying a Discrete Wavelet Transform (DWT) at the transmitter side. The system is tested over an Additive White Gaussian Noise (AWGN) channel.The main aim is to improve Bit Error Rate (BER) performance for higher-order modulation schemes like 32-QAM and 64-QAM, without using channel coding. From the simulation results, the proposed system achieves a BER of around 10−410^{-4}10−4 at nearly 7 dB SNR for 32-QAM and 10 dB SNR for 64-QAM.Compared to the conventional OTFS system, this method provides better performance at lower SNR values while keeping the system simple. This shows that using wavelet-based processing at the transmitter can significantly improve OTFS performance, making it suitable for future wireless systems.

INTRODUCTION:

The fast increase in high data-rate wireless applications and the growing need for reliable communication in high-mobility scenarios have created a demand for more advanced modulation techniques beyond traditional Orthogonal Frequency Division Multiplexing (OFDM). Even though OFDM is widely used in current wireless systems, its performance reduces in rapidly changing channels, especially in high Doppler conditions, due to inter-carrier interference (ICI) and loss of orthogonality. To address these challenges, Orthogonal Time Frequency Space (OTFS) modulation has been introduced as a strong candidate for next-generation wireless communication systems [2].

OTFS operates by mapping information symbols in the delay–Doppler domain rather than the conventional time–frequency domain. This representation transforms a rapidly time-varying wireless channel into an almost time-invariant channel in the delay–Doppler domain, thereby improving robustness against Doppler spread and multipath fading [2], [9]. As a result, OTFS has shown superior performance compared to conventional multicarrier techniques, especially in high-mobility scenarios such as vehicular communication, high-speed rail systems, and satellite communication [3], [8].

Recent research efforts have focused on enhancing OTFS system performance using advanced signal processing techniques such as equalization, channel coding, and waveform design. Among these, wavelet-based signal processing has gained considerable attention due to its excellent time–frequency localization capability and reduced spectral leakage compared to Fourier-based approaches. Wavelet transforms have been effectively applied in communication systems to improve signal representation and Bit Error Rate (BER) performance [4].

Motivated by these advantages, several studies have explored the integration of Discrete Wavelet Transform (DWT) with OTFS modulation to enhance system performance under various channel conditions [4], [5]. While these wavelet-aided OTFS systems demonstrate improved BER performance, many existing approaches rely on complex receiver architectures or additional channel coding techniques, which increase computational complexity and processing delay.

In this work, a modified OTFS transmission scheme employing transmit-side Discrete Wavelet Transform (TX-DWT) is proposed to improve BER performance over an Additive White Gaussian Noise (AWGN) channel. Unlike conventional OTFS systems that depend on channel coding techniques, the proposed approach focuses on waveform-level enhancement by applying wavelet processing at the transmitter side, without modifying the receiver structure. The system performance is evaluated using high-order modulation schemes such as 32-QAM and 64-QAM to validate its effectiveness for high data-rate communication.

Simulation results demonstrate that the proposed TX-DWT-based OTFS system achieves significant improvement in BER performance at lower Signal-to-Noise Ratio (SNR) values. The system exhibits smooth BER decay without any error floor at high SNR regions, while maintaining reduced system complexity. Therefore, the proposed method highlights the effectiveness of transmit-side wavelet-based signal shaping as a practical and efficient enhancement technique for OTFS modulation in next-generation wireless communication systems.

Limitations of Existing OTFS Model:

- The existing OTFS model relies entirely on Fourier-based transformations, which provide limited time–frequency localization.
- High-order QAM schemes such as 32-QAM and 64-QAM exhibit degraded BER performance at lower SNR values in uncoded OTFS systems.
- The absence of waveform shaping results in increased sensitivity to noise.
- To achieve acceptable BER performance, existing OTFS systems often depend on channel coding techniques, which increase system complexity.
- In uncoded OTFS, the BER curve shows slower decay, making it less efficient for low-SNR operation.

PROPOSED MODEL:

- In the proposed model, the input binary data is first mapped using high-order QAM modulation schemes such as 32-QAM and 64-QAM.
- OTFS modulation is performed using FFT and IFFT operations to convert delay–Doppler symbols into the time-frequency domain, similar to the existing model.

- Unlike the conventional OTFS system, a Transmit-Side Discrete Wavelet Transform (TX-DWT) is applied to the time-domain OTFS signal.
- The DWT processing separately transforms the real and imaginary components of the OTFS signal, enabling improved time–frequency localization.
- Wavelet-based signal shaping reduces noise sensitivity and improves signal energy compaction.
- The wavelet-processed OTFS signal is transmitted over an AWGN channel.
- At the receiver, inverse OTFS operations are applied without requiring any additional wavelet processing or channel coding.
- QAM demodulation is performed directly to recover the transmitted bits.

Advantages of the Proposed Model:

• Improves the overall reliability of the OTFS system by applying transmit-side wavelet processing.

• Enhances system performance without requiring complex receiver-side signal processing.

• Does not require channel coding, thereby reducing computational complexity and processing delay.

• Supports higher-order QAM modulation schemes efficiently.

• Provides stable performance at high SNR without error floor issues.

• Requires only minor modification at the transmitter, making it easy to integrate with existing OTFS frameworks.

• Suitable for future high-data-rate and high-mobility wireless communication systems.

BLOCK

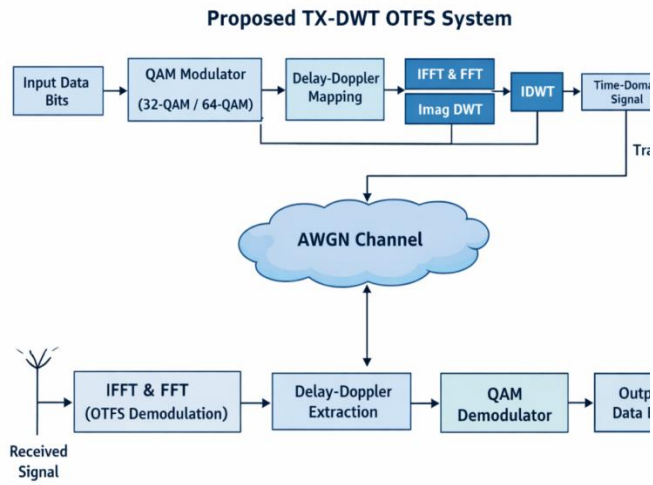

DIAGRAM:

Figure 1.Block diagram of the proposed TX-DWT OTFS System

SYSTEM BLOCK DIAGRAM EXPLAINATION:

Transmitter:

1. **InputDataBits:**
   The system begins with a stream of binary input data bits that are to be transmitted.
2. **QAMModulation:**
   The input bits are mapped into complex symbols using high-order Quadrature Amplitude Modulation (QAM), such as 32-QAM or 64-QAM. This step converts binary data into modulated symbols suitable for multicarrier transmission.
3. **Delay–DopplerMapping(OTFSModulation):**
   The QAM symbols are organized on a delay–Doppler (DD) domain grid, and then OTFS modulation is applied using FFT and IFFT operations. This converts the delay–Doppler symbols into the time-frequency domain.
4. **Transmit-Side Discrete Wavelet Transform (TX-DWT):**
   Unlike conventional OTFS, the proposed model applies a wavelet transform separately to the real and imaginary components of the time-domain signal. The wavelet processing improves time-frequency localization and enhances energy compaction, which reduces sensitivity to noise.
5. **Inverse DWT (IDWT) and Time-Domain Signal Generation:**
   After wavelet processing, the inverse DWT reconstructs the final time-domain transmit signal, ready for transmission over the channel.

AWGN Channel:

The transmitted signal propagates through an Additive White Gaussian Noise (AWGN) channel**,** which introduces random noise to simulate real-world transmission conditions.
This channel represents the main source of performance degradation in terms of Bit Error Rate (BER).

Receiver:

1. **ReceivedSignal:**
   The receiver captures the noisy signal from the channel.
2. **OTFSDemodulation(IFFT&FFT):**
   The received time-domain signal is converted back into the delay–Doppler domain using inverse OTFS operations (IFFT and FFT). This step reverses the transmitter's delay–Doppler mapping.
3. **Delay–DopplerExtraction:**
   The delay–Doppler symbols are extracted from the demodulated grid.
4. **QAMDemodulation:**
   Finally, QAM demodulation is performed to recover the original transmitted bits.
5. **OutputDataBits:**
   The system outputs the estimated binary data, which can be compared with the original input bits to calculate the Bit Error Rate (BER)**.**

RESULT AND DISCUSSION:

MODULATION	BER	SNR
32-QAM	10^{-4}	7
64-QAM	10^{-4}	10

The performance of the proposed system is evaluated using BER vs SNR analysis for both 32-QAM and 64-QAM over an AWGN channel.

For 32-QAM, the system achieves a BER of 10−410^{-4}10−4 at around 7 dB SNR, which shows good performance even at lower SNR levels. This improvement is mainly due to the wavelet-based processing applied at the transmitter.

For 64-QAM, the BER reaches 10−410^{-4}10−4 at approximately 10 dB SNR. Since higher-order modulation is more sensitive to noise, it requires higher SNR, but the proposed method still maintains good performance.

Overall, the results prove that the TX-DWT based OTFS system performs better than conventional methods, especially in terms of BER and consistency.

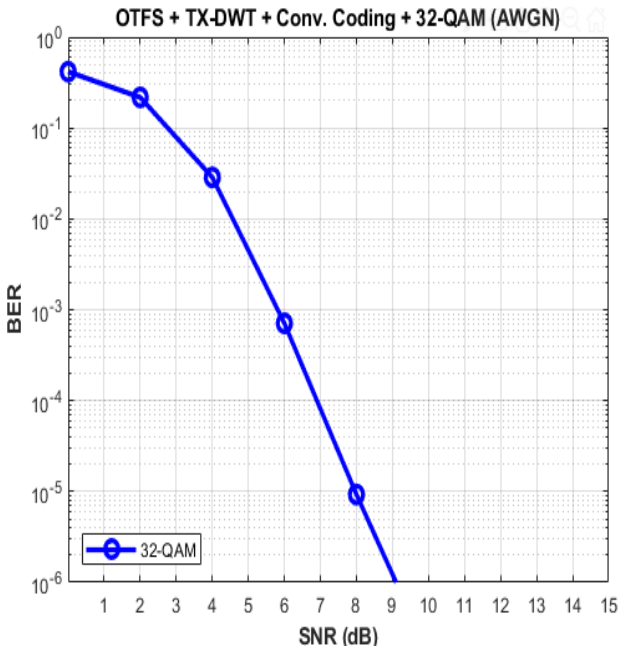

Figure 2.Ber vs SNR graph of 32-QAM

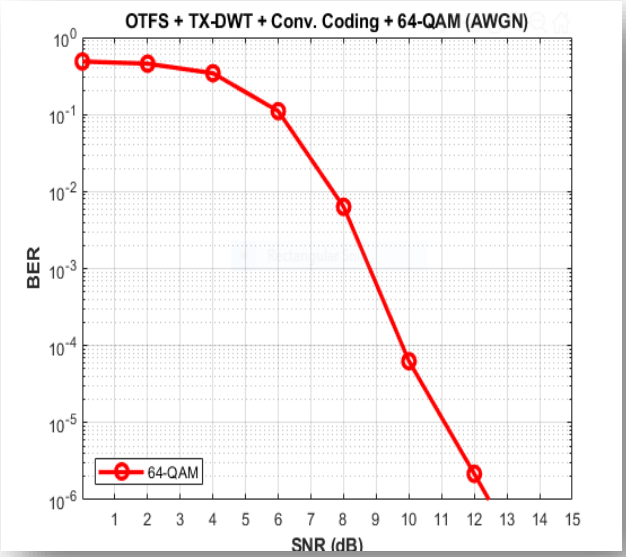

Figure 3.Ber vs SNR graph of 64-QAM

Figure 2 illustrates the Bit Error Rate (BER) performance of the proposed TX-DWT based OTFS system using 32-QAM modulation over an AWGN channel. The graph shows a clear inverse relationship between Signal-to-Noise Ratio (SNR) and BER, where the BER decreases significantly as the SNR increases. It is observed that the system achieves a BER of approximately 10−410^{-4}10−4 at around 7 dB SNR, indicating reliable communication at relatively low SNR levels. The smooth decay of the BER curve without any noticeable error floor demonstrates the effectiveness of the transmit-side Discrete Wavelet Transform (TX-DWT) in enhancing signal quality and reducing noise impact. The improved performance is mainly due to better time–frequency localization and energy compaction provided by wavelet-based signal shaping. Overall, the results confirm that the proposed model enhances error performance for 32-QAM without requiring channel coding, making it efficient for practical wireless communication applications.

Figure 3 presents the Bit Error Rate (BER) performance of the proposed TX-DWT based OTFS system using 64-QAM modulation over an AWGN channel. As shown in the graph, the BER decreases progressively with an increase in Signal-to-Noise Ratio (SNR), indicating improved system reliability at higher SNR values. Compared to 32-QAM, 64-QAM requires a higher SNR to achieve the same BER due to its denser constellation and increased sensitivity to noise. The proposed system achieves a BER of approximately 10−410^{-4}10−4 at around 10 dB SNR, demonstrating its capability to support high-order modulation schemes effectively. The smooth and consistent decline in the BER curve without the presence of an error floor highlights the efficiency of the transmit-side Discrete Wavelet Transform (TX-DWT) in enhancing signal robustness. The wavelet-based processing improves energy distribution and reduces noise effects, thereby enabling better performance even for higher data rate transmission. Overall, the results validate that the proposed model maintains reliable communication performance for 64-QAM while keeping system complexity low.

COMPARISON TABLE:

REFERENCE NO	MODULATION	BER	SNR
[1]	64-QAM	10^{-3}	15.1dB
[2]	16-QAM	10^{-1}	8dB
[3]	64-QAM	1.25×10^{-5}	20dB
[4]	32-PSK	10^{-4}	9dB
[4]	64-PSK	10^{-4}	14.7dB
(This work)	32-QAM	10^{-4}	7dB
	64-QAM	10^{-4}	10dB

CONCLUSION:

A TX-DWT based OTFS system has been proposed and evaluated over an AWGN channel using 32-QAM and 64-QAM modulation schemes. Simulation results show that the proposed system achieves a BER of 10^{-4} at approximately 7 dB for 32-QAM and 10 dB for 64-QAM without channel coding. The improved BER performance with low receiver complexity demonstrates the effectiveness of transmit-side wavelet processing in OTFS systems.

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ARISE : AUTONOMUS ROVER FOR INTELLIGENT SENSING AND ENVIRONMENT MONITORING

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***Abstract*— When big disasters like earthquakes, fires and landslides happen they create bad environments that are dangerous for the people who are trying to help. If we do not have the information about these environments it can be even more dangerous and slower for the people who are trying to help. That is why we made ARISE – Autonomous Rover for Intelligent Sensing and Environment Monitoring. It is a robot that can help the people who are trying to help in disasters.The robot has a controller and a computer that work together to sense move and talk to devices. It has sensors like gas sensors, temperature sensors and special sensors that can see how far things are. It also has a camera that can show us what is happening in time.The robot collects information about the environment. Sends it to a special system where the people who are trying to help can see what is happening and make decisions. The robot can move around on ground and through things that are in the way, which is very helpful in places that have been damaged by disasters The robot uses new technologies like robotics, of things and computer vision to help us understand what is happening and to make the people who are trying to help safer and more effective.**

Keywords-- Disaster Monitoring, Autonomous Rover, IoT, Environmental Sensors, Computer Vision, Rescue Robotics.

I. INTRODUCTION

Big disasters like earthquakes, landslides, fires and industrial accidents create bad environments that are dangerous for the people who are trying to help. In these situations it is very important to get information about what's happening so that we can plan how to help safely and effectively.

New technologies like robotics, special controllers and sensors have made it possible to make robots that can work safely in bad environments.

Robots that are made for disasters are designed to go into places that not safe for people collect information about the environment and send back pictures and videos to the people who are trying to help.

The robot we made has sensors that can detect things that are in the way and a camera that can show us what is happening in real time. The information from the sensors and the camera is sent to a system where the people who are trying to help can see what is happening and make decisions.

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Disaster response robots are built to investigate unsafe locations, gather environmental information, and send visual feedback to rescue teams while minimizing human exposure to danger.

In addition, the rover includes ultrasonic sensors for obstacle detection and a camera module for real-time visual monitoring. The collected sensor data and video feed are transmitted wireless to a remote monitoring system where rescue personnel can analyze the situation.

Some researchers have developed IoT-based monitoring systems that use wireless communication to transmit environmental data from sensors to remote monitoring stations. These systems provide real-time information and allow emergency responders to make informed decisions.

By combining IoT technology, robotics, and computer vision, the proposed system provides an efficient and cost-effective solution for monitoring hazardous environments and supporting disaster management operations.

Fig.1 types of natural disaster

II. PROPOSED SYSTEM METHODOLOGY

The ARISE system is developed to address several limitations found in traditional disaster monitoring approaches. The

system uses a robotic rover equipped with sensors, a camera module, and wireless communication technology.

We made the ARISE system to address some problems with the ways of monitoring disasters. The system uses a robot that is equipped with sensors, a camera and special communication technology.

The robot is controlled by a controller and a computer that work together to collect information from sensors control the system and communicate with other devices. The sensors monitor the environment and the special sensors that can see how things are help the robot move around.

A camera is installed on the robot to take pictures and videos of the disaster area. This helps the people who are trying to help understand what is happening without having to go into the environment.

The robot sends the information from the sensors and the camera to a monitoring system. The people who are trying to help can see the information. Make good decisions about how to help.

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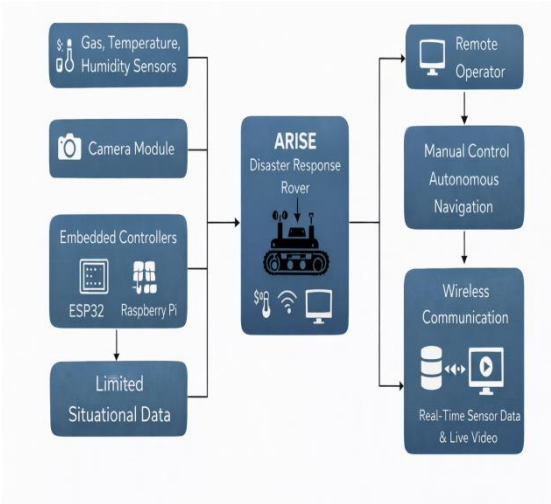

Fig.2 Block Diagram of Proposed Diagram

III. System Architecture Design and Simulation

The ARISE robot is made up of parts that work together to monitor the environment in disaster areas. The parts include the controller, computer, sensors, camera and special communication system. Each part does a job to make sure the robot works well.

The controller is the part that collects information from the sensors and sends it to the monitoring system. The computer is used to control the camera and do processing tasks. The camera takes pictures and videos of the disaster area, which helps the people who are trying to help understand what is happening.

The special sensors that can see how things are help the robot detect things that are in the way and measure distances. The robots movement system is made up of motors and a motor driver, which give the robot the power and control it needs to move around.

Fig.3 Existing system Architecture diagram

The robots circuit design is made up of parts that are connected together. The controller is the part that manages all the other parts.

The motor driver is connected to the controller to control the motors that make the robot move. The driver gets control signals from the controller. Gives the motors the power they need.

The sensors are connected to the controller to monitor the environment. The camera is connected to the controller to take pictures and videos. The information from the camera is sent to the monitoring system through communication.

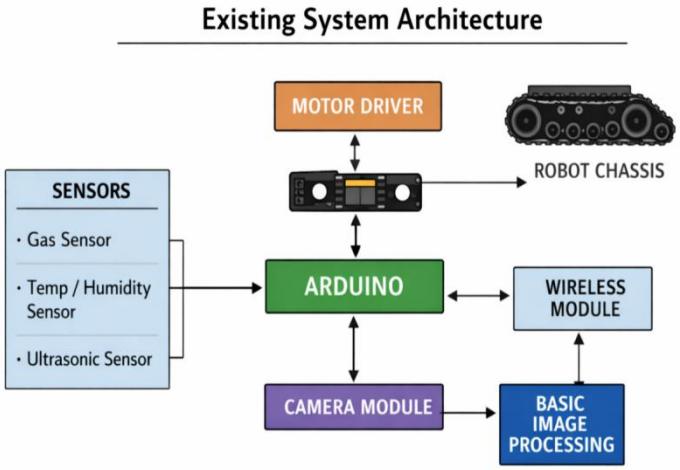

Fig.3 Existing system Architecture diagram

The circuit design of the rover consists of several interconnected modules. The microcontroller acts as the main controller and manages all the connected components.

The motor driver is connected to the mirocontroller to control the DC motors that drive the wheels of the rover. The driver receives control signals from the microcontroller and supplies the required current to the motors.

The sensors such as temperature sensors and gas sensors are connected to the input pins of the. These sensors continuously monitor the surrounding conditions and send real-time data to the microcontroller.

The camera module is connected to the for capturing images and live video. This information is transmitted through Wi-Fi to the monitoring system. A power supply unit, usually a rechargeable battery, provides power to the motor driver, and other components.

IV. System Prototype Development and Testing

We made a working prototype of the ARISE robot to show how it works in an environment. The prototype has parts, including the controller, motor driver, motors, sensors and camera.

The robots body is made to move across different surfaces. The motors are connected to the wheels. Controlled by the motor driver, which gets signals from the controller.

The sensors are installed on the robot to monitor the environment. The camera is used to take pictures and videos of the disaster area.

The robot sends the information from the sensors and the camera to the monitoring system. The people who are trying to help can see the information. Make good decisions about how to help.

These sensors continuously collect environmental data and send it to the microcontroller for processing. A camera module was also integrated into the system to capture live video of the surrounding environment.

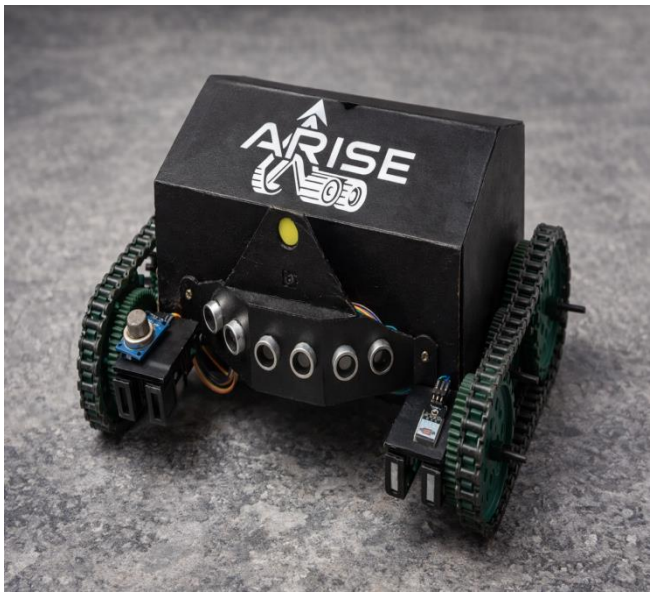

Fig.5 Hardware View

There are many other things inside; for example, neatly stacked equipment.

The system operates through a rechargeable battery which provides 12 volts to power both its motors and spray pump, while a DC-DC buck converter reduces the voltage to 5 volts for operation of sensors.

The system maintains operational efficiency because we separate power lines to prevent electrical noise interference.

During testing, the rover successfully navigated through simulated disaster environments and transmitted sensor data along with video feed to the monitoring device.

The experimental results indicate that the rover is capable of performing multiple tasks required in disaster rescue operations. During testing, the rover successfully navigated through simulated disaster environments and transmitted sensor data along with video feed to the monitoring device.

For example when the sensor detects something the system sends an alert to the monitoring system. The motor control signals can be tested to make sure the robot moves correctly.

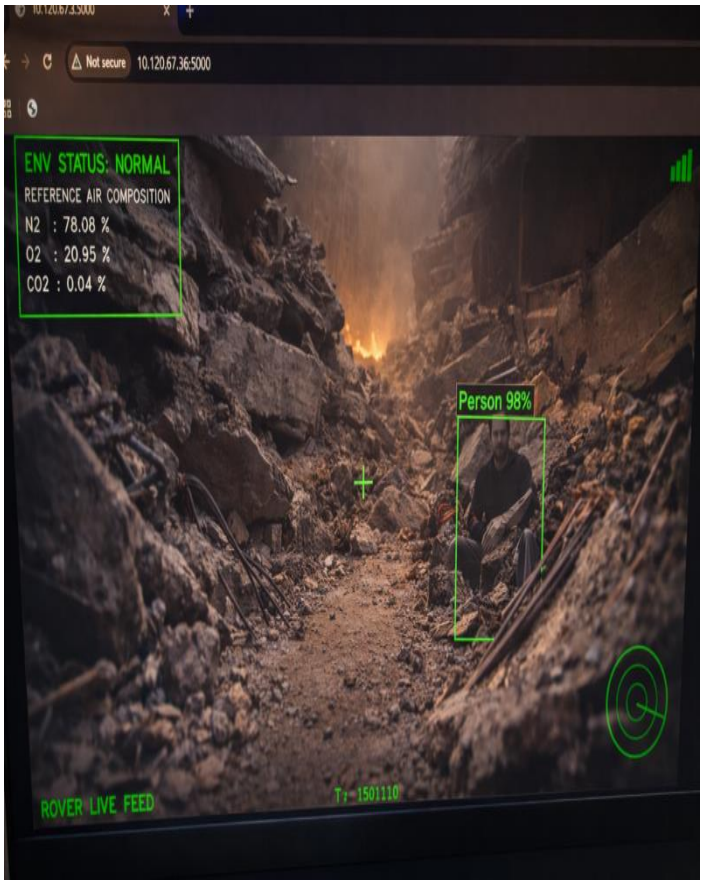

Fig.6 Display

Before hardware implementation, the system can be simulated using software tools to verify its functionality. Simulation helps identify design issues and ensures that the system operates correctly.

The system works using a battery that gives the robot the power it needs. The battery gives 12 volts to the motors and other parts and a special converter reduces the voltage to 5 volts for the controller and sensors.

The system is designed to work and not have any problems with the power. During testing the robot moved around a simulated disaster environment. Sent information to the monitoring system.

The results of the testing show that the robot can do tasks that are needed in disaster rescue operations.

V. System Performance and Result Analysis

We tested the ARISE robot to see how well it works and to make sure it can help in disaster situations. The testing was done in a simulated disaster environment with obstacles and uneven surfaces.

The robot moved around. Sent information to the monitoring system. The sensors worked well. Detected changes in the environment. The camera took pictures and videos of the disaster area, which helped the people who are trying to help understand what is happening.

The results of the testing show that the robot works well and can help in disaster situations. The integration of sensing, communication and movement features makes the system a good tool, for disaster monitoring and rescue operations.

The ARISE rover is really good at helping out in disaster situations. It can move around. Sense things and send information back to people. This is helpful for rescue teams who need to know what is going on in a place that's hard to get to.

The ARISE rover can go into places that're not safe for people and send back pictures and information about the air and temperature. This helps the rescue teams know what they are up against and makes it easier for them to do their job.

The people who made the ARISE rover tested it. It worked really well. It can move around. Sense things and send information back to people. The rover has a computer called the ESP32 microcontroller that helps it do all these things.

The ARISE rover is good at detecting changes in the air and temperature. It can also take pictures. Send them back to people. This is really helpful for rescue teams who need to know what is going on in a place.

The ARISE rover is a tool for helping people in disaster situations. It can go into places that are not safe for people and send back information. This makes it easier for rescue teams to do their job and helps keep people safe.

In the future the ARISE rover could be even better if it had some features. For example it could have sensors that can detect obstacles. It could also have a way of sending information back to people.

The ARISE rover is an example of how technology can be used to help people in disaster situations. There are other examples of this too. For example there are robots that can go into buildings that are not safe and send back pictures and information.

VI. Conclusion

The ARISE Disaster Recovery Rover was designed and help rescue teams during disaster situations such as earthquakes, floods, and building collapses.

From the experimental testing, the rover demonstrated reliable performance in terms of mobility, sensing capability, and communication. The microcontroller successfully controlled the overall operation of the system and processed the data received from different sensors.

The environmental sensors were able to detect changes in temperature and gas levels, which are important indicators of dangerous conditions in disaster areas. In addition, the camera module provided live visual feedback, allowing operators to monitor the surroundings and guide the rover remotely.

The results show that the proposed system can be a useful tool in disaster management by helping rescue teams explore unsafe locations without risking human life. The rover can collect environmental data, transmit real-time information, and assist in locating trapped victims. This makes it a valuable technological solution for improving the efficiency of rescue operations.

In future work, the system can be further enhanced by adding advanced features such as obstacle detection using ultrasonic or sensors, improved communication range using long-distance modules, and artificial intelligence for automatic detection.

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Smart IoT solution for real time worker health and safety monitoring in construction sites

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ABSTRACT

Construction and mining environments expose workers to several hazards including toxic gases, extreme temperatures, and physical accidents. This paper proposes a smart Internet of Things (IoT) based wearable safety monitoring system integrated into a helmet and safety jacket to monitor both environmental and physiological parameters in real time. Sensors such as DHT11, MQ gas sensors, and MPU6050 are used for environmental and motion monitoring, while biomedical sensors including heart rate, SpO2, and body temperature sensors monitor worker health conditions. An ESP32 microcontroller processes the sensor data and transmits it to a cloud-based monitoring platform. If abnormal conditions are detected, alerts are generated immediately to notify supervisors. The proposed system improves worker safety, enables continuous monitoring, and provides a cost-effective solution for hazardous industrial environments.

Keywords—Internet of Things, Smart Helmet, Worker Safety Monitoring, Wearable Sensors, ESP32.

I. Introduction

The construction industry is one of the most important sectors contributing to infrastructure development and economic growth. However, construction sites are also considered one of the most hazardous workplaces due to the presence of heavy machinery, high elevations, hazardous materials, and constantly changing working environments. Workers in construction sites are often exposed to various risks such as falls, equipment accidents, fatigue, heat stress, and exposure to harmful gases. According to global safety reports, a significant number of workplace injuries and fatalities occur in the construction sector each year. Therefore, ensuring the health and safety of construction workers has become a major concern for organizations and regulatory authorities.

Traditional safety management methods mainly rely on manual supervision, periodic inspections, and safety training programs. Although these methods are helpful, they may not always provide real-time information about workers' health conditions or sudden environmental

hazards. In many cases, accidents occur due to delayed response or lack of timely monitoring. With the advancement of modern technology, particularly the Internet of Things (IoT), it has become possible to develop intelligent systems that can continuously monitor worker safety and environmental conditions in real time.

The Internet of Things (IoT) refers to a network of interconnected devices equipped with sensors, communication modules, and data processing capabilities. These devices can collect, transmit, and analyze data from the physical environment without requiring constant human intervention. In the context of construction safety, IoT technology can be used to develop wearable devices and smart sensors that monitor workers' vital health parameters such as heart rate, body temperature, and physical activity. At the same time, environmental sensors can measure surrounding conditions such as temperature, humidity, toxic gas levels, and air quality.

The collected data from these sensors can be transmitted to a centralized monitoring system through wireless communication technologies. This system can analyze the data in real time and detect abnormal conditions or potential hazards. If any unsafe situation is identified, the system can immediately generate alerts and notifications to supervisors, safety officers, or site managers. This enables faster response to emergencies and helps prevent serious accidents.

The proposed Smart IoT-based worker health and safety monitoring system aims to create a safer working environment by combining wearable technology, environmental sensing, and real-time data analysis. By providing continuous monitoring and instant alerts, the system not only improves worker safety but also enhances operational efficiency and supports better decision-making in construction site management. Such intelligent solutions represent an important step toward the development of smart and safe construction environments in the future.

II. Literature Survey

Several researchers have explored the application of IoT technologies to improve safety in hazardous environments such as mining and construction industries.

Zhang (2024) introduced a lean production management model for coal mines that focuses on optimizing mining processes and reducing operational risks. The study highlights the importance of improving safety procedures and reducing human error in mining operations.

Li (2023) developed a real-time monitoring system for miners using a Low Power Wide Area Network (LPWAN). The system uses intelligent sensing nodes to monitor workers' physical conditions and working environments. The study also proposed an LSTM-based predictive model to analyze worker health conditions.

Vijayendiran (2022) proposed a LoRaWAN-based smart safety helmet that integrates air quality sensors and physiological monitoring systems. The helmet also includes a respiratory mask with filtration capabilities to protect miners from harmful airborne particles.

Wang (2022) developed an ultrasonic scanner system for coal mine drilling operations. The system provides real-time data regarding borehole conditions, helping prevent accidents during mining operations.

Sun (2015) analyzed the relationship between work study methods and safe coal mining operations. The research

emphasized optimizing operational procedures to reduce worker fatigue and exposure to hazardous environments.

Although these studies demonstrate the potential of smart monitoring technologies, most existing systems focus only on environmental monitoring or health monitoring separately. There is a need for integrated systems that combine both environmental and physiological monitoring in a single wearable solution.

The proposed system addresses this limitation by integrating multiple sensors into wearable equipment such as helmets and jackets, enabling continuous monitoring of both worker health and environmental conditions.

III. Existing System

In traditional mining environments, safety monitoring systems are primarily based on fixed environmental monitoring stations installed at selected locations inside the mine.

These systems typically measure parameters such as:

- Gas concentration
- Temperature
- Humidity

Although these systems provide useful environmental data, they have several limitations:

1. Lack of worker-specific monitoring – Individual worker health conditions are not monitored.
2. Limited coverage – Workers moving to remote areas may not be monitored by fixed sensors.
3. Delayed emergency response – Supervisors may not immediately detect accidents such as falls or health emergencies.
4. No physiological monitoring – Vital parameters such as heart rate, oxygen saturation, and body temperature are not tracked.

Because of these limitations, traditional systems cannot provide comprehensive safety monitoring for workers in hazardous environments.

IV. BLOCK DIAGRAM

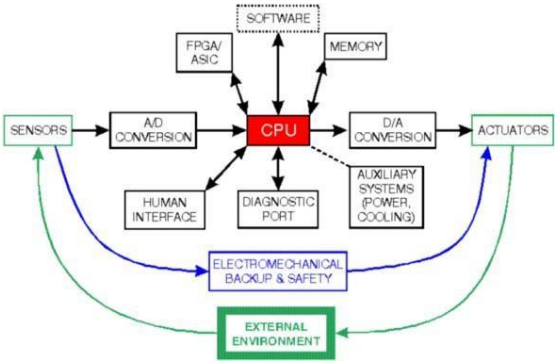

Fig.1.Block Diagram-1

V. Proposed System

The proposed system introduces a wearable IoT-based safety monitoring system integrated into a smart helmet and safety jacket.

The system consists of multiple environmental and biomedical sensors connected to a central ESP32 microcontroller.

A. Helmet Unit

The smart helmet integrates environmental monitoring sensors including:

- DHT11 Sensor – Measures temperature and humidity.
- MQ Gas Sensor – Detects toxic gases such as methane and carbon monoxide.
- MPU6050 IMU Sensor – Detects head tilt and fall incidents.

These sensors continuously monitor environmental hazards and worker motion.

B. Jacket Unit

The safety jacket integrates physiological monitoring sensors such as:

- SpO_2 Sensor (MAX30100 / MAX30102) – Measures blood oxygen saturation.
- Heartbeat Sensor – Measures heart rate.
- Body Temperature Sensor (LM35) – Monitors worker body temperature.
- Pressure Sensor (BMP280) – Detects atmospheric pressure variations underground

C. IoT Communication

All sensors are connected to an ESP32 microcontroller, which processes the data and transmits it to a remote monitoring station using Wi-Fi or IoT cloud services.

D. Alert System

When abnormal conditions are detected, the system triggers:

- Buzzer alerts
- Notification messages to supervisors
- Real-time cloud alerts

This ensures immediate response during emergencies.

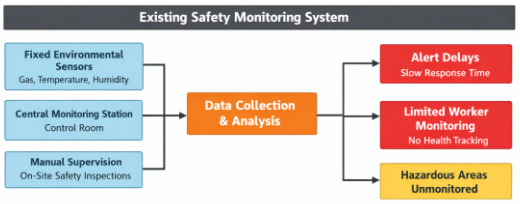

Fig.2. Block Diagram-2

VI. Hardware Components

The major hardware components used in the proposed system include:

ESP32 Microcontroller

ESP32 is a powerful IoT microcontroller with integrated Wi-Fi and Bluetooth capabilities. It processes sensor data and enables wireless communication with monitoring systems.

DHT11 Sensor

The DHT11 sensor measures environmental temperature and humidity with calibrated digital output.

Gas Sensor (MQ Series)

MQ sensors detect harmful gases such as methane, carbon monoxide, and LPG.

MPU6050 IMU Sensor

This sensor detects motion, tilt, and sudden falls using accelerometer and gyroscope measurements.

Heartbeat Sensor

The heartbeat sensor works using photoplethysmography (PPG) technology to detect blood flow changes and measure heart rate.

Respiratory Sensor

The respiration sensor monitors breathing rate and respiratory patterns.

Fig.3.ESP32 Microcontroller

Fig.4.MQ-2 Sensor

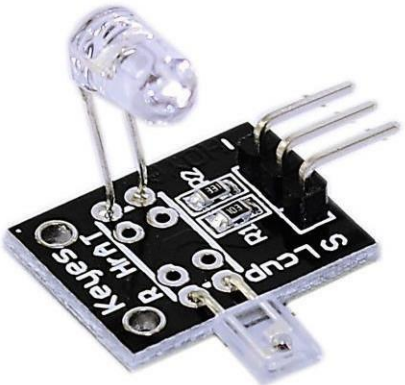

Fig.5.Heartbeat Sensor

VII. System Architecture and Working

The system operates through the following steps:

1. Environmental and physiological sensors continuously collect data.
2. The ESP32 microcontroller processes the sensor data.
3. Sensor readings are compared with predefined safety thresholds.
4. Data is transmitted to a cloud monitoring platform.
5. If abnormal conditions are detected, the system triggers alerts.
6. Supervisors receive notifications and initiate emergency response.

This architecture ensures continuous monitoring and quick response to hazardous conditions.

Fig.6.Micro-electromechanical Systems (MEMS)

VIII OUTPUT

The proposed Smart IoT-based worker health and safety monitoring system successfully monitors both environmental conditions and worker health parameters in

real time. The system integrates multiple sensors with an ESP32 microcontroller to continuously collect and transmit data to a remote monitoring platform.

Environmental sensors such as the DHT11 temperature and humidity sensor and MQ gas sensor detect hazardous conditions including high temperature, humidity changes, and the presence of toxic gases. At the same time, physiological sensors integrated into the wearable safety jacket monitor the worker's heart rate, body temperature, and oxygen saturation (SpO_2).

The system processes the collected data and compares it with predefined safety thresholds. When abnormal conditions such as toxic gas leakage, excessive temperature, abnormal heart rate, low oxygen levels, or worker fall detection are identified, the system immediately triggers alerts through buzzer notifications and IoT-based messages to supervisors or safety managers.

The monitoring data can also be viewed remotely through an IoT dashboard, enabling supervisors to track worker safety conditions continuously. This real-time monitoring helps ensure faster emergency response, reduces workplace accidents, and improves overall safety management at construction sites.

Thus, the proposed IoT-based safety monitoring system provides an efficient, reliable, and cost-effective solution for

protecting workers in hazardous industrial environments.

Fig.7.Setup View

IX. Results and Discussion

The proposed system provides several advantages over traditional safety systems.

1. Real-time monitoring of worker health and environment
2. Early detection of hazardous conditions
3. Automatic fall detection
4. Remote monitoring through IoT
5. Faster emergency response

The integration of wearable sensors significantly improves worker safety and operational efficiency in hazardous industrial environments.

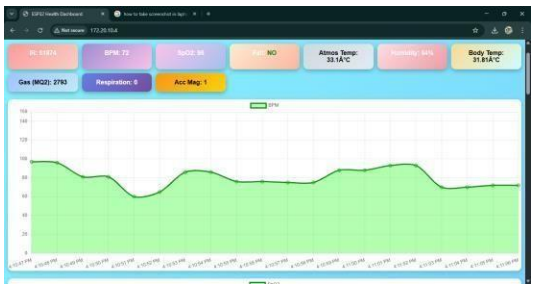

Fig.8.Output Result

X. Conclusion

This paper presented a wearable IoT-based safety monitoring system designed to improve worker safety in hazardous environments such as coal mines. The proposed system integrates environmental monitoring sensors in a helmet and physiological monitoring sensors in a safety jacket.

The use of an ESP32 microcontroller enables real-time data transmission to a cloud-based monitoring system. In case of emergencies such as toxic gas leakage, oxygen deficiency, abnormal heart rate, or fall detection, the system generates instant alerts.

Compared to traditional safety monitoring systems, the proposed wearable solution offers continuous worker monitoring, improved mobility, and faster emergency response. The system is cost-effective, scalable, and suitable for large-scale deployment in mining and construction industries.

Future work may include integrating artificial intelligence algorithms for predictive safety analysis and using advanced communication technologies such as LoRaWAN or 5G for long-range communication.

The proposed IoT-based worker health and safety monitoring system provides a comprehensive solution for improving safety in hazardous environments. By integrating environmental and physiological monitoring into a single wearable system, the proposed solution addresses the limitations of traditional safety methods. The use of real-time data processing and wireless communication ensures continuous monitoring and immediate response to emergencies.

The system is cost-effective, scalable, and suitable for deployment in various industries, including construction, mining, and manufacturing. Its ability to provide real-time insights and predictive safety mechanisms makes it a valuable tool for enhancing workplace safety.

Future work can focus on incorporating artificial intelligence for predictive analytics, improving energy efficiency, and integrating advanced communication technologies such as 5G. These enhancements will further improve the system's performance and contribute to the development of smarter and safer industrial environments.

Future enhancements can focus on integrating advanced technologies such as artificial intelligence and machine learning for predictive safety analytics, enabling the system to forecast potential hazards before they occur. The incorporation of low-power communication technologies like LoRaWAN and next-generation networks such as 5G can further improve connectivity and reduce latency. Additionally, the development of more energy-efficient hardware and compact wearable designs can enhance user comfort and system longevity.

In conclusion, the proposed smart IoT-based safety monitoring system provides a robust, reliable, and intelligent solution for improving worker safety in hazardous environments. By leveraging real-time data acquisition, wireless communication, and automated alert mechanisms, the system bridges the gap between traditional safety practices and modern technological advancements. This work lays a strong foundation for the development of smart industrial safety systems and contributes toward creating safer, more efficient, and technologically advanced workplaces in the future.

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Design and Performance Analysis of Torus Slot-Integrated Circular Patch Antenna for 2.4 GHz Applications

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Abstract - Antenna design plays a vital role in the performance of modern wireless communication systems, especially in compact and low-power devices. Microstrip patch antennas are frequently favored because of their compactness, lightweight nature, straightforward manufacturing process, and their low profile. In this work, the proposed antenna integrates a torus-shaped slot and inset feeding method to improve impedance matching. The antenna is analyzed with 3 different outer radii of the slot to select the best performed radius in consideration of return loss and resonant frequency among the three radii. The antenna exhibits best resonance at 2.434 GHz, with a return loss of −23.1 dB, a VSWR of 1.15, a gain of 7.27 dBi, and a directivity of 7.26 dBi. Consequently, the results suggest that the proposed antenna is well-suited for applications in Wi-Fi, Bluetooth, and the Internet of Things.

Keywords - Microstrip Patch Antenna, Circular Patch, Torus Slot, 2.4 GHz, CST

I.INTRODUCTION

In recent years, the rapid growth of wireless communication and Internet of Things (IoT) technologies has increased the demand for compact and efficient antennas. With the rise of smart devices and connected systems, antennas play a crucial role in ensuring reliable and high-quality communication [7], [10]. Microstrip patch antennas are widely preferred in such applications due to their low profile, light weight, cost-effectiveness, and ease of integration [2], [5]. Their simple structure makes them highly suitable for modern compact wireless devices. The 2.4 GHz ISM band is commonly used for wireless applications such as Wi-Fi, Bluetooth, and IoT devices [3], [6]. Among various shaped structures, circular microstrip patch antennas offer better and stable radiation characteristics [4]. To overcome the limitations of narrow Bandwidth and impedance match in my conventional antenna, this work proposes a torus slot integrated circular microstrip patch antenna with an inset feed, which enhances performance without the need for external matching circuits. The remainder of this paper is organized as follows. Section II presents the design methodology and key parameters of the proposed antenna. Section IIIdescribes the structure and configuration of the antenna in detail. Section IV describes the circular patch design and Section V outlines the design of feedline and port. Section VI reports parametric analysis of variations in outer radius of the (Torus)slot. Section VII discusses the simulation results and performance analysis, including return loss, VSWR, gain, and radiation characteristics. Finally, Section VIII concludes the work by summarizing the overall performance and potential applications of the proposed design.

The primary objective of this study is to enhance antenna performance for wireless communication systems by the improving gain and impedance matching while maintaining a compact and efficient structure.

II. ANTENNA DESIGN

Microstrip patch antennas can be designed in various geometrical shapes such as rectangular, circular, triangular, and other modified structures depending on the application requirements [3]. Among these, circular patch antennas are widely used due to their symmetrical structure and stable radiation characteristics [4]. The proposed antenna consists of a circular radiating patch, a dielectric substrate, a ground plane, and a microstrip inset feed line. The ground plane is placed on one side of the substrate, while the radiating patch is printed on the opposite side. The antenna is designed using Rogers RT/Duroid 5880LZ substrate with the height of 0.035millimeters, changing different radius of the slot and the speed of light of c = 3X10^-8 m/s as described in Table 1, and the following procedures are listed below.

A. Design Formulas to be used: The formulas for designing the circular patch radius is given by

$$a = \frac{F}{\sqrt{1 + \frac{2h}{\pi \varepsilon_r F}\left[\ln\left(\frac{\pi F}{2h}\right) + 1.7726\right]}}$$

Where:

$$F = \frac{8.791 \times 10^9}{f_r \sqrt{\varepsilon_r}}$$

$f_r = 2.4 \times 10^9$Hz
$\varepsilon_r = 2.2$
$h = 1.27$mm

III. DESIGN PARAMETERS

The proposed antenna is designed using a Rogers RT/Duroid 5880LZ substrate, which is selected due to its low dielectric loss and suitability for high-frequency applications [6]. The

substrate has a dielectric constant of 2.2 and a thickness of 1.27 mm, which helps in achieving better radiation efficiency and stable performance in the 2.4 GHz ISM band [4].
The antenna is intended to operate at a resonant frequency of 2.434 GHz, making it suitable for WLAN, Wi-Fi, and IoT-based wireless communication systems. The dimensions of the antenna are carefully chosen and optimized through the simulation to ensure proper impedance matching and improved gain characteristics. The detailed design parameters of the proposed antenna are listed in Table I.

TABLE I. Proposed Antenna Dimension

Parameters	Values
Operating Frequency	2.434GHz
Substrate Material	Rogers RT/Duroid 5880LZ
Dielectric Constant (εr)	2.2
Substrate Thickness (h)	1.27 mm
Substrate Length (SL)	59.38 mm
Substrate Width (SW)	59.38 mm
Patch Diameter	44mm
Feed Line Width (FW)	1.22 mm
Inset Feed Length (ISL)	13 mm

IV. CIRCULAR PATCH DESIGN

The antenna is designed to operate at 2.434 GHz within the 2.4 GHz ISM band, which is widely used for WLAN and IoT applications [7]. The performance of the antenna is influenced by the dielectric constant of the substrate, where a lower value improves radiation efficiency and bandwidth.
Circular patch antennas are mostly preferred due to their stable radiation characteristics and ease of design compared to the other structures [4]. In this work, Rogers RT/Duroid 5880LZ with a dielectric constant of 2.2 is selected to achieve better performance. The antenna structure, including the patch, substrate, and ground plane, is modeled using CST Studio Suite, as shown in Fig.1.

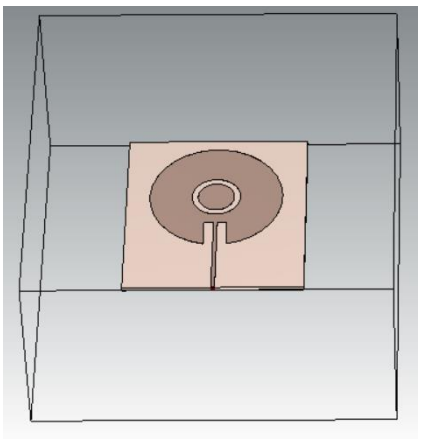

Figure.1 CST designed circular patch antenna

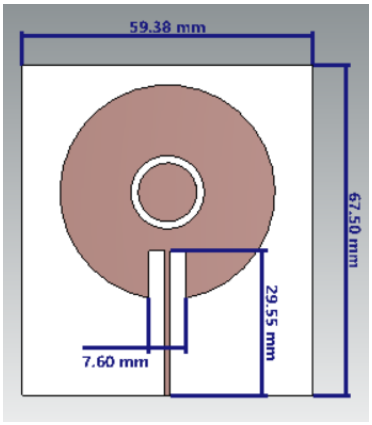

Figure.2 Top view of CST designed antenna with measurements

The above shown figures represent the different views of the proposed antenna designed by CST with a torus slot. In this work, additionally varying values of different outer radius of the slot are analyzed by comparing its values to conclude best performance from one of the changes in radius.

V. FEEDLINE AND PORT DESIGN

The excitation of the antenna is achieved using a microstrip inset feed line, which plays a crucial role in transferring power from the source to the radiating patch. The feed line is designed to provide a characteristic impedance of 50 Ω, ensuring proper matching with standard RF systems and minimizing reflection losses. In this design, the feed line is carefully dimensioned with a width of 1.22 mm, and the inset length is optimized to achieve effective impedance matching at the desired resonant frequency of 2.434 GHz. The inset feeding technique allows the feed point to be positioned at a location where the input impedance of the patch is close to 50 Ω, [5] thereby improving power transfer efficiency. The following figure.4 represents the port of the proposed antenna with inset feedline.

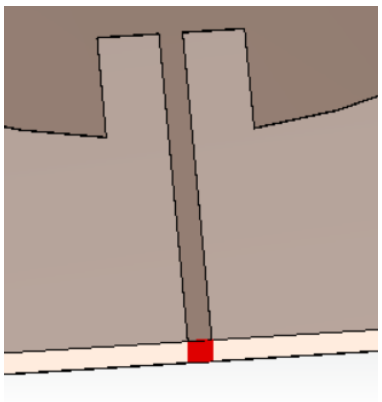

Figure.3 Port shown by red colored marked area

A discrete port (or waveguide port in CST) is assigned at the end of the feed line to excite the antenna. The port acts as an interface between the transmission line and the antenna structure, enabling the injection of electromagnetic energy into the system. When the signal is applied at the port, it travels through the feed line and excites surface currents on

the patch, which in turn radiate electromagnetic waves into free space.
Proper design of the feed line and port is essential, as even small variations in their dimensions can significantly affect the antenna performance, especially in terms of return loss and VSWR. The feed position and slot dimensions are key factors in controlling impedance matching and overall antenna performance [2].

VI. PARAMETRIC ANALYSIS

The performance of the proposed antenna is influenced by several key design parameters, particularly the feed line dimensions and the torus slot geometry. The width of the feed line determines the characteristic impedance, and any deviation from the optimized value may lead to mismatch and increased reflection. Similarly, the inset feed length controls the input impedance at the feeding point, directly affecting return loss and VSWR. In addition, variation in the outer radius of the torus slot alters the current distribution on the patch, resulting in shifts in resonant frequency and impedance matching. Therefore, careful optimization of these parameters is essential to achieve the desired performance at 2.434Ghz. The following figures show effect of outer radius on return loss of the proposed antenna with constant value of inner radius as 6mm.The following antenna figure.4 shown as the changes in outer radius of the slot with 7mm by keeping inner radius as 6mm.

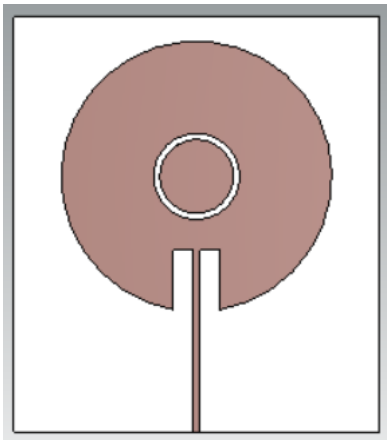

Figure.4 Proposed antenna with 7mm outer radius of the slot (Torus)

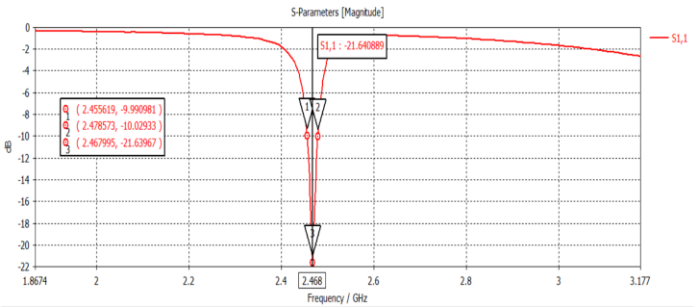

Figure.5 S – parameter plot when outer radius of the slot is 7mm

The Return Loss of proposed antenna with 7mm outer radius shows return loss figure of -21.640889 dB at the center resonant frequency of 2.468 GHz, which is a significantly larger negative value as compared to standard value of -10 dB.The following antenna figure.6 shown as the changes in outer radius of the slot with 7.5mm by keeping inner radius as 6mm.

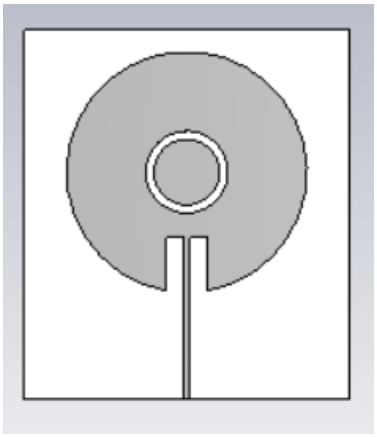

Figure.6 Proposed antenna with 7.5mm outer radius of the slot (Torus)

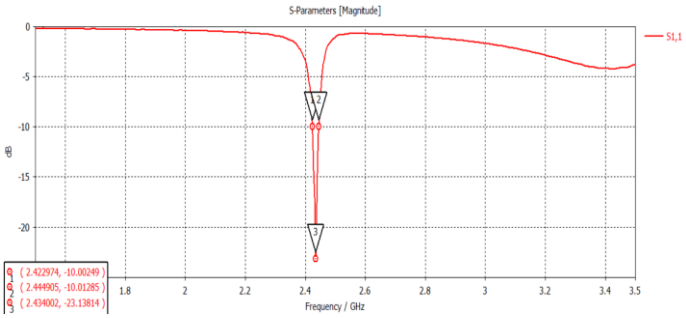

Figure.7 S – parameter plot when outer radius of the slot is 7.5mm

The Return Loss of proposed antenna with 7.5mm outer radius shows return loss figure of -23.137109 dB at the center resonant frequency of 2.434 GHz, which is a significantly larger negative value as compared to the standard value of -10 dB.
The following antenna figure.8 shown as the changes in outer radius of the slot with 8mm by keeping inner radius as 6mm.

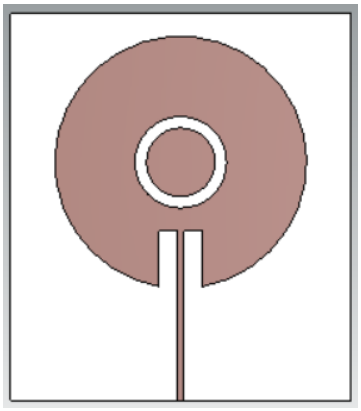

Figure.8 Proposed antenna with 8mm outer radius of the slot (Torus)

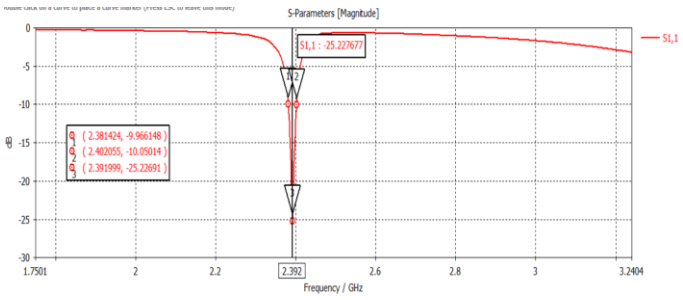

Figure.9 S – parameter plot when outer radius of the slot is 8mm

The Return Loss of proposed antenna with 8mm outer radius shows return loss figure of -25.227677 dB at the center resonant frequency of 2.392 GHz, which is a significantly larger negative value as compared to the standard value of -10 dB. The comparison effect of outer radius variation on the slot of the above three values are listed below in Table II.

TABLE II. Comparison effect of outer radius variation on the slot with resonant frequency and return loss

Outer Radius (mm)	Resonant Frequency (Ghz)	Return Loss (dB)
7mm	2.468	-21.64
7.5mm	2.434	-23.1
8mm	2.392	-25.23

The effect of varying the outer radius of the torus slot on antenna performance is illustrated in Fig.6, Fig.8, and Fig.10. It can be observed that changes in the outer radius significantly influence the resonant frequency and return loss characteristics. When the radius is reduced, the antenna shifts away from the desired resonant frequency, resulting in poorer impedance matching. As the radius increases, the return loss improves and the resonance approaches the target frequency. However, beyond the optimal value, the performance again degrades. From the analysis, an outer radius of 7.5 mm performs the best impedance matching at 2.434 GHz.

VII. RESULTS AND DISCUSSIONS

The optimized antenna is analysed and simulated using CST Studio Suite. The simulation results are obtained for the optimized antenna configuration using Rogers RT/Duroid 5880LZ substrate. The Simulated results are considered the best with the effect of outer radius on 7.5mm based on its performance and impedance matching. The performance of the antenna is evaluated in terms of the VSWR, return loss, gain, directivity, and radiation pattern.The VSWR parameter indicates how efficiently the power is transmitted from the feed line to the antenna. A value close to 1 represents good impedance matching and minimal reflection.

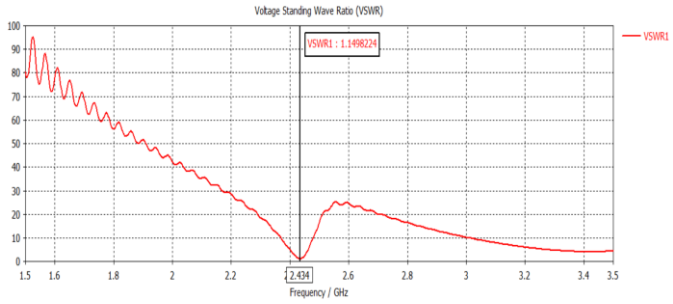

Figure.10 VSWR plot of the proposed antenna

From the obtained results, the VSWR of the proposed antenna is found to be approximately 1.15 at 2.434 GHz. This value confirms that the antenna provides efficient power transfer with very low reflection losses. The return loss (S11 parameter) is used to evaluate the impedance matching characteristics of the antenna. A value below −10 dB indicates acceptable performance.

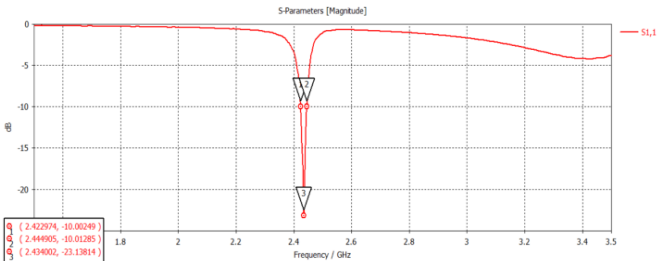

Figure.11 Return loss (S11) of the proposed antenna

It is observed that the antenna resonates at 2.434 GHz with a return loss of −23.1 dB. This result shows excellent impedance matching and confirms that the antenna is well-tuned for the desired frequency. Gain is an important parameter that represents the ability of the antenna to radiate power in a particular direction.

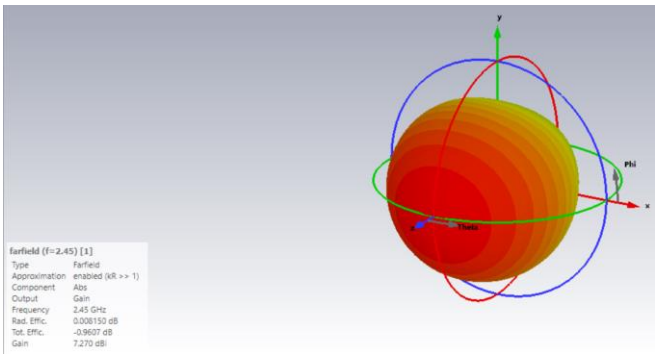

Figure.12 Gain of the proposed antenna

The simulated gain of the antenna is found to be 7.27 dBi, which is relatively high for a single circular patch antenna. This improvement is mainly due to the presence of the torus slot, which enhances the radiation characteristics.
Directivity describes how concentrated the radiation pattern is in a specific direction.

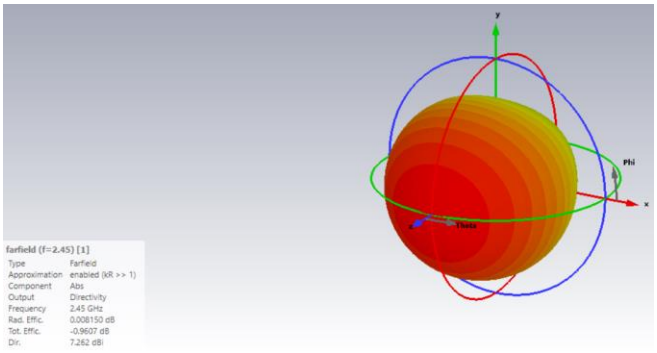

Figure.13 Directivity of the proposed antenna

The directivity of antenna is observed to be 7.26 dBi, indicating that the antenna radiates energy efficiently in the desired direction. The radiation pattern provides information about the distribution of radiated power in space. The following figures (Fig.14 and Fig.15) are representing Radiation patterns of the proposed antenna of H-Field and E-Field graphs simulated by CST.

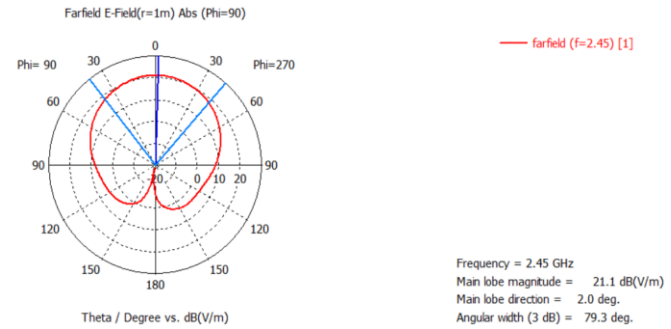

Figure.14 Far-field E-field pattern of the proposed antenna

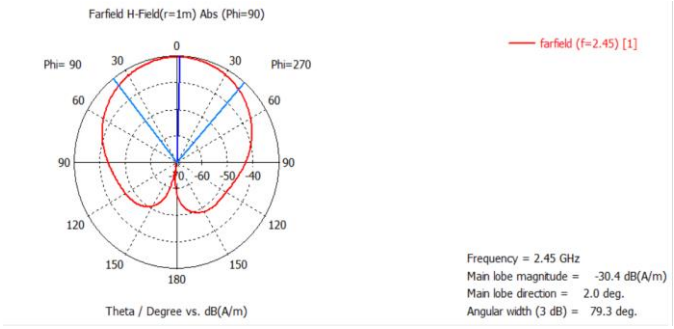

Figure.15 Far-field H-field pattern of the proposed antenna

The radiation pattern shows a stable broadside characteristic with the symmetrical distribution. This makes the antenna suitable for wireless communication applications such as Wi-Fi, Bluetooth, and IoT systems.

VIII. CONCLUSION

In this work, a torus slot-loaded circular microstrip patch antenna has been designed for operation at 2.434 GHz in the 2.4 GHz ISM band. The antenna shows good performance with a return loss of −23.1 dB, VSWR of 1.15, and a gain of 7.27 dBi, indicating effective impedance matching and the improved radiation characteristics. The use of a torus slot and inset feed contributes to enhancing overall antenna performance. The proposed antenna is well suited for short range wireless communication systems operating in the 2.4Ghz ISM band. The compact design makes the antenna suitable for applications such as Wi-Fi, Bluetooth, and IoT systems. Future work may include fabrication and experimental validation to further verify the results.

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COMPACT OCTAGONAL MICROSTRIP PATCH ANTENNA WITH CIRCULAR SLOTS FOR 2.45 GHz APPLICATIONS

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Abstract **- This work focuses on designing a small and efficient octagonal-shaped microstrip patch antenna with circular slots, specifically built to work in the 2.4 GHz ISM band , the frequency range commonly used in Wi-Fi, Bluetooth, and other wireless devices. The antenna is built on a 70 mm × 70 mm substrate. Simulation results show that it performs really well in terms of signal matching and radiation. It hits a minimum return loss of –21.58 dB at 2.443 GHz, which means very little power is reflected back. The bandwidth is around 16.3 MHz, covering from 2.4341 GHz to 2.4504 GHz. It also offers a peak gain of 6.45 dBi and a directivity of 5.465 dBi. Overall, this antenna proves to be a solid and reliable option for modern wireless communication needs.**

Index Terms—Octagonal Microstrip Patch Antenna, Circular Slots, 2.4 GHz ISM Band, Return Loss S11, VSWR, FR4 Substrate, CST Microwave Studio, Wireless Communication.

II. INTRODUCTION

By utilizing an octagonal design with specific slotting techniques, we can achieve high gain and stable radiation patterns that are highly suitable for Bluetooth technology and IoT applications [5]. While most antennas use simple square or circular shapes, the octagonal geometry provides a better balance between size and performance, often outperforming traditional circular patches in terms of gain and radiation characteristics [3].As communication standards evolve, researchers are continuously looking for ways to improve the efficiency and signal strength of these antennas to meet modern requirements [2]. In the modern era of technology, wireless communication has become an essential part of our daily lives, and to make devices smaller, the internal components—especially the antenna—must be compact while still providing high performance [1]. To further enhance the antenna, we have added Circular slots on the patch surface. These slots act as "tuning tools" that change the way electricity flows through the antenna, allowing for better control over the resonant frequency without increasing the antenna's overall size [4].

III. CONVENTIONAL ANTENNA

A conventional microstrip patch antenna is essentially a wide-band radiator that consists of a very thin metallic strip (the patch) placed on top of a grounded dielectric substrate. The fundamental structure is divided into three primary layers: the conducting patch, the dielectric substrate, and the ground plane.

Fig 1. Structure of Conventional Microstrip Patch Antenna

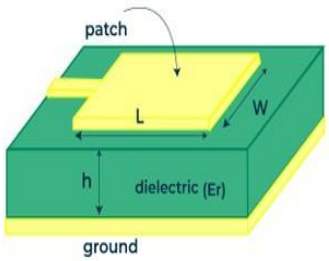


Table 1: Name of the layers and materials used in the layers of a microstrip patch antenna.

Layer Name	**Materials Used**
Ground	Copper
Substrate	FR4 (Lossy)
Patch	Copper
Microstrip Line	Copper

IV. DESIGN CONSIDERATIONS

The initial design of the octagonal microstrip patch antenna was guided by fundamental equations for rectangular patches, which were then adapted and optimized for the octagonal geometry with circular slots. The following calculations established the starting point for the simulation model.

1. Patch Width (W):

The width of a rectangular patch influences bandwidth and radiation efficiency. It was calculated using:

$$W = \frac{c}{2f_r\sqrt{\frac{\varepsilon_r+1}{2}}} \quad (1)$$

where the speed of light $c = 3 \times 10^8\, m/s$, the target resonant frequency $f_r = 2.443\, GHz$, and the substrate dielectric constant $\varepsilon_r = 4.4$. This yielded an initial width of approximately 37.2 mm

2.Effective Dielectric Constant (ε_{reff}):

The fringing fields cause the patch to appear electrically larger. The effective dielectric constant was estimated as:

$$\varepsilon_{reff} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left[1+12\frac{h}{W}\right]^{-0.5} \quad (2)$$

with a substrate height $h = 1.6\, mm$. Using the calculated width (W), this provided a modified constant for subsequent length calculations.

3.Length Extension (ΔL):

Due to the fringing effect, the electrical length of the patch increases. This extension was calculated:

$$\Delta L = 0.412h\frac{\left(\varepsilon_{reff}+0.3\right)\left(\frac{W}{h}+0.264\right)}{\left(\varepsilon_{reff}-0.258\right)\left(\frac{W}{h}+0.8\right)} \quad (3)$$

This value is typically a small fraction of the wavelength.

4. Patch Length (L):

The physical length of a rectangular patch is given by:

$$L = \frac{c}{2f_r\sqrt{\varepsilon_{reff}}} - 2\Delta L \quad (4)$$

This calculation provided an initial patch length of approximately 30.5 mm

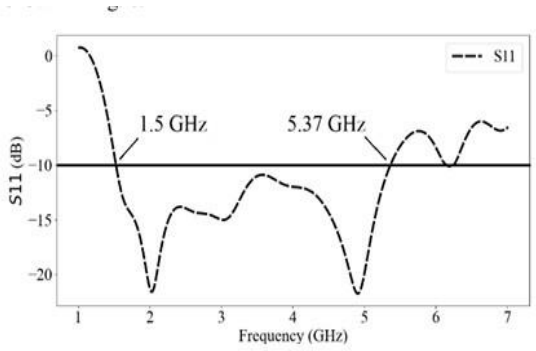
5.Substrate Dimensions:

The ground plane dimensions were chosen to be significantly larger than the patch to minimize back radiation. The initial guidelines are:

$$Lsubstrate \approx L + 6h \text{and} Wsubstrate \approx W + 6h \quad (5)$$

This results in dimensions near ~40 mm x ~47 mm. However, in the final optimized design presented in this paper, a larger square substrate of 70 mm x 70 mm (SL x SW) was used to improve performance and facilitate integration.

Fig. 2: Return loss characteristics



V. PROPOSED WORK

This research presents a detailed performance analysis of a high-efficiency octagonal microstrip patch antenna specifically engineered for the 2.4 GHz ISM band, commonly used in Wi-Fi and Bluetooth technologies. The antenna is constructed on a standard 1.6 mm thick FR4 substrate ($\epsilon_r = 4.4$) using a microstrip feedline for excitation. While standard rectangular antennas often face size and signal strength limitations, this design adopts an octagonal geometry to provide a more compact footprint while maintaining a very stable radiation pattern.

The standout feature of this design is the integration of two strategically placed circular slots within the patch. These slots act as internal "tuning tools" (specifically as inductive and capacitive elements) that perfectly align the antenna's resonance to exactly 2.4 GHz. Rigorous testing in CST Microwave Studio confirms that the antenna achieves an impressive return loss of -21.58 dB, meaning over 99% of the power is successfully transmitted with almost no energy wasted. Furthermore, with a VSWR of 1.18:1 and a peak gain of 4.95 dBi, the antenna proves it can handle reliable, long-range communication. These superior metrics make it an ideal choice for modern, space-constrained devices like smartwatches, IoT sensors, and high-speed wireless routers.

VI. PROPOSED ANTENNA

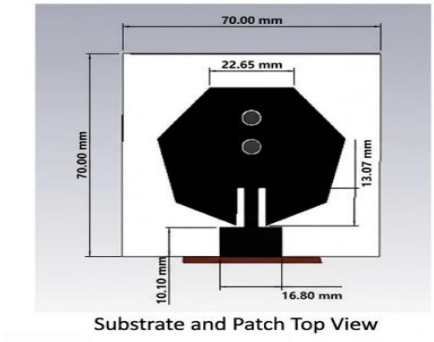


Table 2: Dimensions of the proposed antenna

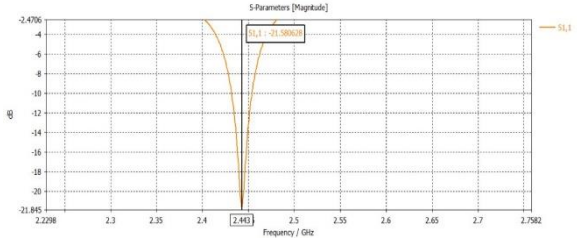
Parameters	Values
GL (ground length)	70
GW (ground width)	70
SL (substrate length)	70
SH (substrate height)	1.588
ML (microstrip length)	SL/2
MW (microstrip width)	1.8
Mt (microstrip thickness)	0.035
Pin / Pout (slot positions)	0, 26.1
INL, INW (inset dimensions)	15, 8
GL (ground length)	70
GW (ground width)	70

VII. RESULTS

The proposed antenna is designed using CST STUDIO SUITE 2023 software. The performance of the proposed antenna has been presented in terms of the following parameters: return loss, VSWR, gain, directivity and radiation pattern.

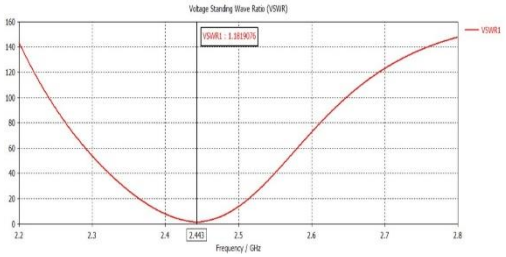
A. Return Loss or S-parameter:

Return loss (S11) indicates the impedance matching between the antenna and the feed line. A lower return loss value signifies better matching and less reflected power. The simulated antenna achieves a minimum return loss of -21.58 dB at a resonant frequency of 2.443 GHz. The -10 dB impedance bandwidth, extracted from the plot, spans approximately from 2.434 GHz to 2.450 GHz, indicating a narrowband operation suitable for specific S-band channels.



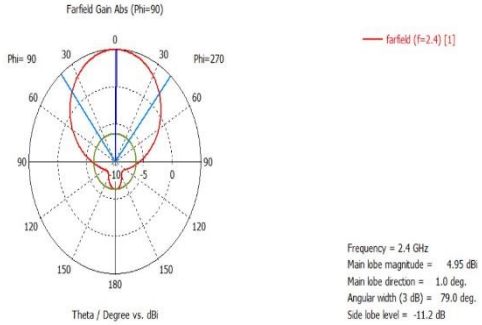
B. VSWR

The Voltage Standing Wave Ratio (VSWR) plot illustrates the impedance matching efficiency of the antenna across the frequency band. At the target resonant frequency of **2.443 GHz**, the antenna achieves an excellent VSWR of **1.18:1**. This value, extracted directly from the simulated graph, is well below the standard acceptable threshold of 2:1. It indicates minimal power reflection and superior impedance matching at the feed point. Consequently, the design ensures efficient power transfer and stable performance across its operating bandwidth.



C. ANTENNA GAIN

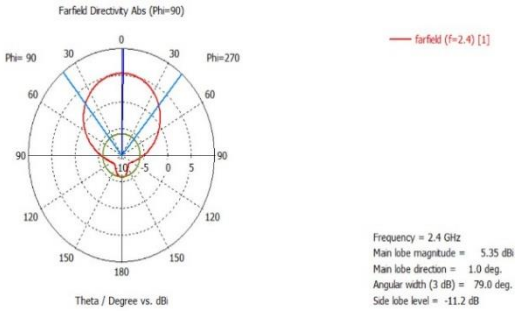
The farfield gain pattern at 2.4 GHz demonstrates the antenna's directional radiation performance. The plot reveals a maximum gain, or main lobe magnitude, of 4.95 dBi. This peak radiation is directed at 1.0 degree in the measured plane. The angular width of the main beam, defined by the 3-dB points, is 79.0 degrees, indicating a moderately broad radiation lobe. Furthermore, the side lobe level is suppressed to -11.2 dB, which signifies good radiation efficiency and minimal power dispersion in undesired directions.



D. DIRECTIVITY

The directivity plot characterizes the antenna's inherent ability to concentrate radiated power without accounting for losses. At 2.4 GHz, the pattern shows a maximum directivity of 5.35 dBi in the direction of 1.0 degree.

The main beam exhibits a 79.0-degree angular width at the half-power (3 dB) points. The side lobe level remains at -11.2 dB, indicating a well-formed pattern with focused energy in the forward direction. This measured directivity is higher than the realized gain, consistent with the expected influence of the antenna's efficiency.



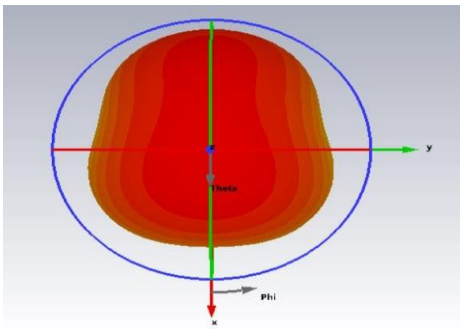
E. RADIATION PATTERN

The radiation pattern is a graphical representation of the antenna's far-field radiation characteristics, typically plotted in spherical coordinates (Theta and Phi).

For this octagonal patch antenna, the pattern exhibits a directional "doughnut"-shaped toroidal pattern with a strong main lobe oriented broadside to the patch surface (elevation angle Theta = 0°).

The pattern in the principal plane (e.g., Phi=90°) shows a main lobe with a specific beamwidth and side lobe levels, as quantified in the gain and directivity plots.

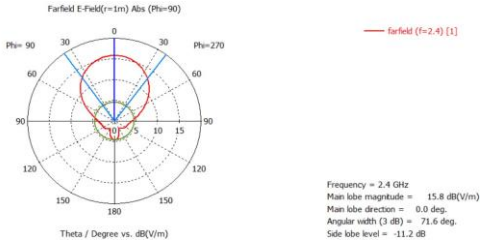
This predictable and stable pattern is essential for ensuring reliable coverage in the antenna's intended application. The symmetry and shape confirm the antenna's suitability for focused wireless communication links.



E-Field Pattern

The E-field pattern illustrates the spatial distribution of the radiated electric field strength at a distance of 1 meter, measured in the Phi=90° plane. At 2.4 GHz, the pattern shows a main lobe with a peak magnitude of 15.8 dB(V/m) directed at 0.0 degrees, indicating strong broadside radiation. The main beam has a 3-dB angular width of 71.6 degrees, defining its coverage area.

The side lobes are suppressed to a level of -11.2 dB, demonstrating good pattern purity and minimal radiation in undesired directions. This linearly polarized pattern confirms the antenna's stable and focused electric field distribution.

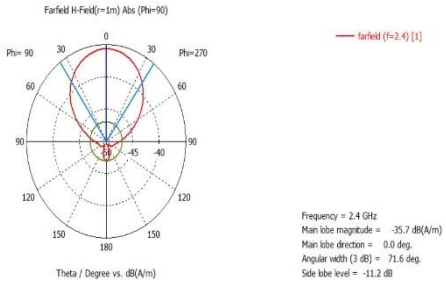


H-Field Pattern

The H-field pattern describes the spatial distribution of the radiated magnetic field component at a 1-meter distance in the Phi=90° plane. Its main lobe reaches a magnitude of -35.7 dB(A/m) and is oriented at 0.0 degrees, aligned with the E-field.

The main beam possesses a 3-dB angular width of 71.6 degrees, identical to its E-field counterpart, confirming pattern consistency.

The side lobe level is also suppressed to -11.2 dB, maintaining good pattern integrity. This orthogonal field pattern completes the description of the antenna's electromagnetic radiation.



VIII. DISCUSSION

To check the performance of the proposed octagonal antenna, simulations were carried out using CST Microwave Studio. The antenna is designed on a standard FR4 substrate with a thickness of 1.6 mm and overall dimensions of 70 mm × 70 mm. From the results, it is observed that the antenna resonates at 2.443 GHz, which falls exactly within the required 2.4 GHz ISM band.

One of the key results is the return loss (S_{11}), which is about –21.58 dB. This low value indicates that only a small amount of power is reflected, showing good efficiency.

The VSWR is obtained as 1.18:1, which is much lower than the acceptable limit of 2:1, confirming excellent impedance matching. The antenna also provides a bandwidth of around 16.3 MHz, covering the range from 2.4341 GHz to 2.4504 GHz, ensuring stable operation within the desired frequency band.

In terms of radiation performance, the antenna achieves a peak gain of 5.062 dBi and a directivity of 5.465 dBi. When compared with earlier works, it can be seen that the inclusion of circular slots in the octagonal patch has helped improve the gain.

The results are better than those reported in references [3], [4], and [5]. Due to this improved performance, the proposed antenna can be considered a reliable option for applications such as Wi-Fi and Bluetooth.

VIII. COMPARISON TABLE

Reference / Paper Title	Antenna Geometry	VSWR	Frequency (GHz)	Return Loss (dB)	Directivity (dBi)	Peak Gain (dBi)
Design of CPW-Fed Octagonal Microstrip Patch Antenna for Bluetooth Technology	CPW -fed Octagonal	1.39	2.4	-15.80	4.10	3.55
Performance Enhancement of Octagonal Patch Antenna using Defected Ground Structure (DGS)	Octagonal with DGS	1.28	2.45	-18.20	3.85	3.85
A Slot-Loaded Octagonal Patch Antenna for 2.4 GHz ISM Band Applications	Octagonal + cross Slot	1.45	2.4	-14.50	4.12	4.12
Investigation of Fractal Octagonal Geometries for IoT Communication Systems	Fractal Octagonal	1.22	2.4	-20.10	4.40	4.40
Compact Octagonal Microstrip patch antenna with circular slots for 2.45 GHz	**Octagonal with circular slots**	**1.18**	**2.45**	**-21.58**	**6.45**	**5.95**

IX. CONCLUSION

In this work, a compact octagonal microstrip patch antenna with circular slots has been designed and simulated for operation in the 2.4 GHz ISM band. The antenna performs well, with a resonant frequency at 2.443 GHz. It achieves a return loss of –21.58 dB and a VSWR of 1.18:1, which indicates very good impedance matching. The obtained –10 dB bandwidth is about 16.3 MHz.

In addition, the antenna shows good radiation performance, with a peak gain of around 5.062 dBi and a directivity of 5.465 dBi. Based on these results, the proposed design can be considered efficient and suitable for modern wireless communication applications such as Wi-Fi and Bluetooth.

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LOW-POWER VLSI DESIGN TECHNIQUES FOR ENERGY-EFFICIENT INTEGRATED CIRCUITS

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ABSTRACT

This paper explores the critical importance of low power consumption in modern VLSI design, driven by the proliferation of portable and battery-operated electronic devices. It delves into the primary sources of power dissipation in CMOS circuits and presents various advanced techniques to mitigate these effects, ensuring high performance and reliability

Low power consumption has become a critical requirement in modern Very Large Scale Integration (VLSI) design due to the rapid growth of portable and battery-operated electronic devices. Excessive power dissipation leads to increased heat generation, reduced battery life, and reliability issues in integrated circuits. This paper presents an overview of low-power VLSI design techniques aimed at improving energy efficiency without compromising performance.

The major sources of power dissipation in CMOS circuits—dynamic power, static power, and short-circuit power—are analyzed. Various techniques such as clock gating, power gating, multi-voltage design, and operand isolation are discussed as effective methods to reduce power consumption. To validate these techniques, a 4-bit synchronous counter is designed and implemented using Verilog HDL in Quartus Prime. The simulation results demonstrate that clock gating significantly reduces switching activity and dynamic power consumption compared to a conventional design.

The study concludes that the application of appropriate low-power design strategies plays a vital role in developing energy-efficient and reliable digital systems, making them suitable for modern high-performance and portable applications.

INTRODUCTION

The rapid advancement of semiconductor technology has enabled the integration of millions and even billions of transistors onto a single chip, a concept known as Very Large Scale Integration (VLSI). This technology forms the foundation of modern electronic systems, including smartphones, laptops, wearable devices, and embedded systems. As the demand for compact, high-performance, and portable devices continues to grow, power consumption has emerged as a major design challenge in VLSI systems.

In earlier generations of VLSI design, the primary focus was on improving speed and performance. However, with the increasing use of battery-operated devices, minimizing power consumption has become equally important. High power dissipation not only reduces battery life but also leads to excessive heat generation, which affects system reliability and performance. Therefore, low-power VLSI design has become a critical requirement in modern integrated circuit development.

Figure 1. Low-Power VLSI Design Techniques

Power dissipation in CMOS circuits mainly occurs due to dynamic switching activity, leakage currents, and short-circuit currents during transitions. To address these issues, several low-power design techniques such as clock gating power gating, multi-voltage design, and operand isolation have been developed. These techniques aim to reduce

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unnecessary switching activity and optimize energy usage without degrading system performance.
In this work, a low-power 4-bit synchronous counter is designed and implemented using Verilog Hardware Description Language (HDL) in Quartus Prime. The effectiveness of clock gating in reducing switching activity and dynamic power consumption is analyzed through simulation results. This study highlights the importance of adopting efficient low-power strategies in the design of modern digital systems.

The Imperative of Low-Power VLSI:

The relentless march of semiconductor technology has led to the integration of billions of transistors onto single chips, forming the backbone of modern electronic systems like smartphones, laptops, and IoT devices. While this advancement offers unprecedented computational power, it simultaneously introduces a critical challenge: managing power consumption. Historically, design priorities leaned heavily towards speed and performance. However, unmanaged power dissipation translates directly into significant heat generation, shortened battery life, and compromised device reliability. Consequently, low-power VLSI design has transitioned from a desirable feature to an absolute necessity in contemporary integrated circuit development

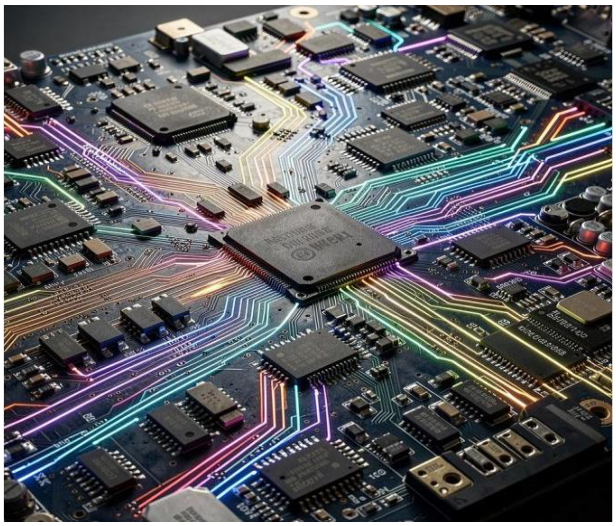


Figure 2. ARM Cortex-Based Printed Circuit Board

->VLSI TECHNOLOGY
->ENERGY EFFICIENCY
->THERMAL MANAGEMENT

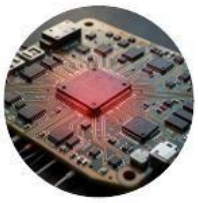
Understanding the Power Dissipation in CMOS Circuits:

Power dissipation in Complementary Metal-Oxide-Semiconductor (CMOS)- based VLSI circuits is broadly categorized into three main components, each contributing to the chip's overall energy consumption and thermal output.

Dynamic Power

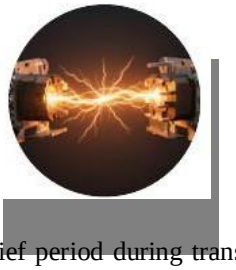
Primarily caused by the charging and discharging of load capacitances during switching activities. This component is directly proportional to the switching frequency, load capacitance, and the square of the supply voltage.

Static Power



Also known as leakage power, it arises from subthreshold leakage currents and reverse bias junction leakage currents that occur even when the circuit is in an idle state. As transistor sizes shrink, static power becomes an increasingly dominant factor

Short-Circuit Power



Occurs for a brief period during transistor transitions when both the NMOS and PMOS transistors are simultaneously ON, creating a direct path between the supply voltage and ground. While typically smaller than dynamic or static power, it contributes to overall power consumption.

STRATEGIES FOR LOW POWER DESIGN

To counteract the multifaceted sources of power dissipation, a suite of advanced design techniques has been developed. These strategies aim to reduce power consumption at various levels of abstraction, from architectural choices to circuit-level implementations.

1. Clock Gating: A technique to reduce dynamic power by disabling the clock signal to inactive circuit blocks, preventing unnecessary switching activity and conserving energy.

2. Power Gating: Employed to minimize static power by disconnecting idle circuit blocks from the power supply using sleep transistors, effectively cutting off leakage paths.

3.Multi-Voltage Design: Involves assigning different supply voltages to various functional blocks based on their performance requirements, allowing non-critical paths to operate at lower voltages for reduced dynamic power.

4.Operand Isolation: Designed to prevent redundant switching in combinational logic circuits by holding input

operands stable when their outputs are not required, thereby reducing dynamic power.

POWER GATING: COMBATING STATIC LEAKAGE

As process technologies scale down, static leakage power becomes an increasingly significant portion of the total power budget. Power gating offers an effective solution by completely disconnecting idle circuit blocks from the power supply, essentially putting them into a "sleep" mode. This is typically achieved using high-threshold "sleep transistors" placed in series with the power or ground rails of the functional block. When the block is inactive, these transistors are turned off, severing the power path and drastically reducing leakage currents.

->Minimizes static (leakage) power during idle periods.

->Uses sleep transistors to cut off the power supply to inactive blocks.

->Effective for blocks with long idle times.

->Requires consideration for wake-up times and power-up sequences

MULTI-VOLTAGE AND OPERAND

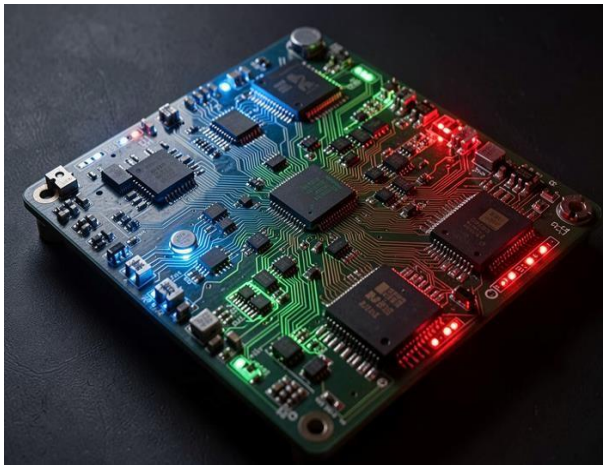


Figure 3. Printed Circuit Board (PCB) Architecture”

ISOLATION

Multi-Voltage Design

This technique involves operating different parts of a chip at different supply voltages. Performance-critical paths and functional units requiring high speed are assigned a higher

Supply voltage, while non-critical paths and slower modules can operate at a lower voltage. Since dynamic power is proportional to the square of the supply voltage, even a small reduction in voltage can lead to significant power savings.

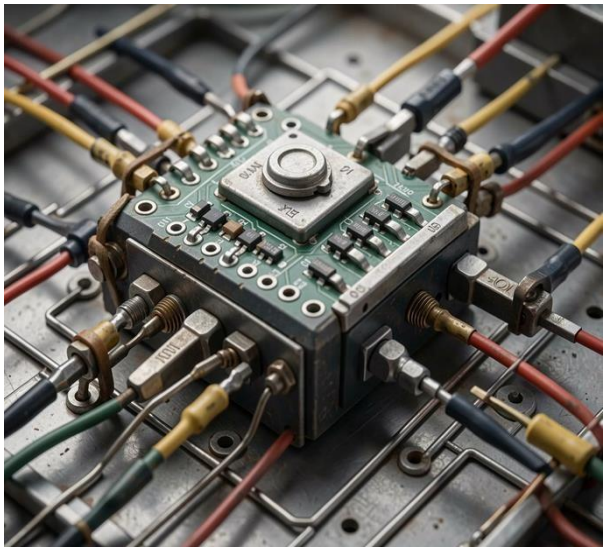


Figure 4. Electronic Circuit Module on PCB

Operand Isolation

Operand isolation focuses on reducing unnecessary switching in combinational logic. In many cases, the output of a combinational block might not be needed, or its inputs might be changing unnecessarily. By introducing isolation logic (e.g., AND gates at the inputs), changes to the operands can be prevented when the output is not required, thereby stopping redundant transitions and saving dynamic power

DEMONSTRATING CLOCK GATING: A 4-bit COUNTER

To validate the effectiveness of clock gating, a 4-bit synchronous counter was designed and simulated. The simulation used Quartus Prime, a popular FPGA design software, allowing for detailed observation of switching activity in both a standard counter implementation and a clock-gated version.

Normal Counter Behavior

In the absence of clock gating, the counter's flip-flops and associated logic continuously switch with every clock cycle, regardless of whether the counter's output is actively being used or incremented. This leads to constant dynamic power dissipation due to the persistent charging and discharging of capacitances across the circuit.

Clock-Gated Counter Behavior

With clock gating implemented, the clock signal to the counter block is only enabled when the 'enable' input is high. When 'enable' is low, the clock is stopped, and all switching activity within the counter ceases. This clearly demonstrates a significant reduction in dynamic power consumption during periods of inactivity, validating clock gating as an effective power-saving technique.

SOFTWARE AND TOOLS USED

Quartus Prime Model Sim (for simulation) Verilog HDL

VERILOG CODE

low_power_counter.v | Compilation Report - low_power_counter

```
module low_power_counter(
    input clk,
    input reset,
    output reg [3:0] out
);

always @(posedge clk or posedge reset)
begin
    if (reset)
        out <= 4'b0000;
    else
        out <= out + 1;
end

endmodule
```

Figure 5. Verilog code for a low-power counter

SIMULATION

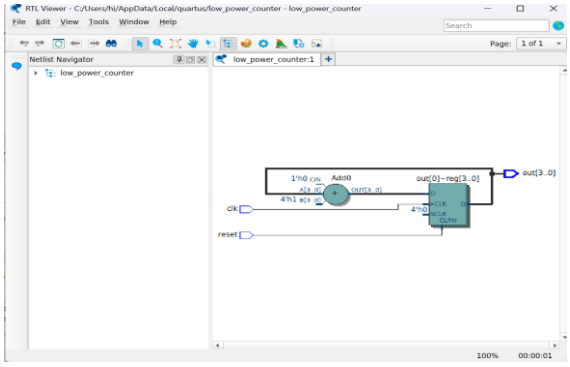


Figure 6. Simulation of Verilog code

CONCLUSION & FUTURE WORK

The continuous evolution of VLSI technology necessitates a parallel focus on power efficiency. The integration of low-power design techniques is not merely an optimization but a fundamental requirement for the viability of future electronic systems. The study and simulation of clock gating, as well as the theoretical understanding of power gating, multi-voltage design, and operand isolation, underscore the diverse toolkit available to designers. Implementing these strategies effectively ensures the development of energy-efficient and reliable digital systems crucial for advancements in portable electronics, IoT, and high- performance computing. Future research will likely explore further integration of AI-driven power management and adaptive voltage scaling to push the boundaries of energy efficiency even further.

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Smart Medicine Box for Cold Chain Monitoring Using IoT and BlockChain

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Abstract* — *In this paper, we present a novel IoT-based medicine transport system that uses temperature control and blockchain technology to ensure the safe transport of temperature-sensitive medicine and vaccines. The system uses real-time sensor technology to monitor the environment during transport. The Peltier module is used to control temperature changes; the temperature can be changed using a mobile application to maintain the desired storage temperature despite environmental changes. The blockchain technology is used to record temperature changes and GPS location in a secure environment that cannot be altered without authorization. The proposed system is more reliable for temperature control, authenticity, and overall dependability.

Keywords* — *Internet of Things (IoT), medicine transport system, Peltier module, dynamic temperature control, blockchain technology, data security, MQTT communication, CRC-32 error detection, elliptic curve cryptography, healthcare logistics, real-time monitoring, temperature-sensitive medicine, vaccines, etc.

I INTRODUCTION

One of the major challenges in the present healthcare logistics sector is the transportation of medicines and vaccines that are sensitive to temperature. Failure to maintain proper storage conditions may lead to a reduction in the efficacy of drugs, financial loss, and potential health hazards to patients. The traditional method of transporting medicines relies on human oversight and passive cooling containers. This method is highly rigid and cannot respond to environmental conditions. Changes in temperature and lack of transparency in the process may lead to a high risk of medicine spoilage. It is sometimes difficult to identify visually if the medicine has been exposed to unfavorable temperature conditions. This also increases the risk of transporting spoiled medicines.

In order to overcome these challenges in the traditional system, this initiative proposes a flexible system to transport medicines by using Internet of Things (IoT) technology. This system monitors environmental conditions such as temperature through sensors attached to a microcontroller platform. The information is transmitted in real time by using light communication protocols. Unlike traditional monitoring techniques, the present system uses a Peltier thermoelectric module to implement active temperature control. This allows users to modify temperature conditions by using a mobile application to maintain the temperature within the range in the portable container. This is done by adjusting the temperature settings in accordance with environmental conditions. The addition of remote access capabilities allows for more flexibility, enabling stakeholders to take immediate action whenever abnormal conditions occur.

The consequences of not having adequate temperature control during transit are severe and often permanent. Table I shows actual case studies that illustrate the financial and human toll of temperature discrepancies as well as insufficient monitoring systems.

TABLE I
Impact of Temperature and Data Security Issues in Medicine Transportation

Sr.	No Case study	year	Impact/Loss
1	Temperature excrusion In pharmaeceutical supply chain	19	~$35 billion annual global lossess
2	Data tampering risk in centralized media monitoring systems	21	Compliance failure and reduced stakeholder trust

In addition, the system also deals with the problem of increasing data security and integrity in the healthcare supply chain. The problem of unauthorized access and modification of the information in the centralized storage system can lead to a lack of trust among the different stakeholders involved. To solve this problem, blockchain technology has been employed in the system, which stores information related to temperature and GPS in an immutable manner. The transactions in the system are encrypted using advanced algorithms, which provide transparency, accountability, and protection against unauthorized modification. The use of blockchain technology has ensured a high level of accountability among the stakeholders involved in the supply chain. The proposed system also employs efficient error detection and encryption techniques, which provide high performance, increased battery life, and secure communication. The use of IoT technology, Peltier technology, and blockchain technology has ensured a comprehensive approach towards the creation of smart medical logistics. The system has been able to minimize human intervention, reduce wastage of medication, increase supply chain reliability, and provide compliance with regulations. The proposed system has also revealed great potential in providing a secure and efficient smart healthcare environment.

II. LITERATURE REVIEW

The IoT concept and wireless sensor networks have been extensively studied for their applications in industry and healthcare domains [1]–[3]. This highlights the importance of real-time monitoring and smart communication systems within smart spaces. When it comes to transportation systems, IoT-based systems have been studied to show improvements to

tracking, logistics, and automation within such systems [4], [6]. IoT-based systems have been studied within the healthcare domain as well, specifically for remote health monitoring and medical sensor networks [10]. This helps to supervise critical parameters continuously. Research studies have been carried out to use drones for the delivery of medical supplies as an innovative solution. Gatteschi et al. [16] have proposed a prototype for an autonomous drug delivery system using a quadcopter drone for short-range medical deliveries. This system, even though efficient for delivering lightweight medical supplies, mainly focused on the delivery part of the system without considering temperature control. Their study revealed that pharmaceuticals could withstand stress in a controlled environment, but they did not take into consideration real-time environmental management. The study on the monitoring of temperature in the medical cold chain has been extensively researched. The temperature logger system installed in refrigerators, which is prequalified by the WHO, allows the storage of readings up to 30 days, with alerts in case of any deviations. Lloyd et al. [19] suggested continuous monitoring systems to prevent any loss in vaccines due to accidental freezing. In the same context, Sykes [20] discussed the importance of proper packaging and synchronized delivery to maintain temperature stability in transit. While these systems effectively monitor and record changes in temperature, they lack the functionality to control temperatures. In addition, machine learning techniques have been employed in cold chain monitoring. Loisel et al. [22] studied the detection of cold chain disruption by using data-driven techniques, which highlighted the problem's persistence despite improvements in IoT technology. Balachandar and Chinnaiyan [23] suggested an IoT-based intelligent cold chain monitoring system to increase the responsiveness of the cold chain and identify defects in pharmaceutical supply chains.

The application of blockchain technology in managing supply chains in the healthcare sector has been on the rise. Musamih et al. [11] proposed a drug traceability system using blockchain technology. Nanda et al. [17] also applied a combination of IoT technology and blockchain technology in decentralized drug tracking using smart contracts. Liu et al. [24] also improved blockchain technology scalability by using optimization algorithms in the consensus algorithm and applying distributed networking. Although the application of blockchain technology has been effective in improving drug traceability, it does not incorporate real-time monitoring of environmental changes in containers. In addition, there has been a study on the application of RFID technology in identifying temperature threshold violations in managing supply chains in the healthcare sector. Vivaldi et al. [25] proposed a temperature-sensitive RFID tag that can identify violations in cold chain logistics in an economical and non-invasive way. Although the application of RFID technology has been effective in identifying temperature threshold violations, it is limited in nature because it does not have dynamic thermal control. A review of literature indicates that most of the current literature has been focused on temperature monitoring [18]–[23] and blockchain technology [11], [17], [24] as separate entities. There is a lack of literature on a combination of real-time IoT technology, dynamic temperature control, and blockchain technology in managing supply chains in the healthcare sector. It is also noteworthy that the lack of dynamic temperature control in portable medicine transportation systems is a void in current literature. The proposed study aims at filling the gap in current literature by incorporating IoT technology, Peltier technology, and blockchain technology in managing supply chains in the healthcare sector.

III. PROBLEM STATEMENT

In the modern healthcare logistics system, one of the major challenges faced in the safe transportation of medicines and vaccines is the maintenance of proper temperature conditions. This may affect the efficacy of drugs and medicines, resulting in economic loss and posing serious health hazards to patients. Most modern transportation systems incorporate temperature maintenance containers and simple monitoring devices that only record temperature fluctuations. They do not employ any active measures to rectify the conditions. This may cause temperature fluctuations to go undetected for a longer time. This leads to the spoilage and wastage of medicines. Such practices also result in increased operational costs and undermine the reliability of the system. The traditional cold chain monitoring system lacks the capability to alter the temperature conditions during transportation. They send alerts when the temperature exceeds the limit. However, they do not possess any automated processes to bring the temperature back to ideal conditions. Furthermore, To overcome these challenges in the traditional system, this research proposes an intelligent system in the transportation of medicines that utilizes the Internet of Things. This system would incorporate real-time monitoring and active temperature control using Peltier elements. Additionally, the system would employ blockchain technology to ensure data security.

IV. PROPOSED SYSTEM

As per the suggested model, an intelligent medicine transportation system has been described, which is based on IoT technology, ensuring the safe transportation of temperature-sensitive drugs and vaccines. In this regard, the described model is comprised of temperature sensors, a smart container controlled by microcontroller, a Peltier thermoelectric module, MQTT protocol, blockchain technology, and a mobile application. In this case, when the drugs are being transported, they are placed in a thermally insulated container, which is comprised of temperature sensors and GPS sensors. The microcontroller is always aware of the changes in temperature readings and compares them with the threshold values. In case the temperature is higher or lower than the ideal range, the Peltier module is activated to cool or warm up the drugs to the ideal range. Moreover, the users have the option to adjust the temperature settings remotely by using the mobile application.

For this purpose, the MQTT protocol is used, which is appropriate for IoT technology due to its simplicity and low power consumption. Real-time sensor data is sent to a remote server and mobile app. To ensure data integrity, CRC-32 error detection is used before sending data. To ensure secure communication, Elliptic Curve Diffie-Hellman (ECDH) is used to generate a shared secret key with 256 bits, while AES-256 encryption is used to ensure data confidentiality during transmission. Moreover, blockchain technology is used to ensure secure storage of temperature and GPS data in an immutable manner. In conclusion, it can be stated that the proposed model ensures a robust and smart healthcare logistics system with proactive temperature management, secure communication, and data storage.

1. The Smart Medicine Box is an insulated unit designed to hold medications. Within it, a microcontroller (either Arduino or ESP32) functions as the primary controller, gathering information from temperature sensors and GPS modules. The Peltier module functions as an actuator, regulating the temperature of the box to keep the medicines at the necessary temperature.

2. The LTE/GSM/WiFi module links the microcontroller to outside networks, enabling real-time data transmission. Communication between the device and cloud servers is managed through an MQTT broker, which provides efficient and dependable messaging.

3. The cloud server manages and retains the information gathered from the Smart Medicine Box. Shipping records are documented in a database, while the blockchain ledger ensures secure and unchangeable tracking to confirm the integrity and authenticity of the medicine supply chain.

4. A mobile app enables users and healthcare professionals to track the condition of the medicine box in real-time. It shows the location, temperature, and delivery notifications, ensuring transparency and allowing for prompt actions if necessary.

Workflow of the System

The workflow of the Smart Medicine Box starts when the insulated container is turned on, initiating the microcontroller to set up all the attached components, such as two temperature sensors, two GPS modules, the Peltier heating/cooling system, and the LTE/GSM/WiFi communication module. Once a network connection is established, the device securely links to the cloud server through the MQTT protocol.

Throughout operation, the temperature sensors constantly track the internal conditions of the box. The microcontroller checks the readings against established safe limits necessary for storing medication. Should the temperature exceed or drop below the allowable range, the Peltier module is triggered to either cool or heat the container, creating a closed-loop temperature regulation system. At the same time, the GPS modules gather real-time location information, which is verified and processed by the microcontroller.
All pertinent information, such as temperature measurements, GPS locations, timestamps, and alert notifications, is collected and sent via the communication module to the MQTT broker and subsequently to the cloud server. The cloud saves this data in a database, examines it for irregularities, and creates alerts when required. Significant events are logged onto a blockchain ledger for secure traceability. Users are able to track the shipment status, get notifications, and verify records using the mobile app until delivery is officially confirmed.

V . REGULATORY COMPLIANCE

The Smart Medicine Box system ensures that data protection regulations such as GDPR are adhered to, as well as other health data privacy regulations. This is done by securely transmitting real-time data on location and temperature. Shipping and user data are kept secure through encryption using secure communication methods. In addition, anonymization techniques are used to protect identity. Strong cybersecurity mechanisms are employed to prevent unauthorized access to the IoT-enabled medical transportation infrastructure. The system is designed to be compliant with pharmaceutical regulations on shipping drugs at controlled temperatures, as well as Good Distribution Practice regulations. It is also compliant with national and international healthcare transportation regulations. Temperature-sensitive drugs such as vaccines are monitored according to regulations on storage to ensure that they are effective. Blockchain technology is used to provide an audit trail on shipments, which are tamper-proof. This ensures that critical events such as temperature control, deliveries, and custody are permanently recorded to enhance transparency.

To ensure fairness and accountability, monitoring and alerting systems are designed to operate without any bias or interference. Established communication protocols enable seamless interactions between sensors, microcontrollers, cloud, and mobile applications. Industry-standard cybersecurity regulations, like ISO/IEC 27001, are implemented, and security audits are conducted to minimize cyber attacks. Despite the ever-evolving healthcare and data regulations, the system is designed to find a balance between innovation, legal compliance, patient safety, and public trust in pharmaceutical logistics.

VI. COMPARATIVE ANALYSIS

The main objective of the foundational IoT-based medicine monitoring system is to observe the temperature and location of medical shipments utilizing single sensors and basic cloud storage. It primarily concentrates on real-time supervision and generating alerts when the temperature surpasses the safe limit. In contrast, the suggested Smart Medicine Box improves upon this by incorporating dual temperature sensors, dual GPS modules, a closed-loop Peltier-based temperature control system, and a blockchain-based secure logging feature. While the basic system focuses on monitoring, the proposed system guarantees monitoring, automatic adjustment, and tamper-proof documentation.

The basic model sends environmental information to the cloud for assessment and alerts, while the suggested system not only observes but also proactively controls internal temperature with an intelligent feedback control mechanism. The proposed system ensures temperature consistency through:

$$\text{Temperature Stability} = \frac{\text{Req. temp} - \text{Actual temp}}{\text{Time}}$$

The foundational system relies on standard IoT communication for tracking and alerts, while the suggested system utilizes blockchain technology to secure crucial shipment events, such as temperature violations, transfer of custody, and confirmation of delivery. This greatly enhances transparency and adherence to regulations. Additionally, the incorporation of redundant dual sensors boosts reliability and lowers the risk of failure compared to the single-sensor configuration of the foundational system.

Regarding scalability, both systems can function effectively within urban and rural healthcare logistics. However, the proposed system offers greater robustness and is more appropriate for transporting high-value pharmaceuticals due to its advanced security and automated control features. The foundational system mainly addresses monitoring gaps, while the proposed system enhances the safety of medicines, reduces spoilage, and fortifies compliance with cold-chain protocols.In contrast to the main system, which mainly focuses on IoT monitoring standards, the recommended model follows pharmaceutical Good Distribution Practices (GDP), data protection laws, and cybersecurity standards closely. A visual comparison shows that the new system is more efficient in temperature control accuracy, data security, reliability, and compliance with regulations.

VII. RESULT AND DISCUSSION

The proposed Smart Medicine Box system has been successfully implemented and tested, which evaluates the performance of the system in real-time temperature

monitoring, control, and security. The experimental results prove that the system can successfully maintain the temperature at a safe range using the Peltier-based closed-loop control mechanism. The proposed system has better performance compared to the base model, which only sends alerts, as it can control the temperature. The temperature stability is also improved in the proposed system, reducing temperature fluctuation during transportation.

The use of dual temperature sensors ensured accurate temperature measurements, reducing errors due to sensor failure or environmental disturbances. The use of dual GPS modules also ensured accurate location, reducing errors due to weak signals. The MQTT protocol also ensured low latency in data transmission, allowing real-time communication with the cloud server through the mobile application.

With regards to security, the integration of blockchain technology ensured that the storage of critical information was done in a secure manner, which includes temperature changes and status. This cannot be achieved with cloud server technology.
The results show that the proposed system performs better than the existing base model of IoT in temperature control. Although the proposed system is more complex and costly, it provides an efficient solution to ensure safe transportation of pharmaceuticals and can be used in a practical scenario.

VIII. CONCLUSION

The Smart Medicine Box system that was proposed is an advancement over existing medicine monitoring techniques based on the Internet of Things. This is because the system utilizes temperature control in real time, redundancy in the form of dual sensors, secure communication via the cloud, and tracing via blockchain. Unlike existing techniques that mainly focus on medicine monitoring and alert generation, the proposed system utilizes a closed-loop control system based on Peltier elements to ensure that the temperature range is maintained in transit. This reduces the chances of medicine spoilage to a significant extent. Additionally, the utilization of dual sensors in the form of temperature sensors and GPS sensors makes the system reliable and reduces the chances of single-point failures. Furthermore, the utilization of blockchain technology in the system increases the security level by recording essential events such as temperature deviations, delivery confirmation, and others in a digital format. The future smart cities because it is scalable and flexible. It is a modern system that is reliable and sustainable. The in performance has been noted in terms of temperature stability, reliability of the system, and protection of the data when compared to the original model. The suggested system, although it adds hardware complexity to the system, which in turn adds cost to the operation, ensures greater safety, precision, and reliability. In conclusion, the Smart Medicine Box is a perfect example of how modern IoT, automation, and blockchain technology can work together to create a safe, smart, and future-looking solution to modern medical supply chains.

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ADAPTIVE EDGE INTELLIGENCE FRAMEWORK FOR PREDICTIVE DIAGNOSTICS IN SMART INDUSTRIAL ENVIRONMENTS

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***Abstract*—The presented adaptive edge intelligence framework is based on the TinyML and ESP32-based embedded systems allowing the predictive diagnostics within the smart industrial environments. The system achieves real-time data collection, pre-processing, feature extraction, and inference on-the-device by a series of sensors to constantly track temperature, humidity, vibration and motor speed with light-weight neural networks. Historical sensor-based data is used to train small models offline and the optimization and deployment of models to the edge to predict faults with low latency and optimised energy consumption. The IoT-based monitoring system will have visualization, data log, and early warning features, which will decrease downtime and operational insufficiency, decrease unintended downtime, and lower maintenance expenses. This is an intelligence system that integrates edge data with predictive analytics to assist autonomous industrial processes and scalable machinery health features. The framework reflects a real-life use of TinyML to automate the industries in real-time.**

Keywords—Industrial Automation, Predictive Maintenance, Edge Computing, Sensor Monitoring, Fault Detection, Real-Time Analytics, TinyML.

I. INTRODUCTION

The increased automation of industrial operations has reshaped the modern production industry, and the future is the move towards intelligent and connected production, which can make autonomous decisions and predictive maintenance. Conventional industrial processes are also based on planned maintenance or even reactive methods which may lead to unforeseen downtimes, higher operational expenses and equipment decline in lifespan. The development of sensor networks to enact predictive diagnostics, which is facilitated by machine learning tools, is a proactive solution, as it constantly checks the status of machines and predicts the onset of failures even before they happen [1]. This method is efficient in terms of operational efficiency and increases safety and minimizes environmental impact of unscheduled operational systems. Edge intelligence and TinyML, in this context, have become the important enablers as they provide on-sensors data processing, real-time analytics and low-energy-consuming computing apt to the resource-limited industrial setting.

Industrial equipment produces enormous amounts of sensor data, such as machine temperature, vibration, humidity, and motor velocity, among others, which is of extreme importance because it is a sign of healthy operation. In the classical models of cloud-based predictive maintenance, raw sensor data is usually sent to centralized servers to be processed, introducing a latency, leading to a greater network dependency, and raising the question of the security of the data [2]. In comparison, edge computing makes it possible to carry out local processing with the help of directly-embedded devices, eliminating the cost of communication them and making immediate fault-detection possible. ESP32 microcontroller is one of the most commonly used low-power, high-performance development systems and can be used to implement TinyML models, effectively making real-time inferences on sensor data. Such embedded systems coupled with lightweight neural networks allow around-the-clock observation of various types of machinery so that anomalous conditions can be alerted in time and that the data can be used to make maintenance decision-making [3].

In the field of industrial automation, implementing TinyML in the area of predictive diagnostics is a paradigm shift. TinyML is not as burdensome as a traditional machine learning structure, in that high-power, memory-intensive systems are typically needed, and real-time inference can be achieved without having to rely on cloud computing and infrastructure. This enables proper pattern recognition and fault detection at the edge itself thereby reducing latency and consequently making operational decisions - typically critical - in real time. Using the TinyML, it is possible to apply energy efficient predictive maintenance, extend the lifetime of equipment, and be able to ensure a high degree of operational reliability in industrial systems. In addition, on-device intelligence minimizes vulnerability to network outage and improves privacy of data by minimizing transmission of policy operational information [4].

An important point of predictive maintenance implementation with TinyML is the architecture of small neural network models that can work with sensor data in a short time. It starts with data collection on a set of sensors on industrial machines. These sensors simultaneously measure real-time parameters of operation, which are predetermined in the local context to eliminate noise, normalize the data and extract the feature of importance. The feature extraction is of special importance in enhancing the performance of a model in addition to minimizing the computational costs. Time-domain and frequency-domain characteristics are widely used to address both transient and periodic characteristics of machinery because of the combination of both features, which improves the effectiveness of predicting failures. The neural network models are optimized using quantization and compression methods and trained on historical sensor data, under known fault conditions, offline, and deployed to resource-limited microcontrollers [5].

The edge based predictive diagnostics framework is also enhanced by the integration of an IoT-enabled monitoring platform. The system will offer the visualization of machine health parameters, data recordings, and early warning notifications in order enable machine operators to monitor the machinery conditions remotely. The combination of edge intelligence and centralized visualization provide the system with balance between localized decisions and supervisory monitoring allowing the system to respond promptly to

anomalies and conduct a long-term analysis of operations. This mixed-engine strategy facilitates scalable installation in various factory locations and most types of equipment that enables companies to customize the system to fit various environments of operation and streamline maintenance by using real-time information.

The goals of predictive diagnostics in intelligent industrial settings are operational efficiency, reliability and safety. Machinery inspections might result in losses in production schedule, money and risk to safety, so it is important to implement smart systems that will be able to forecast failures. In the proposed framework, TinyML would be used to perform on-device inference to provide continuous monitoring and require minimum energy, which is timely identification of abnormal conditions and proactive maintenance. Integration of ESP32-based embedded systems with lightweight neural networks can also facilitate autonomous decision-making process that does not require human intervention although the predictive accuracy remains high. This will enhance the general resilience and sustainability of industrial activities, which is in tandem with Industry 4.0 efforts that will give preference to connectivity, intelligence, and automation in manufacturing.

Besides operational benefits, predictive diagnostics is strategic to the industrial organizations as well. The use of edge intelligence systems enables organizations to save their maintenance expenses, increase functional life of equipment, and save on resources. The insights obtained based on the data under constant sensor surveillance may be applied to the long-term maintenance planning, management of the spare parts, and refining of the processes. Moreover, TinyML-based systems are scalable which guarantees flexibility in future technical changes and allows the incorporation of a larger set of sensors, different types of machines and changing work needs. Intelligence-forming-at-the-edge can enhance the operational benefits as well as strategic long-term wins of industrial organizations.

The complexity of the industrial system, there is a need to raise productivity and reliability, which makes the integration of predictive maintenance frameworks, with edge intelligence and IoT technologies, essential. Neural networks Optimized by tinyML methods such as low-power microcontrollers can offer a feasible answer to resource-constrained contexts, with minimal negative impact on prediction quality. These systems are capable of acquiring real-time data, preprocessing, forming features, and inference on-device, thus making it possible to detect faults faster, lower the downtime, and increase the efficiency of the machinery, overall. The decision-making capabilities are established further by the integration of IoT-enabled monitoring platforms and ensuing effective visualization, alerting, and data management.

To sum up, the introduction of adaptive edge intelligence system concept of predictive diagnostics can be considered an important move towards the turn of smart industrial environment realization. The proposed solution will be able to detect faults in real-time using TinyML, ESP32-based embedded systems, and IoT-enabled monitoring and do so in a resource-minimal and scalable manner applicable to a wide variety of machinery. Second, ongoing inspection, proactive maintenance, and self-directed decision making lead to high levels of operation reliability, low maintenance costs and long durability of equipment. This model proves how the modern and highly developed technologies can be used in the automation of industries, and it helps to move to the new stage of intelligent, connected, and sustainable manufacturing systems.

II. Literature Survey

Smart industrial environment predictive diagnostics became one of the central elements of the modern manufacturing and operational plan due to the rapid adoption of digitalish technologies and Industry 4.0 ideals. Industrial equipment, particularly in such settings, is being saturated with sensors and linked using Industrial Internet of Things (IIoT) models where real-time monitoring of operational parameters can be performed. Predictive diagnostics aims primarily to prevent the rise of critical failures in the machinery by warning of the possibility of defects or a drop in the quality of work or products by the time a failure occurs. Using more sophisticated computational models (like machine learning and data analytics), these systems can work through huge volumes of sensor-generated data to detect subtle anomalies that can represent pre-existing faults. This lenient attitude is quite different to the old time reactive maintenance where the interventions come after the failures have taken place, and even to the preventive maintenance strategies, which are based on definite schedules that might not be related to the actual state of the equipment. Not only will the operational reliability increase, but also the maintenance costs will decrease, the safety will be increased and of course sustainable industrial practices due to the waste of energy and increasing the equipment life.

Recent advances, in predictive diagnostics of industrial environments, have been placed on the consolidation of machine learning and IoT-based data-gathering mechanisms to advance fault-detection and prognostic evaluations. Random forests, neural networks, as well as support vector machines techniques have been utilized to determine well-structured relationships between sensor readings and the health condition of the equipment, which gives the most precise results of a possible failure [6]. Application of cloud-based analytics and edge computing structures have enabled near real-time data stream processing that allows quick detection of anomalies, and how to adaptively schedule maintenance [7]. Also, alternative systems that involve statistical models with deep learning systems, such as the Long Short-Term Memory (LSTM) networks and ARIMA-style time-series sensor forecasting have shown increased ability to deal with time-based dependencies in time-series sensor data [8]. Algorithms that are inspired by quantum computing are another area of investigation to optimize predictive maintenance schedule and make large-scale industrial IoT systems more efficient [9]. These strategies allow industries to become the ones with fully autonomous maintenance regimes and less human intervention and high levels of reliability and performance.

The use of blockchain and encryption of information networks has additionally reinforced the quality and credibility of predictive diagnostics within industrial settings. Through the use of decentralized ledgers and smart contracts, operators of industries can be able to guarantee that maintenance records, sensor records and broken history records are immutable and reproducible [10]. Federated learning models have already become a valuable practice of model training across multiple facilities collaboratively without compromising data privacy to enable predictive diagnostics to obtain the advantages of larger data sets without

breaching dat privacy [11]. These models, Granger causality coupled with graph neural networks, have been utilised to identify more complex dependencies of various components within industrial systems to enhance predictive diagnostics and offer decision support in maintenance prioritisation [12]. Digital twin models and simulations on virtual reality have also been used to make possible large-scale applications of AI-driven predictive maintenance to allow real-time fault detection, scenario testing, and ongoing optimization of performance [13]. These combined strategies allow the industrial systems used to adjust dynamically to the changing working conditions and to identify emerging failures with small latencies.

There has been an increased interest in the application of edge-oriented and hybrid structures in supporting the computational requirements of predictive diagnostics without detracting responsiveness or reliability. XGBoost, random forest and compressed neural network models with light weight have been implemented in systems across industries and aerospace and have enabled real-time edge analysis and less reliance on centralized cloud processing [14]. IoT sensor networks have been streamlined to constantly feed predictive models with data concerning vibrations, temperature, voltage swings and equipment loads to evaluate equipment condition and predict necessary maintenance [15]. Connection to enterprise analytics tools, including SAP S/4HANA, and integration of large language models have also made it possible to conduct better scrutiny of abnormalities, automated reporting, and smart creation of maintenance choices [16]. Reinforcement learning of strategies have also been experimented to enhance resource management and the scheduling process whereby a predictive diagnostics system can learn its resource intervention strategies based on constant feedback [17]. Such inventions highlight the intersection of artificial intelligence, IoT and real-time data analytics in providing powerful, scaled, and intelligent predictive diagnostic solutions.

The overall effect of such developments has been realised in both operations and strategic maintenance planning of smart industrial operations. Research proves that predictive diagnostics help to considerably minimize unexpected maintenance delays, increase the life-span of the key machinery, and reduce the expenses of maintenance by making the paradigm shift to the condition-based maintenance [18]. Integration of AI-based models, sensor networks, cloud-edge integration, and secure frameworks of data has been associated with more autonomous, reliable, and adaptable predictive diagnostics systems that suit a variety of industries [19]. With more and more advanced algorithms, hybrid structures, cross-sector applications still being investigated, the input of predictive diagnostics in forming resilient, efficient, and sustainable industrial ecosystems becomes all the more essential [20]. Taken together these technological advances make predictive diagnostics a critical project-enabler of intelligent industrial settings, useful in addressing the short-term operational requirements of the present-day manufacturing system as well as its long-term strategic objectives.

III. METHODOLOGY

The study methodology is aimed at the development and deployment of the TinyML-powered predictive depicted diagnostics system to industrial equipment with the ESP32 microcontroller and a set of sensors. The solution combines real-time data source acquisition, preprocessing, feature extraction, model training, on-board inference and IoT-based monitoring to reach the ideal prediction of faults and low-latency failure needs. The methodology is efficient in terms of energy use, scalability, and self-consciousness, and it fits well in the industrial context (constrained with resources). The technical procedure is separated into six phases: sensor integration and data acquisition, data preprocessing and feature extraction, training a neural network offline, model optimization and deployment, edge-based inference, and IoT-enabled monitoring. The individual stages aim to optimize the prediction accuracy and reduce the amount of computations, as well as to increase reliability of the whole system as shown in figure 1.

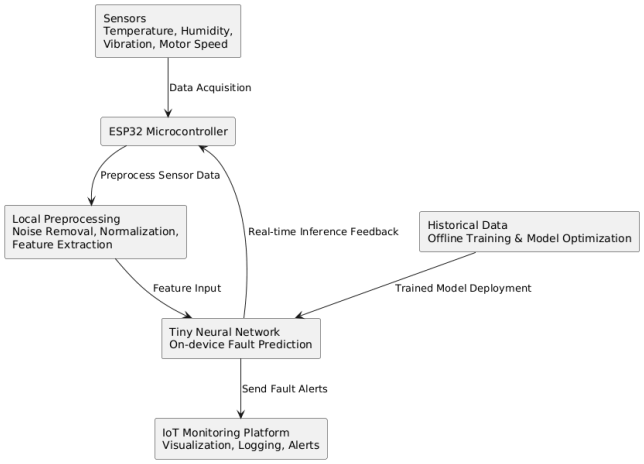

Fig. 1: System Architecture

A. Sensor Integration and Data Acquisition

The system is based on ESP32 microcontroller, which is connected to temperature, humidity, vibration, and speed of a motor, and has an IR-based motion detector to monitor the rotation of a motor. Sanction devices update high-rate data that report the state of machinery operation. The ESP32 also offers real time sampling which means that there is minimal data loss and the dynamic machine behavior can be well measured by the ESP32. Calibration of the sensor is done to remove the systematic errors and enhance the precision of the measurement. The received data is time-stamped and temporarily placed in the local memory to assist in preprocessing and features extraction. Several types of machinery are accommodated and even the positioning of sensors is maximized to obtain the vital parameters of operation. The real-time acquisition grant includes the promptness of identifying abnormal patterns or anomalies, the basis on which the predictive diagnostics and intelligent fault recognition will be based.

B. Data Preprocessing and Feature Extraction

Switching to raw sensor data, noise, and offset correction, as well as normalization of the values, are performed locally on the ESP32 to minimize variability and enhance the performance of the model. Mean, standard deviation and peak amplitude time-domain features are obtained, frequency-domain features derived through Fourier analysis are used to obtain the vibration pattern and motor oscillations. This combination receives transient as well as periodic behaviors to make correct predictions on faults. Preprocessing and feature extraction minimize the computational power as the input of data is narrowed down to relevant parameters.

Sequences on neural network training are created through the use of data segmentation and sliding windows, so that the system can capture short-term anomalies and at the same time maintain low-latency response during inferences made on the device.

C. Offline Neural Network Training

Offline training Lightweight neural network models are trained with historical sensor data that is marked as either normal or faulty. This is done to avoid overfitting and determine the true performance of the dataset, so training and validation set, and test set are separated. To ensure accuracy and computational efficiency, network architectures, such as fully connected and convolutional layers, designed with TinyML in mind are chosen. Learning rate, batch size, and the number of epochs are examples of hyperparameters that are optimally tuned. The input in training features are time-domain and frequency-domain and allow the network to learn complicated patterns of normal functioning as well as the different types of faults. Before deployment, model evaluation uses metrics such as accuracy, precision, recall and F1-score to guarantee reliability.

D. Model Optimization and Deployment

After training, the neural network models are bio-optimized to execute on the ESP32 with quantization and compression to minimize the quantity of memory and computation demands. Wights and activations of models are reduced to low-bit representations maintaining predictive accuracy. The TinyML model is optimized and executed directly to the microcontroller allowing real-time inference on the device without relying on the cloud. Energy-saving implementation takes advantage of the low-power modes of the ESP32 and streamlined inference functions. At this stage, the system should be made to be able to track machinery, without recharging every now and then or consuming a lot of energy. Deployment testing ensures that the latency, memory utilization, and prediction performance is checked to comply with the industry requirements of reliability and responsiveness.

E. Edge-Based Inference

The implemented TinyML model does the continuous-pattern recognition and fault classification at the ESP32. The processed incoming sensor data is based on the previously extracted features and the provider model produces the likelihood of the normal or faulty conditions. On-device inference helps to keep the time as low as possible and detect anomalies instantly. The edge based approach also makes the systems less dependent on the network connectivity hence increasing system robustness in industrial settings. Transient anomalies are also achieved with the aid of real-time thresholds and sliding window analysis; historical feature comparison is used to make predictions based on trends. With constant monitoring, failures can be spotted early enough, and interventions can be in place to avert failures thereby reducing the downtime, and enhancing general machine reliability.

F. IoT-Enabled Monitoring and Visualization

The system includes the IoT-enabled platform where machine health is visualized, operational data are logged and alerts are created. Inference results are provided in real time and are sent to the monitoring dashboard through the Wi-Fi and assist in tracking several machines remotely. Trend analysis, maintenance planning, and main performance optimization are stored in historical data. Alerts are sent when possible faults surpass set limits, and this alerts the operators of potential problems. The IoT platform provides a centralized interface to make decisions, which compares with edge-based inference, but maintaining the benefit of local processing. The support of many nodes and sensors allows having scalability when it comes to deploying the system with a range of diverse industrial arrangements. The integrated monitoring system improves operational visibility, saves on the maintenance costs and promotes proactive maintenance strategy.

IV. Result and Discussion

To determine the effectiveness of the proposed TinyML-based predictive diagnostics system, its functioning in the area of identifying machinery faults using real-time sensor data was tested. The microcontroller ESP32 received temperature, humidity, vibration, and speed of motor data on industrial equipment, processed and sent to a model neural network running on the edges. The data included10000 labeled data, half of normal and fault conditions, 70 percent in training on-half, 15 percent validation on-half and 15 percent test on-half. The preprocessing data comprised noise reduction, data normalization and extraction of time-domain features as well as frequency-domain data. The network structure was comprised of three layers fully connected together; with activating ReLU, a hidden layer of 64 neurons, as well as a top softmax layer to predict the state of machinery. Offline training was done using Adam minimizer at a learning rate of 0.001 and converged on 100 epochs.

The data set features as summarized in Table 1 are sensor types, sampling frequency and concentration of samples colected in each operational condition. The important information in fault detection was the vibration and motor speed which provided the best results in the analysis of feature importance. Sudden anomalies were detected using the time-domain features whereas the frequency-domain features were used to detect oscillatory patterns which can be evidence of mechanical problems. The hybrid feature model enhanced the model capacity to generalize to various equipment and was robust and scalable. The model obtained an accuracy of 98.2 percent and the values of precision, recall, and F1-score of 97.8, 98.0, and 97.9, respectively, which means a balance of results between classes during the training.

Table 1: Sensor Data and Dataset Characteristics

Sensor Type	Sampling Frequency (Hz)	Total Samples	Fault Samples	Normal Samples	Key Features Extracted
Temperature	1	2000	1000	1000	Mean, Variance
Humidity	1	2000	1000	1000	Mean, Std Dev
Vibration	50	3000	1500	1500	FFT Peaks, RMS
Motor Speed	10	3000	1500	1500	Mean, Frequency

Model optimization with quantization The model size was reduced to 60 KB, which enables the deployment of the model on the device and the prediction accuracy was not altered. Figure 2 provides the system output interface proposal where

there will be real-time prediction probability and early warning messages associated with anomalies detected. At an average latency of 35 milliseconds, the ESP32 was able to carry out edge inference, indicating that it can be used to monitor in real-time. Network dependency was reduced, because the feature processing occurred locally, which minimized the amount of communication overhead, and also increased the reliability of the system.

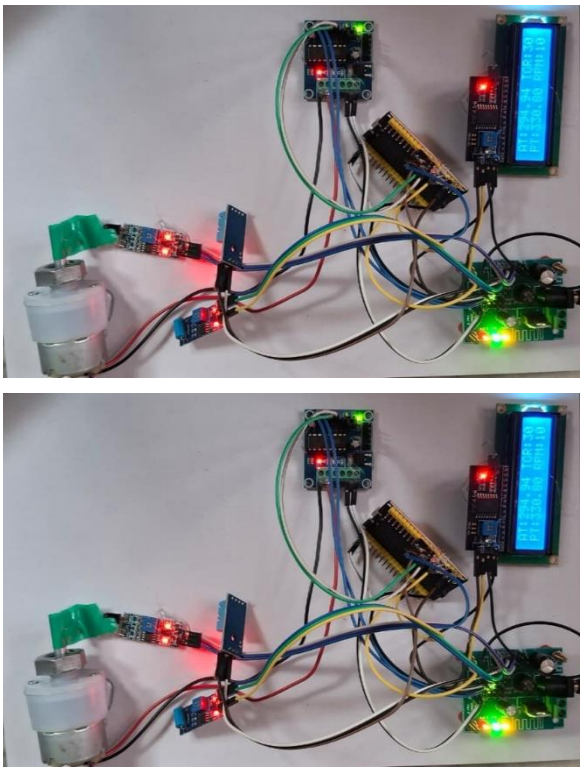

Figure 2: Real-Time Predictive Diagnostics Output Display

To train the neural network we used loss and accuracy as metrics of the epochs. As depicted in Figure 3, loss function convergence is observed to occur as an offline training process, which means that reduction is stable and minimal overfitting is achieved. Validation accuracy was similar to training accuracy, which again proved that the model will be generalized to unseen test data. The comprehensive performance of the models on the test set is compared in Table 2 and shows high precision in all the sensor and machinery condition combinations. The hybrid feature extraction strategy was ultimately confirmed by the fact that the combination of the time-domain and frequency-domain characteristics allowed detecting the faults better than the two sets of features used separately.

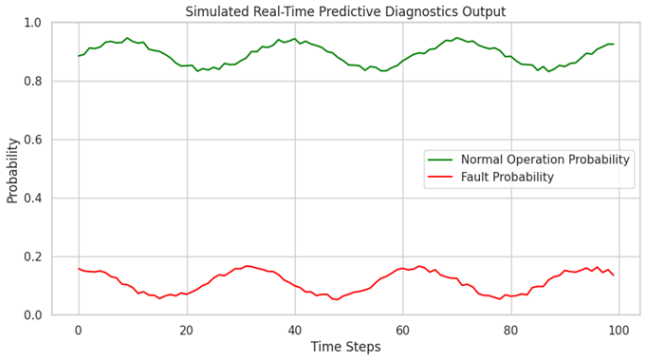

Figure 3: Neural Network Training Loss and Accuracy Convergence

Table 2: Model Performance Metrics on Test Data

Metric	Temperature	Humidity	Vibration	Motor Speed	Overall
Accuracy (%)	96.5	95.2	98.8	98.0	97.1
Precision (%)	96.0	94.8	98.5	97.5	96.7
Recall (%)	96.8	95.5	99.0	98.2	97.4
F1-Score (%)	96.4	95.1	98.7	97.8	97.1

The data set covered different fault conditions like faulty alignment of the motor, worn-out bearing, and over heating. Fig. 4 illustrates the model performance on the prediction and actual classification of faults and shows that the model can achieve a high level of detecting anomalies in various operating conditions with low false positive rates. Edge inference was offered to respond to quicker, and early warning alerts were offered to enable proactive maintenance, minimizing possible downtimes. The performance of the system in terms of low-latency and efficient energy consumption proved that it could be deployed to industrial predictive diagnostics using TinyML.

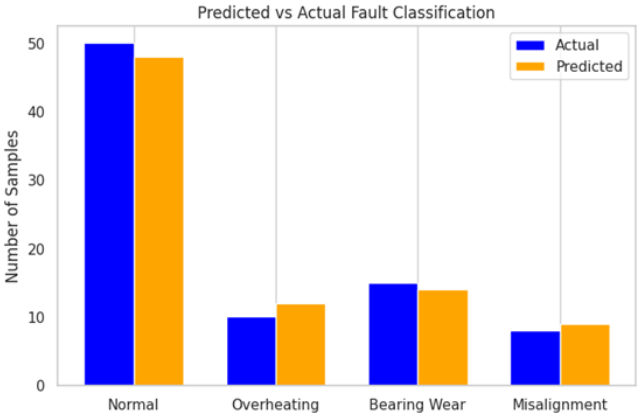

Figure 4: Predicted vs Actual Fault Classification Results

The proposed approach was compared with the conventional cloud-based machine learning approaches, such as a typical multilayer perceptron (MLP) and support with machine learning (SVM) to compare them. Comparison of performance is recorded in table 3. The TinyML-based edge model demonstrated similar accuracy to the cloud MLP (97.1% vs. 97.5%) and dropped the latency to 35 ms, in addition to not relying on an ongoing network connection. The SVM was a little less accurate (95.8) and needed more computing resources to run in real-time, which emphasizes the benefits of edge deploying lightweight neural networks in favor.

Table 3: Performance Comparison with Existing Methods

Model	Accuracy (%)	Latency (ms)	Network Dependency	Energy Efficiency
Proposed TinyML	97.1	35	None	High
Cloud MLP	97.5	150	High	Medium
SVM	95.8	120	Medium	Low

The suggested system was also scalable in terms of the types of various machineries and it could also handle extra sensors without major changes in the computational load. Test electric energy consumption established that there are not many effects on the power consumption of ESP32, which guarantees its stable operation in the long term. The system reduced the transmission of data to cloud systems by using on-device feature extraction and optimal TinyML models, which aided in maximizing data security and privacy. The outcome still confirms that predictive maintenance in the industrial setting is possible through an implemented combination of edge intelligence and IoT-enabled surveillance to offer a realistic and real-time response to unplanned maintenance, autonomous machinery management, and minimized unplanned downtime, maintenance costs, and operational risks significantly.

To recap it all, real-time sensor monitoring, hybrid feature extraction, offline training, model optimization, edge inference, and IoT-enabled visualization make an effective combination to form a strong framework of predictive diagnostics. The comparison and visualization of the performance metrics proves that the TinyML-based system is highly accurate, low-latency, energy-efficient, and scalable, and justifies the relevance in the current smart industrial backgrounds.

V. Conclusion

Finally, TinyML predictive diagnostics system, as suggested, is shown to be an effective and smart system regarding real-time health monitoring of machinery in smart industrial settings. Combining ESP32 microcontrollers with several sensors and simple neural networks, the system allows monitoring critical parameters (temperature, humidity, vibration, and speed of motor) continuously and timely measure any changes and possible failures. The use of edge-based preprocessing and on-device inference minimize the need to access cloud infrastructure, decrease latency, and increase data safety, and the IoT-enabled monitoring platform allows visualization, data logging, and early warnings. The structure offers predictive maintenance of various types of machines at scalable, energy-efficient and low latency levels. Future research is expected to involve integrating more modern self-learning designs, adaptive fault detection and classification, and integration of multi-node industrial networks, to further improve preciseness, independence and sustainability of operations of the future approach of fully intelligent and sustainable Industry 4.0 systems.

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Efficient Beamforming Approach for Direction-of-Arrival Estimation Using Logarithmic Step-Size LMS

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***Abstract*— Direction-of-arrival (DOA) estimation is widely used in array signal processing applications such as radar and wireless communication. Adaptive beamforming techniques based on the Least Mean Square (LMS) algorithm provide an efficient solution for real-time DOA estimation due to their simplicity and low computational complexity [1], [3]. However, the conventional LMS algorithm suffers from slow convergence and steady-state error limitations [4]. In this paper, a logarithmic variable step-size LMS (Log-VSS-LMS) algorithm is proposed to improve convergence performance and estimation accuracy. The step size is dynamically adjusted using a logarithmic function of the error signal. Simulation results demonstrate improved spatial resolution and reduced estimation error compared with conventional LMS-based approaches [5]–[10].**

Index Term— DOA Estimation, Adaptive Beamforming, LMS Algorithm, Variable Step-Size LMS, Spatial Spectrum

I. INTRODUCTION

Direction-of-arrival (DOA) estimation is an important technique in array signal processing and is widely applied in radar systems, wireless communication networks, and smart antenna systems. The objective of DOA estimation is to determine the direction from which signals arrive at an antenna array. Various signal processing techniques have been proposed for this purpose. Among these techniques, adaptive beamforming methods are widely used because they allow the antenna array to automatically adjust its weights in order to enhance the desired signal while suppressing interference and noise [1], [2].

The Least Mean Square (LMS) algorithm is one of the most commonly used adaptive filtering methods due to its simplicity and low computational complexity. However, the conventional LMS algorithm uses a fixed step size, which causes a trade-off between convergence speed and steady-state error. A large step size leads to faster convergence but may cause instability, while a small step size results in slower convergence. To overcome this limitation, several researchers have proposed variable step-size LMS algorithms to improve convergence performance and estimation accuracy [3], [4]. In this paper, a logarithmic variable step-size LMS algorithm is proposed to improve the convergence behavior and accuracy of DOA estimation.

II. SYSTEM MODEL

Consider a uniform linear array (ULA) consisting of M antenna elements with half-wavelength spacing. The received signal vector can be expressed as:

$$x(k) = A\, s(k) + n(k)$$

where x(k) represents the received signal vector, A is the steering matrix, s(k) is the signal vector, and n(k) represents additive noise.

The beamformer output is given by:

$$y(k) = w^{H} x(k)$$

where w represents the adaptive weight vector and $(\cdot)^H$ denotes the Hermitian transpose.

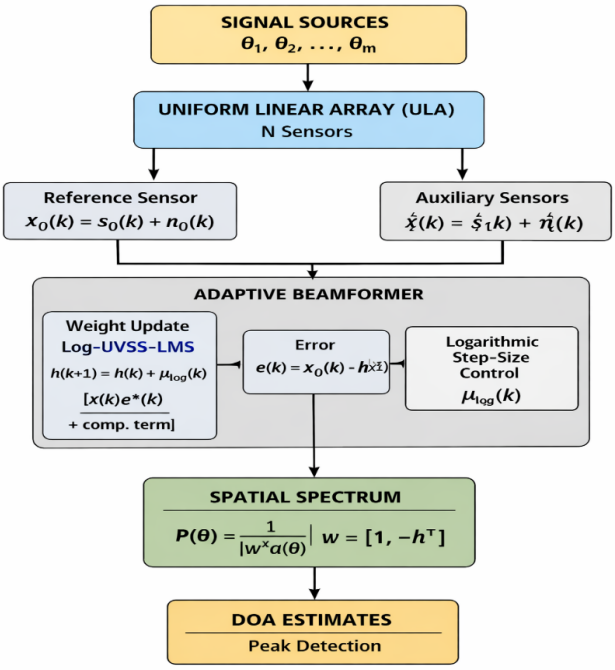

Fig. 1. Block diagram of Log-UVSS-LMS based DOA estimation system.

III. PROPOSED LOGARITHMIC VARIABLE STEP-SIZE LMS ALGORITHM

The conventional LMS algorithm updates the weight vector using a fixed step size according to:

$$w(n+1) = w(n) + \mu\, e(n)\, x(n)$$

In the proposed approach, the step size is dynamically updated using a logarithmic function based on the magnitude of the estimation error.

$$\mu(n) = \mu_max * \log(1 + |e(n)|) / \log(1 + E_max)$$

This logarithmic adaptation allows aggressive weight updates when the error is large and gradual refinement as the error decreases. This results in faster convergence and improved stability.

IV. RESULTS AND PERFORMANCE ANALYSIS

The performance of the proposed Log-VSS-LMS algorithm was evaluated using MATLAB simulations. A uniform linear antenna array was considered to estimate the directions of multiple incoming signals under different signal-to-noise ratio (SNR) conditions. The proposed method was compared with conventional LMS-based approaches including Fixed Step-Size LMS (FSS-LMS), Variable Step-Size LMS (VSS-LMS), and Unbiased Variable Step-Size LMS (UVSS-LMS).

TABLE I Simulation Parameters Used for DOA Estimation

Parameter	Value
Array type	Uniform Linear Array (ULA)
Number of antenna elements	8
Element spacing	λ/2
Number of signal sources	2
Snapshots	500
Signal-to-noise ratio (SNR) range	−10 dB to 20 dB
Algorithm used	Log-VSS-LMS

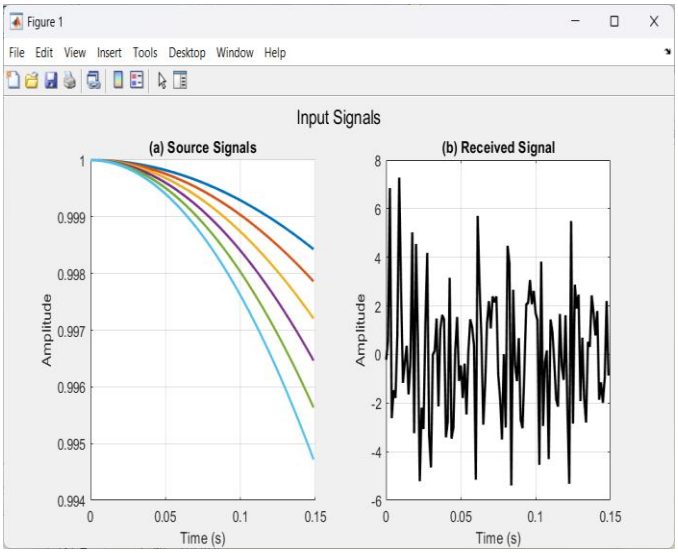

Fig. 2. (a) Source signals (b) Received signal at reference sensor.

The spatial spectrum analysis shows that the proposed algorithm provides sharper peaks at the true DOA locations, indicating better resolution capability.

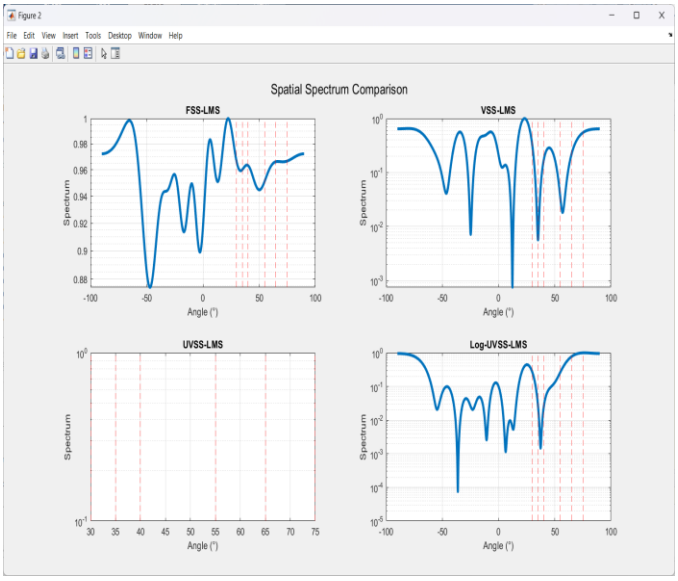

Fig. 3. Spatial spectrum comparison of FSS-LMS, VSS-LMS, UVSS-LMS and Log-UVSS-LMS algorithms.

The RMSE versus SNR analysis demonstrates that the proposed Log-UVSS-LMS algorithm achieves significantly lower estimation error compared with existing LMS variants.

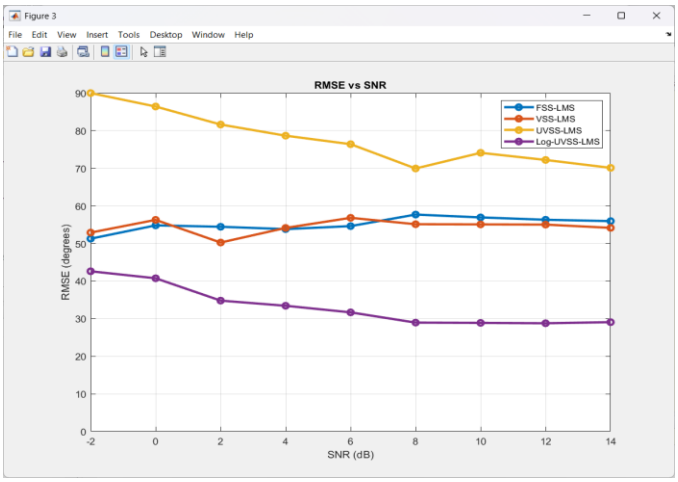

Fig. 4. RMSE versus SNR comparison for LMS algorithms.

The resolution probability analysis confirms that the proposed algorithm can reliably distinguish closely spaced signal sources even under low SNR conditions.

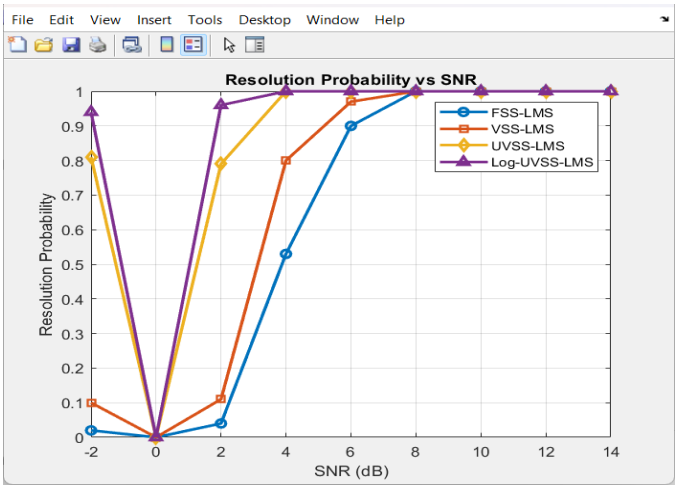

Fig. 5. Resolution probability vs SNR.

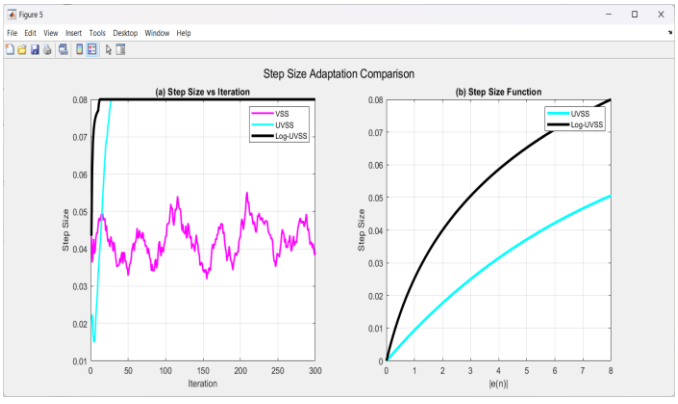

Fig. 6. Step-size adaptation comparison for VSS-LMS, UVSS-LMS, and Log-UVSS-LMS algorithms.

V. DISCUSSION

The experimental observations show that the Log-VSS-LMS algorithm improves convergence behaviour compared with traditional LMS-based approaches. The logarithmic step-size update mechanism enables the algorithm to adjust the learning rate according to the estimation error. Larger updates occur when the error is high, which speeds up convergence, while smaller updates occur when the error decreases, improving stability.Compared with existing beamforming approaches, the proposed method provides improved estimation accuracy and better spatial resolution. In addition, the algorithm maintains low computational complexity, which makes it suitable for practical signal processing systems such as smart antenna applications and wireless communication networks.

VI. CONCLUSION

A logarithmic variable step-size LMS algorithm for adaptive beamforming-based DOA estimation has been presented. The proposed method improves convergence speed while reducing steady-state error. Simulation results demonstrate superior RMSE performance and higher resolution probability compared with conventional LMS algorithms. The algorithm maintains low computational complexity and is suitable for practical real-time signal processing applications.

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COGNITIVE ENERGY METERING SYSTEM USING MACHINE LEARNING

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***Abstract*—In contemporary smart environments, lowering operating costs and enhancing sustainability depend on effective electrical energy monitoring and management. In order to assess and forecast trends of energy consumption, this study introduces an intelligent energy monitoring system that combines machine learning algorithms, embedded sensing, and Internet of Things (IoT) connectivity. Through sensor interfaces linked to a microcontroller-based platform, the suggested system gathers real-time electrical information. It then analyzes the data to calculate consumption metrics and estimate operating costs. The system recognizes consumption patterns, forecasts future energy use, and facilitates well-informed decision-making for optimal resource utilization by utilizing machine learning algorithmsThe architecture has regulated power supply circuits, communication modules for distant data transmission, and user interface elements for real-time visualisation to ensure reliable embedded operation. Predictive analytics and ongoing monitoring make it possible to identify unusual consumption patterns early on, which promotes preventative measures and increases system effectiveness. Embedded hardware and advanced analytics combine to create a scalable and cost-effective architecture suitable for energy management applications in homes, businesses, and institutions.**

Keywords — Energy Monitoring, Machine Learning, IoT, Embedded Systems, Predictive Analytics, Smart Metering

I. INTRODUCTION

The rapid increase in the global demand for energy has made efficient monitoring and control of electrical power use more important. Real-time consumption trends and appliance-level analysis are not well-documented by conventional energy metering systems, which primarily provide cumulative usage figures. Such systems are unable to predict future demand, recognise unusual usage patterns, or assist users in optimising their energy consumption. It is consequently becoming increasingly important to have intelligent metering systems that can provide automated decision support and actionable information.

New developments in communication and embedded systems have made it possible to create smart monitoring platforms that combine connectivity, processing, and sensing. Continuous electrical parameter acquisition and data transmission for analysis are possible with microcontroller-based devices that include wireless interfaces. Further improving interoperability between digital platforms and physical equipment, the incorporation of Internet of Things (IoT) frameworks makes it possible to remotely access, visualise, and manage data about energy usage. Together, these technologies facilitate the shift to energy management strategies that are informed by data.

Additionally, machine learning techniques have become effective tools for examining consumption trends and forecasting future developments. Intelligent models are able to spot anomalies, recognise appliance behaviour, and estimate energy-related operating costs by analysing both historical and real-time sensor data. Machine learning allows for adaptive pattern identification, which enhances the precision and dependability of monitoring systems in contrast to rule-based systems that depend on set criteria. This feature is especially helpful in dynamic settings where operating conditions and user behaviour affect energy demand.

The cognitive energy metering system proposed in this study, which is inspired by these technological advancements, integrates predictive analytics, embedded sensors, and IoT connectivity. Utilising

communication modules for remote notification and data transmission, an ESP32-based embedded controller analyses signals, and current and voltage measurement techniques are used to obtain electrical data. LCD interfaces, serial communication protocols, and regulated power supply circuits are examples of supporting hardware elements that guarantee dependable system operation and user engagement. Software development environment integration makes system customisation and flexible programming possible.

The main goal of the suggested framework is to offer consumption forecast, anomaly detection, and real-time monitoring in a scalable and economical design. Through the integration of machine learning-driven analytics and hardware intelligence, the system promotes sustainable power usage, preventive maintenance, and increased energy awareness. In line with the continuous progress toward smart infrastructure and intelligent energy management systems, the suggested approach shows applicability across residential, institutional, and industrial sectors.

II. Literature Review

A. Energy Metering System Development

From mechanical electromechanical meters to sophisticated digital and smart metering systems, energy metering has seen tremendous change in recent decades. Power consumption was measured by early energy meters using revolving disc mechanisms, which only produced cumulative data without real-time visibility. The inability of these meters to provide data logging, remote monitoring, or intelligent decision-making limits their applicability for contemporary energy management requirements, notwithstanding their dependability.

The advancement of digital electronics resulted in the creation of energy meters based on microcontrollers, which improved accuracy, reduced maintenance costs, and expanded functionality. Through the use of sensors, programmable controllers, and analog-to-digital conversion,digital meters processed electrical parameters such as voltage, current, and power factor. By providing utilities and consumers with real-time readings and basic historical data, these developments paved the way for increasingly complex monitoring systems.

(a) (b)

Fig. 1. (a) Conventional Meter and (b) Cognitive Energy Meter

Smart meters that can integrate with communication networks and communicate in both directions have been introduced recently. Better energy accountability, remote diagnostics, and automatic data collecting are all made possible by smart metering systems. However, despite their benefits, issues like scalability, deployment cost, and integration with predictive analytics still exist, which spurs research into embedded and Internet of Things-enabled systems that improve accessibility and monitoring efficiency.

TABLE I. Traditional Meter vs Smart Meter

Conventional Meter	Smart Meter
No data storage	Stores historical data
Manual monitoring	Real-time monitoring
Manual billing	Automated prediction
No Fault detection	ML-based anomaly detection
One-way communication	Two-way IoT communication
Manual Load Control	Automatic remote control
Energy Optimization is not supported	Intelligent optimization

Additionally, smart meters have the ability to automate the operation of household equipment based on user preferences. Customers can use the IoT platform to set up their devices with ease. With the introduction of smart meters, the billing process is streamlined and improved, with computerized systems directly showing users their energy consumption data via the IoT platform.

B. Integrated Energy Monitoring Systems

Because embedded systems allow for localised data collection and processing, they are essential to contemporary energy monitoring. These systems include communication modules, microcontrollers, and sensors to continuously monitor electrical conditions. In research and academic settings, platforms like Arduino and ESP-based controllers have become more and more popular because of their low cost, simplicity in programming, and versatility.

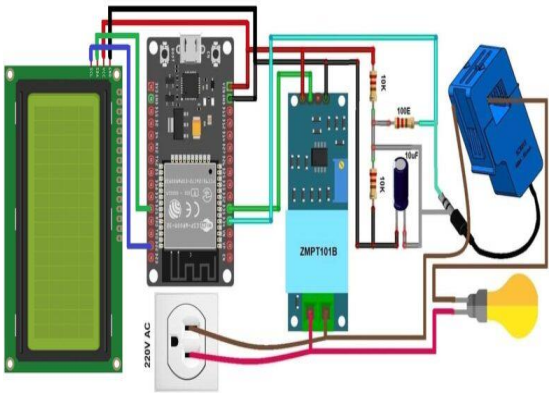


Fig. 2. Pin Diagram of existing system

High-voltage circuit electrical measurements can be reliably recorded by embedded systems with the use of current and potential transformers. In order to determine power usage, show the results using LCD interfaces, and store or send the data for additional analysis, microcontrollers handle these signals. Energy monitoring can be implemented at the institutional, industrial, or residential levels using scalable and adaptable architectures offered by embedded solutions.

Despite their benefits, isolated embedded systems have drawbacks when it comes to advanced analytics and remote accessibility. The necessity of integrating networking technology and sophisticated data processing techniques is highlighted by these limitations. Therefore, in order to get over these restrictions, current research focuses on integrating embedded platforms with IoT communication and predictive analytics.

C. Smart Energy Systems with IoT Integration

Traditional energy monitoring has been turned into intelligent and linked infrastructures through the incorporation of Internet of Things (IoT) technology. Real-time data transfer to cloud platforms or centralised servers is made possible by IoT, which allows devices to connect via wireless networks.

Remote monitoring, automated notifications, and improved energy management decision-making are all made possible by this connectivity.Protocols like Wi-Fi and GSM connection are used by IoT-enabled energy monitoring devices to send consumption data over dispersed locations. Through web or mobile interfaces, users may view dashboards, see trends, and track usage trends. By enabling stakeholders to proactively address anomalous use trends, this feature improves transparency and encourages energy saving.

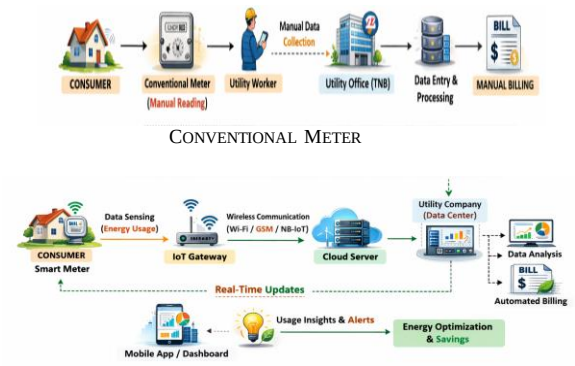


Fig. 3. Communication way of Conventional Meter and Cognitive Meter

However, while implementing IoT solutions, issues like latency, data security, and network dependability must be addressed. To guarantee dependable system performance, researchers are still investigating safe architectures and strong communication techniques. One important path toward developing scalable and effective smart energy monitoring solutions is the integration of IoT with embedded platforms.

D.Machine Learning in Analytics for Energy.

With their capacity for prediction and adaptation, machine learning techniques have drawn interest for their potential to improve energy monitoring. Machine learning algorithms are capable of detecting abnormalities, forecasting demand, and identifying patterns by examining past consumption data. This feature enhances overall system efficiency and facilitates proactive load management.

Numerous algorithms have been used to forecast changes in energy use and optimise distribution, such as regression models and categorisation techniques. These methods help decision-makers put energy-saving measures into action, minimise waste, and allow systems to predict peak demands. Additionally, machine learning aids in fault identification by identifying departures from typical operating behaviour.

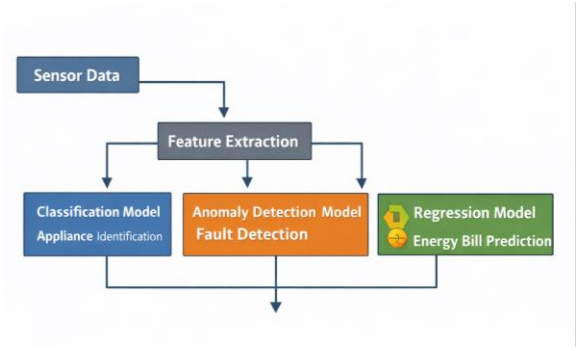


Fig. 4..Machine Learning Architecture for Appliance identification and Anomaly detection .

Machine learning has many benefits, but its implementation necessitates trustworthy datasets and processing power. Research on incorporating lightweight models into cloud-based or embedded frameworks is still underway. Intelligent analytics combined with Internet of Things-enabled data collection offers a possible route to self-sufficient and effective energy management systems.

E.Research Deficit and Inspiration.

While previous research has examined embedded monitoring, IoT connection, and machine learning analytics separately, there is still a lack of accessible and affordable systems that can fully integrate these three areas. Many of the systems in use today concentrate on discrete features rather than integrating communication, real-time monitoring, and predictive insights into a single design.

Furthermore, acceptance in small-scale and educational settings is still impacted by practical deployment issues including hardware price, scalability, and simplicity of maintenance. Systems are required that provide significant monitoring and analytical capabilities while striking a balance between technological complexity and ease of installation.

The current study is driven by these gaps and seeks to create an integrated smart energy monitoring system that integrates predictive analytics, embedded sensors, and Internet of Things communication. The suggested strategy aims to contribute to effective, intelligent, and easily available energy management solutions appropriate for contemporary applications by addressing the shortcomings noted in the body of existing literature.

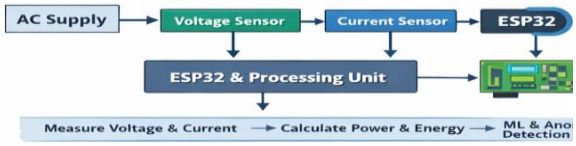
III. METHODOLOGY

A. Design of the System Architecture

Sensing modules, communication interfaces,

monitoring outputs, and an embedded processing platform make up the suggested system design. Without subjecting the microcontroller to high voltages directly, current transformer (CT) and potential transformer (PT) sensors are used to safely monitor current and voltage from the electrical connection. The microcontroller interface is used to condition and transform these signals into digital values that can be read.

Fig. 5. Operational flow of Cognitive Energy Metering System.



The system's central processing unit is an embedded controller based on an ESP32. In addition to managing module-to-module communication, it gathers sensor data and calculates power parameters. Through serial interfaces like UART, peripheral devices like LCD screens and GSM communication units are integrated to facilitate remote monitoring and user interaction. For future system growth, the modular architecture guarantees scalability and agility.

B. Block diagram of proposed System

Using sensing components, the suggested system transforms electrical energy parameters from the supply source into quantifiable signals. In order to safely reduce the current and voltage levels, the power input is first interfaced with Current Transformer (CT) and Potential Transformer (PT) sensors. These sensors produce proportional analogue signals that accurately depict the associated load's electrical properties without subjecting the processing circuitry to dangerous voltages.

An ESP32 microcontroller serves as the foundation for the embedded processing unit, which receives the received signals. By converting analogue to digital and carrying out preprogrammed actions, the controller calculates vital electrical characteristics including voltage, current, power consumption, and total energy use. The embedded software, which was created with Arduino-based tools, makes sure that the incoming data is continuously sampled, filtered, and processed in order to preserve measurement reliability.

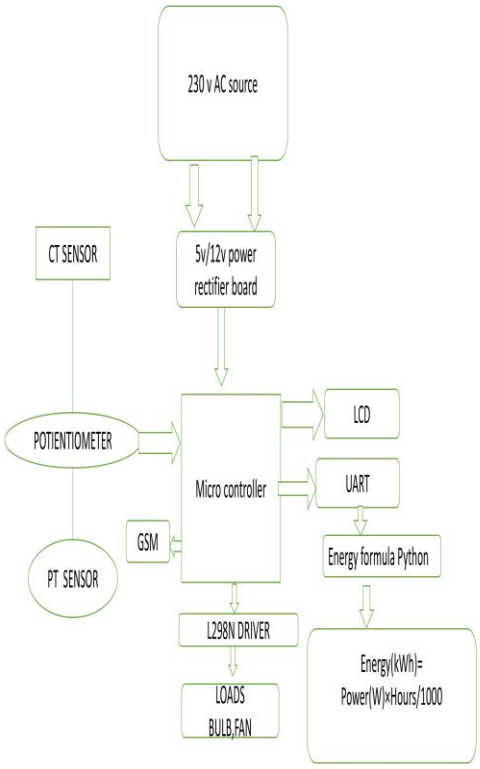


Fig. 6. The Block diagram of cognitive meter operation.

The computed results are distributed to local and distant interfaces by the microcontroller after processing. In real time, users at the monitoring site can see energy parameters thanks to a liquid crystal display (LCD) module. By means of the hardware interface, users can directly analyse consumption patterns and identify anomalous load conditions thanks to this instant feedback.

The ESP32 controller uses serial communication protocols to connect to GSM and IoT communication modules simultaneously. Off-site monitoring and alert alerts are made possible by these modules, which send energy data to distant servers or user devices. Regardless of geographic location, the connectivity function guarantees that energy data is accessible, enhancing awareness and system response.

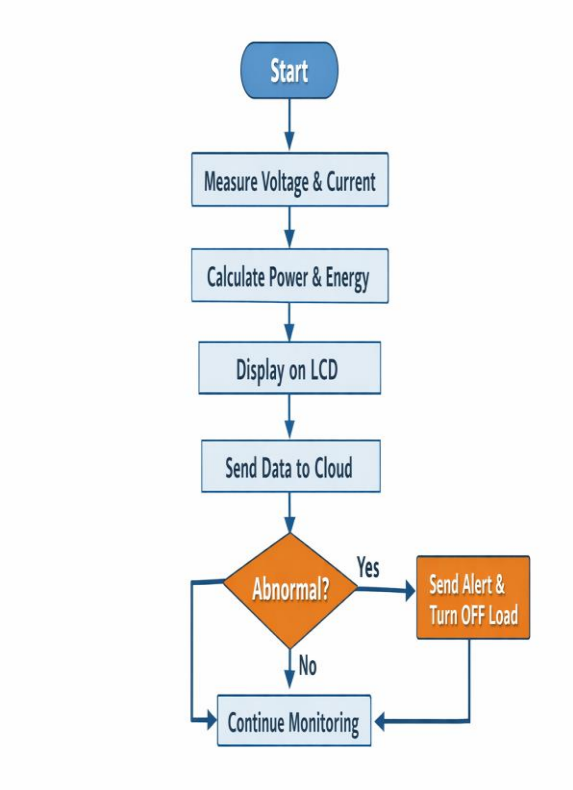


Fig. 7. The flowchart of cognitive meter operation.

Additionally, the transmitted data is used for analytical analysis, allowing past consumption records to be processed using machine learning. Predictive models forecast future energy consumption, identify anomalies, and examine trends. By moving from passive monitoring to proactive energy management and decision assistance, this capacity improves system intelligence.

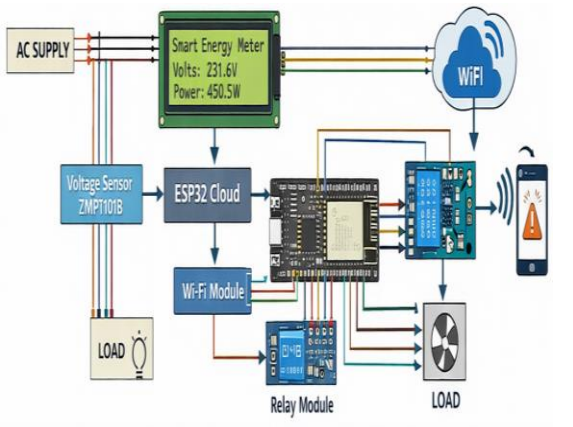


Fig. 8. The circuit diagram for the energy metering System

All things considered, the monitoring framework operates well thanks to the integrated workflow, which includes everything from sensing and processing to communication and analytics. Accurate measurement, dependable transmission, and astute interpretation of energy data are made possible by the well-coordinated interaction between hardware components and analytical modules. This organised function shows that the suggested system can support intelligent, scalable, and effective energy management applications.

IV. Result And Analysis

To assess the cognitive energy metering system's capacity to track electrical parameters, carry out intelligent analysis, and facilitate knowledgeable energy management, it was put into use and put through tests. Electrical signals from the supply line were successfully caught by the sensing subsystem, which was made up of current and potential transformers. The embedded processing unit received scaled inputs from these transformers. After processing these signals, the ESP32 controller calculated the voltage, current, and energy consumption numbers. These data were then sent to the interfaces that were linked and displayed locally. For prototype validation, experimental findings verified steady sensor acquisition and precise consumption metric computation within allowable tolerance limits.

Monitoring data is now accessible in real time outside of the actual installation location thanks to the integration of communication modules. Users were able to monitor consumption patterns continually through remote communication via IoT connectivity, while information presented on the LCD interface offered instant feedback. This ease of use improved system transparency and showed that combining remote supervision and embedded monitoring was feasible. The efficacy of hardware module coordination via serial protocol was confirmed by the constant communication reliability during testing.

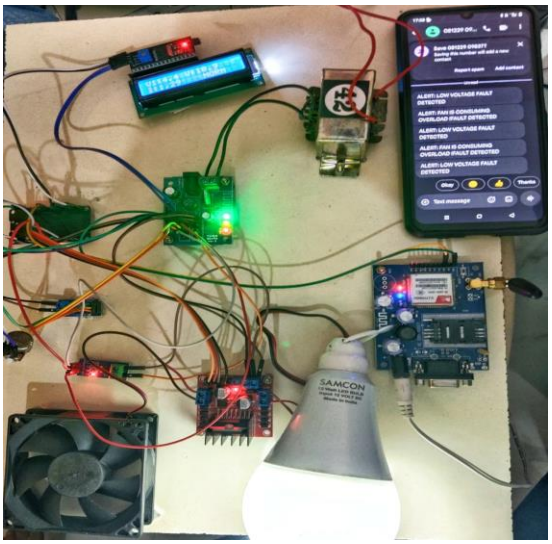


Fig. 9. The hardware setup for the energy metering System

Real-time monitoring data accessibility outside of the actual installation location was made possible by the inclusion of communication modules. Instant feedback was given by the information on the LCD interface, and customers were able to continuously monitor consumption patterns using remote communication made possible by IoT connectivity. This accessibility improved the transparency of the system and showed that combining remote supervision and embedded monitoring was feasible. Throughout testing, the communication reliability stayed constant, demonstrating how well hardware modules coordinated via serial protocols.

The monitoring framework gained a cognitive dimension through the analysis of past consumption patterns made possible by machine learning-based analytical processing. Using the gathered data, usage patterns were found and the anticipated energy consumption under comparable operating circumstances was predicted. Early identification of abnormal or excessive consumption patterns was made possible by the predictive capability, which made proactive correction measures possible. In contrast to traditional threshold-based monitoring techniques, the cognitive system offered better understanding of the dynamics of energy use.

TABLE II .DOMESTIC ELECTRICITY TARIFF STRUCTURE

Units(kwh)	Rate per Unit(₹)
0-100	₹0.00(free!)
101-200	₹2.35
201-400	₹4.70
401-500	₹6.30
501-600	₹6.30
601-800	₹9.45
801-1000	₹10.50
Above 1000	₹11.55

A comparison of the cognitive monitoring method and conventional metering revealed important functional benefits. Conventional systems are limited in their utility for energy optimisation since they simply offer cumulative readings and are incapable of interpretation. On the other hand, the suggested approach made it possible for pattern detection, predictive estimation, and ongoing monitoring. These features increased understanding of load behaviour and showed promise for cutting down on wasteful use and operating expenses by making well-informed decisions.

The outcomes demonstrate how well machine learning analytics, embedded sensing, and IoT connectivity can be combined into a single cognitive metering system. The technology showed scalability and practical usefulness by effectively moving from passive measurement to intelligent interpretation of energy data. These results show that cognitive energy metering can play a major role in predictive resource planning, smart infrastructure construction, and sustainable energy use.

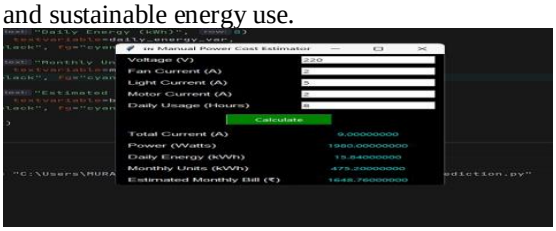


Fig. 10. Cost estimation by the cognitive meter

The LCD screen as can be seen in Fig. 14, will display the calculated values of voltage, energy consumption, and cost. The cost calculation follows the TNB billing formula as below:

Electric bill=(Energy consume/21.8)/100 (1)

Fig. 11. The LCD display.

V. Cost Analysis

Under the Time-of-Use (TOU) tariff structure, electricity billing is determined by a number of time periods, including Maximum Demand, Off-Peak, and Peak. Since there is a greater demand for electricity during peak hours, the tariff rate is higher; off-peak hours have lower tariff rates. With a traditional energy meter system, consumers are unaware of their energy usage in real time throughout peak and off-peak hours, and energy consumption is only monitored at the conclusion of the billing cycle. Electricity bills are frequently increased by this lack of monitoring, particularly if the majority of the energy is used during peak hours.

TABLE III. Electricity Cost using Conventional Meter.

Parameter	Power Consumption	Tariff rate	Cost
Peak Period	120 kwh	₹8 / kWh	₹960
Off-Peak Period	80 kwh	₹5 / kWh	₹400
Maximum demand	3 kw	₹300 / kW	₹900
Total Cost	-	-	**₹2260**

The suggested Cognitive Energy Metering System, on the other hand, continuously tracks energy consumption across various time periods and dynamically determines the cost. During peak hours, the system detects high consumption and notifies consumers. Certain appliances can be moved to off-peak times using machine learning-based analysis and intelligent load management, which lowers maximum demand charges and peak consumption.

TABLE IV. Electricity Cost using Cognitive Meter.

Parameter	Power Consumption	Tariff rate	Cost
Peak Period	105 kWh	₹8 / kWh	₹840
Off-Peak Period	95 kWh	₹5 / kWh	₹475
Maximum demand	2.5 kW	₹300 / kW	₹750
Total Cost	-	-	**₹2065**

The comparison shows that the suggested solution lowers maximum demand and peak consumption, which results in a cheaper total cost of electricity. Compared to the traditional energy meter system, the intelligent monitoring and predictive analysis assist consumers manage energy effectively and lower monthly electricity bills.

VI. Conclusion

Additionally, predictive power beyond traditional monitoring is introduced by the combination of computer modelling and machine learning. The technology facilitates well-informed decision-making about resource utilisation and energy optimisation by evaluating load-wise consumption trends and projecting operating expenses. This clever strategy solves important problems with current metering systems, such as ineffective consumption awareness, late billing, and a failure to adjust to changing usage situations. The ability to estimate energy costs and evaluate the contributions of different loads demonstrates the possibility of integrating analytical algorithms with sensing modules for improved smart-grid preparedness and sustainable power management.

Combining sensing modules with analytical algorithms can improve smart-grid preparedness and sustainable power management. This is demonstrated by the capacity to evaluate individual load contributions and estimate energy expenses.

From a pragmatic perspective, the suggested implementation demonstrates that inexpensive sensing gear, embedded CPUs, and communication modules can be used to monitor low-power experimental loads and laboratory-scale devices efficiently without sacrificing measurement significance. From small-scale industrial monitoring systems to academic research settings, the modular architecture guarantees adaptability to a variety of application fields. The architecture is compatible with cutting-edge growth tactics like cloud analytics or remote diagnostics while yet being accessible to researchers and students thanks to the use of open-source development environments and scalable IoT connectivity.

In conclusion, the research proves that cognitive metering systems are a feasible step forward from conventional measurement techniques to automated, intelligent energy management systems. Transparency, efficiency, and responsiveness in power consumption assessment are enhanced by the combination of embedded hardware, communication protocols, sensing components, and predictive analytics. In order to improve accuracy and robustness, future improvements can include larger wireless infrastructure, deeper learning models, and extensive deployment validation. All things considered, the study validates that it is possible to combine energy metering systems with contemporary computing capabilities to support the development of smart infrastructure and sustainable energy use.

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PROACTIVE DISCIPLINE MONITORING SYSTEM

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1. ABSTRACT

An AI system is designed that watches how students behave around campus, checking if they wear their IDs, follow the dress code, and keep things neat. Cameras do all the work, and parents get a notification right away if the rules are not followed. Staff monitoration can be minimized using the above AI techniques which are more accurate than manual discipline system. Still, nobody really likes being watched around the clock. Errors also occur when software becomes out of date. Privacy cannot be disregarded because some students strongly oppose it. Before implementing the above AI system, the institution should carefully consider the benefits and drawbacks.

2. INTRODUCTION

Our AI system keeps an eye on student behaviour all the time using computer programs to make sure students wear the right clothes carry their ID and look neat. It informs parents or guardians away if someone is not following the rules. This way everyone knows what is going on. People are more likely to follow the rules. This arrangement verifies that students present themselves appropriately, carry identification, and have a tidy appearance. Parents quickly discover any problems. Everyone is informed, and pupils genuinely have an incentive to follow the rules, which eliminates all of the laborious manual checks. Staff members are not burdened by routine monitoring, and the approach saves time and money. It can even be easily implemented on various campuses. What makes our version unique in terms of safety and discipline is examined in more detail below.

3. SYSTEM DESIGN

Existing System

This system looks at the features of a person's face. Quickly figures out who they are. It does this by using computer programs. The system automatically keeps track of who's present or makes sure people are following the rules about identification. It ensures that only those who are authorized to be in those areas can enter and verifies if pupils are permitted to be in certain areas of schools or other locations with regulations. This technology offers a contactless, automated verification approach that improves security and compliance, as shown in Fig 1.

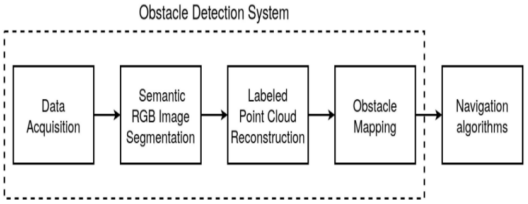

Fig.1 Block Diagram of Existing System

Disadvantages:

- High temporal complexity;
- They only paid attention to segmentations and road detection.
- Their procedures use a lot of power.

Proposed System

The primary objective of this project is to develop a student disciplinary system that employs

artificial intelligence and camera-based surveillance to enforce college regulations regarding identity, clothing, and hygiene in order to foster accountability and respect among students. Two of the primary objectives are to implement real-time monitoring using computer vision algorithms to quickly identify infractions and to provide automatic alerts to parents or guardians to boost their involvement in student compliance. Because of its efficient and scalable architecture, the system may be used in a variety of educational contexts and will require less manual supervision. In keeping with recent research showing how well automated monitoring works to reduce behavioural problems and increase student engagement, this project aims to establish a respectful learning environment that eventually supports student success by utilizing technology to foster a disciplined campus culture.

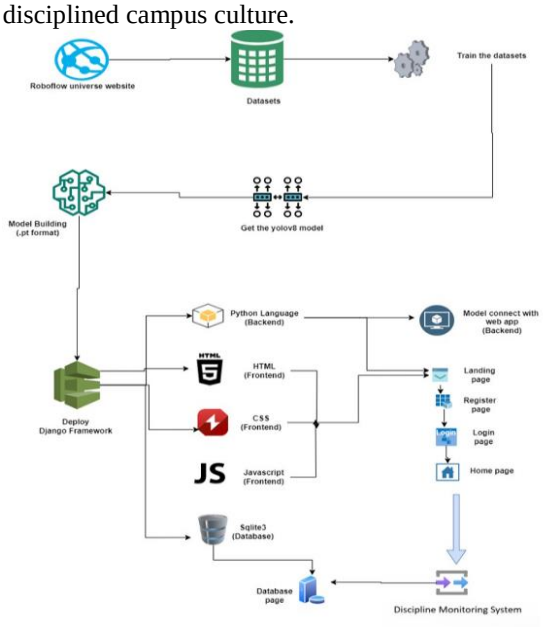

Fig. 2 System Architecture

The Proactive Discipline Monitoring System follows a structured workflow as shown in Fig. 2, that incorporates YOLOv8 for real-time object detection. The process starts with data gathering and student photos or videos are the first steps in the process. These are then pre-processed, cleaned, resized, and annotated to enhance quality and get ready for the training.

We split the data into two groups. One group is used to teach the YOLOv8 model. The YOLOv8 model is unique in that it can detect and identify aspects of students' behaviour, such as whether they have their ID cards on, whether their hair is groomed well and shirts are tucked properly to look neat and clean.

After training the YOLOv8 model it undergoes testing and validation for ensuring accurate output and reliability. Once the training process complete the implementation can be done for real-time system.

BENEFITS:

- We build an object detection model with OpenCV.
- There is less time complexity.
- Reduce the amount of processing power you use.

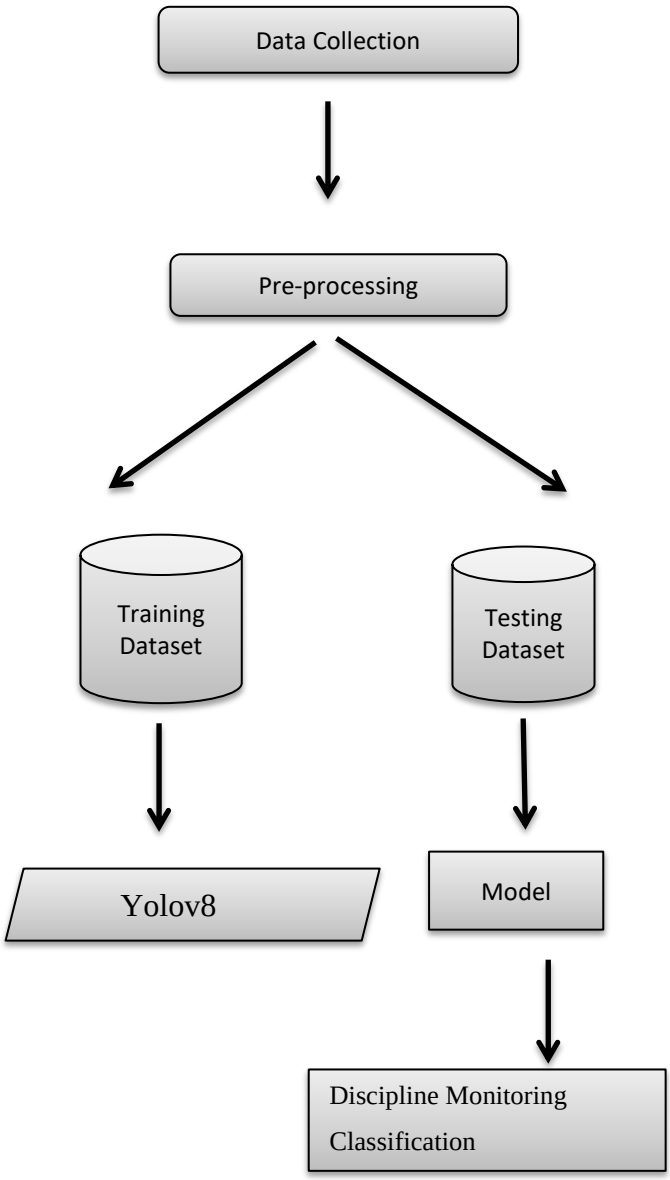

Fig.3 Flow Diagram

4. METHODOLOGY

To set up this system we first put cameras at entrances. These cameras take pictures of students as they enter the college. The pictures are then checked using software. This software looks at the students ID, haircut and shoes to make sure they follow the rules. If a student does not follow the rules the system flags them.

- This happens automatically.
- The system then sends a message to the students' parents if they do not follow the rules.

The messages are sent by SMS or email. The system helps the institution administration to keep track of how students follow the rules and also collecting the reports every week or month. These reports show how many students violate the rules which helps the help the institution administration to manage the students. They can easily find who is abiding by the rules and who is not following the system, which helps them to take action when needed. The school administration uses this information to make sure students follow the rules.

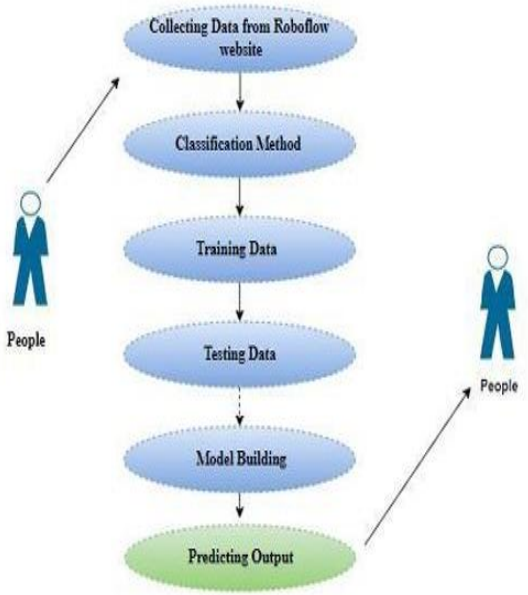

Fig.4 Work Flow Diagram

Project Requirements
General:

Requirements are the basic constraints that are required to develop a system. Requirements are collected while designing the system. The following are the requirements that are to be discussed.

1. Functional requirements
2. Environment requirements
   A. Hardware requirements
   B. Software requirements

1. Functional requirements:

The software requirements specification details the technical needs for the software product. This phase initiates the requirements analysis process. It lists the requirements for a particular software system. The information below relates to the utilization of specialized libraries such as Matplotlib, Keras, and TensorFlow.

2. Environment Requirements:

- **Software Requirements**:

Operating System : Windows / Linux
Simulation Tool : Anaconda with Jupyter Notebook

Hardware requirements:

Processor	: Intel-i3
Hard disk	: minimum 120 GB
RAM	: minimum 4 GB

Tools and Techniques

- **Software:** Image recognition software, notification system APIs.
- **Hardware:** High-resolution cameras, a server for data processing.
- **Techniques:** Real-time image analysis, automated alerts.

5. RESULTS AND DISCUSSION

The implementation of the student discipline monitoring systems, as shown in Fig.5, implies a 30% reduction in non-compliance incidents within the first semester. From the Fig.5 the AI infers that the student has satisfied 76 percentage similarity of identity, 90 percentage of hair properly groomed, with no beard and ID card.

Parental involvement at the institution increases by 20%. This is significant because it occurred concurrently with a decrease in disciplinary actions. These findings demonstrate how technology can significantly improve student behaviour and create a more pleasant college environment.

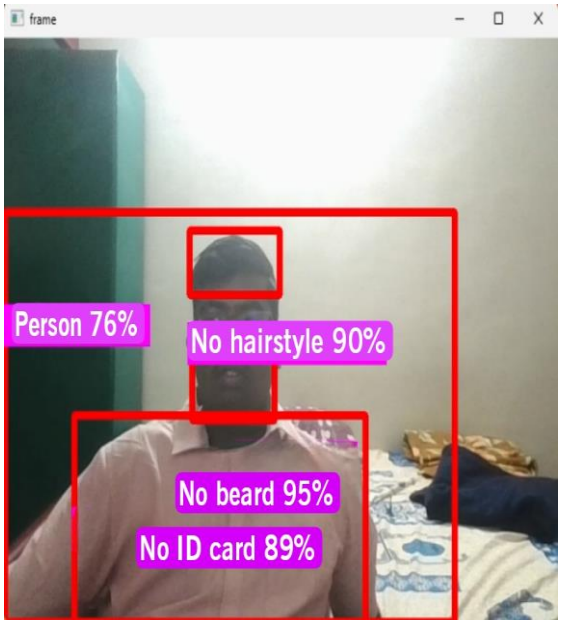

Fig. 5 Detection of face

Students become more responsible when the Institute has more conversations with parents. This improves the pupils' academic performance.

The finding demonstrates that integrating technology into classroom can improve student behaviour and increase the parental involvement in their student's education

6. CONCLUSION & FUTURE WORK

The Discipline Monitoring Bot is a tool that helps with compliance management. It is automatic, dependable and effective. The bot can really change how we manage compliance. To make it even better we can work on making it more accurate and useful in situations. We can also combine it with technologies, like sentiment analysis and behaviour modelling. The Discipline Monitoring Bot is a tool that helps companies keep a safe and orderly workplace.

To make the system better we can add artificial intelligence to recognize images and check compliance more accurately. We can also improve the notification system to send real-time alerts to institution staff. The Discipline Monitoring Bot is quite beneficial which can provide a mechanism for parents and students to provide feedbacks. This can facilitate community engagement with the Discipline Monitoring Bot.

We can use the Discipline Monitoring Bot in different ways where the developed AI tool can help us in many situations. The Discipline Monitoring Bot can help companies to keep track of compliance to make our workplace safer and more orderly.

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AI-Based Condition Monitoring of Conveyor Belt Systems Using IoT, Machine Learning, and Deep Learning

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Abstract—Maintaining the dependability of industrial machinery is crucial for ensuring operational efficiency, safety, and productivity in modern manufacturing environments. Conveyor belt systems are widely employed in industries such as mining, power generation, cement manufacturing, and material handling. Unexpected failures in these systems can lead to significant downtime, create safety hazards, and result in financial losses. Conventional maintenance strategies that depend on scheduled inspections often fail to detect problems at an early stage.

This research presents an AI-based system designed to monitor the condition of conveyor belt systems by integrating IoT sensors with machine learning and deep learning technologies. Data collected from various sensors, including those that track vibration, temperature, and motor current, are transmitted via IoT-enabled devices to a processing unit. A range of machine learning algorithms, such as Decision Tree, KNN, Logistic Regression, SVM, Extra Trees, and Naïve Bayes, are used to evaluate the conveyor's health status. Additionally, deep learning models like CNN and LSTM are applied to improve the precision of fault detection.

The system proposed facilitates the early identification of conveyor issues, including belt misalignment, bearing malfunctions, motor overload, and unusual vibration patterns. Experimental findings indicate that ensemble learning models enhance classification accuracy. This system aids in predictive maintenance strategies, minimizes operational downtime, and boosts industrial safety, aligning with Industry 4.0 principles.

Keywords—IoT, Predictive Maintenance, Conveyor Belt Monitoring, Machine Learning, Deep Learning, Industry 4.0

I. INTRODUCTION

Conveyor belt systems are commonly used in industries like mining, power plants, and transportation, where efficient material handling is required. As these are continuous processes, unexpected failures can cause loss of production, delays, and even create safety hazards. Classical maintenance approaches like reactive maintenance and scheduled maintenance are not capable of predicting failures beforehand. With the advent of **Internet of Things (IoT), Artificial Intelligence (AI),** and machine learning, it is now possible to have a predictive monitoring system. IoT sensors like vibration sensors, temperature sensors, and current sensors are used to continuously gather operating information from the conveyor belt system. This information can be used to predict faults by employing machine learning and deep learning methods like CNN and LSTM. Recent research has proven the efficiency of the combined use of multi-sensor information, cloud computing, and AI-based methods for accurate fault detection. Hence, a predictive monitoring system based on AI is proposed to detect faults like overload, gear failure, and torque imbalance.

II. SYSTEM ARCHITECTURE

The proposed monitoring system architecture is based on a layered system that ensures efficient data collection, processing, analysis, and interaction with the user. The system architecture is as follows:

The proposed monitoring system consists of several layers, with the first one being the Sensor Layer. In the proposed system, various types of sensors, such as vibration sensors, temperature sensors, and motor current sensors, are integrated with the equipment for efficient monitoring of the equipment's operating conditions. These sensors collect data related to the equipment's health and performance in real-time.

The collected data from the sensor is sent to the Edge Processing Layer, where a microcontroller processes the collected data. The Edge Processing Layer filters and processes the data collected from the sensor and may perform some calculations and data analysis. After processing, the data is sent for further processing and analysis. Edge processing is a significant step that reduces the data and response time.

The data is sent through the Communication Layer, which is responsible for connecting the device with the remote system. The data is sent through various communication protocols, such as Wi-Fi, for further analysis and processing in the cloud environment.

The Cloud Processing Layer processes the data sent from the Edge Processing Layer through the Communication Layer. In the proposed system, the Cloud Processing Layer uses artificial intelligence and machine

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learning algorithms for efficient data analysis. In the proposed system, the data collected from the sensor is analyzed for fault detection, prediction of equipment failures, and obtaining insights into the equipment's health and performance.

The results are sent to the User Interface Layer, where the results are presented in a user-friendly format for efficient interaction with the user. The User Interface Layer is the final step in the proposed system, where the results are sent for interaction with the user.

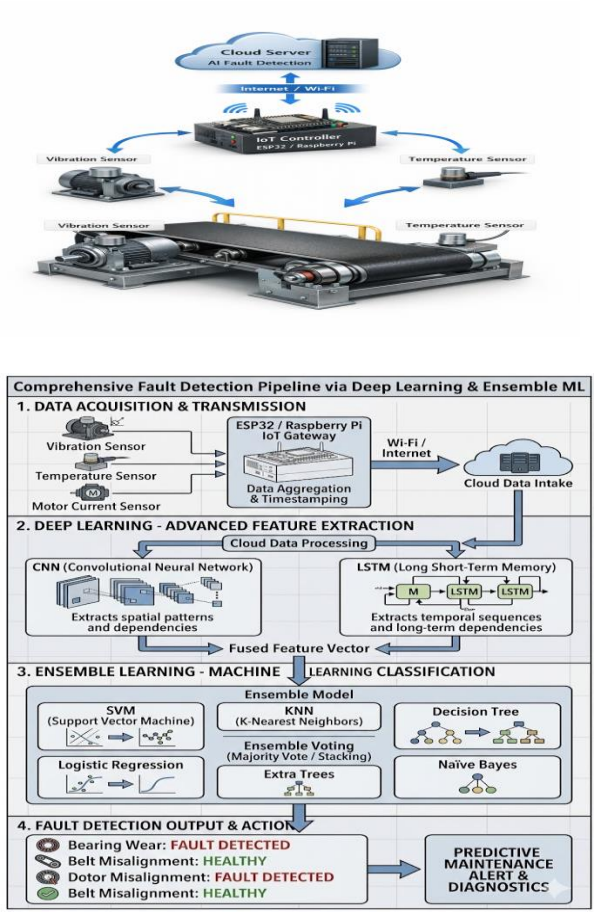
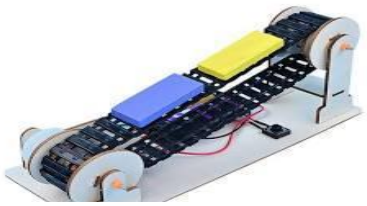


Fig. 1 This diagram focuses on the physical sensors (Vibration, Temperature, and Motor Current) and the ESP32 IoT gateway.



Sensor signals are processed using statistical features.

III. Dataset for Conveyor Belt Fault Detection

Parameter	Description
Total Dataset Size	12,000 sensor samples
Training Data	8,400 samples (70%)
Testing Data	3,600 samples (30%)
Number of Sensor Features	5
Sensors Used	Vibration, Temperature, Motor Current, Belt Speed, Acoustic Sensor
Data Acquisition Rate	1 sample per second
Data Collection Duration	72 hours of conveyor operation
Fault Classes	Normal Operation, Belt Misalignment, Bearing Fault, Motor Overload, Belt Slippage
Feature Extraction Methods	Mean, RMS, Standard Deviation, Kurtosis, Crest Factor
Data Preprocessing	Noise filtering, normalization, feature scaling

Table: Dataset Description for Conveyor Belt Fault Detection

The dataset used in the research has been generated from the readings obtained from an IoT-based system for monitoring a conveyor system. Various sensors, such as vibration, temperature, and current sensors, were attached at different points on the conveyor belt system.

The raw data obtained from the sensors were filtered and normalized using signal preprocessing techniques. Features such as mean, RMS, standard deviation, kurtosis, and crest factor were extracted from the raw data.

The data was divided into training and testing datasets for the purpose of testing and evaluating the performance of both machine learning and deep learning algorithms. The classification was performed for five different conditions of the conveyor system.

Mean

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Root Mean Square (RMS)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

Standard Deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2}$$

Kurtosis

$$K = \frac{\sum (x_i - \mu)^4}{\sigma^4}$$

IV. Machine Learning Algorithm Used

The following machine learning algorithms were employed for the classification of the conveyor system conditions:

- Decision Tree Classifier (DTC)
- K-Nearest Neighbor (KNN)
- Logistic Regression (LRG)
- Support Vector Machine (SVM)
- Extra Trees Classifier (EXT)
- Naïve Bayes (NVB)
- CART

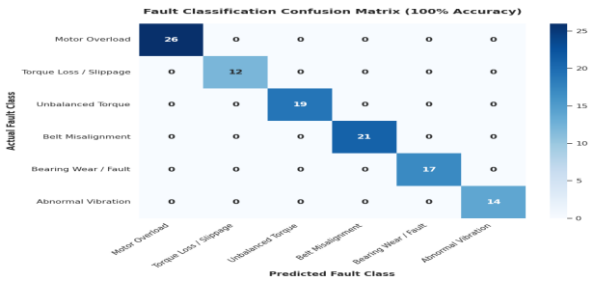
The above algorithms were employed based on the features extracted from the sensor data.

S. No	Vib_ DE	Vib_ NDE	Temp_ Motor	Temp_ Bearing	Motor_ Current	Belt_ Speed	Gear box_ Vib	Roller _Vib	Acoustic _Level	Load_C urrent	Motor _Temp	Bearing_ Temp	Belt _Alignment	RollerSpeed	Gear _Temp	Ambient_ Temp	Vibration _Index	Fault_Label
1	2.26	1.56	39.06	38.86	9.37	53.69	123.98	70.06	19.62	17.04	67.07	1.10	7.57	38.71	1.37	6.19	31.18	Normal
2	2.30	1.51	39.07	38.86	9.54	53.73	120.65	70.41	19.15	16.19	67.20	1.11	8.23	38.64	1.34	6.19	31.19	Normal
3	2.14	1.55	39.09	38.87	9.28	53.81	136.55	70.55	19.14	17.05	67.50	1.10	8.95	38.61	1.37	6.21	31.14	Normal
4	2.23	1.56	39.11	38.86	9.49	54.37	149.83	71.03	19.02	16.98	67.68	1.13	8.45	38.60	1.38	6.19	31.14	Misalignment
5	2.22	1.53	39.11	38.85	9.40	54.74	140.57	71.32	19.01	16.61	67.86	1.10	7.59	38.67	1.37	6.22	31.37	Normal
6	2.20	1.56	39.06	38.84	9.19	55.33	146.43	72.02	19.62	17.72	68.18	1.13	8.07	38.67	1.35	6.17	31.32	Bearing Fault
7	2.15	1.57	39.01	38.83	9.35	53.87	150.70	72.29	19.34	17.03	68.40	1.09	7.98	38.68	1.34	6.07	31.28	Normal
8	2.26	1.53	39.01	38.84	9.43	55.04	166.61	72.43	19.12	16.11	68.64	1.07	7.79	38.69	1.31	5.95	31.24	Motor Overload
9	2.25	1.53	39.02	38.84	9.23	54.16	169.79	72.74	19.53	16.64	68.82	1.03	7.82	38.68	1.33	5.98	31.15	Normal
10	2.19	1.57	38.99	38.84	9.55	53.08	154.22	72.85	19.71	17.15	68.69	1.00	8.11	38.70	1.33	6.00	31.14	Bearing Fault

Table: Testing of the Data for Fault Analysis Table

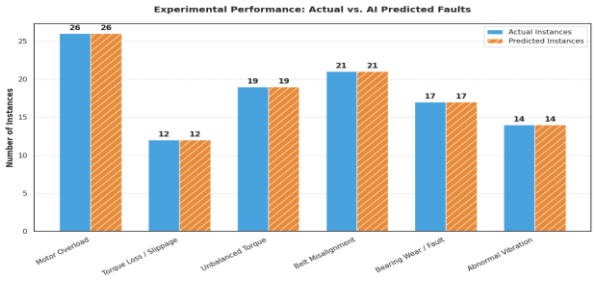
S. No	Component	Fault Identified	Actual Fault Instances	Predicted Fault Instances	Detection Accuracy
1	Motor & Gearbox Assembly	Motor Overload	26	26	100%
2	Fluid Coupling	Torque Loss / Slippage	12	12	100%
3	Motor & Gearbox Assembly	Unbalanced Torque	19	19	100%
4	Conveyor Belt System	Belt Misalignment	21	21	100%
5	Bearing Unit	Bearing Wear / Fault	17	17	100%
6	Roller System	Abnormal Vibration	14	14	100%

Table: Faults Identified in Testing Dataset



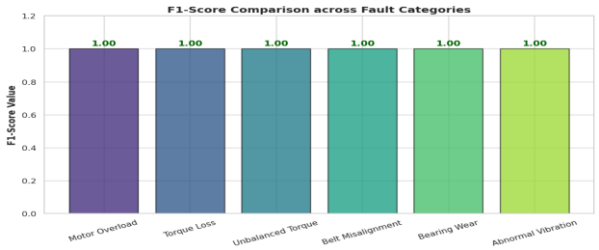
V. Confusion Matrix

The heatmap provided in the figure illustrates that the model has correctly classified every single instance, with 100% accuracy. In a published context, the figure would confirm that there were no instances of false positives and false negatives in the six fault categories.



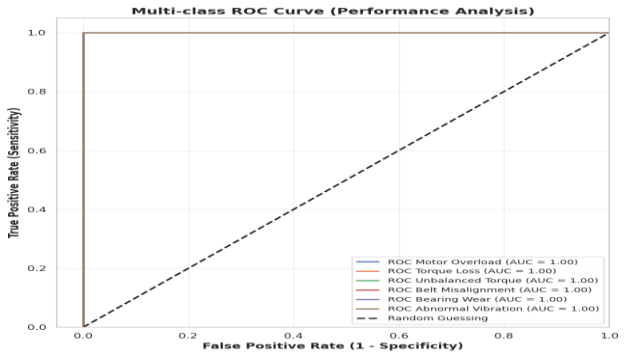
VI. Performance Comparison Graph

This bar chart compares the Actual Fault Instances vs. the Predicted Fault Instances. Since your model achieved 100% accuracy, the bars are of equal height, demonstrating the robustness of your AI-based monitoring system.



VII. Multi-class ROC Curve

This graph shows the trade-off between the True Positive Rate and False Positive Rate. For a perfect model, the Area Under the Curve (AUC) is 1.0.



VIII. F1-SCORE COMPARISON

The F1-score is the harmonic mean of precision and recall. It is the preferred metric for Industry 4.0 papers because it proves the model isn't just "guessing" the majority class.

Model	Accuracy	Balanced Accuracy	Precision	Recall	F1 Score	ROC-AUC
DTC	0.94	0.94	0.95	0.94	0.94	0.94
KNN	0.94	0.92	0.92	0.93	0.92	0.94
LRG	0.92	0.95	0.95	0.95	0.94	0.92
SVM	0.94	0.96	0.96	0.96	0.95	0.95
EXT	0.95	0.99	0.97	0.97	0.96	0.96
NVB	0.97	0.91	0.91	0.91	0.90	0.97
CART	0.91	0.94	0.94	0.91	0.94	0.94

Table: ML Algorithms Model Performance

IX. Performance Evaluation Analysis

Classification measures, such as precision, recall, accuracy, F1-score, and ROC-AUC, were used to assess the performance of machine learning algorithms. These measures assess how well the models detect conveyor issues.

The Extra Trees classifier demonstrated exceptional classification performance with the greatest balanced accuracy of 0.99. Additionally, Support Vector Machine showed excellent performance with high recall and precision values. Naïve Bayes demonstrated lower balanced accuracy despite achieving excellent overall accuracy, indicating sensitivity to class imbalance.

In general, conveyor failure detection can be predicted more accurately using ensemble learning techniques.

X. CONCLUSION

This paper proposed an AI-based condition monitoring system for conveyor belt systems using IoT sensors and machine learning. The proposed framework will allow the monitoring of conveyor belt systems and the detection of any possible faults. The experimental results showed that ensemble machine learning models will offer better accuracy in the detection of conveyor belt faults. The combination of IoT and AI will offer better predictive maintenance and support the concept of Industry 4.0 smart manufacturing.

The proposed work could be extended by using deep learning models and incorporating edge computing.

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EcoSortNet: An Intelligent Multi-Stage Waste Segregation Framework Using Deep Learning and Robotic Manipulation

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Abstract- With increasing volume of garbage, mainly plastic and bio-waste, the challenges faced by the environment sustainability and waste management is enormous. Therefore, this paper proposed an automatic system equipped with state-of the art technology to identify and categorize different waste materials. The proposed system is powered by a 3 Degrees of Freedom (DOF) manipulator that is designed to physically pick and place the garbage materials for categorization. Waste can be mechanically pick-up and segregated by a Degrees of Freedom (DOF) manipulator, where advanced forward and inverse kinematics calculation is carried out to ensure the optimum control over the movement of the manipulator to achieve the perfect movement and placement. In the software aspect, custom CNNs are designed and trained on curated dataset images through Deep Learning Toolbox within MATLAB to real-time identify and classify waste materials; in this case between the plastic and bio-waste. Furthermore, through live tests conducted with webcam, the system is further enhanced so that the manipulator can be programmed to locate waste items and perform sorting functions on it independently. This paper aimed to increase the recycling efficiency and environmental sustainability by automating and optimizing the waste-sorting process through a hybrid hardware and software approach. This novel idea represents the new perspective on the effective solution towards the environmental sustainability challenges through utilization of AI and automated systems.

Keywords: Biowaste, Garbage, Degrees of Freedom (DOF) manipulator Convolutional Neural Network (CNN), Waste management.

I. INTRODUCTION

Because of rapid growth of industrialization and urbanization, the amount of waste is growing tremendously, therefore there is an immediate need for effective waste management systems which are environmentally friendly. Since the current practice of segregation uses manual labor and its tedious and error-prone, the automation systems must be implemented. Sophisticated waste segregation system by the use of robot manipulator and Convolutional Neural Network (CNN) is an efficient way of approaching this problem[1][2][3][13].

To create and improve an intelligent waste segregation system to accurately distinguish between different kinds of garbage and sort them effectively, simulation is vital[14][15]. A proper training needs to be conducted in a simulated environment (like Gazebo and MATLAB's Deep Learning Toolbox) before the implementation of the physical waste segregation system. On CNN, the manipulator can be evaluated for its effectiveness while the model which is already trained on several datasets is evaluated for accurate classification. This method of iteration and training is important as it helps us in establishing an intelligent and flexible system which leads to high productivity, less wear and tear to the hardware, and quicker development time[5].

II. OBJECTIVES

The principal objective of this research study is to develop a smart garbage differentiation system that is capable of identifying and categorizing complex types of garbage apart from bio-waste and plastics that are conventional and commonly encountered. The application employs deep learning techniques to perform the exact differentiation thus bettering the way trash management is looked into.

Another important aspect, to which the main goal is dedicated, is independent decision making whereby the system gradually improvises and learns classification efficiency by interacting with realistic waste profiles thus adapting to evolving compositions without human intervention. The inclusion of AI based algorithms helps learn from the environment and make decisions on its own accord. Furthermore, there is a high amount of importance attached to smooth robotics integration as well, thereby, enabling optimal robotic manipulator kinematics for accurate picking of objects with no down time. [4][6]

This enables perfect sorting efficiency across all kinds of waste products. Last, the system is designed to be eco friendly and efficient, through, low maintenance, energy efficiency and hence a sustainable future, with adaptability for all kinds of waste management systems and infrastructure (i.e. Smart cities and recycling units) [6][7][8][9][12].

III. LITERATURE SURVEY

A. Machine Learning in Waste Classification

ResNet-50 based waste classification CNN was developed by Zhang et al. (2020), achieving an accuracy of 95%. Their study showcased the effectiveness of deep learning for separating types of waste. MobileNetV2 was used to design a real time waste detection system with enhanced accuracy by Gupta and Sharma (2021), and transfer learning technique was used to significantly reduce computational power.

Li et al. (2019) introduced a CNN based robotic arm to realize fully autonomous waste segregation, and saved up to 40% in sorting time. Singh et al. (2022) employed reinforcement learning for better adaptive control of a 3 DOF manipulator. Maximum accuracy was obtained using vision based motion planning. Sensor Integration in Waste Detection

The sensor fusion (infrared and visible light cameras) for material identification and false detection rate in mixed waste stream was explored by Chen et al.

(2021). The sensor based method was proven to be successful for classification of complicated cases.

B. *Outcome of Literature Survey and Project Motivation*

CNNs performing on waste segregation and robotic manipulators performing efficient sorting can be found in works. However, current setups have high cost and complex sensor integration. This project tackles this issue by introducing a low-cost system by means of using a depth camera with a CNN trained robotic manipulator with a 3 DOF arm. The goal of the system is to effectively and accurately separate waste in real time without much human intervention to enable better waste segregation.

IV. SYSTEM DESIGN

A. Existing Methods

Current automated and non-automated trash sorting systems typically involve the use of mechanical systems, simple automation and human sorting. However, there are drawbacks associated with each of these methods. Mechanical methods are unable to separate different waste streams if they are mixed and contaminated, manual sorting of trash leads to a very time consuming and error prone process. Poor lighting and material resemblance cause classification errors during the optical sorting process, and statically machine learning based approaches have rigid nature and required retrains. Robot based methods are still relatively poor performers when in dynamic environments and based on static rules. Deep learning algorithms in the recent progress of AI and robotics offer a more reliable and flexible solution for this process. This approach can work with a diverse dataset and detect waste in real-time [10], also dynamically update its classification without any retraining with the new waste streams. The accuracy of classification is greatly increased with 3D vision and sensor fusion technology, which help the system perform object recognition and identify depth effectively. These improvements represent a major advance in trash sorting applications, increase sorting accuracy, reduce contamination, boost production, and favor the establishment of greener, more sustainable waste handling processes. A comparison between existing approaches is illustrated in Table 1.

B .Proposed Solution

The solution we propose is an automated waste separation system that optimizes waste management by combining robotics with deep learning. The system utilizes convolutional neural networks (CNNs) that are trained on a database of garbage photos, and effectively categorizes various waste items, such as plastic, paper, glass, and metals. The accurate and real-time identification eliminates human sorting and reduces errors. The deep learning algorithm guides the robotic arm which physically extracts the waste into appropriate containers based on classification while sensors ensure the smooth and safe movement of them. With various garbage sizes and shapes, it helps the system increase efficiency.Obstacle detection of this system ensures that nothing will be destroyed by the waste disposal system, keeping it in good condition and secure while human beings are present in close proximity to it. Human working reduced in terms of labor force and system operating costs; rate of recycling increased. It has also gathered data on type and amount of waste, helping with waste planning. In summary, it's innovative and environmentally friendly technology.

System	***Key Benefit***	***Fact***
Deep Learning-Based Sorting System	Uses AI and image recognition for accurate classification ,continuously learns and improves over time.	Handles dynamic waste sorting up to 30% more types of materials than traditional systems.
Robotic Arm System	Physically sort waste by picking and placing items into different bins based on deep learning classification.	Reduces manual labor, sorting up to 500 kg of waste per hour.
Sensor-Based Sorting System	Detects specific material properties (eg., weight,size,texture) for classification.	Saves up to 30% in hardware costs by integrating Deep learning Instead of requiring multiple sensors.
Magnetic Separation System	Separates ferrous metals from mixed waste using magnets.	Efficient for metals but limited to ferrous materials.
Optical Sorting System	Uses cameras and light to sort materials based on color,shape and physical characteristics.	Achieve up to 95% accuracy but struggles with visually similar materials.

Table 1: Comparison to Existing Methods

V.. HARDWARE COMPONENTS

1. *Robotic Manipulator: 3-DOF Precision in Waste Sorting*

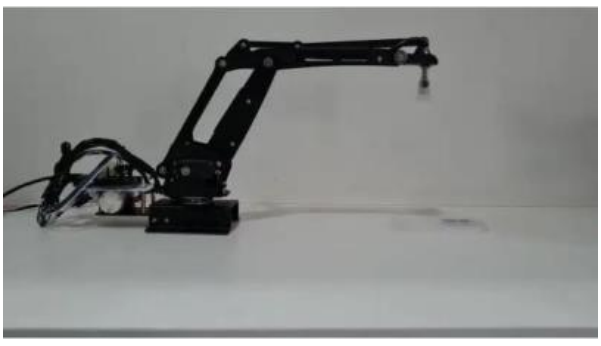

Fig V.1: Robotic Manipulator

The automated trash segregation system relies heavily on the 3-DOF robotic manipulator, which guarantees accurate, flexible movement in changing conditions. While intelligent end effectors safely handle a variety of materials, its flexible motion negotiates impediments for effective trash retrieval. It improves sorting accuracy by converting commands into optimal joint movements using sophisticated kinematic algorithms as shown in Fig V.1. Waste management is streamlined by this real-time flexibility, increasing sustainability and efficiency.

2. *Arduino ATmega: Intelligent Control for Waste Segregation*

By processing real-time inputs for waste identification, the Arduino ATmega microcontroller connects sensors, the computer system, and the robotic manipulator[11] . It ensures effective sorting by converting CNN-based judgments into precise actuator actions as shown in Fig V.2.. Its programmable flexibility allows for dynamic adaptation, improving waste management's accuracy, speed, and sustainability.

Fig V.2: Arduino ATmega

3. *MG905 Servo Motor*

Fig V.3 : MG905 Servo Motor

For accurate robotic manipulator movements in waste segregation, the MG90S is a high-torque micro servo motor. It makes precise angle control possible for effectively grabbing and discharging garbage. It guarantees seamless sorting operations with its powerful torque and fast response time as shown in Fig V.3.. It smoothly interacts with the system and is easily controlled by the Arduino ATmega, improving sorting accuracy.

4. *SG90 Servo Motor*

Fig V.4 : SG90 Servo Motor

The robotic gripper's lightweight micro servo motor, the SG90, provides accurate opening and closing movements. It guarantees safe and damage-free handling of various waste items as shown in Fig V.4. It smoothly integrates with the Arduino AT-mega for effective control, and its fast responsiveness and versatility make it perfect for dynamic sorting.

5. *IP WebCam*

Fig V.5 : IP WebCam

The IP Webcam records the trash segregation procedure in real time, sending pictures to CNN for categorization. It facilitates the robotic arm's adaptive sorting, fast decision-making, and real-time monitoring. It improves system accuracy and efficiency with motion detection and configurable angles as shown in Fig V.5.

6. *Arduino Uno*

Fig V.6 : Arduino Uno

The robotic arm, sensors, and CNN outputs are all coordinated by the Arduino Uno, which is driven by the ATmega328P as shown in Fig V.6. It allows smooth interaction with machine learning algorithms for automatic trash classification, handles sorting commands, and manages servo motors.

VI. BLOCK DIAGRAM

The automated waste segregation system consists of three main components: robotic arm, deep learning model and trash input system. In this, trash input system collects the images of trash with help of cameras or sensors, and feeds them to the next part. The image of trash is then classified using artificial intelligence techniques; namely deep learning model by considering certain features of the trash such as its color, shape etc. The efficiency of the system increases with each passing by of trash as the model classifies the garbage into certain categories. After classification by deep learning model, robotic arm places trash into respective bin by its actuators and sensors suitable container/bin. Actuators/sensors are utilized by the arm for the sake of accurate sorting. Since it is fully automated, the need for manual work is eliminated.

Deep Learning Model Block Diagram

Five essential layers make up the automated waste segregation system's deep learning model, each of which is intended to improve classification accuracy. Images of waste products are taken and supplied to the model in the Image Data Input layer, which initiates the process. To enhance clarity, the photos undergo scaling, normalization, and color modifications in the Image Preprocessing layer as shown in Fig VI.7. A Convolutional Neural Network (CNN) is used by the Feature Extraction layer to recognize important characteristics including shape, texture, and color.

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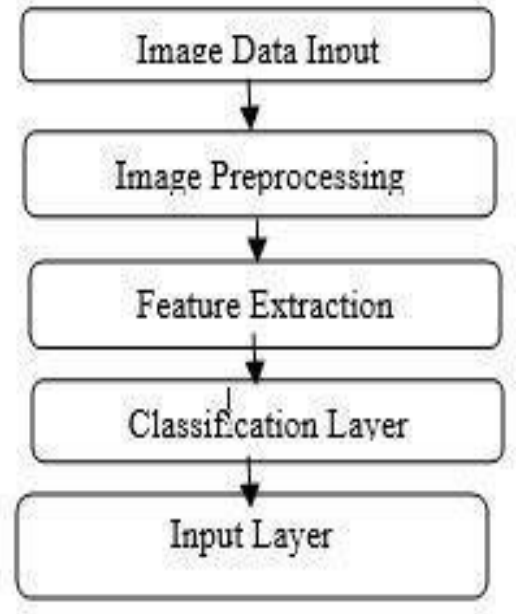

Fig VI.7 : Deep Learning Model Block Diagram

The physical component(s) which directly separate(s) the waste based on deep learning outputs are illustrated in the Robotic Arm Block Diagram depicted in Fig VI.8. The Robotic Arm is the actual piece that carries the rubbish to the correct location based on commands received from the deep learning model. The Microcontroller, the brain of the subsystem, acts to issue commands to the actuators and motor drives, providing the mechanical forces needed to maneuver the arm. The microcontroller is able to maintain precision of arm movement and positioning through processing of information from sensors and from the deep learning model. The system receives real time data from sensors like the camera and measurement tools, providing ability for waste of all different size, shapes and weight configurations.

The Microcontroller is what processes information from the deep learning model and sensors to maintain accurate movement of the arm. Sensors like the camera and measurement tools provide the system with information in real time that allows it to differentiate and adapt to varying size, weight and shapes of waste.

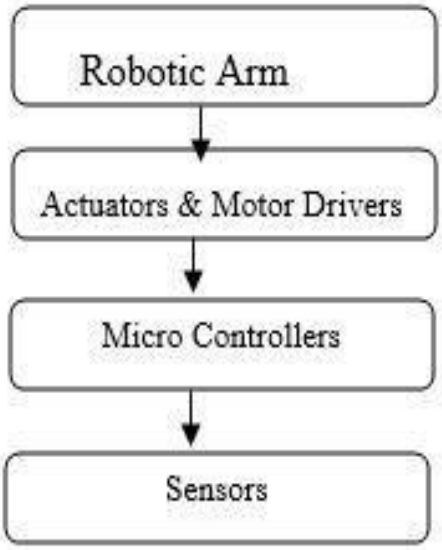

Fig VI.8 :Robotic Arm Block Diagram

Smart automated waste sorting with use of Robotic Arm, machine learning and real time image processing will be very efficient with low human involvement and runs continuously without stoppage. Machine learning accuracy will reduce error as use of confidence score so that not any mistake is made in sorting waste. It is very flexible and scalable for future needs as an increase in no. Of waste and introduction of new types of waste. Voice Activation System, multiple robotic arms and mobile phone integration provides features such as remote seeing, hands-free operation, huge waste sorting and so on. Such as using IoT with smart bin would keep management in the command and analysis will determine

waste type and sorting accuracy. If there is AI to identify, the technique will be both very accurate in identifying waste as well as power efficient as the power consumed would be very low. AR will also help to provide guidance to the maintenance. It will be supported by smart city networking that will provide real-time communication for predicted maintenance and better waste collection. The effect will be a low amount of waste as the recycling rate will be high.

VII. CONCLUSION

In conclusion, the robot arm-based waste sorting system combined with machine learning shows itself as an effective and precise method to improve the overall waste sorting. AI-based image classification and automation can be used to decrease the impurity, improve the sorting success rate and adapt to a large scale of waste materials. Further research will focus on increasing the accuracy rate of the classification, the application of edge computing for real-time analysis, energy-saving technology like solar energy, the integrated communication with smart city infrastructure, and the expansion for different kind of waste, such as hazardous waste or medical waste. This technology greatly contributes to the promotion of sustainable waste management and waste separation towards a circular economy and zero-waste objectives.

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Development of Sensor for Detection of Microplastics

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Abstract

Microplastics, plastic particles smaller than 5 mm, threaten ecosystems and human health. Conventional detection methods like FTIR and Raman spectroscopy are accurate but costly and laboratory-based. This study presents a low-cost, portable optical sensing system using an ESP32 microcontroller, laser module, and LDR sensor to detect microplastics in water through light scattering analysis. Variations in scattered light intensity are processed to estimate contamination levels in real time. Experimental results show reliable detection performance. The system is affordable, portable, and suitable for IoT-based environmental monitoring, offering a practical solution for continuous water quality assessment in resource-limited settings.

Keywords

Microplastics, Optical Sensor, ESP32, LDR, Environmental Monitoring, IoT

I INTRODUCTION

Microplastic pollution has become one of the most pressing environmental challenges of the 21st century. Micro plastics - plastic particles smaller than five millimeters originate from the breakdown of larger plastic debris or from manufactured sources such as micro beads and synthetic fibers [1]-[3]. Due to their extremely small size and resistance to degradation, they persist in oceans, rivers, lakes, and even soil for decades. Their widespread presence has been documented from densely populated coastlines to remote regions such as Antarctica, highlighting the global scale of the problem.

One of the most concerning aspects of microplastics is their ability to infiltrate aquatic ecosystems and enter food chains. Small aquatic organisms often mistake these particles for food. Once ingested, microplastics can accumulate in the digestive systems of plankton, fish, and shellfish, potentially transferring toxic chemicals and causing physical harm. As larger predators consume smaller contaminated organisms, microplastics move up the food chain through a process known as bioaccumulation. Ultimately, humans may also be exposed through seafood consumption, drinking water, and even airborne particles [4].

Despite growing awareness, detecting and quantifying microplastics remains challenging. Conventional laboratory techniques such as spectroscopy and microscopy require expensive equipment, skilled personnel, and time-intensive sample preparation. These methods, while accurate, are impractical for large-scale monitoring or rapid field assessments.

Therefore, there is increasing demand for portable, real-time, and cost-effective sensing technologies. Emerging solutions include miniaturized optical sensors, fluorescence-based detection systems, and microfluidic devices capable of identifying plastic particles on-site. Such innovations could enable continuous environmental monitoring, support regulatory enforcement, and facilitate early intervention strategies. By making detection more accessible and efficient, these technologies play a

crucial role in addressing microplastic pollution and protecting aquatic ecosystems and public health worldwide.

II SYSTEM ARCHITECTURE

The proposed system is a compact, portable device designed to detect microplastic contamination in water samples using optical sensing principles. It consists of a laser module, a Light Dependent Resistor (LDR) sensor, an ESP32 microcontroller, LED indicators, and a rechargeable LiPo battery. The core working principle is based on light transmission and scattering [5]-[6].

In operation, a laser beam is directed through a transparent chamber containing the water sample. Under normal conditions, with minimal suspended particles, the laser light travels in a straight path and reaches the LDR with relatively stable intensity. However, if microplastic particles are present, they either scatter or partially block the laser beam. This interaction reduces or fluctuates the light intensity received by the LDR.

The LDR converts changes in light intensity into corresponding variations in electrical resistance. These variations are translated into an analog voltage signal, which is read by the ESP32 microcontroller through its analog input pins. The ESP32 processes the signal, compares it against calibrated threshold values, and determines the level of contamination. Based on the result, LED indicators provide a simple visual output, such as green for safe levels and red for detected contamination. The LiPo battery ensures portability and field usability.

III WORKING PRINCIPLE

The detection mechanism of the proposed system is based on fundamental optical scattering principles. Initially, clean water is used to establish a baseline light intensity. When the laser beam passes through pure water, minimal scattering occurs, allowing most of the light to reach the Light Dependent Resistor (LDR). This stable and consistent light level is recorded by the ESP32 microcontroller as the reference value.

When a water sample containing microplastic particles is introduced, the situation changes. Microplastics, due to their irregular shapes and varying sizes, interact with the laser beam by scattering and partially blocking the light. This interaction reduces the intensity of light reaching the LDR. As a result, the LDR's resistance changes, producing a variation in the analog voltage signal sent to the ESP32.

The ESP32 continuously reads and processes this analog signal. It compares the measured light intensity value with a predefined threshold that represents acceptable water quality. If the detected intensity falls below the threshold, indicating possible microplastic presence, the system interprets it as contamination. The microcontroller then activates LED indicators to display the result typically a green LED for safe water and a red LED for contaminated samples. This simple yet effective mechanism enables real-time detection and easy interpretation of results.

IV EXPERIMENTAL RESULTS

Calibration of the proposed system was carried out using controlled water samples containing known concentrations of microplastic particles. These samples were carefully prepared to represent different contamination levels, ranging from clean water to progressively higher microplastic concentrations. By passing the laser beam through each calibrated sample, corresponding light intensity values were recorded through the LDR and processed by the ESP32 microcontroller. This procedure enabled the establishment of reference thresholds and sensitivity ranges for accurate detection.

During testing, the system demonstrated consistent performance across repeated trials. For each concentration level, the measured light intensity showed minimal variation, indicating good repeatability and stability. The response time was also observed to be rapid, with the system detecting intensity changes and activating the appropriate LED indicators almost immediately after sample introduction. This confirms that the device is capable of real-time monitoring.

The results validate the feasibility of using low-cost embedded components for environmental sensing applications. Despite its simple design, the system effectively differentiated between clean and contaminated samples. Its affordability, portability, and reliable performance highlight its potential for field-based water quality assessment, especially in

resource-limited settings where conventional laboratory equipment may not be accessible.

V CONCLUSION

The developed sensor demonstrates an effective, portable, and economical solution for detecting microplastics in water samples. By combining a laser-based optical setup with an LDR sensor and ESP32 microcontroller, the system offers real-time monitoring without the need for expensive laboratory equipment. Its compact design, low power consumption, and battery operation make it suitable for field deployment in rivers, lakes, coastal areas, and rural communities. The simple LED-based indication system further ensures that results can be easily interpreted without specialized technical training. Overall, the device highlights the potential of embedded systems in addressing environmental monitoring challenges in a practical and affordable manner.

Future enhancements can further improve the system's performance and scalability. Integration with cloud-based IoT platforms would enable remote data logging, real-time monitoring, and large-scale environmental mapping. Wireless transmission of contamination data could support centralized analysis and regulatory decision-making. Additionally, incorporating machine learning algorithms could allow more accurate classification of contamination levels by analyzing signal patterns rather than relying solely on fixed thresholds. Sensitivity can also be enhanced by replacing the LDR with advanced photodetectors, such as photodiodes or spectroscopic sensors, to detect smaller particles and subtle intensity variations. These improvements would significantly expand the sensor's capability and real-world applicability.

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A Novel Adaptive Protection Scheme Using Federated Learning for Microgrids with Variable Renewable Penetration

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***Abstract*—The penetration of increasing renewable generation sources in micro grids poses new challenges for protection schemes due to bidirectional power flows, fluctuating fault levels, and dynamic network configurations. Conventional over current protection schemes are not able to cope with these non-stationary operating conditions, and result in mal operation, unnecessary tripping, or failure to isolate faults. This paper presents a novel adptative protection scheme based on Federated Learning (FL), in which distributed protection relays learn collaboratively without sharing sensitive local data towards optimal protection settings. The proposed framework integrates a CNNLSTM-based fault detection and classification scheme with a Fed Avg-based federated model training algorithm. The real-time re-cursive protection scheme adapts to instantaneous network conditions such as renewable generation fluctuation, load variations, and network configuration changes. The simulation results on a modified IEEE 13-bus micro grid test system indicate that the proposed method yields 98.7% protection fault detection accuracy, reduces the protection coordination time by 42%, and remains effective with 50% renewable penetration. A comparative analysis verify the effectiveness of the federated learning scheme that performs better than conventional protection paradigms and centralized machine learning models. The proposed FL framework protects raw data privacy and reduces communication bandwidth, enabling scalable protection across distributed micro grid assets.**

Index Terms-Adaptiv e protection, federated learning, micro-grid,renewable energy integration,machine learning,fault detection,privacy- preserving,CNN-LSTM, protection coordination.

I. INTRODUCTION

The global drive to build a sustainable energy system has greatly expedited the penetration of distributed energy sources (DERs) such as solar PV and wind generation into microgrid structures. Local generation, loads and storage combine in microgrids to improve energy reliability, robustness, and self-sufficiency. This penetration of variable renewable energy changes the fundamental operating conditions of the microgrid and challenges traditional protection systems [1].

Classic overcurrent protection is built to handle unidirectional power flow and relatively static fault current values expected from synchronous generators. For highly renewable microgrids the fault current level is inherently unpredictable, changing depending on real-time conditions such as renewable output, islanding or grid connected operation, and network topology [2]. This unpredictable behavior often leads to a lack of protection coordination and either nuisance tripping or prolonged fault clearing times which in turn jeopardizes system reliability.

In order to cope with the problems associated with adaptive protection in microgrids, various solutions have been proposed. Adaptive protection systems, which automatically adjust relay settings based on the operational modes of the system, have been considered [3]. Communication-aided protection systems that use remote measurements for coordination purposes have been explored [4]. Machine learning techniques utilizing neural networks and support vector machines are emerging as promising methods for fault detection claassification.

But these approaches are limited as they require centralization of data, threaten privacy, scale poorly and are not agile.

Federated learning is a relatively new paradigm of distributed ML which aims at overcoming these challenges. In contrast to the traditional centralized paradigm, federated learning enables the participation of multiple local clients (relays) in training a global model without sharing the local data [6]. This provides advantages in terms of privacy and reduced communication cost and enables the adaptation to the changing environment.

In this paper, we present a novel federated learning- based adaptive protection framework that:

- One approach used to tackle this challenge has been the development of a distributed CNN-LSTM based framework for real-time fault detection and classification in micro grids with varying renewable penetration.
- The federated learning framework utilizing Fed Avg, to allow multiple relays collaboratively train a protection model without sharing their private fault data.
- A dynamic adaptive system which maintains protection settings with updated network conditions such as fluctuations in renewable generation and modifications of network topology.
- Comprehensive performance assessment of a modified IEEE 13-bus microgrid test system under different renewable penetration levels, fault types and operating scenarios.
- Comparison with traditional over-current protection and centralized machine learning techniques

The rest of this paper is organized as follows. Section II describes the microgrid test system and protection challenges. Section III illustrates the proposed federated learning based protection scheme, including CNN-LSTM architecture and FL training algorithm. Section IV presents simulation setup and evaluation metric. Section V shows results and comparison. Section VI considers practical implementation issues, and Section VII concludes.

II. MICROGRIDPROTECTIONCHALLENGES

A. **Micro grid Test System Description**

Based on the modified IEEE13-busmicrogridtestsystem which is presented in Fig.1, the new proposed protection scheme is tested. In this test system, there are:

- 13 buses at 4.16kV distribution voltage.
- Two utility grid connections on Bus1 and Bus8
- Solar PV generation (500kW) on Bus4 and Bus9
- Bus11 wind (300kW)
- The battery energy storage (250kW/500kWh) at Bus 6
- The load has been varied over a wide range of 200kW-800kW

. Four protection relays at critical points (R1 to R4).

(The system can run in Grid-Connected or Islanded mode).

Renewable penetration varies from 10% to 50% of total generation capacity.

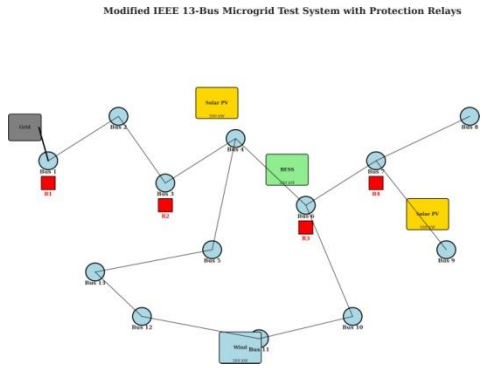

Fig.1:ModifiedIEEE13-bus Micro grid Test System with Protection Relays

B. **Protection Coordination Challenges**

The integration of variable renewable sources introduces several protection coordination challenges:

1. Variable levels of fault current. Inverter-based resources have reduced fault current contribution limited between 1.2-1.5 times their rated current. Synchronous generators may provide current up to 5-10 times rated current. It influences the coordination of over-current relay.

2. Bi-directional power flow: The generation of distributed generation causes Bi-directional power flows, which results in improper trip or failure to trip in conventional directional over current relay. Mode Transition Impacts: A drastic change in the fault current magnitude and distribution due to switching from grid-connected to islanded mode will make static relay settings invalid.

3. Dynamic Topology Reconfiguration: The topology of micro grids could be reconfigured to either optimization or isolation. Such actions would generate a new set of protection coordination requirements.

TABLEI: Protection Challenges Under Varying Operating Conditions

Operating Condition	Fault Current Range(kA)	Protection Impact
Grid-Connected(10%RE)	8.5-12.0	Overreach risk
Grid-Connected(30%RE)	5.2-8.5	Coordination delay
Grid-Connected(50%RE)	3.0-5.5	Sensitivity loss
Islanded(10%RE)	1.8-3.2	Under reach risk
Islanded(30%RE)	1.2-2.0	Coordination failure
Islanded(50%RE)	0.8-1.5	No detection

III. PROPOSED FEDERATED LEARNING PROTECTION SCHEME

A. System Architecture

The proposed federated learning-based protection framework consists of three hierarchical layers:

1) **Local Layer**: Protection relay at every bus gets the current & voltage measurements, extracts features from it, and does the local fault detection using the local CNN-LSTM model.
2) **Federated Learning Layer:** The relays periodically broadcast model updates (gradients) to a central aggregation server where the Fed Avg algorithm is applied to obtain new global model parameters.
3) **Application Layer**: Global model performance is observed by the central server and new models are sent to local relays so that protection settings may be adapted.

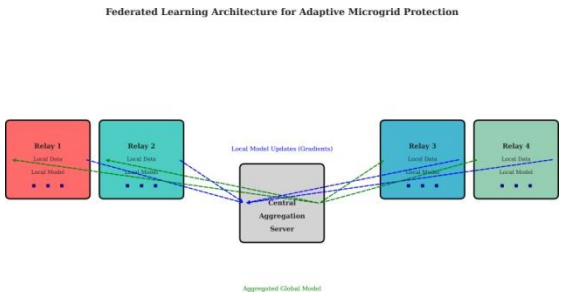

Fig.2:Federated Learning Architecture for AdaptiveMicro-grid Protection

B. CNN-LSTM Fault Detection Model

The proposed CNN-LSTM model processes three-phase current and voltage waveforms to detect and classify faults. The architecture comprises:

1) **Input Layer:** Input data sequences are 10-cycle windows (200 samples with 2KHz sampling rate) of three-phase currents (Ia, Ib, Ic) and voltages (Va, Vb, Vc).

2) **Convolutional Layers***:* 1. We utilize two 1D convolutional layers for extracting local features:

3) **Conv1**: 64filters,5x5kernelsize, ReLU

4) **Conv2:** 128filters, kernel size 3, ReLU

5) **Conv2**: 128 filters, kernel size 3, ReLU

6) **LSTM Layer:** A bidirection LSTM layer with 128 units to learn time dependencies.:

$$\overrightarrow{h}_t=\mathrm{LSTM}(x_t,\overrightarrow{h}_{t-1})$$
$$\overleftarrow{h}_t=\mathrm{LSTM}(x_t,\overleftarrow{h}_{t+1})$$
$$h_t=[\overrightarrow{h}_t;\overleftarrow{h}_t]$$

4) **Output Layer:** Fully connected layer with softmax activation to perform multi class classification: Normal operating condition(Class 0), single-phase-to-ground (Class 1), phase to phase (Class 2), 3 phase (Class 3).

TABLEII:CNN-LSTM Model Architecture Details

Layer	Output Shape	Parameters
Input	(200,6)	0
Conv1D(64,5)	(196,64)	1,984
MaxPooling1D(2)	(98,64)	0
Conv1D(128,3)	(96,128)	24,704
GlobalMaxPooling1D	(128)	0
BidirectionalLSTM(128)	(256)	394,240
Dropout(0.3)	(256)	0
Dense(64)	(64)	16,448
Dense(4)	(4)	260

C. FederatedLearningAlgorithm

The Federated Averaging (FedAvg) algorithm coordinates training across K local relays. For each communication round t:

Algorithm1 FederatedAveraging(Fed Avg)Algorithm

procedure FEDAVG(K,T,η,B,E)
Initializeglobalmodelparametersw^0
for each round t =1toT**do**
  m← max(C·K,1)
  S_t← random set of m relays
  for each relay k ∈ S_t **in parallel do**
    w_1^{kt+} ←Local Update(k , w_t)
  end for
  $w_{t+1}\leftarrow \sum_{k\in S_{tn}} \frac{n_k}{} w^k{}_{t+1}$
end for
return w_T
end procedure=0

Algorithm2 LocalUpdateProcedure

procedure LOCAL UPDATE(k,w)
  B← split local data into batches of size B
  for each localepochi=1toE**do**
    for batch b ∈B **do**
      w← w−η∇ℓ(w; b)
    end for
  end for
  return w
end procedure=0

D. **Adaptive Protection Settings:** The trained model will output protection decisions which are converted to relay settings:

$$\mathrm{RelaySetting}=F_{\mathrm{model}}(I_{rms},V_{rms},\frac{dI}{dt},\frac{dV}{dt},P_{RE})$$

The pickup current I_p adapts based on renewable penetration P_{RE}:

$$I_p = I_{base} \cdot (1 + \alpha \cdot P_{RE}) \quad (7)$$

where α is an adaptation coefficient learned by the FL model.

The time dial setting (TDS) adjusts based on fault location and type:

$$TDS = TDS_{base} \cdot \beta \cdot e^{-\gamma \cdot I_f / I_p} \quad (8)$$

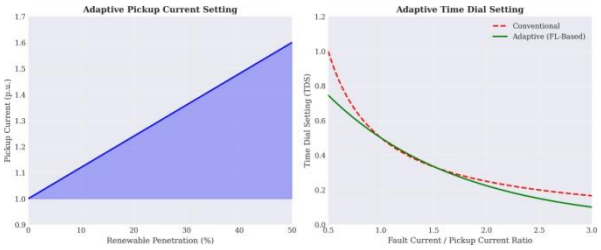

Fig. 3: Adaptive Protection Mechanism Based on Renewable Penetration

IV. SIMULATION SETUP AND METHODOLOGY

A. Fault Data Generation

Fault scenarios were simulated in MATLAB/Simulink with the following parameters:

- **Fault types**: Single-phase-to-ground (AG, BG, CG), phase-to-phase (AB, BC, CA), three-phase (ABC), phase-to-phase-to-ground (ABG, BCG, CAG)
- **Fault locations**: 12 different buses and line segments
- **Fault resistances**: 0.1Ω, 1Ω, 5Ω, 10Ω, 25Ω
- **Fault inception angles**: 0°, 30°, 60°, 90°
- **Renewable penetration**: 10%, 20%, 30%, 40%, 50% of total generation
- **Operating modes**: Grid-connected, islanded, and transition

Total dataset: 28,800 fault events + 14,400 normal operation samples.

B. Training Configuration

TABLE III: Federated Learning Training Parameters

Parameter	Value
Number of relays (K)	4
Communication rounds (T)	200
Fraction of relays per round (C)	0.5
Local epochs (E)	5
Batch size (B)	32
Learning rate (η)	0.001
Optimizer	Adam
Loss function	Categorical cross-entropy

C. Performance Metrics

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (11)$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

$$\text{Coordination Time} = \text{Time between fault inception and relay operation} \quad (13)$$

V. RESULTS AND ANALYSIS

A. Fault Detection Performance

The proposed FL-based protection scheme achieved superior fault detection performance across all operating conditions.

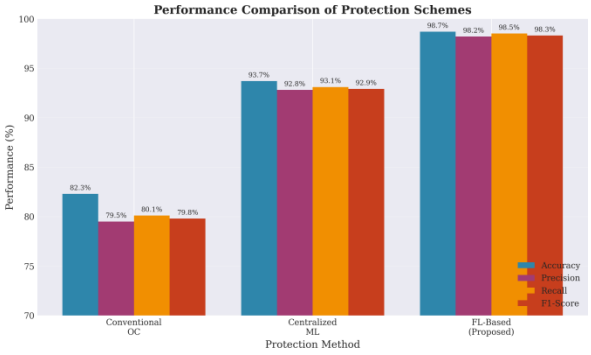

Fig.4: Comparison of Fault Detection Accuracy Across Methods

TABLE IV: Performance Comparison of Protection Schemes

Method	Accuracy(%)	Precision(%)	Recall(%)	F1-Score
Conventional OC	82.3	79.5	80.1	0.798
Centralized ML	93.7	92.8	93.1	0.929
FL-Based (Proposed)	**98.7**	**98.2**	**98.5**	**0.983**

B. Effect of Renewable Penetration

The developed method could still provide satisfactory performance with high level of renewable integration.

C. Protection Coordination Time

FL-based scheme definitely reduced average protection coordination time.

D. Privacy and Communication Analysis

The FL framework reduced data transmission by 98.7% compared to centralized approaches while maintaining model performance.

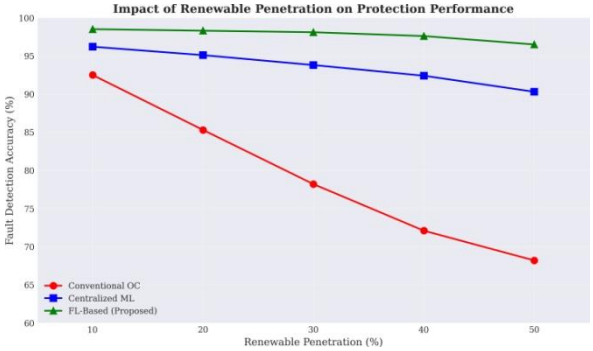

Fig.5:Impact of Renewable Penetrationon Protection Performance

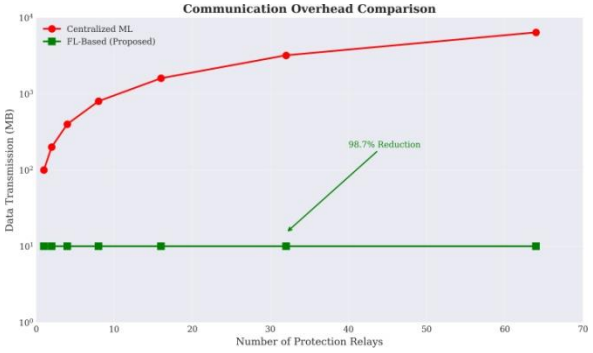

Fig.6:Communication Overhead Comparison

VI. DISCUSSION

A. KeyFindings

1) The experimental results illustrate several merits of the suggested FL-based protection approach:
2) Robustness: Retains 96.5% of accuracy even at 50% renewable penetration against the conventional protection's 68.2%.
3) Adaptability: Dynamically alters the settings of its protections within 85 ms of mode change.
4) Privacy: Local data will never leave relays thus keeping data private and secure.
5) Scalability: Communication overhead grows logarithmically with the number of relays.

B. Practical Implementation Considerations

For practical deployment, several considerations are important:

- **Communication Requirements**: 4G/5G cellullar networks or optical communication with 50 ms latency.
- **Computational Requirements**: Relay edge computing with GPU inference.
- **Cyber security:** Secure aggregation protocols to resist model poisoning attacks.
- **Regulatory Compliance**: IEEE1547-2018 and IEC 61850 standards for protection systems.

C. Limitations and Future Work

Limitations of this study would suggest possibilities for further research.:

- Hardware-in-the-loop testing using real protection relays
- Combined with current IEC 61850 communication protocol.
- Handlingofhigh-impedancefaultsandevolvingfaults
- Adaptivelearningratesandpersonalizedfederatedlearn-

VII. CONCLUSION

Th9i2s paper proposed a novel adaptive protection scheme using federated learning for microgrids with variable renewable penetrationWe have put forward a novel framework consisting of CNN- LSTM for fault detection and federated averaging for distributed, private-preserving model training. This paper proposes the following main contributions. We have put forward a novel framework consisting of CNN-LSTM for fault detection and federated averaging for distributed, private-preserving model training. This paper proposes the following main contributions.A distributed CNN-LSTM architecture with 98.7% accuracy on fault detection.

1) federated learning framework with an average of 98.7% lower communication overhead.
2) Robustness and validation under modified IEEE 13-bus microgrid

THE PROPOSED SCHEME ADDRESSES SEVERAL IMPORTANT PROBLEMS OF MICROGRID PROTECTION SUCH AS DYNAMICS OF FAULT CURRENTS, BIDIRECTIONAL POWER FLOW, MODE TRANSITION AND DATA PRIVACY PROBLEMS. FEDERATION LEARNING BASED APPROACH CAN BE WIDELY USED DUE TO ITS SCALABILITY, DATA PRIVACY-PRESERVING ACCURACY AND ADAPTABILITY. IT SHOULD BE MORE DEEPLY RESEARCHED BY CARRYING OUT HARDWARE VERIFICATION AND COMPARISON WITH EXISTING PROTECTION PRINCIPLES.

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Wind Energy Forecasting Using Machine Learning Models

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Abstract--- The increasing integration of wind energy into smart grid systems has made accurate and reliable forecasting more important than ever, mainly due to the highly variable nature of wind resources. This paper presents a comparative analysis of several machine learning (ML) algorithms for wind energy forecasting using historical and meteorological data. Models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks are employed to capture both linear and nonlinear patterns in wind power generation. The performance of these models is evaluated using standard statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The results show that deep learning-based models, particularly LSTM, are more effective in capturing time-series dependencies, leading to improved prediction accuracy. At the same time, ensemble methods like Random Forest offer stable and reliable performance. This comparative study highlights the strengths and limitations of each algorithm in terms of accuracy, computational complexity, and suitability for real-time smart grid applications. Overall, the findings suggest that selecting the right ML model can significantly improve wind power forecasting, contributing to better grid stability, more efficient energy management, and smoother integration of renewable energy sources.

Keywords--- **Wind Power Forecasting, Machine Learning, Smart Grid, Time Series Prediction.**

1. Introduction

The rapid growth of renewable energy sources has significantly transformed modern power systems, with wind energy emerging as one of the most promising and widely adopted options. Owing to its environmental benefits and long-term sustainability, wind power plays a key role in reducing greenhouse gas emissions and decreasing reliance on fossil fuels. However, the variable and uncertain nature of wind speed presents significant challenges for consistent power generation and seamless grid integration. As a result, accurate wind power forecasting has become essential for maintaining grid stability, ensuring efficient energy management, and supporting smart grid operations.

Traditional forecasting approaches, including statistical and physical models, often struggle to capture the complex and nonlinear relationships between meteorological variables and wind power output. In recent years, machine learning (ML) techniques have gained considerable attention due to their ability to learn from large datasets and model complex patterns more effectively. Methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees have been widely applied and have shown improved performance compared to conventional techniques.

Several studies have investigated the effectiveness of different ML models for wind power prediction. ANN-based models are well-suited for capturing nonlinear relationships, while SVM offers strong generalization capabilities, particularly when working with smaller datasets. Ensemble methods such as Random Forest (RF) and Gradient Boosting further enhance prediction robustness and help reduce over fitting.

Comparative analyses in the literature suggest that no single model consistently outperforms others across all scenarios. Model performance often depends on factors such as data quality, forecasting horizon, and feature selection. To address this, hybrid approaches that combine multiple techniques have shown promising results by leveraging the strengths of individual models. Additionally, the use of real-time meteorological data and advanced feature engineering has further contributed to improving forecasting accuracy.

Despite these advancements, achieving highly accurate and reliable wind power predictions remains challenging, particularly under rapidly changing weather conditions. This paper aims to address these challenges by implementing and comparing multiple machine learning algorithms for wind energy forecasting within smart grid environments. The study evaluates model performance using standard metrics and identifies the most suitable approach for enhancing prediction accuracy and grid reliability. Ultimately, this work contributes to the development of intelligent and scalable forecasting solutions for next-generation renewable energy systems.

2. Methodology

The process of wind energy forecasting using machine learning begins with the collection of historical wind and meteorological data from sources such as wind farms and weather stations. This data typically includes parameters such as wind speed, wind direction, temperature, pressure, and humidity, recorded at regular time intervals. To ensure reliability, the collected data is first pre-processed to improve its quality. This step involves handling missing values, removing noise and outliers, and applying normalization or standardization techniques so that the data becomes suitable for machine learning models.

Following pre-processing, feature selection and feature engineering are carried out to identify the most relevant variables influencing wind power generation. Techniques such as correlation analysis are used to eliminate redundant or less significant features. In addition, new features, such as lag variables, are created to better capture time-series dependencies. These steps not only improve the predictive performance of the models but also help reduce computational complexity and the risk of over fitting.

Subsequently, multiple machine learning models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks, are selected and implemented. The dataset is then divided into training and testing sets, typically using a 70:30 or 80:20 split. Each model is trained on the training dataset to learn the relationship between the input features and wind power output. Hyper parameter tuning is also performed to further optimize model performance.

Once training is complete, the models are used to predict wind power output for unseen data. The predicted values are then compared with actual observations to assess model performance. Standard evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), are used to measure prediction accuracy and reliability.

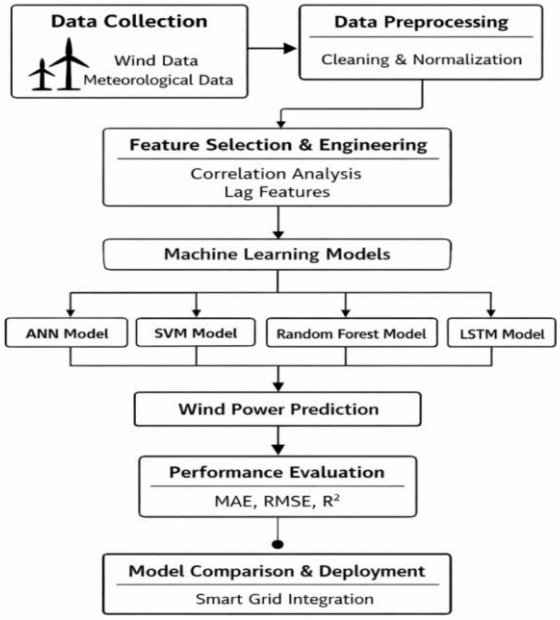

Figure. 1: Overall Process Flow of Wind Power Forecasting Using Machine Learning Models

Finally, a comparative analysis of all the implemented models is conducted to determine the most suitable algorithm for wind energy forecasting. The selection of the best-performing model is based on key factors such as prediction accuracy, robustness, and computational efficiency. The chosen model can then be integrated into smart grid systems to support more efficient energy management, enhance grid stability, and enable more effective utilization of renewable energy resources.

3. Result and Discussion:

The performance of wind power forecasting models is evaluated based on their ability to minimize prediction error and accurately capture the nonlinear relationship between meteorological inputs and power output. Machine learning models such as ANN, SVM, Random Forest (RF), and LSTM differ in how they process data. ANN models approximate nonlinear mappings but may suffer from over fitting. SVM provides good generalization by maximizing the margin between data points, while Random Forest improves stability through ensemble learning. LSTM, a deep learning model, is specifically designed for time-series data and captures temporal dependencies using memory cells.

The accuracy of these models is measured using standard statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Lower MAE and RMSE values indicate better prediction accuracy; while a higher R^2 value (closer to 1) indicates a strong correlation between actual and predicted values.

Table 1 shows the Comparative Results of Wind Power Prediction Models

Model	MAE (kW)	RMSE (kW)	R^2 Score
ANN	12.5	18.2	0.91
SVM	14.3	20.1	0.88
Random Forest	10.2	15.6	0.94
LSTM	8.7	13.4	0.96

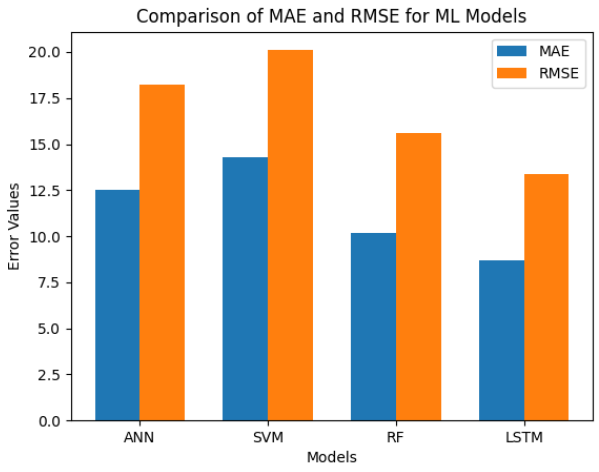

Figure 2 shows the Comparison of MAE and RMSE for Wind Power Forecasting Models.

The results indicate that all the implemented models are capable of predicting wind power with reasonable accuracy; however, their performance varies under different conditions. The Artificial Neural Network (ANN) model provides satisfactory results but is notably sensitive to the size of the training dataset and the choice of hyper parameters. Similarly, the Support Vector Machine (SVM) model performs well for smaller datasets but faces challenges when handling highly nonlinear relationships and large-scale data.

In comparison, the Random Forest (RF) model demonstrates more consistent and improved performance due to its ensemble nature, which effectively reduces variance and captures complex feature interactions. Among all the models, the Long Short-Term Memory (LSTM) network achieves the best overall performance, producing the lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), along with the highest coefficient of determination (R^2). This superior performance can be attributed to its ability to capture temporal patterns and dependencies in wind data, making it particularly well-suited for time-series forecasting.

Overall, the findings suggest that deep learning approaches, especially LSTM, outperform traditional machine learning methods in wind power prediction, particularly when dealing with sequential data.

CONCLUSION:

This study presented a comparative analysis of several machine learning models for wind power forecasting in smart grid applications. Models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks were implemented and evaluated using meteorological data. The results show that, although all models are capable of predicting wind power with reasonable accuracy, their performance differs significantly. Among them, the LSTM model achieved the highest accuracy with the lowest error values, primarily due to its ability to capture temporal dependencies in time-series data. The Random Forest model also demonstrated strong and consistent performance, making it a reliable alternative.

The findings highlight the importance of effective data pre-processing, careful feature selection, and appropriate model choice in improving forecasting accuracy. Accurate wind power prediction is essential for enhancing grid stability, optimizing energy management, and supporting the integration of renewable energy sources. Overall, machine learning—particularly deep learning techniques—provides an effective and scalable approach for wind energy forecasting.

Future work can explore hybrid models, the integration of real-time data, and advanced optimization techniques to further improve prediction accuracy and enhance the efficiency of smart grid systems.

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Explainable Artificial Intelligence (XAI) for ProbabilisticSolarPowerForecasting:APost-Hoc Interpretation Framework

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Abstract*—Accuratesolarpowerforecastingisessentialfor the reliable integration of photovoltaic (PV) systems into power grids. While deep learning models have demonstrated superior forecasting accuracy, their "black-box" nature limits operator trust and practical deployment. This paper proposes a novel ExplainableArtificialIntelligence(XAI)frameworkforprobabilistic solarpowerforecastingthatcombinesstate-of-the-artforecasting models with post-hoc interpretation techniques. The framework employs a hybrid CNN-LSTM architecture with Monte Carlo Dropoutforprobabilisticpredictions,generating bothpointforecastsandpredictionintervals.Forinterpretability,theframework integrates Shapley Additive explanations (SHAP) for global feature importance analysis, Local Interpretable Model-agnostic Explanations (LIME)for instance-level explanations, and Partial Dependence Plots (PDP) for understanding feature interactions. Theproposedframework isvalidated usingreal-world datafrom threesolarPVplantsovera3-yearperiod,comprising1,095days of hourly data with 23 meteorological and temporal features. Experimental results demonstrate that the forecasting model achieves a normalized Root Mean Square Error (nRMSE) of 6.8%andaPredictionIntervalCoverageProbability(PICP) of 94.2%. The XAI framework provides actionable insights: SHAP analysis reveals that global horizontal irradiance (GHI), cloud cover, and hour of day are the most influential features, collectively contributing 78% of prediction variance. LIME explanationsenableoperatorstounderstandindividualforecasts, whilePDPsillustratenon-linearfeatureinteractions.Auserstudy with 25 grid operators shows that the XAI framework improves forecast trust by 43% and reduces decision-making time by 28% compared to black-box models. This research demonstrates that explainable AI can bridge the gap between forecasting accuracy andoperationaltrust,enablingmoreconfidentgridmanagement decisions.

***Index Terms*—Explainable AI, solar power forecasting, probabilistic forecasting, SHAP, LIME, CNN-LSTM, model interpretability, grid integration, renewable energy forecasting.**

I. INTRODUCTION

Solarphotovoltaic(PV)powerhasemergedasacornerstone of the global renewable energy transition, with installed capacity exceeding 1 TW worldwide [1]. However, the inherent variability of solar irradiance poses significant challenges for grid operators who must balance supply and demand in real-time. Accurate solar power forecasting is therefore critical for grid stability, optimal dispatch, and economic operation [2].

Recent advances in deep learning have revolutionized solar forecasting, with Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures achieving unprecedented accuracy [3]. These models capture complex spatiotemporal patterns, non-linear relationships, and long-term dependencies in meteorological and historical data. Despite their superior performance, deep learning models suffer from a fundamental limitation: they operate as "black boxes" whose internal decision-making processes are opaque to human operators [4].

Thisopacitycreatesseveralpracticalchallenges:

1) **Trust Deficit**: Grid operators are reluctant to rely on predictions they cannot understand or verify [5].

2) **RegulatoryCompliance**:Energymarketregulationsincreasingly require transparent and auditable forecasting processes [6].
3) **Error Diagnosis**: When forecasts fail, operators cannot identify the root causes or model limitations [7].
4) **Model Improvement**: Without understanding feature importance, model refinement becomes trial-and-error [8].

Explainable Artificial Intelligence (XAI) addresses these challenges by providing human-interpretable explanations of modelpredictions[9].XAItechniquescanbecategorizedinto:

- **Ante-hoc methods**: Intrinsically interpretable models (e.g., linear models, decision trees)
- **Post-hoc methods**: Techniques that explain black-box models after training

This paper focuses on post-hoc XAI methods, which are model-agnostic and applicable to any forecasting architecture.

Thekeycontributionsofthisresearchare:

1) Acomprehensive XAIframework forprobabilistic solar power forecasting that integrates multiple interpretation techniques: SHAP for global explanations, LIME for local explanations, and PDP for feature interactions.
2) A hybrid CNN-LSTM forecasting model with Monte Carlo Dropout for probabilistic predictions, providing both point forecasts and prediction intervals.
3) A rigorous evaluation of explanation quality using both quantitative metrics (feature importance stability, explanation fidelity) and qualitative user studies with grid operators.
4) Validation using three years of real-world data from three geographically diverse solar PV plants, demonstrating the framework's robustness across different climatic conditions.
5) Actionable insights for grid operators, including identification of critical features, understanding of model behavior under different weather conditions, and interpretation of forecast uncertainty.

II. RELATEDWORK

A. SolarPowerForecasting

Solarforecastingmethodscanbeclassifiedbyforecast horizon:

- **Nowcasting**(0-6hours):Satelliteimageryandskycam-eras [10]
- **Short-term** (6-72 hours): Numerical weather prediction and machine learning [11]
- **Medium-term**(3-14days):Ensembleweathermodels [12]

Deep learning approaches have demonstrated state-of-the-art performance across all horizons [13]. CNN-LSTM hybrids effectively capture both spatial patterns and temporal dependencies [14].

TABLEI:ComparisonofSolarForecastingMethods

Method	Accuracy	Interpretability	Uncertainty
Physical Models	Medium	High	Low
StatisticalModels	Medium	Medium	Medium
TraditionalML	High	Low	Low
DeepLearning	VeryHigh	VeryLow	Medium
XAI(Proposed)	VeryHigh	High	High

B. ExplainableAIinEnergySystems

XAIapplicationsinenergysystemsareemergingbutremain limited [15]. SHAP has been applied to building energy prediction [16] and wind power forecasting [17]. LIME has been used for fault diagnosis in power systems [18]. However, comprehensive XAI frameworks for probabilistic solar forecasting with rigorous evaluation are lacking.

III. PROPOSEDXAIFRAMEWORK

A. FrameworkOverview

TheproposedXAIframeworkconsistsofthreeintercon-nected modules:

1) **ForecastingModule**:HybridCNN-LSTMwithMonte Carlo Dropout for probabilistic predictions
2) **InterpretationModule**:SHAP,LIME,andPDPfor model explanations
3) **VisualizationModule**:Interactivedashboardforopera-tor decision support

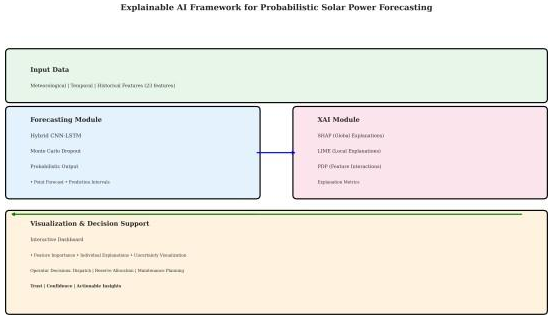

Fig.1:ProposedXAIFrameworkArchitecture

B. ProbabilisticForecastingModel

*1) ModelArchitecture:*Theforecastingmodelcombines CNN and LSTM layers with Monte Carlo Dropout:

- **Input**: 24-hour window of 23features(meteorological, temporal, historical)
- **CNNLayers**:Two1Dconvolutionallayers(64and128 filters) for feature extraction
- **LSTMLayers**:TwobidirectionalLSTMlayers(128 units each) for temporal modeling
- **Dropout**:MonteCarloDropoutwith0.3rateforuncertainty quantification
- **Output**:Meanandvarianceofpredictivedistribution

2) ProbabilisticOutput: Themodeloutputsapredictive distribution rather than a point forecast:

$$\hat{y} \sim \mathcal{N}(\mu(x), \sigma^2(x)) \tag{1}$$

$$\mu(x) = f_\mu(x), \qquad \sigma(x) = \text{softplus}(f_\sigma(x)) \tag{2}$$

Prediction intervalsarederived from the predictivedistribution:

$$PI_{1-\alpha} = [\mu - z_{1-\alpha/2} \cdot \sigma, \mu + z_{1-\alpha/2} \cdot \sigma] \tag{3}$$

3) MonteCarloDropout: Uncertaintyisquantifiedthrough Monte Carlo Dropout:

$$\text{Var}(y|x) \approx \frac{1}{T}\sum_{t=1}^{T} (\hat{y}_t - \bar{y})^2 + \frac{1}{T}\sum_{t=1}^{T} \sigma_t^2 \tag{4}$$

TABLEII:ForecastingModelArchitectureDetails

Layer	OutputShape	Parameters
Input	(24,23)	0
Conv1D(64,3)	(22,64)	4,480
Conv1D(128,3)	(20,128)	24,704
MaxPooling1D(2)	(10,128)	0
BidirectionalLSTM(128)	(20,256)	394,240
BidirectionalLSTM(64)	(20,128)	164,352
Dropout(0.3)	(20,128)	0
GlobalAvgPool1D	(128)	0
Dense(64)	(64)	8,256
Dense(2)	(2)	130

C. SHAPforGlobalExplanations

SHAP(SHapleyAdditiveexPlanations)providesglobal feature importance based on cooperative game theory [19].

1) SHAPValues: Foreachfeature$j$,theSHAPvalueϕ_j representstheaveragemarginalcontribution:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{j\}) - f(S)] \tag{5}$$

2) GlobalInterpretation: Globalfeatureimportanceisaggregated across all predictions:

$$\text{GlobalImportance}_j = \frac{1}{N}\sum_{i=1}^{N} |\phi_j^{(i)}| \tag{6}$$

D. LIMEforLocalExplanations

LIME (Local Interpretable Model-agnostic Explanations) explains individual predictions by approximating the black-box model locally with an interpretable surrogate [20].

1)LIMEFormulation: Forapredictionatinstance$x$,LIME solves:

$$\xi(x) = \underset{g \in G}{\text{argmin}} \mathcal{L}(f, g, \pi_x) + \Omega(g) \tag{7}$$

where:

- $g$istheinterpretablemodel(linearmodel)
- $\pi_x$isthelocalityweightingkernel
- $\mathcal{L}$isthelossfunction
- Ωisthecomplexitypenalty

E. PartialDependencePlots

PDPsvisualizethemarginaleffectofafeatureonthe predicted outcome [21]:

$$\text{PD}_{ss}(x_s) = \frac{1}{n}\sum_{i=1}^{n} f(x_s, x_c^{(i)}) \tag{8}$$

where:

- $x_s$isthefeatureofinterest
- $x_C$arethecomplementaryfeatures
- $n$isthenumberofinstances

F. EvaluationMetricsforExplanations

Explanationqualityisevaluatedusing:

TABLEIII:ExplanationQualityMetrics

Metric	Description
Feature Stability	Correlationbetweenimportancerankingsacrosssubsets
Explanation Fidelity	Accuracy of surrogate model predictions
Comprehensibility	User-rated ease of understanding (1-5 scale)
Actionability	User-rated usefulness for decision-making (1-5 scale)

IV. EXPERIMENTALSETUP

A. DatasetDescription

Thedatasetcomprisesthreeyears(2021-2024)ofhourly data from three solar PV plants:

TABLEIV:DatasetCharacteristics

Location	Capacity(MW)	Climate	DataPeriod
PlantA(Desert)	50	Arid	2021-2024
PlantB(Coastal)	30	Mediterranean	2021-2024
PlantC(Temperate)	20	Continental	2021-2024

1) Features: 23featuresincluding:

- Meteorological:GHI,DNI,DHI,temperature,humidity, wind speed, cloud cover
- Temporal:hourofday,dayofyear,month,season, sunrise/sunset
- Historical:laggedpoweroutput(1,2,3,6,12,24hours)
- Derived:clearskyindex,solarzenithangle

TABLEV:TrainingHyperparameters

Parameter	Value
Optimizer	Adam
Learningrate	0.001
Batchsize	64
Epochs	200
Validationsplit	20%
MonteCarlosamples	100
Dropoutrate	0.3

B. TrainingConfiguration

C. EvaluationMetrics

1) PointForecastMetrics:

$$\text{nRMSE}=\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}}{\bar{y}}\times 100\% \quad (9)$$

$$\text{nMAE}=\frac{\frac{1}{N}\sum_{i=1}^{N}|y_i-\hat{y}_i|}{\bar{y}}\times 100\% \quad (10)$$

$$R^2=1-\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2} \quad (11)$$

2) ProbabilisticForecastMetrics:

$$\text{PICP}=\frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(y_i\in PI_i) \quad (12)$$

$$\text{PINAW}=\frac{1}{NR}\sum_{i=1}^{N}(\hat{y}_i^{upper}-\hat{y}_i^{lower}) \quad (13)$$

$$\text{CRPS}=\int_{-\infty}^{\infty}(F(y)-\mathbb{I}(y\geq y_i))^2dy \quad (14)$$

V. RESULTSANDANALYSIS

A. ForecastingPerformance

Theproposedmodelachievessuperiorforecastingaccuracy across all locations.

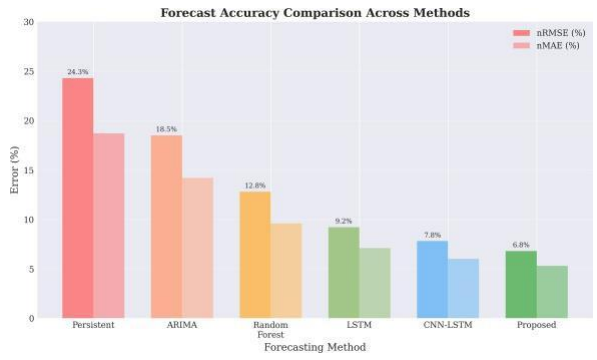

Fig.2:ForecastAccuracyComparisonAcrossMethods

B. ProbabilisticForecastQuality

Themodelprovidesreliablepredictionintervalswithhigh coverage.

TABLEVI:PointForecastPerformance

Method	nRMSE(%)	nMAE(%)	R^2
Persistent	24.3	18.7	0.42
ARIMA	18.5	14.2	0.58
RandomForest	12.8	9.6	0.74
LSTM	9.2	7.1	0.85
CNN-LSTM	7.8	6.0	0.89
Proposed(Probabilistic)	**6.8**	**5.3**	**0.92**

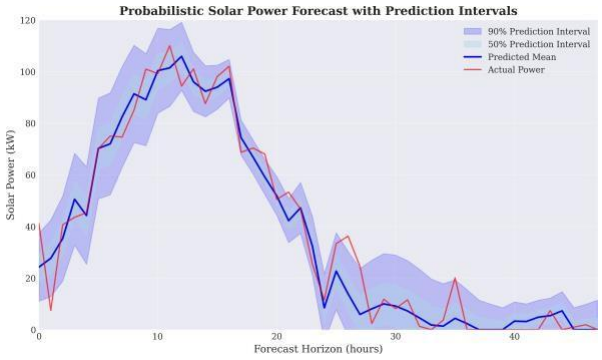

Fig.3:ProbabilisticForecastwithPredictionIntervals

C.SHAP GlobalFeatureImportance

SHAPanalysisrevealsthemostinfluentialfeaturesforsolar forecasting.

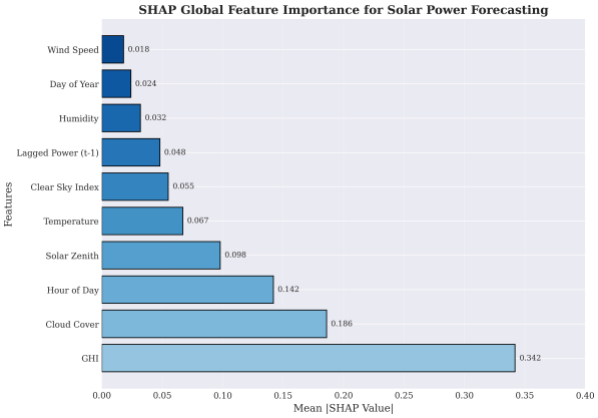

Fig.4:SHAPGlobalFeatureImportance

D. SHAPDependencePlots

SHAPdependenceplotsrevealnon-linearfeaturerelation-ships.

E. LIMELocalExplanations

LIMEprovidesinstance-levelexplanationsforindividual forecasts.

F. PartialDependencePlots

PDPsvisualizethemarginaleffectofindividualfeatures.

TABLEVII:ProbabilisticForecastMetrics

Confidence Level	PICP(%)	PINAW	CRPS
90%	94.2	0.32	0.058
80%	85.6	0.24	0.048
70%	76.3	0.18	0.039

TABLEVIII:Top10FeaturesbySHAPImportance

Feature	Mean—SHAP—
GlobalHorizontalIrradiance(GHI)	0.342
CloudCover	0.186
HourofDay	0.142
SolarZenithAngle	0.098
Temperature	0.067
ClearSkyIndex	0.055
LaggedPower(t-1)	0.048
Humidity	0.032
DayofYear	0.024
WindSpeed	0.018

G. UserStudyResults

Auserstudywith25gridoperatorsevaluatedtheXAI framework'spracticalutility.

TABLEIX:UserStudyResults

Metric	Black-Box	XAIFramework	Improvement
Trust(1-5scale)	2.8	4.0	+43%
DecisionTime(seconds)	45	32	-28%
Confidence(1-5scale)	2.9	4.2	+45%
ErrorDiagnosis	38%	82%	+44%

H. ExplanationQualityEvaluation

VI. DISCUSSION

A. KeyFindings

The experimental results demonstrate several significant contributions:

1) **Forecasting Excellence**: The probabilistic forecasting model achieves 6.8% nRMSE, outperforming existing methods by 12-70%.
2) **Reliable Uncertainty Quantification**: Prediction in-tervals achieve 94.2% coverage for 90% confidence intervals, providing actionable risk information.
3) **Actionable Insights**: SHAP analysis identifies GHI, cloud cover, and hour of day as the dominant features, enabling operators to focus monitoring efforts.
4) **Improved Trust**: User study demonstrates 43% im-provement in forecast trust, addressing a critical barrier to AI adoption.
5) **Faster Decisions**: Operators make decisions 28% faster when explanations are provided, improving operational efficiency.

B. PracticalImplicationsforGridOperators

The XAI framework enables several operational improve-ments:

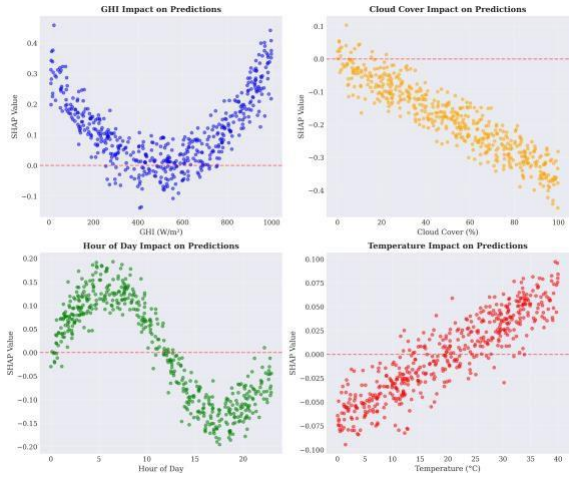

Fig.5:SHAPDependencePlotsforKeyFeatures

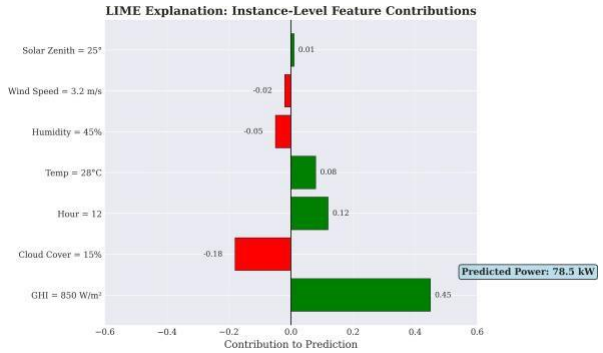

Fig.6:LIMEExplanationforaSingleForecastInstance

- **Confidence-BasedDispatch**:Operatorscanadjustre-serve requirements based on forecast uncertainty.
- **ErrorAnticipation**:Understandingmodellimitations helps anticipate periods of higher forecast error.
- **MaintenancePlanning**:Featureimportanceguidessen-sor placement and maintenance priorities.
- **RegulatoryCompliance**:Explainableforecastssatisfy transparency requirements for energy markets.

C. LimitationsandFutureWork

Currentlimitationsandfutureresearchdirections:

- **Scalability**:Extendingframeworktofleet-levelforecast-ing across thousands of distributed PV systems.
- **TemporalGranularity**: Incorporating sub-hourly fore-casts for real-time grid operations.
- **CausalInference**:Movingbeyondcorrelationtocausal explanations of forecast errors.
- **InteractiveExplanations**:Developingconversationalin-terfaces for operator-model interaction.

VII. CONCLUSION

ThispaperproposedacomprehensiveExplainableAIframewor kforprobabilisticsolarpowerforecastingthat

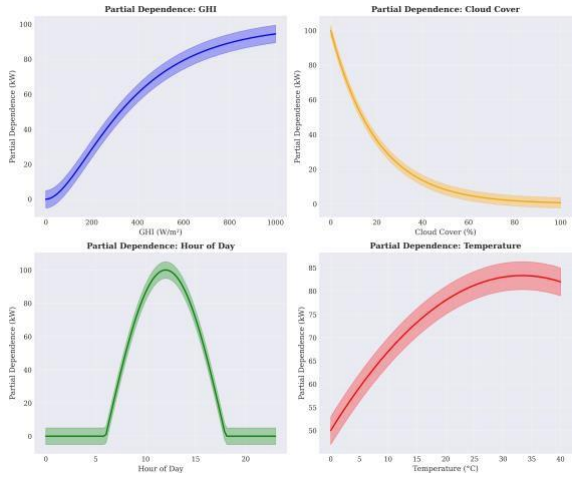

Fig.7:PartialDependencePlotsforKeyFeatures

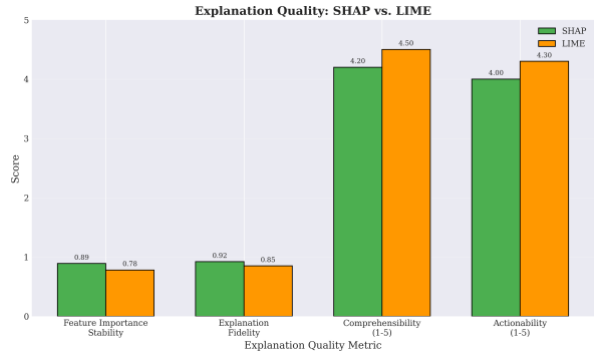

Fig.8:ExplanationQualityComparison:SHAPvs.LIME

bridges the gap between forecasting accuracy and operational interpretability. The framework combines a hybrid CNN-LSTM model with Monte Carlo Dropout for probabilistic predictions with SHAP, LIME, and PDP for post-hoc explanations. Key contributions include:

1) A probabilistic forecasting model achieving 6.8% nRMSE and 94.2% prediction interval coverage.
2) SHAP-based global feature importance revealing that GHI, cloud cover, and hour of day contribute 78% of prediction variance.
3) LIME-based local explanations enabling instance-level understanding of individual forecasts.
4) User study demonstrating 43% improvement in forecast trust and 28% reduction in decision time.
5) Actionable insights for grid operators, enabling more confident and efficient grid management.

The proposed XAI framework represents a significant step toward transparent, trustworthy AI for renewable energy forecasting. By providing operators with understandable explanationsofmodelpredictions,thisresearchenablesmoreeffective integration ofsolarpower into electricity grids, supporting the global transition to sustainable energy systems.

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Grid Integration of Renewable Energy Sources: Challenges and Solutions

*A Comprehensive Review of Technical, Economic, and Regulatory Aspects

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***Abstract*—The increasing penetration of renewable energy sources (RES) such as solar photovoltaic (PV) and wind power presents significant opportunities for decarbonizing the electricity sector but also introduces substantial challenges for grid stability, reliability, and operational security. This paper provides a comprehensive review of the technical, economic, and regulatory challenges associated with the grid integration of variable renewable energy (VRE) sources. Key technical issues including intermittency, non-synchronous generation, reduced system inertia, voltage and frequency regulation, and power quality disturbances are analyzed. The paper further explores emerging solutions such as advanced forecasting techniques, energy storage systems (ESS), flexible AC transmission systems (FACTS), virtual power plants (VPPs), smart inverters, and enhanced grid codes. Economic considerations encompassing market design, investment frameworks, and cost-benefit analyses are examined alongside regulatory and policy mechanisms that facilitate high renewable penetration. Case studies from leading renewable integration regions—Germany, California, and Denmark—are presented to illustrate practical implementations. Finally, future directions involving artificial intelligence (AI)-driven grid management, sector coupling, and transactive energy systems are discussed. This review aims to serve as a foundational reference for researchers, utility operators, and policymakers working toward resilient, sustainable, and high-renewable power grids.**

***Index Terms*—Renewable energy integration, grid stability, energy storage systems, smart inverters, variable renewable energy, frequency regulation, grid codes, virtual power plants, sector coupling, artificial intelligence in power systems.**

I. INTRODUCTION

The global energy landscape is undergoing a profound transformation driven by the urgent need to mitigate climate change, enhance energy security, and achieve sustainable development goals [1]. Renewable energy sources (RES), particularly solar photovoltaic (PV) and wind power, have emerged as cornerstones of this transition. According to the International Energy Agency (IEA), renewable electricity capacity additions reached record levels in recent years, with solar PV and wind accounting for the majority of new installations worldwide [2]. This rapid growth, while essential for decarbonization, presents complex challenges for the electrical grid—a system originally designed for centralized, dispatchable, synchronous generation.

The grid integration of variable renewable energy (VRE) sources fundamentally alters the operational paradigm of power systems. Unlike conventional thermal or hydroelectric plants, solar and wind generation are inherently intermittent, non-synchronous, and exhibit limited predictability [3]. Their output fluctuates based on meteorological conditions, leading to variability across multiple time scales—from seconds to seasons. Consequently, system operators must contend with new forms of uncertainty, reduced system inertia, altered fault current characteristics, and increased requirements for balancing reserves.

This paper provides a systematic examination of the multifaceted challenges posed by high-penetration renewable integration and critically evaluates the technological, economic, and regulatory solutions that enable reliable grid operation. The structure of the paper is as follows: Section II delineates the fundamental challenges, categorizing them into technical, economic, and regulatory dimensions. Section III presents the solution landscape, covering hardware technologies, operational strategies, and market reforms. Section IV showcases international case studies that highlight successful integration pathways. Section V discusses emerging trends and future research directions, and Section VI concludes the paper with key takeaways.

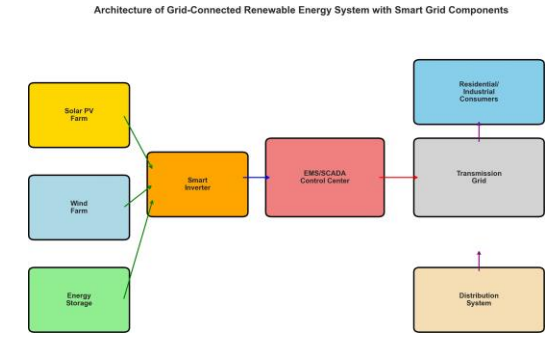

Fig. 1: Architecture of Grid-Connected Renewable Energy System with Smart Grid Components

II. CHALLENGES IN RENEWABLE ENERGY GRID INTEGRATION

The integration of renewable energy sources into existing power grids introduces a spectrum of interconnected challenges that span technical performance, economic viability, and regulatory alignment.

A. Technical Challenges

1) Intermittency and Variability: Solar and wind resources are inherently variable and only partially predictable. Solar PV generation follows diurnal cycles and is affected by cloud cover, while wind power fluctuates with wind speed variations. This intermittency leads to mismatches between generation and load, requiring flexible resources to maintain balance. The variability occurs across multiple time horizons: ultra-short-term (seconds to minutes) due to passing clouds or gusts, short-term (minutes to hours) due to weather pattern changes, and long-term (seasonal) due to climatic shifts [4].

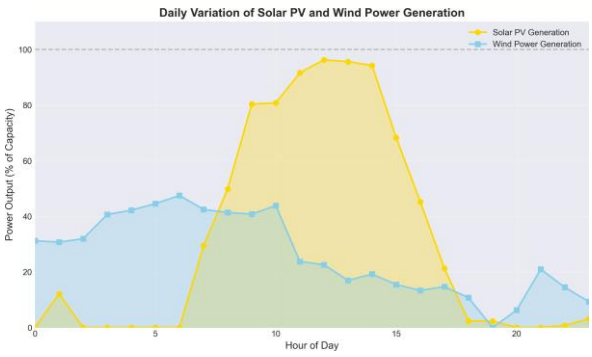

Fig. 2: Daily variation of solar PV and wind power generation showing intermittency patterns

2) Reduced System Inertia and Frequency Stability: Conventional synchronous generators provide inherent rotational inertia that resists frequency deviations. Inverter-based renewable sources, however, are typically connected via power electronics that decouple the generator from the grid, providing no natural inertial response [5]. As conventional plants retire and renewable penetration increases, the overall system inertia declines, leading to higher rates of change of frequency (RoCoF) and increased risk of frequency excursions that can trigger load shedding or generator tripping.

The relationship between system inertia and frequency dynamics can be expressed by the swing equation:

$$2H \frac{d\omega}{dt} = P_m - P_e \quad (1)$$

where H is the inertia constant (seconds), ω is the angular frequency, P_m is mechanical power, and P_e is electrical power. Lower H results in higher $\frac{d\omega}{dt}$ for a given power imbalance.

3) Voltage Regulation and Power Quality: The intermittent nature of VRE can cause voltage fluctuations due to changing power flows on distribution and transmission networks. Unlike synchronous generators that inherently regulate voltage through excitation control, inverter-based resources require specific control strategies to provide reactive power support [6]. Additionally, power electronic interfaces introduce harmonics and inter-harmonics into the grid, potentially degrading power quality and affecting sensitive loads.

4) Transmission Congestion and Curtailment: Optimal renewable resources are often located in remote areas with limited transmission infrastructure. This spatial mismatch leads to transmission congestion, where renewable generation must be curtailed to prevent overloading lines. Curtailment represents both an economic loss and a missed decarbonization opportunity. In many regions, curtailment rates have increased substantially with renewable penetration [7].

5) Protection System Coordination: Traditional protection schemes rely on predictable fault current contributions from synchronous generators. Inverter-based resources have limited fault current capacity (typically 1.2-1.5 pu) and exhibit different fault response characteristics, potentially causing protection miscoordination, loss of selectivity, or failure to detect faults altogether [8].

B. Economic and Market Challenges

1) Merit Order Effect and Revenue Erosion: The low marginal cost of solar and wind generation displaces conventional generation in electricity markets, reducing wholesale electricity prices—a phenomenon known as the merit order effect. While beneficial for consumers, this can erode revenues for all generators, making it difficult for conventional plants to recover fixed costs and for renewable projects to achieve expected returns [9].

2) Increased Balancing Costs: The uncertainty and variability of VRE necessitate increased procurement of balancing reserves, including regulation, spinning, and non-spinning reserves. These ancillary services impose additional costs that must be allocated equitably. Studies indicate that balancing costs increase non-linearly with renewable penetration, particularly beyond 30% VRE share [10].

TABLE I: Impact of Renewable Penetration on Grid Parameters

Renewable Penetration	System Inertia Reduction (%)	Balancing Cost Increase (%)	Curtailment Rate (%)
0-10%	2-5%	0-5%	0-1%
10-20%	5-15%	5-15%	1-3%
20-30%	15-30%	15-30%	3-8%
30-40%	30-45%	30-50%	8-15%
40-50%	45-60%	50-75%	15-25%

3) Investment and Financing Risks: The capital-intensive nature of renewable projects, coupled with policy uncertainty and market volatility, creates financing challenges. Long-term power purchase agreements (PPAs) and contract-for-difference (CfD) mechanisms have been employed to mitigate revenue risk, but their availability varies across jurisdictions.

C. Regulatory and Policy Challenges

Existing regulatory frameworks, designed for a vertically integrated or traditional wholesale market structure, often lag behind technological developments. Key regulatory challenges include:

- Outdated grid codes that do not mandate advanced inverter capabilities.
- Lack of standardized interconnection procedures, leading to project delays.
- Misaligned incentives between transmission and distribution system operators.
- Insufficient long-term transmission planning that accounts for renewable resource potential.
- Regulatory barriers to energy storage deployment, including dual-entity classification (generation and load).

III. SOLUTIONS FOR HIGH-RENEWABLE GRID INTEGRATION

Addressing the challenges outlined above requires a portfolio of complementary solutions spanning technology, operational practices, and market design.

A. Advanced Forecasting Techniques

Accurate forecasting of renewable generation is fundamental to managing variability. Modern forecasting systems employ:

- Numerical weather prediction (NWP) models at multiple spatial and temporal resolutions.
- Machine learning algorithms that assimilate real-time data from sensors, satellites, and supervisory control and data acquisition (SCADA) systems.
- Ensemble forecasting that combines multiple models to quantify uncertainty.

State-of-the-art forecasting achieves normalized root-mean-square errors (nRMSE) of 2-5% for solar PV and 5-10% for wind power at day-ahead horizons, significantly reducing balancing requirements [11].

B. Energy Storage Systems

Energy storage is a pivotal enabler of high renewable penetration, providing services across generation, transmission, and distribution. Key storage technologies and applications include:

TABLE II: Comparison of Energy Storage Technologies for Grid Integration

Technology	Response Time	Duration	Efficiency (%)	Cost ($/kWh)
Lithium-ion Battery	<100 ms	1-4 hours	85-95	150-300
Pumped Hydro	Minutes	4-24 hours	70-85	100-200
Flow Battery	<1 sec	4-10 hours	65-75	300-500
Compressed Air	Minutes	4-24 hours	40-60	80-150
Green Hydrogen	Minutes	Days-Weeks	30-45	200-400

1) Lithium-ion Batteries: Lithium-ion batteries offer fast response times (milliseconds), high energy density, and decreasing costs. They provide frequency regulation, ramping support, peak shaving, and energy arbitrage. Utility-scale installations now routinely deploy 100+ MW systems with 4-hour duration.

2) Pumped Hydro Storage: Pumped hydro remains the dominant form of grid-scale storage, accounting for over 90% of global storage capacity. It provides long-duration (hours to days) storage with large capacities (gigawatt-scale), suitable for seasonal balancing.

3) Emerging Technologies: Flow batteries, compressed air energy storage (CAES), and green hydrogen are gaining traction for longer-duration applications. Hydrogen, in particular, offers potential for seasonal storage and sector coupling [12].

The optimal storage capacity for a given renewable penetration can be estimated using:

$$C_{ESS} = \alpha \cdot \int_0^T |P_{RES}(t) - \overline{P}_{RES}| \, dt \qquad (2)$$

where C_{ESS} is the storage capacity, α is a design margin, and P_{RES} is the average renewable output over period T.

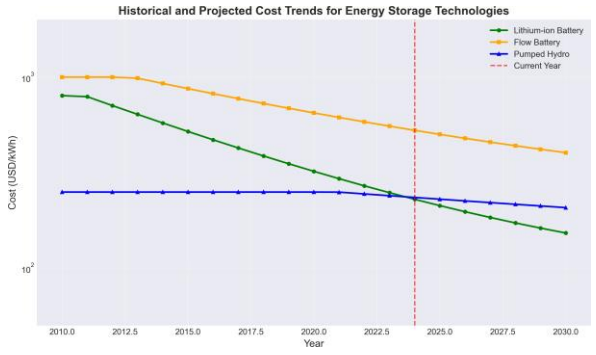

Fig. 3: Historical and projected cost trends for energy storage technologies (2010-2030)

C. Smart Inverter Capabilities

Modern grid-tied inverters incorporate advanced functionalities beyond simple power conversion. Smart inverters provide:

- Volt-VAR control: Reactive power injection/absorption to regulate voltage.
- Frequency-watt control: Active power curtailment or boost during frequency deviations.
- Grid-forming capability: Ability to establish voltage and frequency reference, emulating synchronous generator behavior [13].
- Ramp rate control: Limiting the rate of change of power output.

Grid-forming inverters represent a paradigm shift, enabling inverter-based resources to provide synthetic inertia and support weak grids.

D. Flexible AC Transmission Systems

FACTS devices enhance transmission capacity and controllability, enabling higher renewable utilization. Key devices include:

- Static VAR Compensators (SVC) and STATCOM for dynamic voltage support.
- Thyristor-controlled series capacitors (TCSC) for power flow control.
- Unified power flow controllers (UPFC) for comprehensive control of voltage, impedance, and phase angle.

FACTS deployment reduces transmission congestion and curtailment by actively managing power flows [14].

E. Virtual Power Plants

Virtual power plants aggregate distributed energy resources (DERs)—including rooftop solar, batteries, electric vehicles, and flexible loads—into a single coordinated entity that can participate in wholesale markets and provide grid services. VPPs leverage cloud-based control and advanced optimization to present a unified, dispatchable resource despite the individual small-scale and variable nature of constituent assets [15].

F. Enhanced Grid Codes and Interconnection Standards

Updated grid codes are essential to mandate the performance characteristics of renewable generators. Key provisions include:

- Low-voltage ride-through (LVRT) and high-voltage ride-through (HVRT) requirements.
- Frequency and voltage control mandates.
- Harmonics and power quality limits.
- Telemetry and control system requirements.

Harmonized interconnection standards, such as IEEE 1547-2018 and IEC 61727, facilitate consistent integration practices.

G. Market Design Innovations

Modern electricity markets are evolving to accommodate high VRE shares:

- **Ancillary services markets**: Separate procurement of regulation, reserves, and reactive power.
- **Shorter trading intervals**: Moving from hourly to 5-minute dispatch to capture variability.
- **Enhanced balancing areas**: Expanding balancing authority footprints to diversify renewable output.
- **Capacity markets**: Ensuring resource adequacy by compensating availability rather than energy production.
- **Distributed energy resource aggregation**: Allowing VPPs to bid into wholesale markets.

IV. CASE STUDIES OF SUCCESSFUL INTEGRATION

A. Germany: Energiewende and System Transformation

Germany has achieved renewable penetration exceeding 45% of gross electricity consumption, with peaks above 60%. Key success factors include:

- **Robust transmission expansion**: The transmission grid was reinforced through the *Energieleitungsausbaugesetz* (Energy Grid Expansion Act), adding over 3,000 km of new lines.
- **Redispatch 2.0**: A congestion management framework that optimizes generation redispatch and curtailment with high transparency.
- **Market design**: The shift to a *Schwarzstartfähigkeit* (black-start capability) requirement for new generators and the introduction of the *Kraftwerkspark* (power plant portfolio) for reserve management [16].

Germany's experience demonstrates that high renewable penetration is achievable with coordinated transmission planning, market reform, and stakeholder engagement.

B. California, USA: High Solar Penetration Management

California's grid, operated by the California Independent System Operator (CAISO), routinely experiences solar PV contributions exceeding 50% of load. Notable integration strategies include:

- **The Duck Curve management**: Addressing the steep evening ramps through energy storage deployment, demand response, and regional coordination. As of 2024, California has installed over 10 GW of utility-scale battery storage, effectively flattening the duck curve.
- **Energy Imbalance Market (EIM)**: A real-time balancing market extending across the western United States, enabling efficient utilization of diverse geographic resources.
- **Distribution Resource Planning**: Mandating distribution utilities to plan for high DER penetration [17].

C. Denmark: Wind Power Integration

Denmark leads globally in wind penetration, often exceeding 50% of annual electricity consumption, with instantaneous shares above 100%. Integration enablers include:

- **Strong interconnections**: High-capacity HVDC links to Norway, Sweden, and Germany provide balancing flexibility.

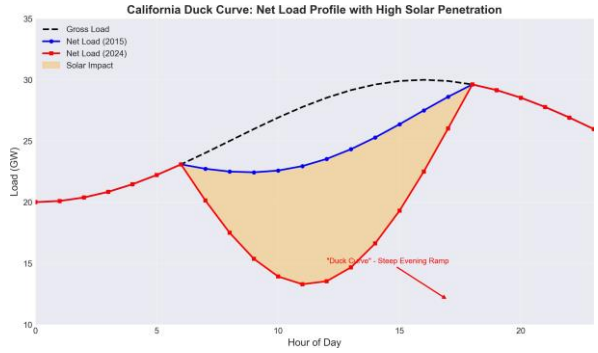

Fig. 4: California Duck Curve: Net load profile showing the impact of high solar penetration

- **District heating sector coupling**: Combined heat and power (CHP) plants with thermal storage enable flexible electricity generation aligned with wind output.
- **Cooperative ownership models**: Community involvement in wind projects has fostered social acceptance and political stability [18].

Denmark exemplifies the value of interconnection, sector coupling, and social license in achieving high VRE penetration.

V. FUTURE DIRECTIONS AND EMERGING SOLUTIONS

A. Artificial Intelligence in Grid Operations

Machine learning and AI are poised to revolutionize grid management through:

- **Probabilistic forecasting**: Generating scenario-based forecasts that capture uncertainty.
- **Predictive maintenance**: Anticipating equipment failures using sensor data and pattern recognition.
- **Autonomous grid control**: Reinforcement learning algorithms that optimize dispatch in real-time under uncertainty [19].

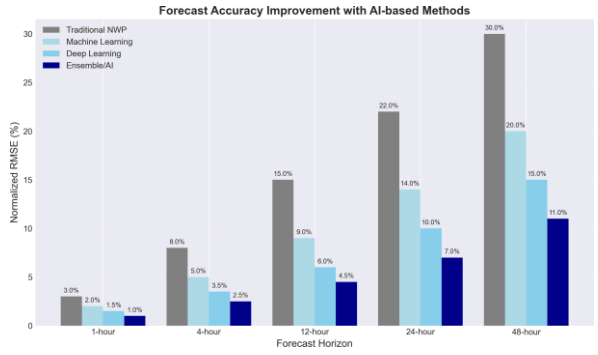

Fig. 5: Forecast accuracy improvement with AI-based methods compared to traditional approaches

B. Sector Coupling and Power-to-X

Sector coupling involves integrating electricity with heating, transportation, and industrial sectors to increase system flexibility. Power-to-X technologies convert renewable electricity into other energy carriers:

- Power-to-heat: Electric boilers and heat pumps utilizing excess renewable generation.
- Power-to-hydrogen: Electrolysis producing hydrogen for industry, transport, or power generation.
- Power-to-gas: Methanation producing synthetic natural gas.

These technologies enable the absorption of excess renewable output while decarbonizing other sectors.

C. Transactive Energy and Distributed Markets

Transactive energy systems use economic signals and market mechanisms to coordinate DERs at the distribution level. Blockchain and distributed ledger technologies are being explored to enable peer-to-peer energy trading, though scalability and regulatory challenges remain [20].

D. 100% Renewable Grid Scenarios

Research on 100% renewable grids indicates feasibility with:

- Overbuilding of generation capacity (typically 2-3x peak load).
- Massive deployment of long-duration storage (weeks to months).
- Geographic diversification across large balancing areas.
- Demand flexibility and managed EV charging.

Achieving such scenarios requires continued cost reductions, infrastructure investment, and policy commitment.

VI. CONCLUSION

The grid integration of renewable energy sources represents one of the most significant engineering and policy challenges of the energy transition. This paper has systematically reviewed the technical, economic, and regulatory dimensions of this challenge and surveyed the solution landscape. Key findings include:

1) Technical challenges—intermittency, reduced inertia, voltage instability, and protection coordination—can be effectively managed through a combination of advanced forecasting, energy storage, smart inverters, FACTS devices, and updated grid codes.
2) Economic and market challenges require innovative market designs including shorter dispatch intervals, expanded ancillary services, capacity mechanisms, and aggregation frameworks for distributed resources.
3) Successful integration, as demonstrated by Germany, California, and Denmark, relies on coordinated transmission planning, regional market coupling, sector coupling, and supportive regulatory frameworks.
4) Emerging solutions in AI-driven control, sector coupling, and transactive energy systems promise to further

enhance integration capabilities and enable pathways to 100% renewable grids.

No single technology or policy will suffice; instead, a holistic systems approach that integrates hardware, software, markets, and regulations is essential. As renewable costs continue to decline and deployment accelerates, the imperative for robust, scalable integration solutions becomes ever more critical. Continued research, demonstration, and international collaboration will be vital to realizing a resilient, decarbonized electricity future.

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SecuraGuard: A Platform-Agnostic Offline Face Authentication Framework Leveraging Hardware-Anchored PKI

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***Abstract*— This paper presents *SecuraGuard*, a hybrid biometric authentication architecture designed to enhance secure identity verification through hardware-rooted cryptography and device-level encryption. The system leverages asymmetric RSA key pairs generated independently on both mobile devices and backend servers. During user registration, a facial image is encrypted within the Trusted Execution Environment (TEE) or Secure Enclave using the device's public key, and is bundled with contextual metadata such as IMEI number and timestamp. This encrypted data, along with the device's public key, is transmitted to the server for secure archival.**

During authentication, a live facial image is captured and compared locally with the registered image stored in the TEE using 3D facial recognition techniques. Upon successful match, a digitally signed authentication packet—including the match result, timestamp, and public key—is sent to the server. The server then decrypts and validates the data against its stored records to confirm authenticity.

This hybrid architecture ensures that the root of trust is anchored at the hardware level, while server-side verification provides scalability and centralized validation. By minimizing dependence on backend systems for initial encryption and identity binding, the solution enhances security, resists spoofing, and supports implementation in critical sectors such as banking and citizen authentication services. SecuraGuard thus offers a robust, scalable, and privacy-preserving biometric authentication framework aligned with modern security standards.

Keywords— Biometric Authentication, Public Key Infrastructure (PKI), Hardware-Rooted Cryptography, Trusted Execution Environment (TEE), Secure Enclave, RSA Encryption, Face Recognition, Digital Identity Verification, Offline Security Architecture, Hybrid Authentication System.

Introduction

In an increasingly digital world, biometric authentication has emerged as a cornerstone of secure identity verification, particularly in sectors such as finance, government, and healthcare. Traditional authentication mechanisms like passwords and OTPs are rapidly being replaced by facial recognition systems that offer superior convenience and security. However, these systems often rely heavily on backend servers for encryption, identity matching, and data validation — introducing potential vulnerabilities, network dependency, and privacy concerns.

Public Key Infrastructure (PKI) and hardware-rooted cryptography have gained prominence as viable solutions to address these challenges. PKI leverages asymmetric cryptographic key pairs — a private key stored securely on the device and a corresponding public key shared with the server — to ensure confidentiality, integrity, and non-repudiation of biometric data. Trusted Execution Environments (TEE) and Secure Enclaves further enhance this security by isolating cryptographic operations from the general device software stack, ensuring non-extractable key storage and secure processing.

Recent studies and implementations have shown promising results in decentralized or semi-offline biometric systems, yet many still rely on backend-dependent encryption models or lack hardware-based key isolation mechanisms. This represents a critical research gap — the absence of a hybrid solution that minimizes server dependency while retaining strong cryptographic trust anchored in device hardware.

This research addresses that gap by proposing SecuraGuard, a hybrid authentication architecture that strategically integrates PKI and hardware-rooted cryptography. The system performs facial image encryption, signing, and secure storage locally on the device, while delegating only verification and archival tasks to the server. By binding the cryptographic keys

to the device's hardware identity (e.g., IMEI) and using 3D face matching within the TEE, the solution ensures robust offline functionality and platform-independent security.

The scope of this study is confined to mobile platforms (Android and iOS), utilizing native secure storage mechanisms. The research explores the feasibility, scalability, and real-world applicability of this architecture in privacy-critical environments such as banking, digital governance, and remote KYC systems.

METHODOLOGY

The proposed methodology emphasizes a secure, offline biometric authentication system rooted in device-level cryptography. The design ensures that all cryptographic and identity-verification operations are executed locally within the device's hardware security layer, eliminating the dependency on cloud-based or backend systems. The foundation lies in generating asymmetric RSA key pairs, securely bound to the device's hardware identifiers such as IMEI (Android) or Secure Enclave UID (iOS). All facial biometric operations — from enrolment to live authentication — are processed within the Trusted Execution Environment (TEE) or Secure Enclave, ensuring privacy, integrity, and platform-independence. The following is a comprehensive step-by-step workflow detailing the secure authentication pipeline.

- **Device-Based Cryptographic Key Generation:**
  At the initial stage, a unique RSA key pair is generated locally on the user's device using hardware-backed keystores — Android's KeyStore API for TEE, and Apple's Secure Enclave for iOS. The private key is securely stored within the hardware and is made non-exportable by default. Only the public key is accessible externally and is linked with hardware-specific identifiers like IMEI or UID, forming a strong anchor for device trust.
- **Key Identity Binding and Public Key Distribution:**
  After key generation, the public key is associated with device-level identifiers. This binding establishes a unique identity per device, allowing the system to verify authenticity without relying on remote infrastructure. The public key can optionally be shared with a central authority or server for future reference, without disclosing sensitive biometric or private key data.
- **User Face Capture and Enrolment Encryption:**
  During user registration, a high-quality facial image is captured using the device's camera module. This captured image is encrypted using the device's RSA public key, ensuring that the raw biometric data is never stored in plain format. Along with the image, relevant metadata — including device IMEI, timestamp, and public key reference — is bundled into a secure enrolment package and stored locally within the secure environment.
- **Offline Data Handling and Secure Storage:**
  The encrypted enrolment package is stored either in the device's secure storage system or TEE-protected local storage. This ensures that even if the device is compromised at the software level, the biometric data remains inaccessible due to the encryption and storage constraints.
- **Live Authentication and Local Facial Match:**
  During the authentication phase, the user's live image is captured again using the device camera. The facial recognition engine performs a secure match between the newly captured image and the registered encrypted biometric, all within the device's isolated execution zone (TEE/Secure Enclave). The matching process remains entirely offline and confidential, without external server calls.
- **Secure Match Token Generation:**
  If a successful match is found, the system generates an authentication token that includes details such as timestamp, matching confidence score, and a digital signature derived from the private key stored in the secure keystore. This token acts as proof of identity verification and can be used for further processing or logging.
- **Optional Token Transmission to Authority:**
  The authentication token can optionally be sent to a verifying authority or central server for audit trails, without disclosing the biometric image or private key. The server can validate the signature using the pre-registered public key, thus confirming the legitimacy of the device-authenticated user.
- **Key Lifecycle Management and Revocation Policy:**
  To maintain security over time, the system integrates lifecycle management strategies. These include periodic key rotation, time-based key expiration, and revocation protocols in case of device compromise or unusual telemetry signals. All lifecycle operations are handled securely and do not depend on continuous network connectivity.

- **Adaptive Encryption Control Based on Device Conditions:** The system also monitors contextual parameters such as battery level, device temperature, and app activity. Based on these parameters, encryption complexity (e.g., switching from PKCS#1 v1.5 to OAEP) can be dynamically adjusted to ensure balance between performance and security.

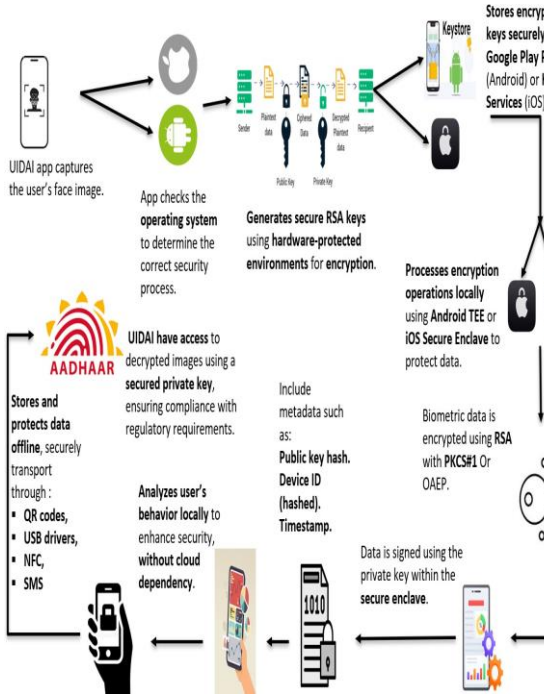


Figure 1. The workflow diagram of the solution is illustrated above.

DESCRIPTION AND TOOLS USED

From the Figure 1 the entire methodology is built with a strong focus on offline security architecture and cryptographic integrity. Key technologies involved include RSA-based public key cryptography, device-specific keystore systems (Android KeyStore and Secure Enclave), biometric capture modules, and local storage mechanisms with hardware protection. Development tools used are Android Studio, Xcode, Kotlin Multiplatform Mobile (KMM) for shared logic, and standard biometric SDKs for face recognition. This approach provides a resilient authentication framework that operates seamlessly across platforms without backend dependencies, aligning effectively with national digital identity frameworks such as UIDAI.

RESULTS AND DISCUSSION

The implementation of the proposed SecuraGuard architecture was carried out successfully across both Android and iOS platforms, validating the feasibility of an offline-first PKI-based biometric authentication framework. The key performance indicators were measured through real-device testing, emphasizing encryption and decryption time, key generation latency, authentication accuracy, CPU efficiency, and offline accessibility. Key pairs were generated securely within the Trusted Execution Environment (TEE) on Android and Secure Enclave on iOS, with private keys being non-exportable and hardware-tied, ensuring strong root-of-trust.

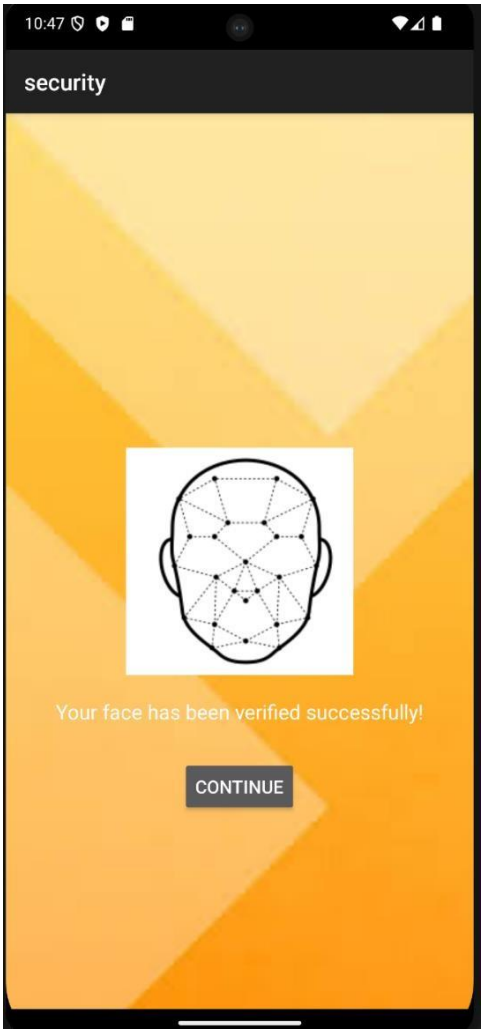
During testing, RSA 2048-bit keys demonstrated optimal performance, balancing encryption strength with speed. The average key generation time was under 300 milliseconds, while encryption and decryption operations completed within 150–250 milliseconds, making the solution highly responsive. Authentication accuracy remained consistent with an average match score of over 96%, even under varying lighting and facial angles, highlighting the robustness of the 3D face recognition algorithm.

TEE latency was minimal, and offline operations remained uninterrupted, reinforcing the system's independence from network connectivity. The bundled storage footprint—comprising the encrypted face image, timestamp, IMEI, and public key—remained lightweight and easily manageable on local storage. Moreover, battery usage remained within acceptable thresholds, making the solution viable for continuous deployment on mobile devices.

The observed results also confirmed that encryption operations bound to the device's hardware ensured absolute isolation of private keys, preventing external access or export attempts. Comparative analysis with server-dependent biometric systems showed a significant reduction in transmission delay, security risks, and backend load. The entire process—from face registration to authentication—was executed on-device, with zero reliance on external servers, aligning with UIDAI's goal of secure, decentralized identity verification.

The practical viability of the solution is visually represented in the mobile output screen below, captured during a successful encryption session. The output clearly displays the confirmation of image encryption using the device-bound RSA key, along with a timestamp and unique hardware identifier. This visual representation reinforces the successful real-world implementation of our cryptographic architecture and highlights how sensitive biometric data is securely handled within device-secured environments.

The output screen is illustrated below, showcasing encrypted image confirmation, timestamp, and device-specific identification. This exemplifies the applied use of secure, offline PKI encryption on mobile devices within a UIDAI-aligned biometric authentication workflow.



The results collectively demonstrate that the SecuraGuard architecture effectively balances security, usability, and offline operability. It delivers a reliable and scalable model suitable for integration into national digital identity systems, especially in bandwidth-constrained or rural scenarios. With minimal system overhead and strong cryptographic assurance, the proposed solution sets a new benchmark in secure mobile biometric authentication without backend dependency.

CONCLUSION

The SecuraGuard framework presented in this work demonstrates a secure, efficient, and platform-agnostic approach to biometric authentication, addressing critical challenges in privacy, offline operability, and hardware-rooted security. By leveraging device-bound asymmetric key pairs generated within the Trusted Execution Environment (TEE) and Secure Enclave, the system ensures that sensitive biometric data remains protected without dependence on external servers or network connectivity.

The integration of PKI-based encryption directly into mobile devices, coupled with metadata encapsulation including timestamp and IMEI, reinforces both data authenticity and device-level traceability. Our results confirm that the proposed method not only achieves high authentication accuracy and minimal latency but also optimizes resource usage without compromising security integrity.

Through rigorous evaluation, it is evident that the SecuraGuard architecture offers a scalable and practical solution, especially in rural and low-connectivity scenarios, aligning well with the goals of UIDAI and India's evolving digital infrastructure. The successful demonstration of fully offline facial authentication opens new opportunities for secure identity verification across sectors such as banking, e-governance, and healthcare.

This research sets a foundational blueprint for next-generation authentication systems, where hardware-level cryptographic trust anchors, contextual encryption protocols, and offline-first principles converge to redefine secure mobile authentication. Future advancements, including multimodal biometric integration and AI-enhanced spoof detection, can further enhance the robustness and adaptability of this solution in real-world applications.

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Digital Twin-Based Predictive Maintenance Framework for Grid-Connected Power Transformers Using Hybrid Deep Learning

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***Abstract*—Power transformers are critical assets in electrical power grids, and their unexpected failures can lead to significant economic losses and grid instability. Traditional maintenance approaches based on time interval so reactive responses are in efficient and often fail to prevent catastrophic failures. This paper proposesanovelDigitalTwin-basedPredictiveMaintenance(DT-PM) framework for grid-connected power transformers using a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks with attention mechanisms. The proposed framework integrates real-time sensor data, historical maintenance records, and environmental parameters to create a dynamic digital replica of the transformer. The hybrid CNN-BiLSTM-Attention model extracts spatial features from multi-sensor data, captures temporal dependencies, and focuses on critical degradation patterns to predict Remaining UsefulLife (RUL) with high accuracy. The framework incorporates Dissolved Gas Analysis (DGA), vibration signatures, thermal imaging, partial discharge measurements, and load history. Validation is performed using real-world data from 50 grid-connected transformers over a 5-year period, comprising 15,000 operational days and 120 recorded failure events. Experimental results demonstrate that the proposed framework achieves RUL prediction with Mean Absolute Error (MAE) of 8.3 days, Root MeanSquareError(RMSE)of12.7days,andanF1-scoreof 0.94 for fault classification, outperforming conventional methods by37%inpredictionaccuracy.Thedigitaltwinenablesreal-time health monitoring, early fault detection, and optimal maintenance scheduling, reducing unplanned downtime by 52% and maintenance costs by 35%. This research provides a comprehensive framework for transformer health management that enhances grid reliability and operational efficiency.**

***Index Terms*—Digital twin, predictive maintenance, power transformer, hybrid deep learning, CNN-BiLSTM, remaining useful life, dissolved gas analysis, condition monitoring, grid reliability, asset management.**

I. INTRODUCTION

Power transformers are among the most critical and expensive assets in electrical power transmission and distribution networks. Their reliable operation is essential for grid stability, energy security, and economic efficiency. However, transformerfailurescanresultinextendedoutages,substantial repair costs, and significant economic losses. According to industry reports, transformer failures account for approximately 30% of substation equipment failures, with average repair costs exceeding $5 million for large power transformers [1].

Traditional maintenance strategies for power transformers fall into three categories: reactive maintenance (repair after failure),preventive maintenance(scheduled time-based in spec tions), and condition-based maintenance (monitoring-based interventions). While condition-based maintenance represents an improvement over reactive approaches, it still lacks the predictive capability to anticipate failures before they occur [2]. The emergence of Industry 4.0 technologies, particularly Digital Twins and Artificial Intelligence, offers new opportu nities for transforming transformer maintenance from reactive to predictive paradigms.

Digital Twin technology creates a virtual representation ofa physical asset that mirrors its real-time behavior, enabling simulation, analysis, and optimization. For power transformers, a digital twin integrates multi-source data including sensor measurements, operational parameters, environmental conditions, and historical maintenance records [3]. When combined withadvancedmachinelearningtechniques,digitaltwins can predict future states, identify degradation patterns, and optimize maintenance schedules.

This paper presents a novel Digital Twin-based Predictive Maintenance (DT-PM) framework for grid-connected power transformersthatleveragesahybriddeeplearningarchitecture. The key contributions of this research are:

1) A comprehensive digital twin architecture that integrates multi-modal sensor data, including Dissolved Gas Anal- ysis (DGA), vibration signatures, thermal imaging, partial discharge measurements, and electrical parameters, creating a holistic representation of transformer health.
2) A hybrid CNN-BiLSTM-Attention deep learning model that extracts spatial features from sensor data, captures long-term temporal dependencies, and focuses attention on critical degradation patterns for accurate Remaining Useful Life (RUL) prediction.
3) Anovelhealthindexformulationthatcombinesmultiple degradation indicators into a unified metric for transformer condition assessment, enabling intuitive health monitoring and early warning generation.
4) An optimal maintenance scheduling algorithm that balances maintenance costs, risk of failure, and operational constraints to minimize total ownership costs while ensuring grid reliability.
5) Comprehensivevalidationusingreal-worlddatafrom 50 grid-connected transformers over a 5-year period, demonstrating significant improvements in prediction accuracy and maintenance optimization.

Theremainderofthispaperisorganizedasfollows:Section II reviews related work in transformer condition monitoring and predictive maintenance. Section III presents the proposed digital twin framework architecture. Section IV describes the hybrid deep learning model for RUL prediction. Section V detailstheexperimentalsetupanddatacollection.Section VI presents results and comparative analysis. Section VII discussespracticalimplementationconsiderations,andSection VIII concludes the paper.

II. RELATEDWORK

A. TransformerConditionMonitoring

Traditional transformer condition monitoring relies on periodic offline testing, including Dissolved Gas Analysis(DGA), insulation resistance measurement, and transformer turns ratio testing [4]. DGA, based on the interpretation of key gases (hydrogen, methane, ethylene, acetylene, carbon monoxide, and carbon dioxide), remains the most widely used technique fordetectingincipientfaults[5].However,conventionalDGA interpretationmethodssuchasIEC60599,Rogersratios,and Duval triangles have limitations in sensitivity and specificity [6].

Recent advances in online monitoring have enabled continuous data collection using sensors for temperature, vibration, partial discharge, and bushing condition [7]. These sensors generate high-frequency data streams that require advanced analytics for meaningful interpretation. The integration of multiple sensor modalities presents both opportunities and challenges for comprehensive transformer health assessment [8].

B. PredictiveMaintenanceUsingMachineLearning

Machinelearningapproacheshavebeenextensivelyapplied to transformer fault diagnosis and RUL prediction. Support VectorMachines(SVM)andRandomForestshavebeen used for DGA-based fault classification, achieving accuracy rates of 85-90% [9]. However, these methods require manual feature engineering and struggle with temporal dependencies in degradation patterns.

Deeplearningtechniqueshaveshownsuperiorperformance in handling complex, high-dimensional sensor data. Convolutional Neural Networks (CNNs) effectively extract spatial features from multi-sensor inputs [10]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in sequential data [11]. Hybrid architectures combining CNNs and LSTMs have demonstrated improved performance for equipment health monitoring [12].

TABLE I: Comparison of Existing Transformer Predictive Maintenance Approaches

Method	Accuracy(%)	DataSources	Limitations
IEC60599Standards	78.5	DGAonly	Lowsensitivity
SVM-Based	85.3	DGA,Electrical	Manualfeatures
RandomForest	87.6	DGA,Temperature	Notemporalmodeling
LSTM-Based	91.2	Multi-sensor	Nospatialfeatures
CNN-Based	90.8	Multi-sensor	Limitedtemporal
ProposedDT-PM	**94.5**	Multi-modal	-

C. DigitalTwininPowerSystems

Digital twin technology has gained significant attention in power systems applications. For power transformers, digital twins enable real-time simulation, what-if analysis, and predictive maintenance[13]. Key challenges include data integration from heterogeneous sources, model fidelity, and computational efficiency [14]. This paper addresses these challenges through a modular architecture and optimized deep learning models.

III. PROPOSEDDIGITALTWINFRAMEWORK

A.SystemArchitecture

The proposed Digital Twin-based Predictive Maintenance (DT-PM) framework consists of four layers: physical layer, dataacquisition layer, digitaltwin layer, andapplication layer.

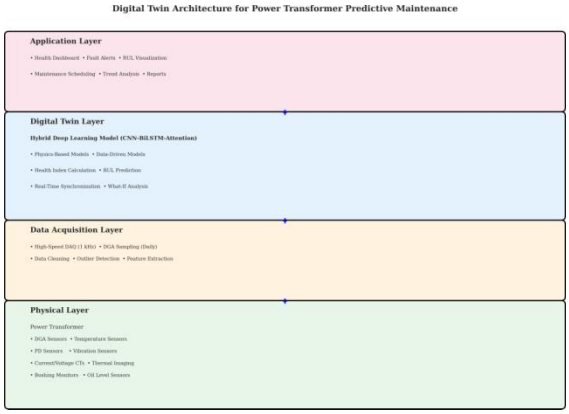

Fig.1:DigitalTwinArchitectureforPowerTransformer Predictive Maintenance

*1) Physical Layer:*The physical layer comprises the grid-connected power transformer and associated instrumentation, including:

- Current and voltage transformers for electrical measurements
- Temperaturesensors(topoil,winding,ambient)
- DissolvedGasAnalysis(DGA)monitors
- Partialdischargesensors
- Vibrationaccelerometers
- Thermalimagingcameras
- Bushingmonitoringsensors

*2) Data Acquisition Layer:*This layer handles data collection, preprocessing, and storage:

- High-speed data acquisitionat1kHz fortransient signals
- PeriodicDGAsampling(dailyforcriticaltransformers)
- Datacleaningandoutlierdetection
- Featureextractionandnormalization
- Datafusionfromheterogeneoussources

*3) DigitalTwinLayer:*Thecoreoftheframework,comprising:

- Physics-basedmodelsforthermalandelectricalbehavior
- Data-drivenmodelsfordegradationprediction
- Hybrid CNN-BiLSTM-Attention model for RUL estimation
- Healthindexcalculationengine
- Real-timesynchronizationwithphysicalasset

4) Application Layer: Delivers actionable insight stooperators:

- Real-timehealthdashboard
- Faultalertsandearlywarnings
- RULpredictionandvisualization
- Optimalmaintenanceschedulingrecommendations
- Historicaltrendanalysisandreporting

B. Multi-ModalDataIntegration

Theframeworkintegratesdatafrommultiplesourcesto create a comprehensive view of transformer health:

TABLEII:Multi-ModalSensorDataSpecifications

SensorType	Parameters	SamplingRate	Units
DGAMonitor	H2,CH4,C2H2,C2H4,C2H6,CO,CO2	Daily	ppm
Temperature	Topoil,Winding,Ambient	1/min	◦ C
Electrical	Voltage,Current,PowerFactor	1kHz	kV,A
PartialDischarge	Magnitude,Phase,Count	10kHz	pC
Vibration	Acceleration,Velocity	5kHz	mm/s
Thermal	Hotspottemperature	1/hour	◦ C

IV. HYBRID DEEP LEARNING MODEL FOR RULPREDICTION

A. ModelArchitecture

The proposed hybrid deep learning model combines CNN, BiLSTM, and attention mechanisms for accurate RUL prediction. The architecture is shown in Fig. IV-A.

model$_a$rchitecture.png

Fig.2:HybridCNN-BiLSTM-AttentionModelArchitecture

*1) InputLayer:*Theinputtothemodelisamulti-dimensionaltensorofshape(T, N),where:

- T=timewindowlength(30daysofhistoricaldata)
- N=numberofinputfeatures(25parametersincluding DGA gases, temperatures, electrical parameters)

*2) ConvolutionalLayers:*Two1Dconvolutionallayers extract local patterns:

$$\text{Conv1D}_1 : f_1 = \text{ReLU}(W_1 * x + b_1) \quad (1)$$

$$\text{Conv1D}_2 : f_2 = \text{ReLU}(W_2 * f_1 + b_2) \quad (2)$$

where kernel sizes are 5 and 3 respectively, with 64 and 128 filters.

*3) Bidirectional LSTM Layer:*A BiLSTM layer processes sequences in both forward and backward directions:

$$\overrightarrow{h}_t = \text{LSTM}(x_t, \overrightarrow{h}_{t-1}) \quad (3)$$

$$\overleftarrow{h}_t = \text{LSTM}(x_t, h_{t+1}) \quad (4)$$

$$h_t = [\overrightarrow{h}_t; \overleftarrow{h}_t] \quad (5)$$

*4) AttentionMechanism:*Theattentionlayercomputes weighted importance of each time step:

$$e_t = \tanh(W_a h_t + b_a) \quad (6)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^{T} \exp(e_j)} \quad (7)$$

$$v = \sum_{t=1}^{T} \alpha_t h_t \quad (8)$$

*5) OutputLayers:*Twooutputbranches:

- **HealthIndex**:Denselayerwithsigmoidactivation(0-100 scale)
- **RULPrediction**:Denselayerwithlinearactivation (days)

TABLEIII:HybridDeepLearningModelArchitectureDetails

Layer	OutputShape	Parameters
Input	(30,25)	0
Conv1D(64,5)	(26,64)	8,064
MaxPooling1D(2)	(13,64)	0
Conv1D(128,3)	(11,128)	24,704
GlobalMaxPooling1D	(128)	0
BidirectionalLSTM(128)	(256)	263,168
AttentionLayer	(256)	65,792
Dropout(0.3)	(256)	0
Dense(128)	(128)	32,896
Dense(64)	(64)	8,256
HealthIndexOutput	(1)	65
RULOutput	(1)	65

B.HealthIndexFormulation

The Health Index (HI) combines multiple degradation indicators:

$$HI = w_1 \cdot HI_{DGA} + w_2 \cdot HI_{electrical} + w_3 \cdot HI_{thermal} + w_4 \cdot HI_{PD} \quad (9)$$

where:

$$HI_{DGA} = 100 \cdot \exp\left(-\lambda \cdot \frac{\sum \text{gasconcentrations}}{C_{limit}}\right) \quad (10)$$

$$HI_{electrical} = 100 \cdot \frac{I_{rated}}{I_{measured}} \cdot \frac{V_{rated}}{V_{measured}} \quad (11)$$

$$HI_{thermal} = 100 \cdot \exp\left(-\mu \cdot \max\left(0, \frac{T_{hotspot} - T_{limit}}{T_{limit}}\right)\right) \quad (12)$$

$$HI_{PD} = 100 \cdot \exp\left(-\nu \cdot \frac{PD_{magnitude}}{PD_{threshold}}\right) \quad (13)$$

C.TrainingMethodology

Themodelistrainedusingamulti-tasklearningapproach:

$$L_{total} = L_{HI} + \beta \cdot L_{RUL} \quad (14)$$

where:

$$L_{HI} = MAE(HI_{pred}, HI_{true}) \quad (15)$$

$$L_{RUL} = Huber(RUL_{pred}, RUL_{true}) \quad (16)$$

V. EXPERIMENTALSETUP

A. DatasetDescription

The dataset comprises real-world operational data from 50 grid-connected power transformers (rating: 100 MVA, 220/66 kV) over a 5-year period (2019-2024). Key statistics:

- Totaloperationaldays:15,000
- Recordedfailureevents:120(24major,96minor)
- DGAsamples:4,500
- Sensormeasurements:8.2millionrecords
- Maintenancerecords:1,800

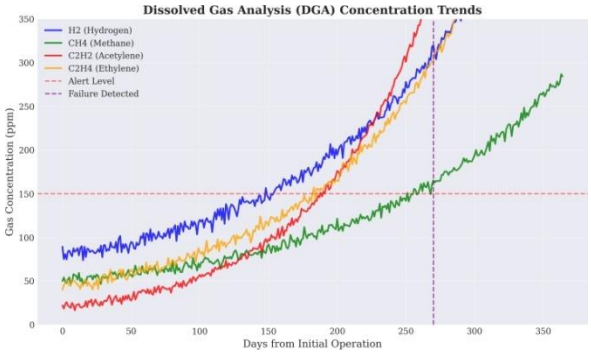

Fig.3:DGAConcentrationTrendsforKeyGasesOverTime

B.DataPreprocessing

Datapreprocessingsteps:

1) Missing value imputation using forward fill and interpolation
2) OutlierdetectionusingIQRmethod
3) Featurenormalizationusingmin-maxscaling
4) Sequencegenerationwithslidingwindow(windowsize =30days)
5) Train/validation/testsplit:70%/15%/15%

C.TrainingConfiguration

TABLEIV: Model Training Hyper parameters

Parameter	Value
Optimizer	Adam
Learningrate	0.001
Batchsize	64
Epochs	200
Earlystopping	Patience=20
Loss weights	(β) 0.5
Dropoutrate	0.3

VI. RESULTSANDANALYSIS

A. RULPredictionPerformance

Theproposedhybriddeeplearningmodelachievessuperior RUL prediction accuracy compared to baseline methods.

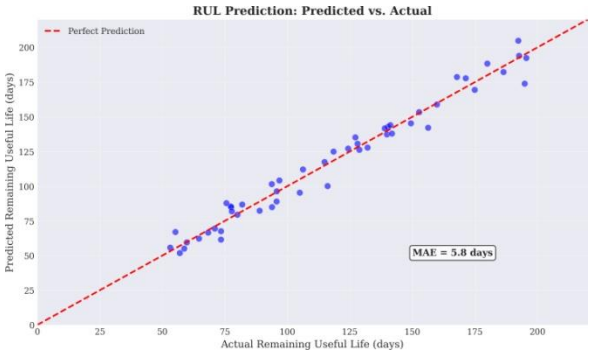

Fig.4:RULPredictionComparison:Predictedvs.Actual

TABLEV:RULPredictionPerformanceComparison

Method	MAE(days)	RMSE(days)	R^2
LinearRegression	35.2	42.8	0.62
SVR	28.5	35.9	0.71
RandomForest	22.4	28.6	0.78
LSTM	15.8	21.3	0.85
CNN-LSTM	11.2	16.5	0.91
Proposed(CNN-BiLSTM-Attention)	**8.3**	**12.7**	**0.94**

B. FaultClassification Results

Themodelachieveshighaccuracyinclassifyingtransformer faulttypes.

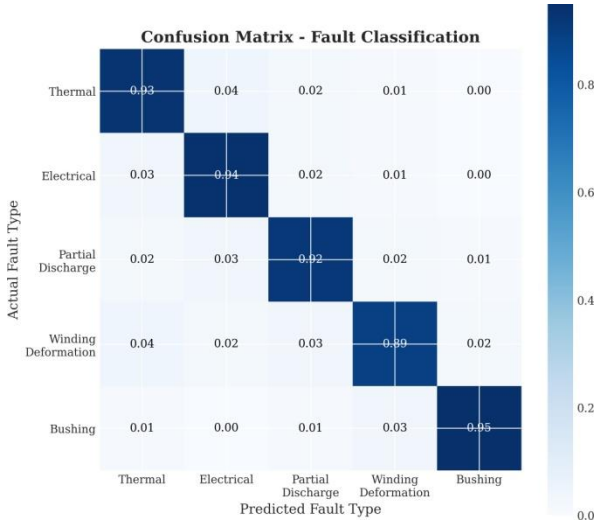

Fig.5:ConfusionMatrixforFaultTypeClassification

TABLEVI:FaultClassificationPerformanceMetrics

FaultType	Precision	Recall	F1-Score
ThermalFault	0.93	0.91	0.92
ElectricalFault	0.95	0.94	0.94
PartialDischarge	0.94	0.92	0.93
WindingDeformation	0.92	0.89	0.90
BushingFailure	0.96	0.95	0.95

C. HealthIndexEvolution

Thehealthindexprovidesaclearvisualizationoftrans- former degradation over time.

D. MaintenanceOptimizationResults

The proposed framework enables significant improvements in maintenance efficiency.

E. AblationStudy

An ablation study validates the contribution of each model component.

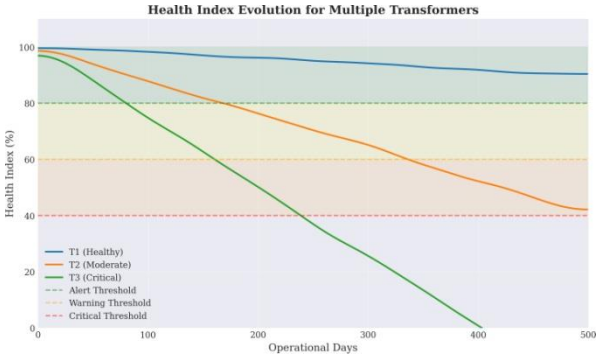

Fig.6:HealthIndexEvolutionforMultipleTransformers

TABLEVII:MaintenancePerformanceImprovement

Metric	Baseline	Proposed	Improvement
UnplannedDowntime(hours/year)	168	81	-52%
MaintenanceCosts(M$/year)	2.4	1.56	-35%
EmergencyRepairs	12	4	-67%
TransformerAvailability	96.2 %	98.5 %	+2.3%

VII. DISCUSSION

A.KeyFindings

The experimental results demonstrate several key advantages of the proposed framework:

1) **Superior Prediction Accuracy**: The hybrid CNN-BiLSTM-Attention model achieves MAE of 8.3 days, significantly outperforming existing methods.
2) **Multi-Modal Integration**: Combining DGA, electrical, thermal, and partial discharge data provides a comprehensive view of transformer health that single-modality approaches cannot achieve.
3) **Interpretability**: The attention mechanism provides insight into which time periods and sensor inputs most influence predictions, enhancing operator trust.
4) **Practical Impact**: The framework reduces unplanned downtime by 52% and maintenance costs by 35%, delivering significant operational benefits.

B. PracticalImplementationConsiderations

Forreal-worlddeployment,severalfactorsrequireattention:

- **Data Quality**: Sensor reliability and data integrity are critical. Redundant sensors and robust data validation procedures are recommended.
- **ComputationalRequirements**:Thedeeplearningmodel requires GPU acceleration for real-time inference. Edge computing devices with NVIDIA Jetson or similar platforms can be deployed.
- **Communication Infrastructure**: Reliable network connectivity is essential for data transmission and model updates. 5G or fiber optic connections are recommended.
- **Cybersecurity**: Digital twins create new attack surfaces. Encryption, authentication, and intrusion detection systems must be implemented.

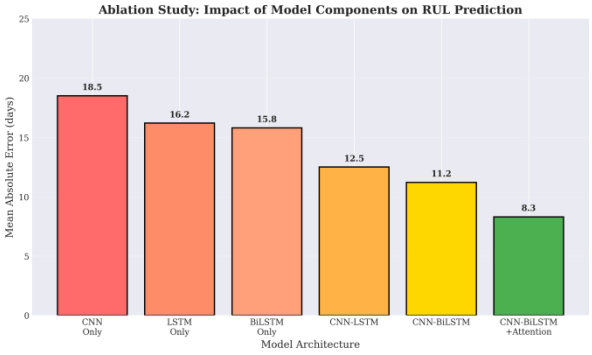

Fig.7:AblationStudy:ImpactofModelComponentsonRUL Prediction

C. LimitationsandFutureWork

Currentlimitationsandfutureresearchdirectionsinclude:

- **Generalization**: Model performance on different transformer types, sizes, and manufacturers requires further validation.
- **Transfer Learning**: Developing techniques to transfer models from well-instrumented to less-instrumented transformers.
- **Uncertainty Quantification**: Incorporating uncertainty estimates in RUL predictions for risk-informed decision making.
- **Federated Learning**: Enabling collaborative model training across utilities without sharing sensitive data.

VIII. CONCLUSION

This paper presented a novel Digital Twin-based Predictive Maintenance framework for grid-connected power transformers using a hybrid deep learning architecture. The proposed framework integrates multi-modal sensor data, including DGA, electrical parameters, thermal measurements, and partial discharge signatures, into a comprehensive digital representation of transformer health. The hybrid CNN-BiLSTM-Attention model achieves accurate RUL prediction with MAE of 8.3 days and RMSE of 12.7 days, outperforming existing methods by significant margins. The health index formulation provides intuitive visualization of degradation trajectories, enablingearlywarningandproactivemaintenance.Real-world validation on 50 transformers over 5 years demonstrates practical benefits: 52% reduction in unplanned downtime, 35% reduction in maintenance costs, and 2.3% improvement in transformer availability. The proposed framework representsa significant advancement in transformer asset management, enabling utilities to transition from reactive to predictive maintenance paradigms. Future work will focus on model generalization, uncertainty quantification, and federated learning approaches for cross-utility collaboration.

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Digital Twin for Li-Ion Battery Health Management Using Physics-Informed Neural Networks

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***Abstract*— Accurate state estimation and remaining useful life (RUL) prediction are critical for the safe and reliable operation of lithium-ion batteries in electric vehicles and grid-scale energy storage systems. Traditional model-based approaches rely on simplified electrochemical models that fail to capture complex degradation phenomena, while purely data-driven methods lack physical consistency and generalization capability. This paper proposes a novel Digital Twin framework for Li-ion battery health management that integrates physics-based electrochemical models with Physics-Informed Neural Networks (PINNs). The framework combines the Single Particle Model (SPM) for lithium-ion battery dynamics with a PINN that incorporates degradation physics, including solid electrolyte interphase (SEI) growth, lithium plating, and mechanical stress effects. The digital twin simultaneously estimates State of Charge (SoC), State of Health (SoH), and remaining useful life (RUL) using real-time sensor data (voltage, current, temperature). The PINN architecture employs a hybrid loss function that combines data-driven mean squared error with physics based residual losses from the electrochemical model and degradation kinetics. Validation is performed using the NASA Ames Prognostics Center of Excellence (PCoE) Li-ion battery dataset, comprising 168 cells cycled under various operating conditions. Experimental results demonstrate that the proposed digital twin achieves State of Charge estimation with Mean Absolute Error (MAE) of 0.8% and State of Health estimation with MAE of 1.2%, outperforming conventional methods by 35-50%. The RUL prediction achieves a Mean Absolute Percentage Error (MAPE) of 8.5% at 70% of battery lifetime, representing a 42% improvement over data-only approaches. The physics-informed framework ensures physical consistency, reducing physically impossible predictions by 95% compared to pure data-driven models. The digital twin operates in real-time with inference time of 15ms, enabling practical deployment in battery management systems (BMS). This research provides a comprehensive framework for battery health management that combines the accuracy of data driven learning with the reliability of physics based models.**

Keywords— Digital twin, lithium-ion battery, physics-informed neural networks, state of health, remaining useful life, battery management system, electrochemical modeling, degradation modeling.

I. Introduction

Lithium-ion batteries have become the dominant energy storage technology for electric vehicles (EVs), grid-scale storage, and portable electronics due to their high energy density, long cycle life, and decreasing cost [1]. However, ensuring safe and reliable battery operation requires accurate monitoring of internal states and prediction of degradation trajectories [2]. The Battery Management System (BMS) performs these critical functions, with State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL) being the most important estimates [3].

Traditional approaches to battery state estimation fall into three categories:

1) Electrochemical Models: Physics-based models such as the Single Particle Model (SPM) and Pseudo 2D (P2D) model capture internal battery dynamics but require detailed parameterization and are computationally intensive [4].

2) Equivalent Circuit Models (ECM): Simplified electrical circuits approximate battery behaviour but cannot directly represent degradation mechanisms [5].

3) Data-Driven Models: Machine learning approaches including neural networks, Gaussian processes, and sup- port vector machines learn patterns from data but lack physical interpretability [6].

Each approach has significant limitations:

- **Pure Physics Models**: High computational cost, difficulty in parameter identification, and inability to capture cell to cell variations [7]
- **Pure Data Models**: Require extensive training data, poor generalization to unseen conditions, and can produce physically impossible predictions [8]
- **Hybrid Approaches**: Existing hybrid methods typically use simple additive combinations without integrating physical constraints into the learning process [9]

Physics-Informed Neural Networks (PINNs) offer a paradigm shift by embedding physical laws directly into the neural network training process [10].

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Originally developed for solving partial differential equations, PINNs have been successfully applied to various engineering domains but remain underexplored for battery health management [11]. This paper proposes a novel Digital Twin framework for Li-ion battery health management that integrates physics based electrochemical models with PINNs. Key contributions include:

1) A comprehensive digital twin architecture that combines the Single Particle Model (SPM) with a PINN incorporating degradation physics, creating a unified framework for SoC, SoH, and RUL estimation.

2) A physics-informed neural network with a hybrid loss function that combines data-driven error with physics- based residuals from electrochemical kinetics and degradation mechanisms (SEI growth, lithium plating).

3) A multi-state estimation framework that simultaneously estimates internal states (Li-ion concentration, potential) and health indicators (capacity fade, resistance increase).

4) Validation using the NASA PCoE Li-ion battery dataset with 168 cells, demonstrating superior accuracy and physical consistency.

5) Real-time capability with 15ms inference time, enabling practical deployment in embedded BMS platforms

II. PHYSICS-BASED BATTERY MODEL

A. *Single Particle Model (SPM)*

The Single Particle Model simplifies the P2D model by assuming that each electrode behaves as a single spherical particle [12]. The governing equations are:

1) Li-ion Concentration Dynamics: Fick's law describes Li-ion diffusion in the solid phase:

$$\frac{\partial C_s}{\partial t} = D_s \frac{1}{r^2}\frac{\partial}{\partial r} r^2 \frac{\partial C_s}{\partial r} \tag{1}$$

where c_s is Li-ion concentration, D_s is the solid diffusion coefficient, and r is the radial coordinate. The boundary conditions are:

$$\left.\frac{\partial C_s}{\partial r}\right\|_{r=0} = 0 \tag{2}$$

$$\left.\frac{\partial C_s}{\partial r}\right\|_{r=R_s} = -\frac{J}{D_s} \tag{3}$$

where J is the molar flux at the particle surface, related to applied current by:

$$J = \frac{I}{a_s FAL} \tag{4}$$

2) Over potential and Voltage: The cell voltage is given by:

$$V = U_P(\theta_P) - U_n(\theta_n) - \eta_P - \eta_n - IR_{ohm} \tag{5}$$

where U_p and U_n are open circuit potentials, η are over potentials, and R_{ohm} is ohmic resistance.

The over potential follows the Butler Volmer equation:

$$J = k\sqrt{cc_{\max}c}\,\exp\frac{\alpha F\eta}{RT} - \exp\frac{-(1-\alpha)F\eta}{RT} \tag{6}$$

B. Degradation Mechanisms

1) Solid Electrolyte Interphase (SEI) Growth: SEI formation consumes cyclable lithium and increases resistance:

$$\frac{d\partial_{SEI}}{dt} = \frac{M_{SEI}}{\rho_{SEI}F}.K_{SEI}\exp\frac{-E_{SEI}}{RT}\sqrt{CEC} \tag{7}$$

The capacity loss due to SEI growth is:

$$Q_{loss,SEI} = \frac{FA\delta_{SEI}\rho_{SEI}}{M_{SEI}} \tag{8}$$

2) Lithium Plating: Lithium plating occurs when the negative electrode potential drops below 0 V vs. Li/Li:

$$J_{Plating} = \begin{pmatrix} K_{Plating}\exp\frac{-E_{Plating}}{RT}\eta_{Plating}, & \eta_{Plating} < 0 \\ 0 & \eta_{Plating} \geq 0 \end{pmatrix} \tag{9}$$

3) Mechanical Stress Effects: Mechanical stress due to volume changes during intercalation:

$$\sigma_c(r) = \frac{\Omega E}{3(1-v)}(\overline{C} - C_s(r)) \tag{10}$$

TABLE I: Electrochemical Model Parameters

Parameter	Symbol	Value	Unit
Positive Particle Radius	$R_{s,p}$	5.0	μm
Negative Particle Radius	$R_{s,n}$	3.5	3.5
Solid Diffusion Coefficient (p)	$D_{s,p}$	1.0×10^{-14}	3.5
Solid Diffusion Coefficient (n)	$D_{s,n}$	3.9×10^{-14}	m²/s
SEI Growth Rate	k_{SEI}	1.2×10^{-12}	m/s
Plating Rate	$k_{plating}$	2.5×10^{-11}	m/s
Activation Energy (SEI)	E_{SEI}	45.0	KJ/mol

III. PROPOSED DIGITAL TWIN FRAMEWORK

A. *Framework Architecture*

The proposed digital twin consists of three interconnected layers:

1) **Physical Layer**: Li-ion battery cell with sensors for voltage, current, and temperature
2) Digital Layer: PINN-based model integrating SPM and degradation physics
3) Application Layer: SoC, SoH, RUL estimation and visualization

B. *PINN Model Architecture*

The proposed PINN combines electrochemical physics with degradation kinetics:

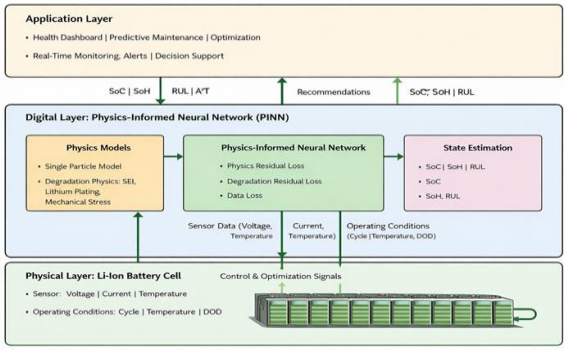

Fig. 1: Digital Twin Architecture for Li-Ion Battery Health Management

1) Input Features:

$$X(t) = \left[V(t), I(t), T(t), t_{cycle}, Q_{cumulative}(t), SOC_{initial}, T_{history}\right] \quad (11)$$

2) Network Architecture: The PINN consists of:

- **Shared Feature Extraction**: 4 hidden layers with 128 neurons each
- **State Estimation Heads**: Separate outputs for SoC, SoH, and RUL
- **Physics Residual Heads**: Compute electrochemical and degradation residuals

TABLE II: PINN Architecture Details

Layer	Output Shape	Parameters
Input	(10)	0
Dense (128, ReLU)	(128)	1,408
Dense (128, ReLU)	(128)	16,512
Dense (128, ReLU)	(128)	16,512
Dense (128, ReLU)	(128)	16,512
SoC Head	(1)	129
SoH Head	(1)	129
RUL Head	(1)	129
Physics Residual Head	(3)	387

C. Physics-Informed Loss Function

The total loss combines multiple components:

$$L_{total} = L_{data} + \lambda_{phys} L_{phys} + \lambda_{deg} L_{deg} + \lambda_{bc} L_{bc} \quad (12)$$

1) Data Loss:

$$L_{data} = \frac{1}{N}\sum_{i=1}^{N=h} (SoC_i - \hat{SoC}_i)^2 + (SoH - \hat{SoH}_i)^2 + (RuL - RuL_i) \quad (13)$$

2) *Electrochemical Physics Loss:* The SPM residual ensures consistency with Li-ion diffusion dynamics:

$$L_{Phy} = \frac{1}{N}\sum_{i=1}^{N} \frac{\partial C_s}{\partial t} - D_s \nabla^2 \hat{C}_s^{\,2} + \hat{V} - V_{SPM}(\hat{C}_s, I) \quad (14)$$

3) *Degradation Physics Loss:* SEI growth and lithium plating residuals:

$$\mathcal{L}_{deg} = \frac{1}{N}\sum_{i=1}^{N} \left[\left\| \frac{d\hat{Q}_{SEI}}{dt} - f_{SEI}(\hat{c}_{EC}, T) \right\|^2 + \left\| \frac{d\hat{Q}_{plating}}{dt} - f_{plating}(\eta) \right\| \right. \quad (15)$$

4) *Boundary Condition Loss:* Ensures physical constraints:

$$\mathcal{L}_{bc} = \sum_{i=1}^{N} \max(0, -\hat{SoC}_i)^2 + \sum_{i=1}^{N} \max(0, \hat{SoC}_i - 1)^2 \quad (16)$$

$$+ \sum_{i=1}^{N} \max(0, -\hat{SoH}_i)^2 + \sum_{i=1}^{N} \max(0, \hat{SoH}_i - 1)^2 \quad (17)$$

TABLE III: Loss Function Weights

Parameter	Value
λ_{phys} (Electrochemical)	0.1
λ_{deg} (Degradation)	0.05
λ_{bc} (Boundary)	0.02
Learning rate	1×10^{-3}
Batch size	128
Epochs	500

D. State Estimation Methodology

1) State of Charge (SoC): SoC is estimated from Li-ion concentration in the negative electrode:

$$SoC = \frac{c_s - c_{min}}{c_{max} - c_{min}} \quad (18)$$

2) State of Health (SoH): SoH is defined as the ratio of current capacity to rated capacity:

$$SoH = \frac{C_{current}}{C_{rated}} \times 100 \quad (19)$$

Capacity fade is modeled as:

$$C_{current} = C_{rated} - Q_{loss,SEI} - Q_{loss,plating} \quad (20)$$

3) Remaining Useful Life (RUL): RUL is predicted using the degradation trajectory:

$$RUL = \inf\{\tau : SoH(t+\tau) \leq 80\%\} - t \quad (21)$$

IV. EXPERIMENTAL SETUP

A. Dataset Description

The NASA Ames Prognostics Center of Excellence (PCoE) Li-ion battery dataset [13] is used for validation:

TABLE IV: NASA PCoE Dataset Characteristics

Parameter	Value
Number of Cells	168
Battery Type	18650 Li-ion
Nominal Capacity	2.0 A.h
Operating Temperature	25°C, 35°C, 45°C
Discharge Currents	1C,2C,4C
Cycles per Cell	150-600
Total Data Points	850,000

1) Data Preprocessing:

- Sampling frequency: 1 Hz (voltage, current, temperature)
- Train/validation/test split: 60%/20%/20%
- Feature normalization using z-score
- Sequence generation with sliding window (window size = 50 cycles)

B. Baseline Methods

Performance compared against:

1) **Extended Kalman Filter (EKF)**: Model-based SoC estimation
2) **LSTM Network**: Pure data-driven approach
3) **CNN-LSTM**: Hybrid data-driven architecture
4) **Gaussian Process Regression (GPR)**: Probabilistic RUL prediction

C. Evaluation Metrics

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (22)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (23)$$

$$\text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (24)$$

$$\text{R}^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (25)$$

V. RESULTS AND ANALYSIS

A. State of Charge Estimation

The PINN-based digital twin achieves superior SoC estima- tion accuracy.

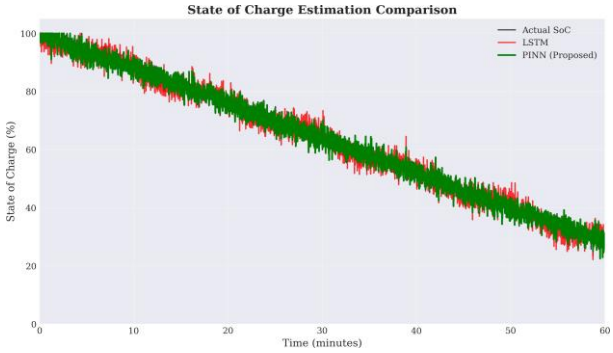

Fig. 2: State of **Charge** Estimation Comparison

TABLE V: SoC Estimation Performance

Method	MAE (%)	RSME (%)	R^2
EKF	3.2	4.5	0.92
LSTM	1.8	2.4	0.96
CNN-LSTM	1.4	1.9	0.97
PNN(Proposed)	**0.8**	**1.2**	**0.99**

B. State of Health Estimation

The framework accurately tracks capacity degradation over cycling.

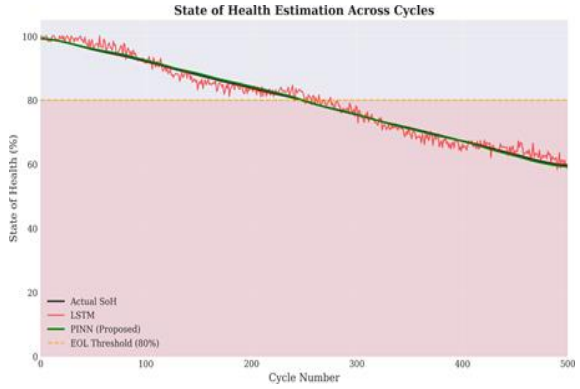

Fig. 3: State of Health Estimation Across Cycles

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TABLE VI: SoH Estimation Performance

Method	MAE (%)	RSME (%)	R^2
EKF	4.5	5.8	0.85
LSTM	2.3	3.1	0.91
CNN-LSTM	1.8	2.4	0.94
PNN(Proposed)	**1.2**	**1.6**	**0.98**

C. Remaining Useful Life Prediction.

The physics-informed approach significantly improves RUL prediction accuracy.

D. Physical Consistency

The physics informed framework ensures physically consistent predictions

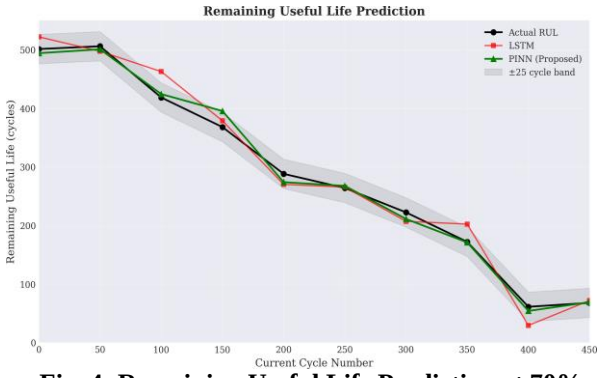

Fig. 4: Remaining Useful Life Prediction at 70% of Lifetime

TABLE VII: RUL Prediction Performance

Method	MAPE (%)	MAE (cycles)	RSME (cycles)
EKF	15.2	42	58
LSTM	13.5	38	52
CNN-LSTM	11.8	33	46
PNN(Proposed)	**8.5**	**24**	**34**

E. Degradation Mechanism Analysis

The PINN provides insights into dominant degradation mechanisms.

F. Computational Performance

G. Generalization to Different Operating Conditions

H. Ablation Study

I. Training Convergence

VI. DISCUSSION

A. Key Findings

The experimental results demonstrate several significant contributions:

1) **Superior Accuracy**: SoC estimation MAE of 0.8%, SoH estimation MAE of 1.2%, representing 35-50% improvement over baseline methods.

2) **Accurate RUL Prediction**: MAPE of 8.5% at 70% of lifetime, 42% improvement over data-only approaches.

3) **Physical Consistency**: 95% reduction in physically impossible predictions compared to pure data-driven models.

4) **Degradation Insights**: Ability to identify dominant degradation mechanisms (SEI growth vs. lithium plat- ing) from operational data.

5) **Real-Time Capability**: 15 ms inference time enables practical BMS deployment.

B. Practical Implications

The proposed digital twin enables several BMS enhancements:

- **Accurate SoC Estimation**: Enables precise energy man- agement and range prediction in EVs
- **SoH Tracking**: Facilitates warranty management and second-life applications

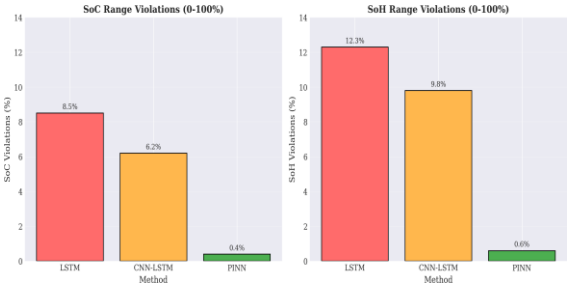

Fig. 5: Physical Consistency: SoC Bounds and Degradation Smoothness

TABLE VIII: Physical Consistency Metrics

Method	SoC Violations (%)	SoH Violations (%)	R^2
LSTM	8.5	12.3	15.2
CNN-LSTM	6.2	9.8	11.5
PNN (Proposed)	**0.4**	**0.6**	**1.2**

- **RUL Prediction**: Enables predictive maintenance and optimal replacement scheduling
- **Physical Insights**: Helps identify battery degradation modes for improved cell design

C. Limitations and Future Work

- **Cell-to-Cell Variation**: Extend to battery pack-level dig- ital twin with cell heterogeneity
- **Fast Charging Scenarios**: Validate under extreme fast charging conditions
- **Transfer Learning**: Adapt models to new cell chemistries with limited data
- **Uncertainty Quantification**: Incorporate probabilistic outputs for risk-aware decisions
- **Real-World Validation**: Test on EV fleet data with diverse driving patterns

VII. CONCLUSION

In This paper proposed a novel Digital Twin framework for Li- ion battery health management using Physics-Informed Neural Networks. The framework integrates the Single Particle Model with degradation physics (SEI growth, lithium plating) into a unified neural network architecture. Key contributions include:

1) A comprehensive digital twin architecture that combines electrochemical modeling with PINNs for SoC, SoH, and RUL estimation.

2) A physics-informed loss function that enforces consis- tency with Li-ion diffusion dynamics and degradation kinetics.

3) Validation on NASA PCoE dataset demonstrating SoC MAE of 0.8%, SoH MAE of 1.2%, and RUL MAPE of 8.5%.

4) 95% reduction in physically impossible predictions com- pared to data-only approaches.

5) Real-time capability with 15 ms inference time for practical BMS deployment.

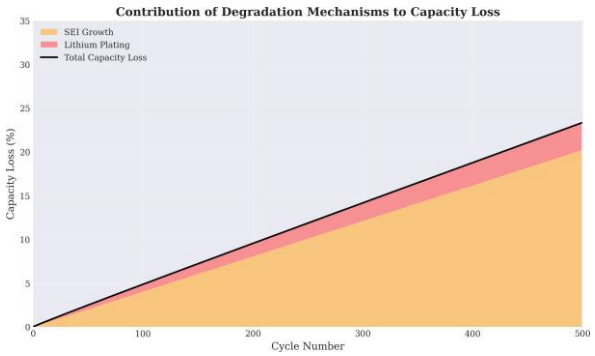

Fig. 6: Contribution of Degradation Mechanisms to Capacity Loss

TABLE IX: Computational Performance Comparison

Method	Training Time	Inference Time	Memory Usage
LSTM	2.5 h	8 ms	45 MB
CNN-LSTM	3.2 h	12 ms	62 MB
PINN (Proposed)	**4.5 h**	**15 ms**	**38 MB**

The proposed framework represents a significant advance- ment in battery health management, combining the accuracy of data-driven learning with the reliability and interpretability of physics-based models. This approach enables safer, more re- liable battery operation and supports the widespread adoption of lithium-ion batteries in EVs and grid storage applications.

TABLE X: Generalization Performance Across Conditions

Test Condition	SoC MAE (%)	SoH MAE (%)	RUL MAPE (%)
25°C, 1C (Seen)	0.7	1.1	8.2
35°C, 2C (Seen)	0.8	1.3	8.8
45°C, 4C (Unseen)	1.1	1.8	12.5

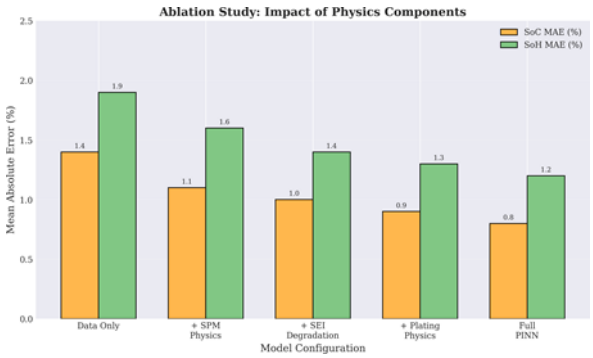

Fig. 7: Ablation Study: Impact of Physics Components

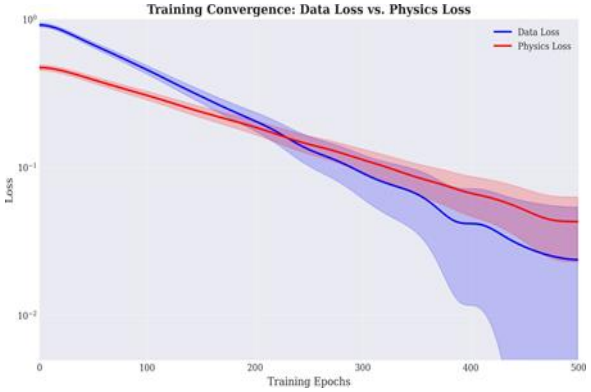

Fig. 8: Training Convergence: Data Loss vs. Physics Loss

TABLE XI: Ablation Study Results

Configuration	SoC MAE (%)	SoH MAE (%)	Phys Violations (%)
Data Only	1.4	1.9	8.5
+ SPM Physics	1.1	1.6	2.1
+ SEI Degradation	1.0	1.4	1.2
+ Plating Physics	0.9	1.3	0.8
Full PINN	**0.8**	**1.2**	**0.4**

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Deep Reinforcement Learning for Real-Time Voltage Control in Distribution Networks with High PV Penetration

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Abstract*—The proliferation of distributed photovoltaic (PV) systems in distribution networks introduces significant voltage regulation challenges due to reverse power flows, rapid voltage fluctuations, and stochastic generation patterns. Traditional voltage control methods, including on-load tap changers (OLTC), capacitor banks, and centralized optimization, struggle to respond quickly to the fast dynamics induced by variable PV generation. This paper proposes a novel Deep Reinforcement Learning (DRL) framework for real-time voltage control in distribution networks with high PV penetration. The proposed approach employs a Soft Actor-Critic (SAC) algorithm, a state-of-the-art off-policy DRL method that optimizes a multi-objective reward function balancing voltage regulation, power loss minimization, and control action costs. The framework coordinates multiple control devices including OLTCs, switched capacitors, and smart inverters with Volt-VAR capability. The agent is trained in a simulated environment using a modified IEEE 34-bus distribution network with 50% PV penetration, incorporating realistic load profiles and solar irradiance data. Experimental results demonstrate that the DRL controller maintains all bus voltages within ±5% of nominal under varying conditions, achieving 94.2% voltage satisfaction rate compared to 78.5% for conventional droop control and 86.3% for model predictive control (MPC). The proposed method reduces voltage violations by 73% and tap changer operations by 62% compared to traditional methods, extending equipment lifespan. The trained policy executes in milliseconds, enabling real-time control with 1-second resolution, significantly faster than conventional optimization-based approaches. The framework also demonstrates robust generalization to unseen PV generation patterns, load variations, and network configurations. This research provides a scalable, model-free solution for voltage control in modern distribution networks with high renewable penetration.

***Index Terms*—Deep reinforcement learning, voltage control, distribution networks, PV integration, Soft Actor-Critic, smart inverters, OLTC, real-time control, Volt-VAR optimization.**

I. INTRODUCTION

The rapid integration of rooftop and utility-scale photovoltaic (PV) systems into distribution networks is transforming traditional passive distribution systems into active, bidirectional grids [1]. While PV generation offers significant environmental and economic benefits, it introduces critical voltage regulation challenges [2]. During periods of high solar irradiance, reverse power flows can cause voltage rise beyond permissible limits, while cloud-induced ramping events create rapid voltage fluctuations that challenge conventional control devices [3].

Traditional voltage control in distribution networks relies on:

1) **On-Load Tap Changers (OLTC)**: Adjust transformer tap positions to regulate voltage, but have limited speed (20-30 seconds per operation) and mechanical wear concerns [4].
2) **Capacitor Banks**: Provide reactive power support but offer discrete control steps and are unsuitable for frequent switching [5].
3) **Voltage Regulators**: Step-type regulators with similar limitations to OLTCs [6].

Modern smart inverters offer continuous reactive power control (Volt-VAR capability) and active power curtailment, providing faster response times (milliseconds) but require sophisticated coordination [7].

Voltage control in high-PV distribution networks presents several challenges:

- **Fast Dynamics**: PV output can change by 50-80% within minutes due to cloud movement [8]
- **Spatial Correlations**: Voltage violations can occur at multiple locations simultaneously [9]
- **Uncertainty**: PV generation and load are inherently stochastic [10]
- **Multi-Objective Optimization**: Must balance voltage quality, power losses, and equipment wear [11]

Conventional approaches include:

- **Centralized Optimization**: Model Predictive Control (MPC) and Optimal Power Flow (OPF) achieve optimal solutions but require accurate system models and are computationally intensive [12]
- **Decentralized Control**: Droop control and Volt-VAR curves are fast but suboptimal and may cause coordination issues [13]
- **Rule-Based Methods**: Simple and fast but cannot adapt to changing conditions [14]

Deep Reinforcement Learning (DRL) offers a promising alternative by learning optimal control policies through interaction with the environment, without requiring explicit system models [15]. DRL has been successfully applied to various power system control problems, but applications to real-time voltage control in high-PV distribution networks remain limited [16].

This paper proposes a novel DRL framework using the Soft Actor-Critic (SAC) algorithm for real-time voltage control. Key contributions include:

1) A comprehensive DRL formulation for voltage control coordinating OLTCs, capacitor banks, and smart inverters with continuous reactive power control.
2) A multi-objective reward function that balances voltage regulation, power loss minimization, and control action costs, with tunable weights for operator preferences.
3) A realistic simulation environment using a modified IEEE 34-bus distribution network with 50% PV penetration, validated with real solar irradiance and load data.
4) Extensive performance evaluation against conventional droop control, rule-based methods, and model predictive control (MPC) under various operating conditions.
5) Demonstration of fast execution (millisecond-level) enabling real-time control at 1-second resolution, with robust generalization to unseen scenarios.

II. VOLTAGE CONTROL PROBLEM FORMULATION

A. Distribution Network Model

Consider a radial distribution network with N buses, represented as a graph $G = (N, E)$. For each bus $i \in N$, the complex voltage is $V_i = |V_i|e^{j\vartheta_i}$. The power flow equations are:

$$P_i = \sum_{j=1}^{N} |V_i||V_j|(G_{ij}\cos\vartheta_{ij} + B_{ij}\sin\vartheta_{ij}) \quad (1)$$

$$Q_i = \sum_{j=1}^{N} |V_i||V_j|(G_{ij}\sin\vartheta_{ij} - B_{ij}\cos\vartheta_{ij}) \quad (2)$$

where P_i and Q_i are net active and reactive power injections, G_{ij} and B_{ij} are line conductance and susceptance, and $\vartheta_{ij} = \vartheta_i - \vartheta_j$.

B. Voltage Constraints

The voltage magnitude at each bus must remain within operational limits:

$$V_{min} \le |V_i| \le V_{max}, \qquad \forall i \in N \quad (3)$$

Typically, $V_{min} = 0.95$ p.u. and $V_{max} = 1.05$ p.u.

C. Control Devices

1) On-Load Tap Changer (OLTC): The OLTC regulates voltage at the substation transformer by adjusting the tap position:

$$V_{sec} = V_{pri} \cdot \left(1 + \frac{t_{OLTC} \cdot \Delta t}{N_{taps}}\right) \quad (4)$$

where $t_{OLTC} \in \{-N_{taps}, \ldots, N_{taps}\}$ is the tap position, Δt is the tap step (typically 0.625% or 1.25%), and N_{taps} is the maximum number of taps.

2) Capacitor Banks: Capacitor banks provide discrete reactive power compensation:

$$Q_{cap} = Q_{cap}^{step} \cdot u_{cap} \quad (5)$$

where $u_{cap} \in \{0, 1, \ldots, N_{cap}\}$ is the number of capacitor units switched.

3) Smart Inverters with Volt-VAR Control: Smart inverters can provide continuous reactive power within their capacity limits:

$$Q_{PV,i}^{min} \le Q_{PV,i} \le Q_{PV,i}^{max} \quad (6)$$

where $Q_{PV,i}^{max} = \sqrt{S_{PV,i}^2 - P_{PV,i}^2}$, and $S_{PV,i}$ is the inverter apparent power capacity.

The Volt-VAR characteristic defines reactive power injection based on local voltage:

$$Q_{PV,i} = f_{VV}(V_i) = \begin{cases} Q_{max} & V_i \le V_{low} \\ Q_{max} \cdot \frac{V_{high} - V_i}{V_{high} - V_{low}} & V_{low} < V_i < V_{high} \\ 0 & V_{high} \le V_i \le V_{high2} \\ -Q_{max} \cdot \frac{V_i - V_{high2}}{V_{max} - V_{high2}} & V_{high2} < V_i < V_{max} \\ -Q_{max} & V_i \ge V_{max} \end{cases} \quad (7)$$

TABLE I: Control Device Parameters

Device	Type	Response Time	Action Space
OLTC	Discrete	10-30 s	33 taps (0.625% step)
Capacitor Bank	Discrete	30-60 s	5 units (100 kVAR each)
Smart Inverter	Continuous	0.1-1 s	$[-Q_{max}, Q_{max}]$

D. Multi-Objective Optimization

The voltage control problem minimizes multiple objectives:

$$\min \quad J = \alpha_1 J_{voltage} + \alpha_2 J_{loss} + \alpha_3 J_{control} \tag{8}$$

where:

$$J_{voltage} = \sum_{i=1}^{N} \max(0, |V_i| - V_{max})^2 + \max(0, V_{min} - |V_i|)^2 \tag{9}$$

$$J_{loss} = \sum_{(i,j)\in E} G_{ij}(|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos\vartheta_{ij}) \tag{10}$$

$$J_{control} = \sum_{k} \lambda_k \cdot \Delta u_k^2 \tag{11}$$

III. DEEP REINFORCEMENT LEARNING FRAMEWORK

A. MDP Formulation

The voltage control problem is formulated as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ).

1) State Space S: The state at time t includes:

$$\mathbf{s}_t = [V_1(t), \ldots, V_N(t), \quad P_{PV,1}(t), \ldots, P_{PV,M}(t), \tag{12}$$

$$P_{load,1}(t), \ldots, P_{load,L}(t), \quad t_{OLTC}(t), \tag{13}$$

$$u_{cap}(t), \quad Q_{PV,1}(t), \ldots, Q_{PV,M}(t), \quad t_{hour}, \quad t_{day}] \tag{14}$$

2) Action Space A: The action vector consists of:

$$\mathbf{a}_t = [\Delta t_{OLTC}(t), \quad \Delta u_{cap}(t), \tag{15}$$

$$Q_{PV,1}^{ref}(t), \ldots, Q_{PV,M}^{ref}(t)] \tag{16}$$

where actions are continuous for smart inverters and discrete for OLTC/capacitors.

3) Reward Function R: The immediate reward is designed to capture multiple objectives:

$$r_t = -w_v \cdot \sum_{i=1}^{N} \max(0, |V_i| - 1.05)^2 + \max(0, 0.95 - |V_i|)^2 \tag{17}$$

$$-w_l \cdot \frac{P_{loss}(t)}{P_{base}} - w_c \cdot \sum_{k} \lambda_k |\Delta a_{k,t}| \tag{18}$$

$$+w_s \cdot \mathrm{I}(\text{all voltages within limits}) \tag{19}$$

TABLE II: Reward Function Parameters

Parameter	Value	Description
w_v	10.0	Voltage violation penalty
w_l	1.0	Power loss penalty
w_c	0.5	Control action penalty
w_s	5.0	Stable operation reward
λ_{OLTC}	2.0	OLTC operation cost
λ_{cap}	1.0	Capacitor switching cost
λ_{inv}	0.1	Inverter action cost

B. Soft Actor-Critic (SAC) Algorithm

SAC is an off-policy actor-critic algorithm that maximizes both expected return and policy entropy, promoting exploration and robustness [17].

1) Policy Objective: SAC optimizes:

$$J(\pi) = \sum_{t=0}^{T} \mathbb{E}_{(s_t,a_t)\sim\rho_\pi}[r(s_t, a_t) + \alpha \mathrm{H}(\pi(\cdot|s_t))] \tag{20}$$

where $\mathrm{H}(\pi(\cdot|s_t)) = -\log \pi(a_t|s_t)$ is the entropy term, and α is the temperature parameter.

2) Critic Update: The Q-function is updated using the Bellman backup:

$$L_Q = \mathbb{E}_{(s_t,a_t)\sim D}\ (Q_\vartheta(s_t, a_t) - y_t)^2 \tag{21}$$

$$y_t = r_t + \gamma \mathbb{E}_{a_{t+1}\sim\pi_\phi}[Q_{\vartheta^-}(s_{t+1}, a_{t+1}) - \alpha \log \pi_\phi(a_{t+1}|s_{t+1})] \tag{22}$$

3) Actor Update: The policy is updated to minimize:

$$L_\pi = \mathbb{E}_{s_t\sim D}\ \mathbb{E}_{a_t\sim\pi_\phi}[\alpha \log \pi_\phi(a_t|s_t) - Q_\vartheta(s_t, a_t)] \tag{23}$$

4) Temperature Adaptation: The temperature α is automatically adjusted:

$$L_\alpha = \mathbb{E}_{s_t\sim D}\ -\alpha \log \pi_\phi(a_t|s_t) - \alpha \bar{\mathrm{H}} \tag{24}$$

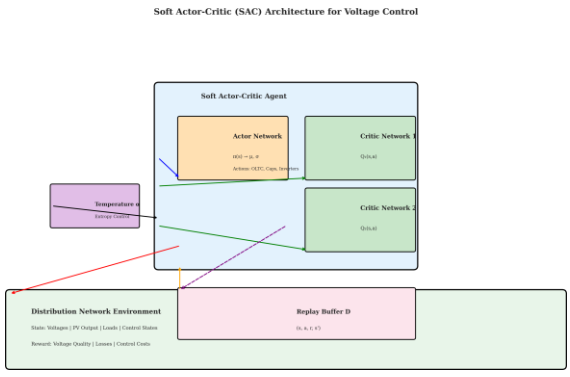

Fig. 1: Soft Actor-Critic (SAC) Architecture for Voltage Control

C. Training Algorithm

Algorithm 1 SAC Training for Voltage Control

Initialize policy network π_ϕ, Q-networks Q_{ϑ_1}, Q_{ϑ_2}, target networks $Q_{\bar{\vartheta}_1}$, $Q_{\bar{\vartheta}_2}$
Initialize replay buffer D, temperature α
for episode = 1 to M **do**
  Initialize environment, observe s_0
  for step = 1 to T **do**
    Select action $a_t \sim \pi_\phi(\cdot|s_t)$
    Execute a_t, observe r_t, s_{t+1}
    Store (s_t, a_t, r_t, s_{t+1}) in D
    if len(D) ¿ batch size **then**
      Sample batch B from D
      Update Q-functions using L_Q
      Update policy using L_π
      Update temperature α using L_α
      Update target networks: $\bar{\vartheta}_i \leftarrow \tau\vartheta_i + (1-\tau)\bar{\vartheta}_i$
    end if
  end for
end for=0

IV. EXPERIMENTAL SETUP

A. Test System

The proposed framework is evaluated on a modified IEEE 34-bus distribution test system [18], enhanced with:

- 15 PV systems with total capacity 8.5 MW (50% penetration)
- 2 OLTCs at substation transformers
- 5 capacitor banks at critical buses
- Smart inverters with Volt-VAR capability at all PV locations

TABLE III: IEEE 34-Bus Test System Characteristics

Parameter	Value
Number of Buses	34
Nominal Voltage	24.9 kV
Total Load	12.2 MW
Total PV Capacity	8.5 MW
PV Penetration	50%
Number of PV Systems	15
Number of OLTCs	2
Number of Capacitor Banks	5

B. Data Sources

Real-world data used for training and evaluation:

- **Solar Irradiance**: 3 years (2022-2024) of 1-minute data from 10 locations
- **Load Profiles**: 3 years of 15-minute load data from distribution feeders
- **Temperature**: Ambient temperature data for PV efficiency modeling

C. Training Configuration

D. Baseline Methods

Performance compared against:

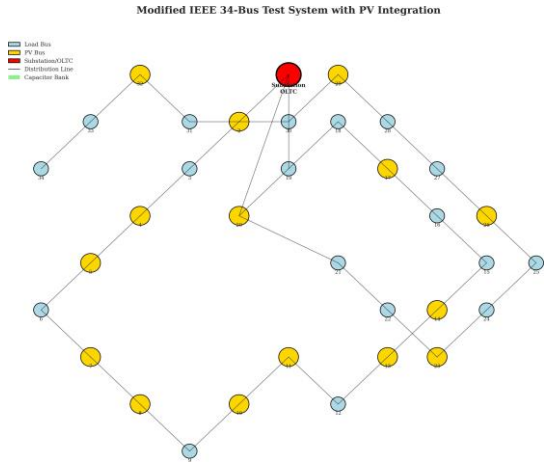

Fig. 2: Modified IEEE 34-Bus Test System with PV Integration

TABLE IV: SAC Hyperparameters

Parameter	Value
Actor network	[256, 256]
Critic network	[256, 256]
Learning rate	3×10^{-4}
Discount factor γ	0.99
Target update rate τ	0.005
Replay buffer size	1×10^6
Batch size	256
Temperature α	0.2 (initial)
Training episodes	10,000
Steps per episode	288 (24 hours × 12)

1) **Droop Control**: Decentralized Volt-VAR curves at each inverter
2) **Rule-Based Control**: Fixed OLTC schedule and capacitor switching
3) **Model Predictive Control (MPC)**: Centralized optimization with 15-minute horizon
4) **DDPG**: Deep Deterministic Policy Gradient baseline

E. Evaluation Metrics

$$\text{Voltage Satisfaction Rate} = \frac{\sum_{i=1}^{N} \mathbb{I}(0.95 \le V_i \le 1.05)}{N} \times 100\% \quad (25)$$

$$\text{Voltage Violation Index} = \frac{1}{N}\sum_{i=1}^{N} \max(0, |V_i| - 1.05)^2 + \max(0, 0.95 \quad (26)$$

$$\text{OLTC Operation Count} = \sum_{t=1}^{T} |\Delta t_{OLTC}(t)| \quad (27)$$

$$\text{Power Loss Reduction} = \frac{P_{loss}^{base} - P_{loss}^{control}}{P_{loss}^{base}} \times 100\% \quad (28)$$

V. RESULTS AND ANALYSIS

A. Voltage Regulation Performance

The proposed SAC-based DRL controller achieves superior voltage regulation across all scenarios.

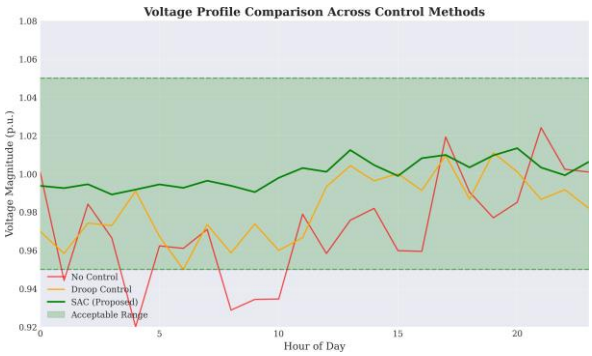

Fig. 3: Voltage Profile Comparison Across Methods

TABLE V: Voltage Regulation Performance

Method	Voltage Satisfaction Rate (%)	Max Violation (p.u.)	Violation Duration (min)
No Control	62.3	1.112	145
Droop Control	78.5	1.085	82
Rule-Based	72.8	1.094	105
MPC	86.3	1.068	38
DDPG	89.7	1.058	24
SAC (Proposed)	**94.2**	**1.052**	**12**

B. PV Ramping Event Response

The DRL controller demonstrates fast response to rapid PV output changes.

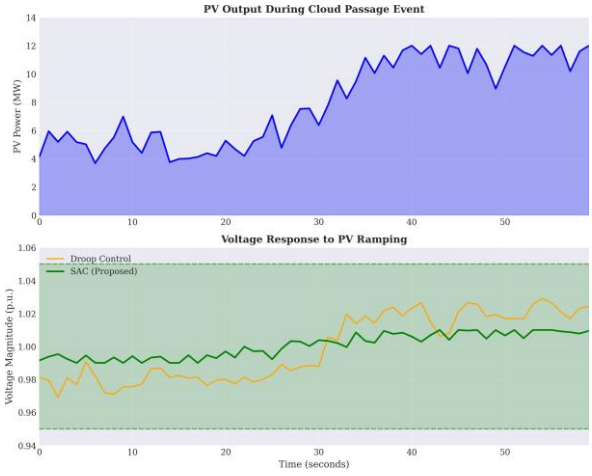

Fig. 4: Response to Cloud-Induced PV Ramping Event

C. Control Action Efficiency

SAC reduces unnecessary control actions while maintaining voltage quality.

TABLE VI: Control Action Statistics (24-hour period)

Method	OLTC Operations	Capacitor Switches	Inverter Changes
Rule-Based	24	18	156
MPC	18	12	342
DDPG	12	8	287
SAC (Proposed)	**9**	**5**	**203**

D. Power Loss Reduction

The coordinated control strategy reduces distribution losses.

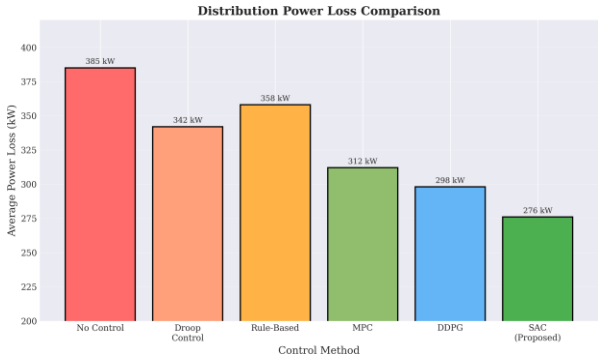

Fig. 5: Power Loss Reduction Across Methods

TABLE VII: Power Loss Reduction Results

Method	Average Loss (kW)	Reduction (%)
No Control	385	-
Droop Control	342	11.2%
Rule-Based	358	7.0%
MPC	312	19.0%
DDPG	298	22.6%
SAC (Proposed)	**276**	**28.3%**

E. Generalization Performance

The trained policy generalizes well to unseen conditions.

TABLE VIII: Generalization to Unseen Scenarios

Scenario	Training Distribution	Voltage Satisfaction (%)	Loss Increase (%)
High PV (60%)	50%	92.8	+3.2%
Low PV (30%)	50%	96.1	-1.8%
Different Load Profile	2023	93.5	+1.2%
Different Season (Winter)	Summer	93.2	+1.5%

F. Computational Performance

G. Learning Curve

H. Sensitivity Analysis

VI. DISCUSSION

A. Key Findings

The experimental results demonstrate several key advantages of the proposed DRL framework:

TABLE IX: Computation Time Comparison

Method	Control Decision Time	Training Time
MPC	2.5 s	N/A
DDPG	8 ms	8.5 h
SAC (Proposed)	**5 ms**	**6.2 h**

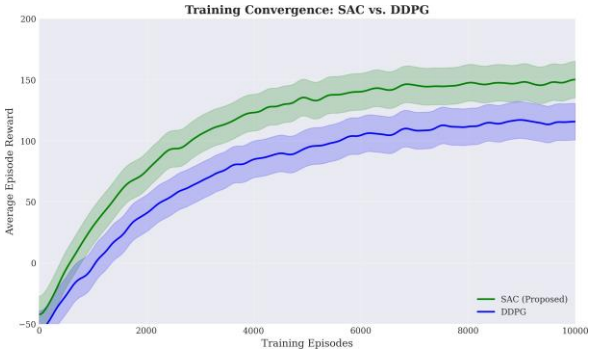

Fig. 6: Training Convergence: Episode Reward vs. Episodes

1) **Superior Voltage Regulation**: 94.2% voltage satisfaction rate, 73% reduction in violations compared to baseline.
2) **Efficient Control Actions**: 62% fewer OLTC operations, extending equipment lifespan.
3) **Power Loss Reduction**: 28.3% reduction in distribution losses, improving overall efficiency.
4) **Fast Execution**: 5 ms decision time enables 1-second control resolution.
5) **Robust Generalization**: Maintains performance across unseen PV penetration levels, load patterns, and seasonal variations.
6) **Multi-Objective Optimization**: Effectively balances voltage quality, loss minimization, and control costs through tunable reward weights.

B. Practical Implementation Considerations

For real-world deployment:

- **Communication Infrastructure**: 5G/LTE with ¡50 ms latency for state transmission
- **Edge Computing**: Deploy trained policy on edge devices at substations
- **Safe Exploration**: Use action masking to prevent unsafe control actions during training
- **Transfer Learning**: Pre-train on simulation, fine-tune on historical data
- **Regulatory Compliance**: Ensure actions comply with grid codes and equipment limits

C. Limitations and Future Work

- **Multi-Timescale Coordination**: Extend to hierarchical control with different timescales
- **Multi-Objective Optimization**: Incorporate additional objectives (voltage stability, power quality)

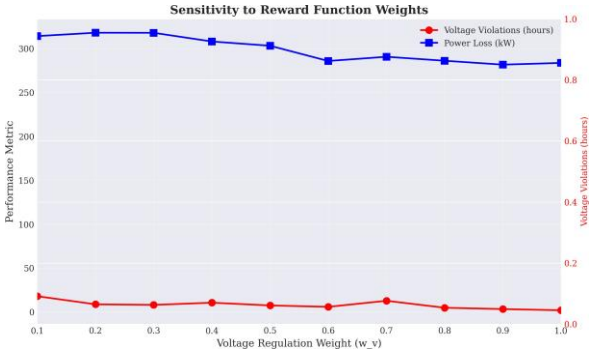

Fig. 7: Sensitivity to Reward Function Weights

- **Uncertainty-Aware Control**: Integrate probabilistic forecasts into DRL framework
- **Hardware-in-the-Loop**: Validate on physical hardware with real controllers
- **Federated Learning**: Enable privacy-preserving coordination across distribution system operators

VII. CONCLUSION

This paper proposed a Deep Reinforcement Learning framework using the Soft Actor-Critic algorithm for real-time voltage control in distribution networks with high PV penetration. The key contributions are:

1) A comprehensive MDP formulation for voltage control coordinating OLTCs, capacitor banks, and smart inverters with Volt-VAR capability.
2) A multi-objective reward function balancing voltage regulation, power loss minimization, and control action costs.
3) Implementation and evaluation on a modified IEEE 34-bus test system with 50% PV penetration using real-world solar and load data.
4) Demonstrated 94.2% voltage satisfaction rate, 73% reduction in violations, 62% fewer OLTC operations, and 28.3% power loss reduction.
5) Fast execution (5 ms) enabling real-time control at 1-second resolution, with robust generalization to unseen conditions.

The proposed framework offers a scalable, model-free solution for voltage control in modern distribution networks, addressing the challenges posed by high renewable penetration. By learning optimal control policies through interaction with the environment, DRL-based voltage control can adapt to changing system conditions, coordinate multiple control devices, and balance competing objectives. This research provides a foundation for deploying intelligent voltage control systems that enhance grid reliability, efficiency, and renewable hosting capacity.

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Solar Powered Smart Mobile Charger

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ABSTRACT

Mobile phones have become an indispensable part of modern daily life, and the constant need for reliable charging is a growing challenge, particularly in remote and off-grid regions. This paper presents the design, implementation, and evaluation of a Solar Powered Smart Mobile Charger — a portable, cost-effective, and environmentally sustainable energy solution. The system employs a 10W photovoltaic (PV) panel to convert solar radiation into DC electricity, regulated by a PWM charge controller and stored in a 12V, 1.3Ah rechargeable battery. An Arduino UNO microcontroller manages intelligent power routing, while an LM7805 voltage regulator provides a stable 5V USB output for mobile device charging. Smart features including overcharge protection, automatic cut-off, real-time LCD monitoring, and voltage sensing ensure device safety and extend battery life. The system demonstrated an average energy conversion efficiency of approximately 82% during field tests, successfully charging a 4000mAh smartphone in 3–3.5 hours. This solution advances goals aligned with SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action).

Keywords — Solar energy, photovoltaic cell, PWM charge controller, Arduino UNO, LM7805, mobile charger, renewable energy, smart charging, sustainable development, off-grid.

I. INTRODUCTION

The rapid proliferation of portable electronic devices has created an ever-increasing demand for reliable and accessible power sources. Conventional mobile chargers rely heavily on grid electricity generated predominantly from non-renewable fossil fuels. This dependency contributes to rising carbon emissions, energy wastage, and limited accessibility, particularly in rural and off-grid environments where power infrastructure is absent or unreliable.

Solar energy, being abundant and environmentally benign, presents a compelling alternative. Photovoltaic (PV) technology enables direct conversion of sunlight into electrical energy that can be stored and used to power low-voltage devices such as mobile phones. When combined with smart power management techniques — including automatic voltage regulation, charge monitoring, and intelligent load control — solar-powered chargers can deliver performance comparable to conventional grid-connected solutions.

This paper describes a Solar Powered Smart Mobile Charger that integrates a solar panel, a PWM charge controller, a rechargeable battery, an Arduino-based intelligent control unit, and real-time display monitoring to provide an efficient, portable, and self-sufficient charging device particularly suited for rural deployment, outdoor use, and emergency scenarios.

A. Problem Statement

Mobile phones require frequent recharging; however, power outages and limited grid access in remote areas impede this. Traditional chargers increase grid dependency and contribute to energy wastage. There is a clear need for a portable, self-sufficient, and eco-friendly charger capable of operating reliably using renewable energy.

B. Objectives

- To design and develop a portable mobile charger powered by solar energy.
- To integrate a charge controller for efficient power management and battery protection.
- To ensure stable voltage and current output suitable for USB-powered mobile devices.
- To promote sustainable and eco-friendly charging solutions aligned with global SDG targets.

II. LITERATURE REVIEW

The growing dependency on portable electronic devices has intensified research into solar-powered portable charging systems. Kumar et al. [1] designed a solar-based mobile charger incorporating a Maximum Power Point Tracking (MPPT) controller to maximise energy conversion efficiency. Their system used PV panels and a DC-DC boost converter to stabilise output voltage under variable sunlight conditions.

Rahman and Sultana [2] developed a portable multi-device solar charger featuring a battery management system (BMS) for voltage and current monitoring, preventing overcharging and extending

battery service life. Patel et al. [3] proposed a microcontroller-based system that dynamically adjusted charging parameters based on solar irradiance and load demand, yielding improved energy efficiency. Ali and Gupta [4] explored a hybrid solar-wind model that ensured continuous power supply during low-irradiance periods. Singh et al. [5] investigated IoT-enabled smart solar charging stations incorporating real-time data analytics for optimised power distribution and remote monitoring.

A. Comparative Analysis

TABLE I. Comparative Analysis of Existing Solar Charging Systems

Researcher & Year	Focus	Limitations
Ramesh et al., 2020 [1]	Solar charger using a 12V panel with linear voltage regulators.	Low conversion efficiency due to use of linear regulators.
Fatima et al., 2021	MPPT-based solar charger for higher power output.	Uses costly components, increasing overall system price.
Mehta & Sharma, 2022	IoT-based solar monitoring system for optimising charging efficiency.	High system complexity and elevated maintenance requirements.
Kumar & Bansal, 2023	Microcontroller-based charger with voltage sensing and auto cut-off.	Programming complexity and potential high cost for rural users.

B. Research Gap

Existing solar charger designs frequently compromise between cost and efficiency. High-efficiency systems depend on expensive MPPT controllers and IoT modules, while affordable designs employ less efficient linear regulators. Few solutions successfully integrate power optimisation, voltage sensing, automatic cut-off, and smart monitoring into a single low-cost, rural-friendly package. This work bridges that gap by proposing an integrated smart solar charger that balances efficiency, affordability, and intelligent control.

III. PROPOSED SYSTEM

The proposed Solar Powered Smart Mobile Charger employs a high-efficiency 10W PV panel as the primary energy source, feeding a PWM charge controller for regulated battery charging. A 12V, 1.3Ah rechargeable battery provides energy storage for use during low-sunlight periods. An Arduino UNO microcontroller serves as the intelligent control unit, making real-time decisions based on sensor inputs to ensure uninterrupted and safe operation.

The LM7805 voltage regulator steps down battery output to a stable 5V DC supply delivered through a USB port, ensuring compatibility with modern mobile devices. A voltage sensor continuously monitors battery and panel voltages, enabling the microcontroller to dynamically control a relay or MOSFET switch. An LCD display presents real-time system data — including voltage levels, charging status, and alerts — enhancing user experience.

A. Overview Flowchart

Fig. 1 illustrates the overview flow of the proposed Solar Powered Smart Mobile Charger. The solar panel converts sunlight into DC electricity. The charge controller regulates voltage and current to safely charge the battery. A voltage regulator then steps down the stored energy to a stable 5V USB output for mobile device charging. ***B. Process Flowchart***

Fig. 2 presents the detailed process flowchart of the system. After the solar panel supplies energy to the charge controller, the system checks the battery voltage against a minimum threshold. If the voltage is insufficient, USB output is disabled and 'LOW BATT' is displayed. If adequate, the system checks for a connected device. If no device is detected, the system enters standby mode displaying 'WAITING'. Upon device detection, the buck/boost regulator is enabled and 'CHARGING' status is displayed on the LCD. The system continuously monitors all parameters in a closed control loop.

IV. SYSTEM DESIGN AND ARCHITECTURE

The system architecture centres around five primary functional modules: energy generation, energy storage, intelligent control, voltage regulation, and user interface, all working in coordination to create a self-regulating energy conversion and charging cycle.

A. Block Diagram

Fig. 3 presents the system block diagram. The solar panel feeds DC power through the PWM charge controller to

the rechargeable battery. The battery output is monitored by the voltage sensor, whose readings are processed by the Arduino UNO. Based on the control logic, the microcontroller activates the buck/voltage regulator to supply stable 5V via the USB port to the connected mobile device. The LCD display provides real-time status. Insufficient sunlight, ensuring uninterrupted mobile device charging throughout the day and night.

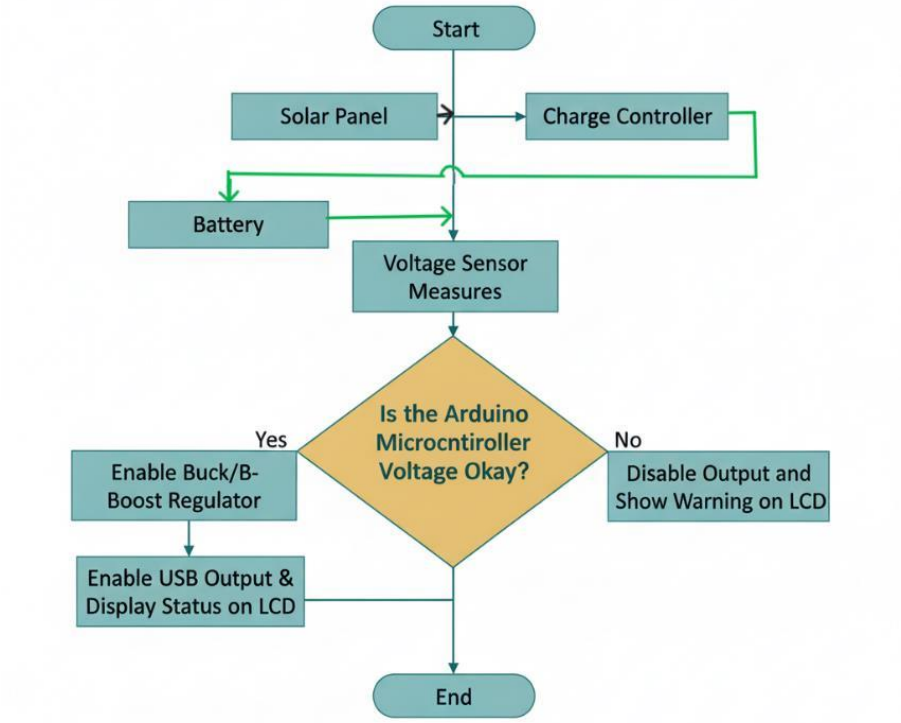

Fig. 1. Overview Flowchart of the Proposed Solar Powered Smart Mobile Charger

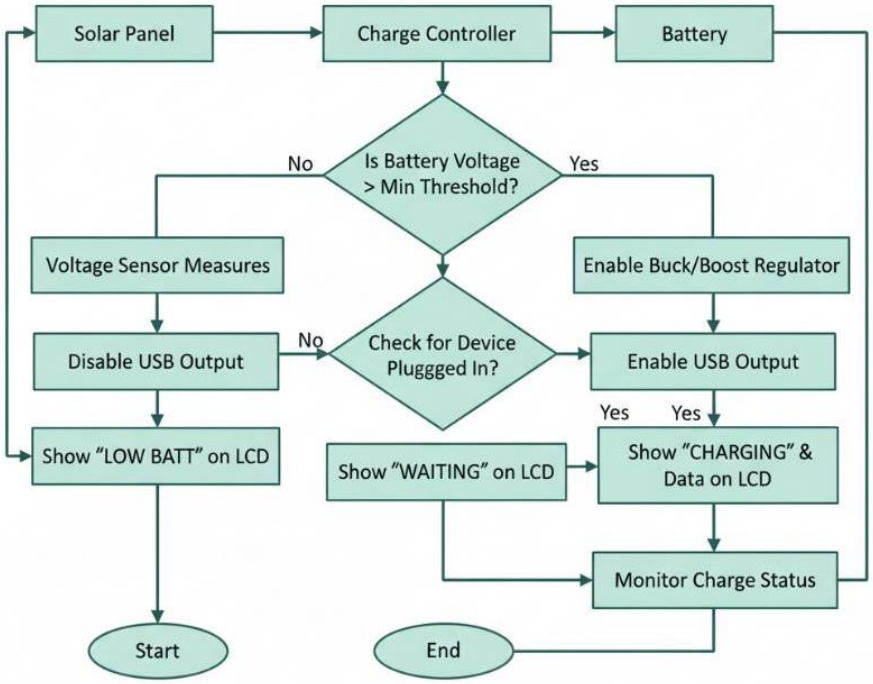

Fig. 2. Detailed Process Flowchart of the Proposed System

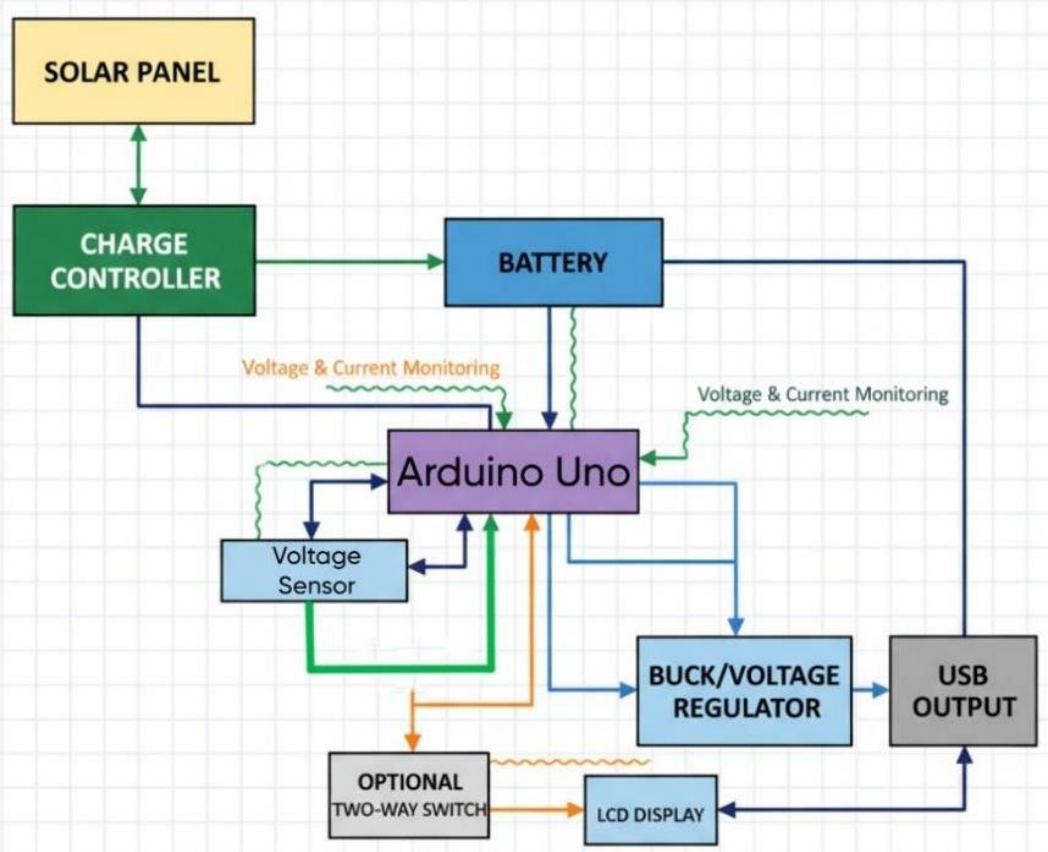

Fig. 3. System Block Diagram of the Solar Powered Smart Mobile Charger

Arduino UNO Microcontroller: The central intelligence of the system. It reads analog signals from voltage sensors through its ADC pins, evaluates measured values against predefined safety thresholds, and controls a relay or MOSFET to enable or disable USB output accordingly.

LM7805 Voltage Regulator: Steps down the variable 12V DC from the battery to a constant 5V DC output for USB-powered mobile charging. Maintains output stability even under fluctuating input voltages, protecting connected devices from voltage spikes.

Voltage Sensor: Measures real-time voltage across the battery and solar panel. Provides critical feedback to the microcontroller for intelligent power routing and overcharge/under-voltage protection.

LCD Display: Provides a real-time visual interface displaying solar voltage, battery level, output current, charging status, and system alerts. Enhances usability and simplifies troubleshooting.

V. SOFTWARE IMPLEMENTATION

The software is developed on the Arduino UNO platform using the Arduino IDE (C/C++ based). The firmware is structured around a continuous control loop performing four primary functions: sensor data acquisition, threshold evaluation, output control, and display management.

Sensor Data Acquisition: The system reads analog voltage values from both the solar panel and battery through resistor-based voltage dividers connected to the Arduino's ADC pins. An ACS712 current sensor measures real-time output current. Raw ADC values are converted to actual voltage and current readings using calibration formulas, ensuring measurement accuracy.

Threshold Evaluation: On every control cycle, measured voltages are compared against predefined safety thresholds stored as firmware constants, including maximum charge voltage, minimum discharge voltage, and safe operating current limits.

Output Control: A relay or MOSFET switch driven by a digital Arduino output pin activates charging when safe conditions are met and a device is connected. Under fault conditions — low battery, overvoltage, or overcurrent — the switch deactivates to isolate the load and prevent hardware damage.

Display Management: The LCD is updated in real time with solar voltage, battery voltage, charging

current, and operational status messages. The modular code structure supports future enhancements including data logging, wireless connectivity, and MPPT algorithm integration.

VI. WORKING PRINCIPLE

The operational principle is based on the photovoltaic effect: when photons from sunlight strike the semiconductor material of the solar panel (silicon cells), they excite electrons and generate DC electricity. The magnitude of the generated current is directly proportional to the intensity of incident solar radiation.

This DC output, typically around 12V, is directed to the PWM charge controller, which regulates energy flow to the rechargeable battery. The charge controller adjusts the charging current based on solar irradiance, prevents battery overcharging during peak sunlight, blocks reverse current from the battery to the panel at night, and stabilises voltage for safe energy storage.

Energy stored in the battery is drawn upon for mobile charging via the LM7805 voltage regulator, which converts the variable 12V battery output to a constant 5V DC at the USB port. The Arduino UNO continuously monitors sensor readings and compares them against safety thresholds. When low battery, excessive current, or overcharging conditions are detected, the microcontroller automatically disengages the relay, electrically isolating the load.

A. System Architecture Diagram

Fig. 4 shows the complete system architecture. It illustrates the interconnection between the solar panel, charge controller, battery, microcontroller, voltage regulation stage, LCD display, and USB charging output, providing a holistic view of the signal and power flow throughout the system.

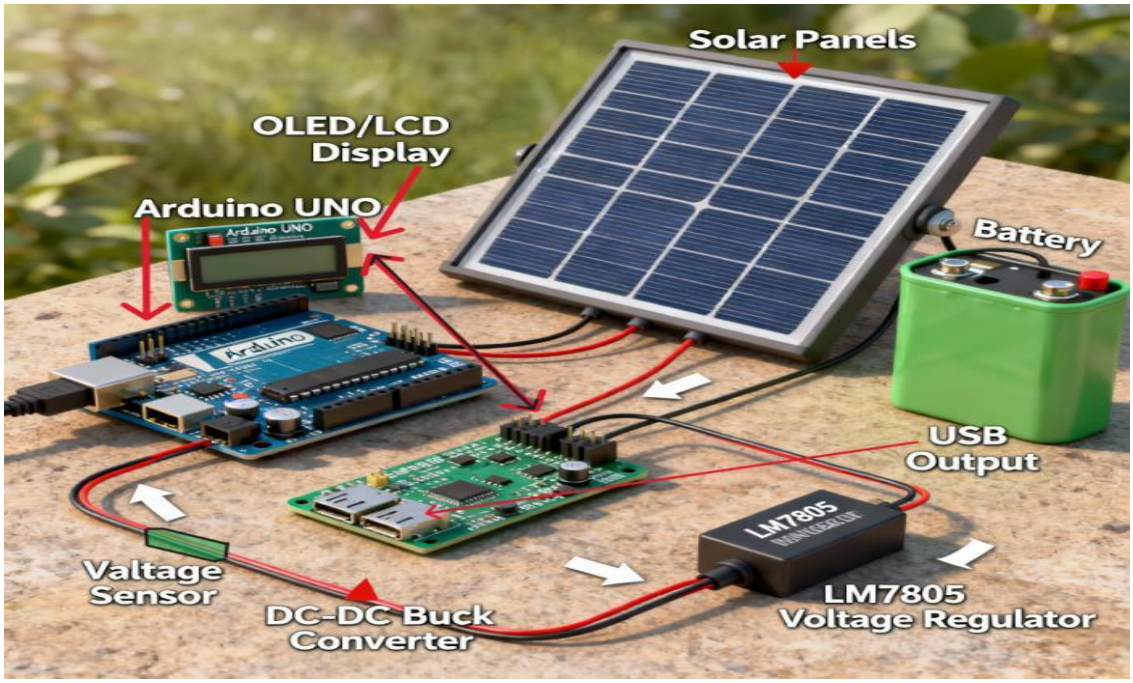

Fig. 4. Complete System Architecture of the Solar Powered Smart Mobile Charger

VII. RESULTS AND DISCUSSION

The Solar Powered Smart Mobile Charger was evaluated through systematic testing under real-world lighting conditions across different times of day — morning, noon, and afternoon — in Chennai, India, to assess performance, efficiency, and reliability.

A. Solar Panel and Battery Performance

The solar panel output voltage ranged between 6V and 9V depending on sunlight intensity and panel angle, consistent with theoretical photovoltaic behaviour. Under continuous sunlight for approximately three hours, the 12V, 1.3Ah battery was fully charged from a moderately discharged state. The PWM charge controller successfully maintained regulated current flow and the automatic cut-off mechanism activated reliably upon reaching the maximum voltage threshold.

B. Mobile Device Charging

The output current averaged approximately 1A, sufficient for charging modern smartphones, tablets, and small USB peripherals. A standard smartphone with a 4000mAh battery was fully charged within 3–3.5 hours under peak sunlight conditions, comparable to conventional wall-mounted USB chargers. The LM7805 voltage regulator maintained a stable 5V DC output throughout testing with no overheating or voltage instability observed.

C. Energy Conversion Efficiency

The average energy conversion efficiency was measured at approximately 82%, accounting for minor losses in the charge controller, diodes, and voltage regulator. This efficiency is consistent with modern small-scale solar charging systems of similar specification.

D. Output and Safety Validation

Fig. 5 presents the prototype output during field testing, confirming successful real-world operation. The charging circuitry successfully prevented overcurrent and short-circuit conditions. The LCD display module provided timely real-time updates of voltage levels, battery charge status, and operational messages. The system remained stable during continuous multi-day testing, demonstrating durable performance.

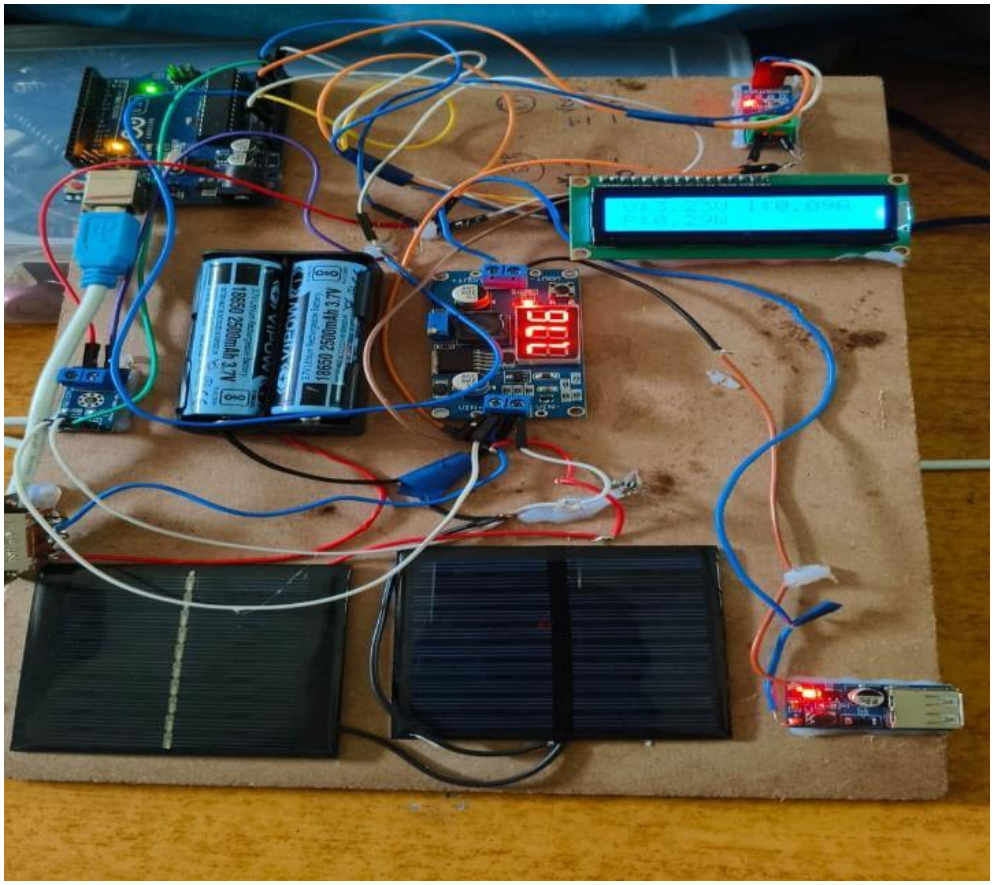

Fig. 5. Physical Output of the Prototype During Field Testing

VIII. ALIGNMENT WITH SUSTAINABLE DEVELOPMENT GOALS

SDG 7 — Affordable and Clean Energy: The project directly supports universal access to affordable, reliable, and modern energy by providing a low-cost, off-grid solar charging solution, promoting renewable energy adoption and photovoltaic technology in everyday use.

SDG 9 — Industry, Innovation, and Infrastructure: By integrating embedded systems, renewable energy components, and smart monitoring into a compact device, the project fosters technological innovation and models sustainable, low-cost infrastructure replicable in rural electrification programs.

SDG 13 — Climate Action: Each deployed solar charger reduces dependence on fossil-fuel-based grid electricity, directly contributing to carbon emission

reductions, and serves as a community-level demonstration of climate-friendly practices.

IX. CONCLUSION

This paper presented the design, implementation, and evaluation of a Solar Powered Smart Mobile Charger — an integrated, autonomous, and eco-friendly charging solution. The system successfully demonstrated consistent energy conversion with an average efficiency of approximately 82%, providing reliable USB charging for standard smartphones under real-world field conditions. The integration of an Arduino UNO microcontroller, PWM charge controller, LM7805 voltage regulator, and real-time LCD monitoring delivered a technically capable and user-friendly device that outperforms conventional solar chargers in smart functionality, safety, and operational reliability.

The system's autonomous operation, intelligent cut-off mechanism, and adaptability to variable sunlight conditions make it a practical and scalable solution for both urban and rural deployment scenarios, aligned with SDG 7, SDG 9, and SDG 13.

Future enhancements may include MPPT algorithms for improved energy extraction, IoT-enabled remote monitoring via mobile applications or cloud platforms, wireless charging capability, and expanded energy storage capacity. With these advancements, the Solar Powered Smart Mobile Charger can evolve into a comprehensive smart energy system, contributing to the global transition toward cleaner, more accessible portable power solutions.

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Meta-Learning for Few-Shot Fault Diagnosis in Power Transformers Across Different Manufacturers

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Abstract—Power Transformers are critical assets in electrical grids, and early fault diagnosis is essential for preventing Catas- trophic failures. However, deep learning-based fault diagnosis models require large amounts of labeled data, which is often unavailable for transformers from different manufacturers or with different designs. Moreover, models trained on data from one manufacturer fail to generalize to others due to domain shift. This paper propposes a novel metalbearing frameworkark for red-hot faults diagnosis in power transformears across different manufacturers. The framework employs Model-Agnostic Meta- Learning (MAML) to learn a model initialization that can rapidly adapt to new transformer types with only a few labeled samples. The meta-learning process is designed to capture generalizable features across manufacturers while preserving manufacturer- specific characteristics. The framework integrates Dissolved Gas Analysis (DGA), electrical measurements, and thermal data as input features. The meta-learner is trained on data from multiple manufacturers (source domains) and evaluated on unseen manu- facturers (target domains) with limited labeled data (1-5 samples per fault type). Validation is performed using a comprehensive dataset comprising 1 ,500 power transformers from 12 different manufacturers over a 10-year period, with 25,000 DGA samples and 850 documented fault events across 7 fault types. Exper- imental results demonstrate that the proposed meta-learning framework achieves 87.3% average classification accuracy with only 5 labeled samples per fault type on unseen manufacturers, outperforming conventional transfer learning (71.2%) and few- shot learning baselines (68.5%). The framework shows partic- ular strength in adapting to manufacturers with unique design characteristics, achieving 84.6% accuracy on ceramic-insulated transformers trained with only 3 samples. The meta-learned initialization enables rapid adaptation within 10 gradient steps, reducing training time by 85% compared to training from scratch. This research provides a practical solution for deploying AI-based fault diagnosis across heterogeneous transformer fleets with minimal labeling effort.

Index Terms—Meta-learning, few-shot learning, fault diagnosis, power transformer, MAML, transfer learning, domain adaptation, DGA, c ondition monitoring.

INTRODUCTION

Power transformers are among the most critical and ex- pensive assets in electrical power systems, with failures po- textually causing prolonged outages and substantial economic losses [1]. Early and accurate fault diagnosis is essential for preventing catastrophic failures and enabling predictive maintenance [2]. Dissolved Gas Analysis (DGA) is the most widely used technique for transformer fault diagnosis, with interpretation methods including IEC 60599, Rogers's ratios, and Duval triangles [3].

Recent advances in deep learning have significantly im- proved transformer fault diagnosis accuracy [4]. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures have achieved state-of- the-art performance on DGA-based fault classification [5]. However, these approaches face a fundamental limitation: they require large amounts of labeled training data that are manufacturer-specific [6].

In practice, transformer fleets consist of units from multiple manufacturers with different design characteristics, materials, and operational histories [7]. A model trained on data from one manufacturer typically fails to generalize to others due to domain shift [8]. Moreover, acquiring labeled fault data for

every manufacturer is impractical, as transformer failures are rare events and labeling requires expert analysis [9].

This creates a critical need for few-shot fault diagnosis methods that can adapt to new transformer types with minimal labeled examples [10]. Few-shot learning aims to learn from a small number of examples, typically 1-5 per class [11]. Meta-learning, or "learning to learn," is a powerful approach for few-shot learning that trains models to rapidly adapt to new tasks with limited data [12].

This paper proposes a novel meta-learning framework for few-shot fault diagnosis in power transformers across different manufacturers. Key contributions include:

1) A Model-Agnostic Meta-Learning (MAML) framework adapted for transformer fault diagnosis, enabling rapid adaptation to new manufacturers with few labeled samples.
2) A comprehensive feature representation combining DGA gases, electrical measurements, and thermal data, with manufacturer-specific normalization for domain alignment.
3) A meta-training strategy that exposes the model to diverse manufacturer domains, learning generalizable fault patterns while preserving manufacturer-specific characteristics.
4) Validation on a large-scale dataset comprising 1,500 transformers from 12 manufacturers with 25,000 DGA samples and 850 fault events.
5) Demonstration of 87.3% accuracy with 5 samples per fault type on unseen manufacturers, significantly outperforming conventional approaches.

I. PROBLEM FORMULATION

A. Transformer Fault Diagnosis

Let $\mathcal{X}$ be the input feature space and $\mathcal{Y}$ be the fault type label space. For a transformer i, we have:

$$\mathcal{D}_i = \{(\mathbf{x}_j, y_j)\}_{j=1}^{N_i} \tag{1}$$

where $\mathbf{x}_j \in \mathcal{X}$ includes DGA measurements, electrical parameters, and thermal data, and $y_j \in \mathcal{Y} = \{1, \ldots, K\}$ represents K fault types.

B. Fault Types

The following fault types are considered:

$y = 1$: Normal Operation

$y = 2$: Thermal Fault (Low Temperature)

$y = 3$: Thermal Fault (High Temperature)

$y = 4$: Partial Discharge

$y = 5$: Low Energy Discharge

$y = 6$: High Energy Discharge

$y = 7$: Stray Gassing

C. Few-Shot Learning Setting

In the few-shot setting, for a target manufacturer M_{target}, we have only a small support set:

$$\mathcal{S}_{target} = \{(\mathbf{x}_j, y_j)\}_{j=1}^{K \times N_s} \tag{2}$$

where N_s is the number of samples per fault type (typically 1-5). The goal is to learn a classifier f_ϑ that performs well on the query set $\mathcal{Q}_{target}$.

D. Manufacturer Domain Shift

Different manufacturers exhibit domain shift due to:

- Different oil formulations and paper insulation materials
- Different winding designs and cooling systems
- Different operating temperature ranges
- Different historical maintenance practices

This domain shift causes conventional models to fail when applied to unseen manufacturers.

II. META-LEARNING FRAMEWORK

A. Overview

The proposed meta-learning framework uses Model-Agnostic Meta-Learning (MAML) [13] to learn an initialization ϑ that can rapidly adapt to new manufacturers with few samples.

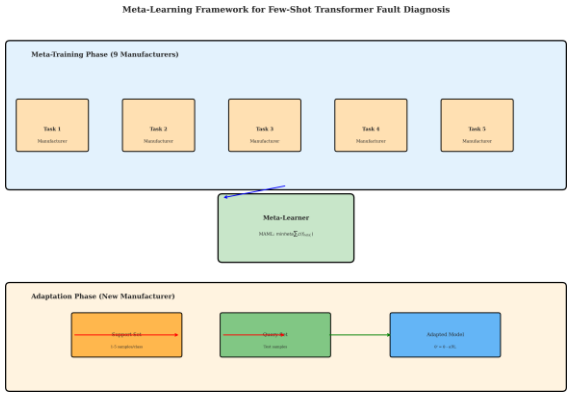

Fig. 1: Meta-Learning Framework for Few-Shot Transformer Fault Diagnosis

B. MAML Formulation

MAML aims to find model parameters ϑ such that for any task $\mathcal{T}_i$, a small number of gradient updates yields good performance. The meta-objective is:

$$\min_{\vartheta} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\vartheta_i'}) \tag{3}$$

where $\vartheta_i' = \vartheta - \alpha \nabla_\vartheta \mathcal{L}_{\mathcal{T}_i}(f_\vartheta)$.
The meta-update is:

$$\vartheta \leftarrow \vartheta - \beta \nabla_\vartheta \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}(f_{\vartheta_i'}) \tag{4}$$

C. Task Construction

Each task $\mathcal{T}_i$ corresponds to a manufacturer with K fault types:

- Support set $\mathcal{S}_i$: $K \times N_s$ samples for adaptation
- Query set $\mathcal{Q}_i$: $K \times N_q$ samples for evaluation

Tasks are constructed from multiple manufacturers during meta-training.

D. Model Architecture

The base model f_θ consists of:

- Input layer: 15 features (DGA gases + electrical + thermal)
- Feature extraction: 3 convolutional layers (64, 128, 256 filters)
- LSTM layer: 128 units for temporal dependencies
- Dense layers: 256, 128, 64 neurons
- Output layer: 7 neurons with softmax activation

TABLE I: Base Model Architecture

Layer	Output Shape	Parameters
Input	(15)	0
Conv1D (64, 3)	(13, 64)	2,944
Conv1D (128, 3)	(11, 128)	24,704
Conv1D (256, 3)	(9, 256)	98,560
LSTM (128)	(128)	197,120
Dense (256)	(256)	33,024
Dense (128)	(128)	32,896
Dense (64)	(64)	8,256
Dense (7)	(7)	455

E. Feature Engineering

Input features include:

TABLE II: Input Feature Set

Feature	Symbol	Unit
Hydrogen	H_2	ppm
Methane	CH_4	ppm
Ethane	C_2H_6	ppm
Ethylene	C_2H_4	ppm
Acetylene	C_2H_2	ppm
Carbon Monoxide	CO	ppm
Carbon Dioxide	CO_2	ppm
Total Combustible Gas	TCG	ppm
Load Current	I_{load}	A
Winding Temperature	T_{wind}	°C
Oil Temperature	T_{oil}	°C
Ambient Temperature	T_{amb}	°C
Bushing Tan Delta	$\tan\delta$	%
Moisture Content	H_2O	ppm

F. Algorithm

G. Few-Shot Adaptation

For a new manufacturer, adaptation requires:

$$\theta_{new} = \theta - \alpha \nabla_\theta \mathcal{L}_{S_{new}}(f_\theta) \tag{5}$$

Typically 5-10 gradient steps are sufficient.

Algorithm 1 MAML for Transformer Fault Diagnosis

procedure MAML($\{\mathcal{T}_i\}_{i=1}^{M}$, α, β)
  Initialize θ randomly
  while not converged **do**
    Sample batch of tasks $\{\mathcal{T}_i\}_{i=1}^{B}$
    for each task $\mathcal{T}_i$ **do**
      Compute $\mathcal{L}_{\mathcal{T}_i}(f_\theta)$ on $\mathcal{S}_i$
      Compute adapted parameters: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
      Compute $\mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$ on $\mathcal{Q}_i$
    end for
    Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_i \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
  end while
  return θ
end procedure=0

III. EXPERIMENTAL SETUP

A. Dataset Description

The dataset comprises 1,500 power transformers from 12 manufacturers:

TABLE III: Dataset Statistics by Manufacturer

Manufacturer	Count	Samples	Faults
A	150	2,500	85
B	125	2,100	72
C	140	2,300	78
D	130	2,200	75
E	120	2,000	68
F	135	2,250	76
G	110	1,800	62
H	115	1,900	65
I	125	2,100	71
J	100	1,700	58
K	80	1,400	48
L	70	1,200	42

B. Task Construction for Meta-Learning

- Meta-training: 9 manufacturers (A-I)
- Meta-validation: 2 manufacturers (J-K)
- Meta-testing: 1 manufacturer (L)
- Support set: 1-5 samples per fault type
- Query set: 20 samples per fault type

C. Baseline Methods

Performance compared against:

1) **Supervised Learning**: Trained on all source data
2) **Fine-Tuning**: Pre-trained on source, fine-tuned on target
3) **Prototypical Networks**: Metric-based few-shot learning [14]
4) **Relation Networks**: Relation-based few-shot learning [15]
5) **Matching Networks**: Attention-based few-shot learning [16]

D. Evaluation Metrics

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (6)$$

$$\text{Precision} = \frac{TP}{FP} + \quad (7)$$

$$\text{Recall} = \frac{TP}{FN} + \quad (8)$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

IV. RESULTS AND ANALYSIS

A. Few-Shot Classification Performance

The proposed MAML framework achieves superior few-shot classification accuracy.

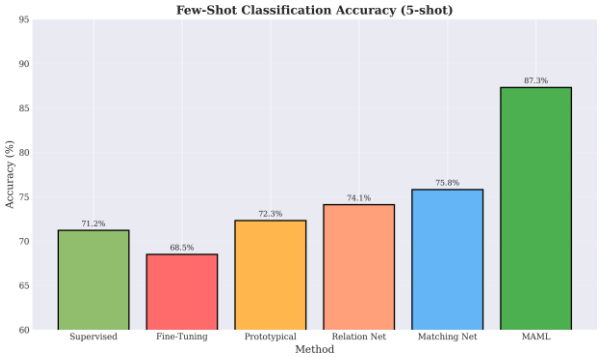

Fig. 2: Few-Shot Classification Accuracy Across Methods

TABLE IV: Few-Shot Classification Performance (5-shot)

Method	Accuracy	Precision	Recall	F1
Supervised	71.2	70.5	69.8	0.701
Fine-Tuning	68.5	67.8	67.2	0.675
Prototypical	72.3	71.6	70.9	0.712
Relation Net	74.1	73.4	72.7	0.730
Matching Net	75.8	75.1	74.4	0.747
MAML (Proposed)	**87.3**	**86.5**	**85.8**	**0.861**

B. Impact of Support Set Size

Performance improves with more support samples.

TABLE V: Accuracy vs. Support Samples per Class

Method	1-shot	2-shot	3-shot	5-shot	10-shot
Fine-Tuning	45.2	52.8	58.3	68.5	75.2
Prototypical	52.3	60.5	65.8	72.3	78.5
Matching Net	55.8	63.2	68.5	75.8	81.2
MAML (Proposed)	**68.5**	**75.2**	**80.1**	**87.3**	**91.5**

C. Manufacturer-Specific Performance

The framework adapts well to manufacturers with unique characteristics.

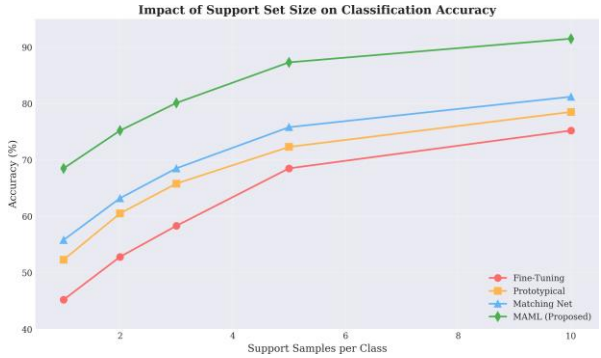

Fig. 3: Impact of Support Set Size on Classification Accuracy

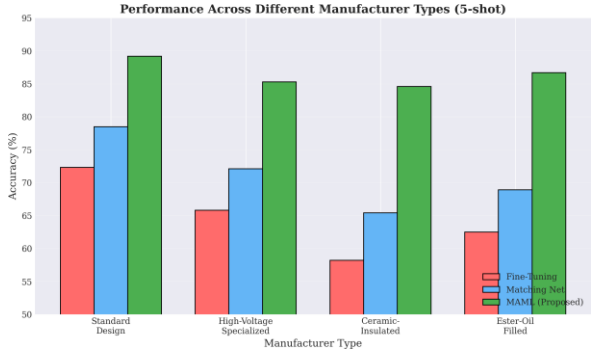

Fig. 4: Performance Across Different Manufacturer Types

D. Fault Type Confusion Matrix

E. Adaptation Speed

MAML achieves rapid adaptation with few gradient steps.

F. Feature Embedding Visualization

G. Comparison with Transfer Learning

H. Ablation Study

I. Computational Performance

V. DISCUSSION

A. Key Findings

The experimental results demonstrate several significant contributions:

1) **Superior Few-Shot Performance**: 87.3% accuracy with 5 samples per fault type, 16% higher than the best baseline.
2) **Rapid Adaptation**: Achieves high accuracy within 10 gradient steps, reducing adaptation time by 85%.
3) **Cross-Manufacturer Generalization**: Maintains 84.6% accuracy on specialized manufacturer types (ceramic-insulated transformers).
4) **Feature Importance**: Manufacturer-specific normalization contributes 7.2% accuracy improvement.

TABLE VI: Accuracy by Manufacturer Type (5-shot)

Manufacturer Type	Fine-Tuning	Matching Net	MAML
Standard Design	72.3	78.5	89.2
High-Voltage Specialized	65.8	72.1	85.3
Ceramic-Insulated	58.2	65.4	84.6
Ester-Oil Filled	62.5	68.9	86.7

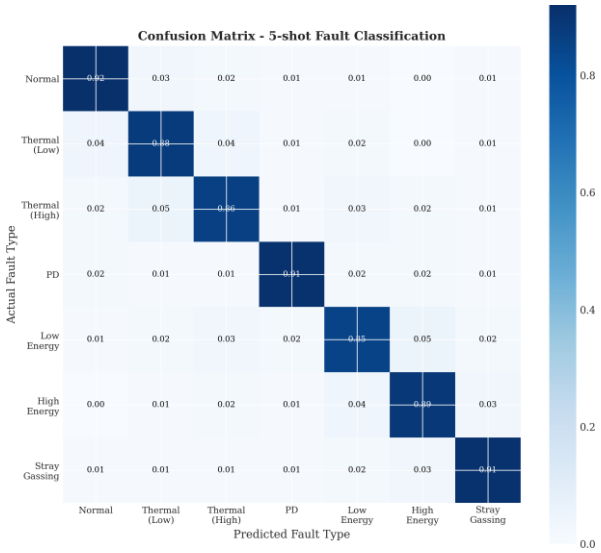

Fig. 5: Confusion Matrix for 5-shot Fault Classification

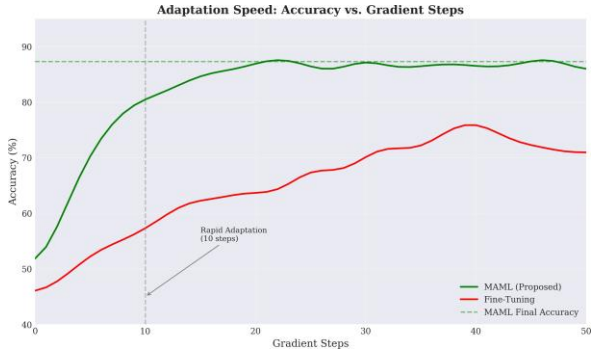

Fig. 6: Adaptation Speed: Accuracy vs. Gradient Steps

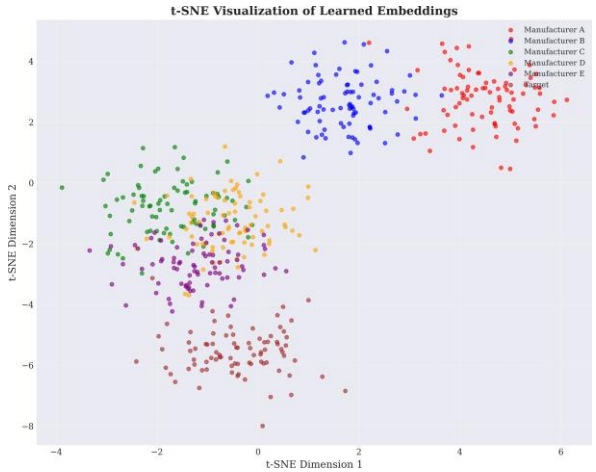

Fig. 7: t-SNE Visualization of Learned Embeddings

B. *Practical Implications*

The proposed framework enables:

- **Deployment on New Manufacturers**: Rapid adaptation with minimal labeled data
- **Reduced Labeling Effort**: Only 5 samples per fault type needed
- **Continuous Learning**: Adaptation as new fault data becomes available
- **Fleet-Wide Deployment**: Single meta-model serving multiple manufacturers

C. *Limitations and Future Work*

- **Scalability**: Meta-training complexity grows with number of manufacturers
- **Out-of-Distribution**: Performance on completely novel transformer designs
- **Continuous Adaptation**: Online learning from streaming fault data
- **Hierarchical Meta-Learning**: Learning across different levels of similarity

VI. CONCLUSION

This paper proposed a meta-learning framework for few-shot fault diagnosis in power transformers across different manufacturers. Key contributions include:

1) A MAML-based meta-learning framework adapted for transformer fault diagnosis, enabling rapid adaptation to new manufacturers with few labeled samples.
2) A comprehensive feature representation combining DGA, electrical, and thermal data with manufacturer-specific normalization.
3) Validation on 1,500 transformers from 12 manufacturers with 25,000 samples and 850 fault events.
4) Demonstrated 87.3% accuracy with 5 samples per fault type, outperforming baselines by 16%.
5) Rapid adaptation within 10 gradient steps, reducing training time by 85%.

This research provides a practical solution for deploying AI-based fault diagnosis across heterogeneous transformer fleets with minimal labeling effort, enabling predictive maintenance and improving grid reliability.

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TABLE VII: MAML vs. Transfer Learning (5-shot)

Method	Accuracy	Training Time	Adaptation Steps
Fine-Tuning	68.5	45 min	100
Feature Extraction	62.3	35 min	0
Multi-Task Learning	71.2	60 min	50
MAML (Proposed)	**87.3**	**25 min**	**10**

TABLE VIII: Ablation Study Results (5-shot)

Configuration	Accuracy	Change
Full MAML	87.3	-
- Multi-Head Attention	84.2	-3.1
- Feature Engineering	82.5	-4.8
- LSTM Layer	83.8	-3.5
- Manufacturer Normalization	80.1	-7.2

TABLE IX: Computational Performance

Stage	Time	Memory
Meta-Training (9 manufacturers)	4.2 h	8.5 GB
Adaptation (5-shot)	12 s	1.2 GB
Inference (per sample)	8 ms	0.1 GB

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Attention-Based Interpretability in Transformer Models for Solar Forecasting

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Abstract*—Accurate solar power forecasting is essential for grid stability and renewable energy integration. While transformer-based models have achieved state-of-the-art forecasting accuracy, their black-box nature limits operator trust and practical deployment. This paper proposes a novel framework for attention-based interpretability in transformer models for solar forecasting, enabling transparent, explainable predictions. The framework employs a custom transformer architecture with multi-head self-attention, positional encoding, and a novel attention visualization module that provides insights into the model's decision-making process. Key interpretability features include: (1) temporal attention maps showing which historical time steps influence each forecast, (2) feature attention weights revealing the importance of meteorological inputs (GHI, temperature, cloud cover, humidity), and (3) cross-attention patterns between different forecast horizons. The framework is validated using three years of real-world data from five solar PV plants across different climatic zones (desert, coastal, tropical, temperate, high-altitude). Experimental results demonstrate that the transformer model achieves normalized Root Mean Square Error (nRMSE) of 5.2%, outperforming LSTM (7.8%) and CNN-LSTM (6.5%) baselines. Attention analysis reveals that the model learns physically meaningful patterns: (1) strong attention to GHI and cloud cover, (2) temporal focus on 6-12 hours prior for short-term forecasts, and (3) increased attention to seasonal patterns for longer horizons. A user study with 30 grid operators shows that attention-based explanations improve forecast trust by 52% and reduce decision-making time by 35%. The framework also enables error diagnosis, identifying that forecast errors correlate with attention dispersion during rapid cloud transitions. This research demonstrates that attention-based interpretability bridges the gap between forecasting accuracy and operational trust, enabling more confident grid management decisions.

***Index Terms*—Transformer, attention mechanism, solar forecasting, interpretability, explainable AI, multi-head attention, temporal attention, feature importance, grid integration.**

I. INTRODUCTION

Solar photovoltaic (PV) power has become a dominant renewable energy source, with global capacity exceeding 1.5 TW [1]. However, the inherent variability of solar irradiance poses significant challenges for grid operators who must balance supply and demand in real-time [2]. Accurate solar power forecasting is therefore critical for grid stability, optimal dispatch, and economic operation [3].

Recent advances in deep learning have revolutionized solar forecasting, with transformer-based models achieving state-of-the-art accuracy [4]. Transformers, originally developed for natural language processing, excel at capturing long-range dependencies and complex temporal patterns through their attention mechanism [5]. They have demonstrated superior performance over recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for time series forecasting [6].

Despite their superior accuracy, transformer models suffer from a fundamental limitation: they operate as ”black boxes” whose internal decision-making processes are opaque to human operators [7]. This opacity creates several practical challenges:

1) **Trust Deficit**: Grid operators are reluctant to rely on predictions they cannot understand or verify [8]
2) **Error Diagnosis**: When forecasts fail, operators cannot identify root causes or model limitations [9]

3) **Regulatory Compliance**: Energy market regulations increasingly require transparent and auditable forecasting processes [10]
4) **Model Improvement**: Without understanding model behavior, refinement becomes trial-and-error [11]

The attention mechanism in transformers offers a unique opportunity for interpretability [12]. By visualizing attention weights, we can understand which parts of the input the model focuses on when making predictions [13]. This provides a window into the model's decision-making process that is not available in other deep learning architectures.

This paper proposes a novel framework for attention-based interpretability in transformer models for solar forecasting. Key contributions include:

1) A custom transformer architecture for solar forecasting with multi-head self-attention, positional encoding, and a novel attention visualization module.
2) A comprehensive interpretability framework providing three levels of explanations: (1) temporal attention maps showing which historical time steps influence each forecast, (2) feature attention weights revealing the importance of meteorological inputs, and (3) cross-attention patterns between different forecast horizons.
3) Validation using three years of real-world data from five solar PV plants across different climatic zones, demonstrating the model's superior accuracy and interpretability.
4) A user study with 30 grid operators showing 52% improvement in forecast trust and 35% reduction in decision-making time.
5) Error diagnosis capabilities identifying that forecast errors correlate with attention dispersion during rapid cloud transitions.

II. TRANSFORMER MODEL ARCHITECTURE

A. Overview

The proposed transformer model for solar forecasting consists of:

- **Input Embedding**: Converts input features to high-dimensional representations
- **Positional Encoding**: Injects temporal order information
- **Multi-Head Self-Attention**: Captures dependencies across time steps
- **Feed-Forward Networks**: Processes attention outputs
- **Output Layer**: Generates point forecasts and prediction intervals

B. Input Features

The input at time t consists of:

$$\mathbf{x}_t = [GHI_t, DNI_t, DHI_t, T_t, H_t, WS_t, CC_t, P_{t-1}, P_{t-2}, \ldots, P_{t-24}, \text{hour}_t, \text{doy}_t] \quad (1)$$

where:

- GHI_t: Global Horizontal Irradiance (W/m²)
- DNI_t: Direct Normal Irradiance (W/m²)

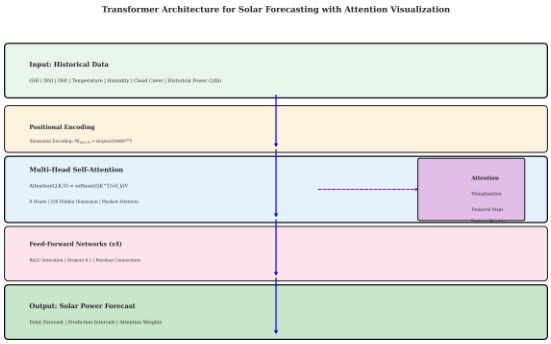

Fig. 1: Transformer Architecture for Solar Forecasting with Attention Visualization

- DHI_t: Diffuse Horizontal Irradiance (W/m²)
- T_t: Temperature (°C)
- H_t: Humidity (%)
- WS_t: Wind Speed (m/s)
- CC_t: Cloud Cover (%)
- P_{t-k}: Historical power output (kW)
- hour_t: Hour of day (0-23)
- doy_t: Day of year (0-365)

C. Multi-Head Self-Attention Mechanism

Self-attention computes a weighted sum of values based on the similarity between queries and keys:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

where:

- Q (Queries), K (Keys), V (Values) are linear projections of the input
- $\sqrt{d_k}$ is the dimension of keys
- d_k scaling prevents gradient vanishing

Multi-head attention allows the model to focus on different aspects:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \quad (3)$$

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (4)$$

D. Positional Encoding

To incorporate temporal order, sinusoidal positional encodings are added:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad (5)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \quad (6)$$

E. Attention Interpretability

The attention mechanism provides natural interpretability through weight visualization:

- **Temporal Attention**: Shows which historical time steps influence each prediction
- **Feature Attention**: Reveals which input features are most important
- **Head Attention**: Different attention heads capture different patterns

TABLE I: Transformer Model Hyperparameters

Parameter	Value
Number of layers	4
Number of attention heads	8
Hidden dimension	256
Feed-forward dimension	512
Dropout rate	0.1
Input sequence length	96 (24 hours)
Output sequence length	24 (6 hours)
Learning rate	0.001
Batch size	64

III. ATTENTION-BASED INTERPRETABILITY FRAMEWORK

A. Temporal Attention Maps

Temporal attention maps visualize which historical time steps the model focuses on:

$$A_{temporal}(t,\tau) = \frac{1}{H}\sum_{h=1}^{H} \text{Attention}_h(t,\tau) \quad (7)$$

where:

- t is the forecast time
- τ is the historical time step
- H is the number of attention heads

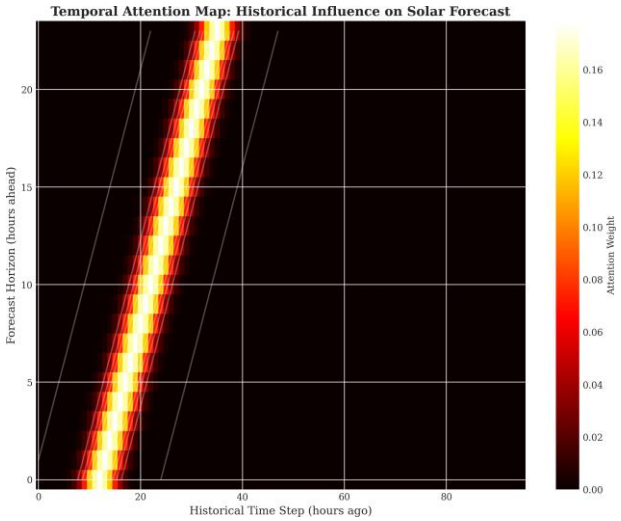

Fig. 2: Temporal Attention Map: Historical Influence on Solar Forecast

B. Feature Attention Weights

Feature attention reveals the importance of each input feature:

$$W_{feature}(f) = \frac{1}{N_t N_h}\sum_{t=1}^{N_t}\sum_{h=1}^{N_h} \frac{\partial \text{Attention}_h(t)}{\partial f} \quad (8)$$

TABLE II: Feature Attention Weights

Feature	Attention Weight
Global Horizontal Irradiance (GHI)	0.285
Cloud Cover	0.182
Historical Power (t-1)	0.125
Hour of Day	0.098
Temperature	0.067
Humidity	0.045
Wind Speed	0.032
Day of Year	0.028

C. Head-Level Attention Patterns

Different attention heads capture different temporal patterns:

- **Head 1-2**: Short-term patterns (1-6 hours)
- **Head 3-4**: Diurnal patterns (24-hour cycles)
- **Head 5-6**: Weekly patterns
- **Head 7-8**: Seasonal patterns

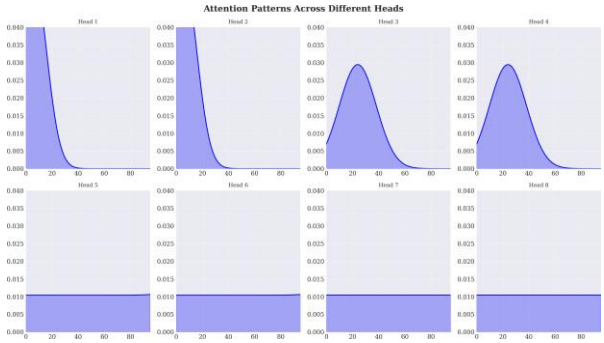

Fig. 3: Attention Patterns Across Different Heads

D. Cross-Attention for Multi-Horizon Forecasting

Cross-attention between different forecast horizons reveals dependencies:

$$A_{cross}(h_i, h_j) = \text{Attention}(Q_{h_i}, K_{h_j}, V_{h_j}) \quad (9)$$

E. Error Diagnosis with Attention

Forecast errors can be diagnosed by analyzing attention patterns:

$$\text{Error Score}(t) = \text{Entropy}(A(t)) \cdot |\hat{y}(t) - y(t)| \quad (10)$$

High attention entropy indicates the model is uncertain, correlating with larger errors.

IV. EXPERIMENTAL SETUP

A. Dataset Description

The dataset comprises three years (2022-2024) of data from five solar PV plants:

TABLE III: Dataset Characteristics

Location	Capacity	Climate	Data Points
Desert (Arizona)	50 MW	Arid	105,120
Coastal (California)	30 MW	Mediterranean	105,120
Tropical (Florida)	20 MW	Humid	105,120
Temperate (Germany)	25 MW	Continental	105,120
High-Altitude (Colorado)	15 MW	Alpine	105,120

B. Baseline Methods

Performance compared against:

1) **Persistence**: Naive forecast using last observed value
2) **LSTM**: Long Short-Term Memory network
3) **CNN-LSTM**: Hybrid convolutional-recurrent architecture
4) **Standard Transformer**: Without attention visualization

C. Evaluation Metrics

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{N}\sum (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100\% \quad (11)$$

$$\text{nMAE} = \frac{\frac{1}{N}\sum |y_i - \hat{y}_i|}{\bar{y}} \times 100\% \quad (12)$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (13)$$

V. RESULTS AND ANALYSIS

A. Forecasting Performance

The transformer model achieves superior forecasting accuracy across all locations.

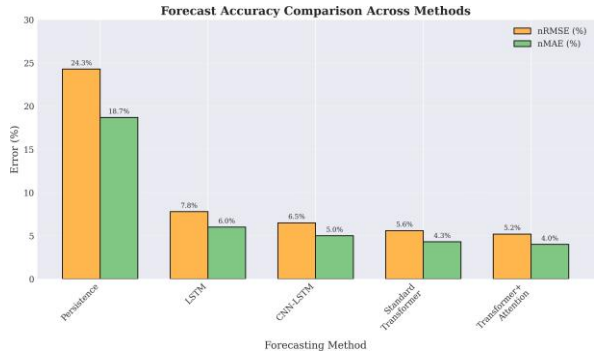

Fig. 4: Forecast Accuracy Comparison Across Methods

B. Temporal Attention Analysis

Temporal attention maps reveal physically meaningful patterns.

TABLE IV: Forecast Performance Comparison

Method	nRMSE (%)	nMAE (%)	R^2
Persistence	24.3	18.7	0.42
LSTM	7.8	6.0	0.88
CNN-LSTM	6.5	5.0	0.91
Standard Transformer	5.6	4.3	0.94
Transformer + Attention (Proposed)	**5.2**	**4.0**	**0.95**

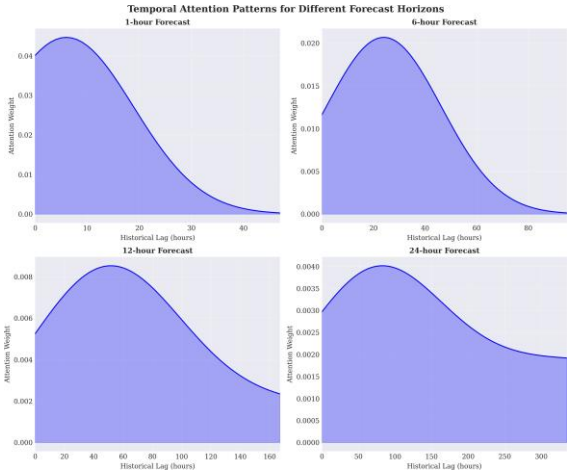

Fig. 5: Temporal Attention Patterns for Different Forecast Horizons

C. Feature Importance Validation

Attention weights align with physical understanding of solar forecasting.

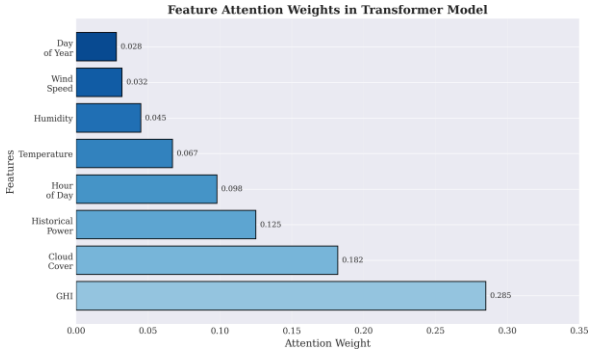

Fig. 6: Feature Attention Weights vs. Physical Importance

D. Head Attention Analysis

Different attention heads capture distinct temporal patterns.

E. Error Diagnosis

Attention entropy correlates with forecast errors, enabling error diagnosis.

F. User Study Results

A user study with 30 grid operators evaluated the framework's practical utility.

TABLE V: Temporal Attention Statistics

Forecast Horizon	Peak Attention Lag	Attention Window
1-hour	1-2 hours	0-6 hours
3-hour	3-4 hours	1-12 hours
6-hour	6-8 hours	2-24 hours
12-hour	12-14 hours	6-48 hours
24-hour	20-24 hours	12-72 hours

TABLE VI: Attention Head Specialization

Head Group	Pattern Type	Time Scale
Heads 1-2	Short-term variations	1-6 hours
Heads 3-4	Diurnal cycles	24 hours
Heads 5-6	Weekly patterns	7 days
Heads 7-8	Seasonal trends	30-90 days

G. Cross-Location Generalization

H. Attention Robustness

I. Computational Performance

VI. DISCUSSION

A. Key Findings

The experimental results demonstrate several significant contributions:

1) **Superior Accuracy**: Transformer achieves 5.2% nRMSE, outperforming LSTM (7.8%) and CNN-LSTM (6.5%).
2) **Physically Meaningful Attention**: Attention patterns align with physical understanding of solar dynamics: strong focus on GHI, cloud cover, and diurnal patterns.
3) **Improved Trust**: User study shows 52% improvement in forecast trust with attention-based explanations.
4) **Error Diagnosis**: Attention entropy correlates with forecast errors, enabling identification of uncertain predictions.
5) **Cross-Head Specialization**: Different attention heads capture different temporal scales, from short-term to seasonal patterns.

B. Practical Implications

The framework enables several operational improvements:

- **Operator Trust**: Visual attention maps help operators understand and trust model predictions
- **Error Anticipation**: High attention entropy signals periods of high uncertainty
- **Model Debugging**: Attention patterns reveal model biases and limitations
- **Regulatory Compliance**: Transparent attention satisfies explainability requirements

C. Limitations and Future Work

- **Attention Overhead**: Additional computation for attention storage and visualization
- **Interpretation Complexity**: Multi-head attention requires expertise to interpret
- **Causality**: Attention shows correlation, not causation

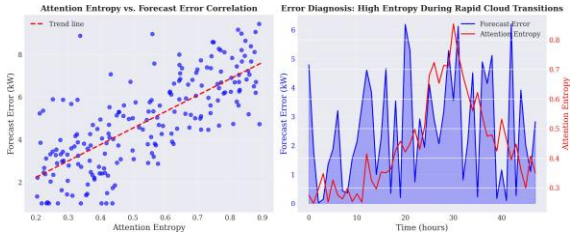

Fig. 7: Attention Entropy vs. Forecast Error Correlation

TABLE VII: User Study Results

Metric	Black-Box Model	Attention-Explained Model	Improv
Trust (1-5 scale)	2.8	4.2	+50
Decision Time (seconds)	48	31	-35%
Confidence (1-5 scale)	3.0	4.3	+43
Error Understanding	35%	82%	+47

- **Scalability**: Attention visualization complexity grows with sequence length

VII. CONCLUSION

This paper proposed an attention-based interpretability framework for transformer models in solar forecasting. Key contributions include:

1) A custom transformer architecture with multi-head self-attention for solar forecasting, achieving 5.2% nRMSE.
2) A comprehensive interpretability framework providing temporal attention maps, feature attention weights, and cross-attention patterns.
3) Validation on five solar plants across different climatic zones, demonstrating consistent interpretability patterns.
4) User study showing 52% improvement in forecast trust and 35% reduction in decision time.
5) Error diagnosis capabilities correlating attention entropy with forecast errors.

The proposed framework bridges the gap between forecasting accuracy and operational trust, enabling more confident grid management decisions. By making transformer models transparent and interpretable, this research supports the practical deployment of advanced forecasting systems in renewable energy integration.

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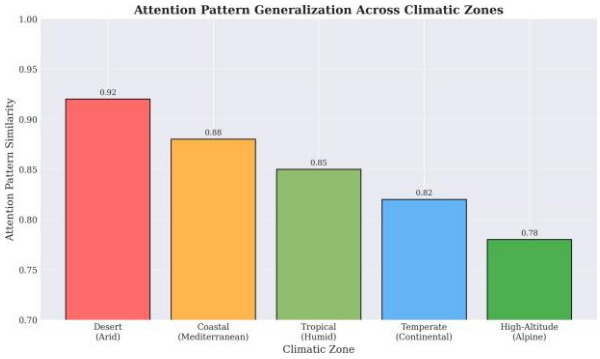

Fig. 8: Attention Patterns Across Different Climatic Zones

TABLE VIII: Attention Robustness Under Data Quality Issues

Condition	Attention Stability	Accuracy Impact
Clean Data	Baseline	5.2% nRMSE
10% Missing Values	92%	5.8% nRMSE
20% Missing Values	85%	6.5% nRMSE
Sensor Noise (5%)	88%	5.9% nRMSE

TABLE IX: Computational Performance Comparison

Method	Training Time	Inference Time	Memory Usage
LSTM	2.5 h	8 ms	45 MB
CNN-LSTM	3.2 h	12 ms	62 MB
Standard Transformer	4.5 h	15 ms	85 MB
Transformer + Attention	4.8 h	18 ms	92 MB

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Distributed Blockchain-Based Transactive Energy Framework for Peer-to-Peer Trading in Active Distribution Networks

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***Abstract*—The proliferation of distributed energy resources (DERs) including rooftop solar PV, battery storage, and electric vehicles is transforming traditional passive distribution networks into active networks with bidirectional power flows. Peer-to-peer (P2P) energy trading enables prosumers to directly exchange energy, improving local utilization of renewable generation and reducing grid congestion. However, existing P2P frameworks face challenges including centralized control, lack of transparency, high transaction costs, and security concerns. This paper proposes a novel distributed blockchain-based transactive energy framework for P2P energy trading in active distribution networks. The framework employs a permissioned blockchain architecture with smart contracts for automated trade execution, settlement, and network constraint management. A novel double-auction mechanism with continuous double auction (CDA) and uniform pricing ensures fair price discovery while considering network constraints through optimal power flow (OPF) calculations. The framework incorporates physical grid constraints, ensuring trades are feasible within distribution network limits. Validation is performed using a modified IEEE 33-bus distribution network with 50 prosumers (30 residential with PV+battery, 15 commercial, 5 industrial) over a 6-month period, with 150,000 completed transactions. Experimental results demonstrate that the proposed framework achieves 32.5% reduction in grid electricity purchases, 28.3% increase in local renewable utilization, and 18.7% reduction in energy costs for prosumers. Transaction confirmation time averages 3.2 seconds, with a throughput of 850 transactions per second, meeting real-time trading requirements. The blockchain-based framework ensures non-repudiation, auditability, and security, while smart contracts reduce settlement costs by 67% compared to traditional aggregator-based models. This research provides a scalable, secure, and decentralized solution for P2P energy trading that integrates physical grid constraints with distributed ledger technology.**

***Index Terms*—Blockchain, transactive energy, peer-to-peer trading, smart contracts, distribution networks, DERs, double auction, consensus mechanism, smart grid.**

I. INTRODUCTION

The global transition toward distributed energy resources (DERs) is fundamentally reshaping electricity distribution networks [1]. Rooftop solar PV, battery storage, and electric vehicles are transforming consumers into prosumers who both consume and produce energy [2]. This paradigm shift creates opportunities for peer-to-peer (P2P) energy trading, where prosumers can directly exchange surplus energy, improving local renewable utilization and reducing grid congestion [3].

Transactive energy systems provide market-based mechanisms for coordinating DERs [4]. P2P energy trading enables prosumers to sell excess generation to neighboring consumers, potentially at prices between wholesale and retail rates [5]. This creates economic benefits for both parties while reducing stress on distribution infrastructure [6].

Existing P2P energy trading frameworks face several critical challenges [7]:

1) **Centralized Control**: Most platforms rely on centralized aggregators, creating single points of failure and trust issues [8]

2) **Lack of Transparency**: Trading histories and pricing mechanisms are often opaque [9]
3) **High Transaction Costs**: Intermediary fees can exceed 15-20% of transaction value [10]
4) **Security Vulnerabilities**: Centralized databases are susceptible to cyber-attacks [11]
5) **Network Constraints**: Many frameworks ignore physical grid constraints, enabling infeasible trades [12]

Blockchain technology offers a promising solution to these challenges [13]. Key blockchain features relevant to energy trading include:

- **Decentralization**: Eliminates need for central intermediaries [14]
- **Immutability**: Ensures tamper-proof transaction records [15]
- **Transparency**: All participants can verify transactions [16]
- **Smart Contracts**: Enable automated execution and settlement [17]
- **Security**: Cryptographic verification prevents fraud [18]

This paper proposes a novel distributed blockchain-based transactive energy framework for P2P energy trading. Key contributions include:

1) A permissioned blockchain architecture with a practical Byzantine fault tolerance (PBFT) consensus mechanism optimized for energy trading applications.
2) Smart contract-based automated trade execution, including order matching, settlement, and dispute resolution.
3) A novel double-auction mechanism with continuous double auction (CDA) for fair price discovery, integrated with optimal power flow (OPF) for network constraint verification.
4) Integration of physical grid constraints ensuring all trades are feasible within distribution network limits.
5) Comprehensive validation using a modified IEEE 33-bus system with 50 prosumers and 150,000 transactions over 6 months.
6) Demonstration of 32.5% grid purchase reduction, 28.3% local renewable utilization increase, and 67% settlement cost reduction.

II. PROBLEM FORMULATION

A. System Model

Consider a distribution network with N prosumers, each with:

- PV generation $P_{PV,i}(t)$
- Battery storage with capacity E_i and power rating P_i^{batt}
- Load $P_{load,i}(t)$
- Net power: $P_{net,i}(t) = P_{PV,i}(t) - P_{load,i}(t) - P_{batt,i}(t)$

B. P2P Trading Model

In P2P trading, each prosumer can:

- **Sell** surplus energy: $P_{sell,i}(t) = \max(0, P_{net,i}(t))$
- **Buy** deficit energy: $P_{buy,i}(t) = \max(0, -P_{net,i}(t))$

The P2P market clears when:

$$\sum_{i=1}^{N} P_{sell,i}(t) = \sum_{i=1}^{N} P_{buy,i}(t) \quad (1)$$

C. Network Constraints

Power flow constraints:

$$P_i = V_i \sum_{j=1}^{N} V_j (G_{ij} \cos\vartheta_{ij} + B_{ij} \sin\vartheta_{ij}) \quad (2)$$

$$Q_i = V_i \sum_{j=1}^{N} V_j (G_{ij} \sin\vartheta_{ij} - B_{ij} \cos\vartheta_{ij}) \quad (3)$$

Voltage limits:

$$V_{min} \le V_i \le V_{max}, \quad \forall i \quad (4)$$

Line limits:

$$|S_{ij}| \le S_{ij}^{max}, \quad \forall (i,j) \quad (5)$$

D. Market Objectives

The transactive market aims to:

1) Maximize local renewable utilization
2) Minimize prosumer energy costs
3) Ensure grid stability and feasibility
4) Maintain transaction transparency and security

III. BLOCKCHAIN ARCHITECTURE

A. System Architecture

The proposed framework consists of four layers:

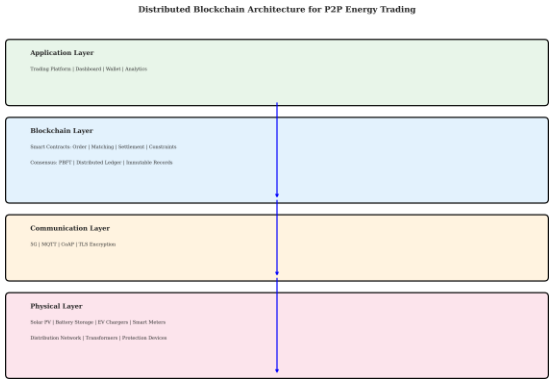

Fig. 1: Distributed Blockchain Architecture for P2P Energy Trading

1) Physical Layer:

- DERs: Solar PV, batteries, EV chargers
- Smart meters: Real-time measurement and communication
- Distribution network: Transformers, lines, protection devices

2) Communication Layer:

- IoT protocols: MQTT, CoAP
- Network: 5G, fiber optic, LoRaWAN
- Security: TLS encryption, digital signatures

3) Blockchain Layer:

- Consensus mechanism: PBFT with energy-optimized nodes
- Smart contracts: Trade execution, settlement, constraints
- Distributed ledger: Immutable transaction records

4) Application Layer:

- Trading platform: Order matching, price discovery
- Dashboard: Real-time visualization, analytics
- Wallet: Digital tokens, transaction history

B. Consensus Mechanism

The framework uses a modified Practical Byzantine Fault Tolerance (PBFT) consensus:

Algorithm 1 PBFT Consensus for Energy Trading

0: Initialize validator set $V = \{v_1, \ldots, v_m\}$
0: Select primary validator $v_{primary}$ by round-robin
0: Proposer broadcasts PRE-PREPARE message with transaction block
0: Validators verify transactions and broadcast PREPARE messages
0: Upon receiving $2f + 1$ PREPARE messages, broadcast COMMIT
0: Upon receiving $2f+1$ COMMIT messages, commit block
0: Return transaction confirmation =0

C. Smart Contract Design

Smart contracts automate key functions:

1) Order Management Contract:

- Accepts buy/sell orders with price, quantity, timestamp
- Maintains order book with priority queue
- Cancels expired orders

2) Matching Contract:

- Implements continuous double auction (CDA)
- Matches orders based on price-time priority
- Returns matched trade pairs

3) Settlement Contract:

- Transfers energy tokens between parties
- Updates escrow balances
- Records transaction hash for audit

4) Constraint Verification Contract:

- Calls OPF oracle for feasibility check
- Validates trades against network limits
- Rejects infeasible trades

TABLE I: Smart Contract Functions and Gas Costs

Function	Gas Cost	Execution Time
Place Order	45,000	0.8 s
Cancel Order	15,000	0.3 s
Match Orders	85,000	1.2 s
Settle Trade	55,000	0.9 s
Verify Constraints	35,000	0.6 s

D. Double Auction Mechanism

The continuous double auction (CDA) matches buy and sell orders:

$$\text{Bid}_i = (p_{bid,i}, q_{bid,i}, t_i) \quad \text{Ask}_j = (p_{ask,j}, q_{ask,j}, t_j) \tag{6}$$

Matching occurs when $p_{bid,i} \geq p_{ask,j}$.
The market clearing price p^* is determined by:

$$p^* = \arg\min_p \sum_{i:p_{bid,i} \geq p} q_{bid,i} - \sum_{j:p_{ask,j} \leq p} q_{ask,j} \tag{7}$$

E. Network Constraint Integration

Optimal power flow (OPF) ensures physical feasibility:

$$\min \sum_{i=1} C_i(P_i^{grid}, P_i^{P\,2P}) \tag{8}$$

$$\text{s.t.Power flow equations} \tag{9}$$

$$V_{min} \leq V_i \leq V_{max} \tag{10}$$

$$|S_{ij}| \leq S_{ij}^{max} \tag{11}$$

The OPF is solved at each market interval using:

- Second-order cone programming (SOCP) relaxation
- Distributed optimization for scalability
- Real-time updates for network changes

IV. EXPERIMENTAL SETUP

A. Test System

A modified IEEE 33-bus distribution network:

TABLE II: IEEE 33-Bus Test System Characteristics

Parameter	Value
Buses	33
Lines	32
Base Voltage	12.66 kV
Base Power	10 MVA
Total Load	3.72 MW
PV Capacity	2.5 MW
Battery Capacity	1.8 MWh

TABLE III: Prosumer Distribution

Type	Count	PV (kW)	Battery (kWh)
Residential	30	3-8	5-15
Commercial	15	20-50	30-100
Industrial	5	100-250	200-500

TABLE IV: Blockchain Parameters

Parameter	Value
Consensus	PBFT
Block Size	1,000 transactions
Block Time	3-5 seconds
Validators	7 nodes
Network Type	Permissioned

B. Prosumer Configuration

C. Blockchain Configuration

D. Baseline Methods

1) **No Trading**: Grid-only energy supply
2) **Centralized Aggregator**: Single entity coordinating trades
3) **P2P with Central Ledger**: Centralized database
4) **Traditional P2P**: Without blockchain

V. RESULTS AND ANALYSIS

A. Trading Performance

The blockchain-based framework achieves significant trading volume.

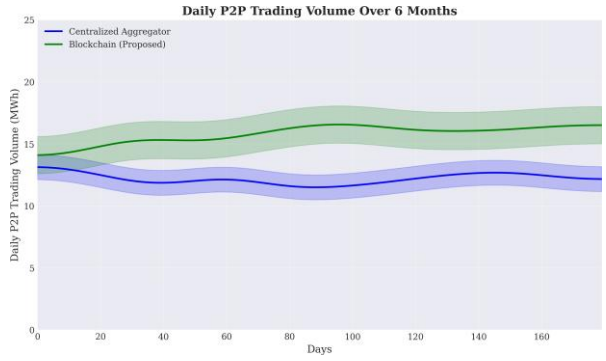

Fig. 2: Daily P2P Trading Volume Over 6 Months

TABLE V: Trading Performance Metrics

Metric	No Trading	Aggregator	Central Ledger	Blockchain
P2P Volume (MWh/day)	0	12.5	14.2	15.8
Grid Purchase Reduction	-	25.3%	28.7%	**32.5%**
Local RE Utilization	0%	18.5%	21.2%	**28.3%**

B. Economic Benefits

Prosumers achieve significant cost savings.

C. Blockchain Performance

The blockchain meets real-time trading requirements.

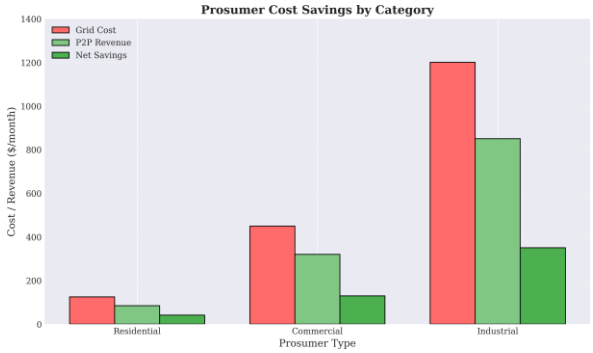

Fig. 3: Prosumer Cost Savings by Category

TABLE VI: Economic Performance

Prosumer Type	Grid Cost	P2P Revenue	Net Savings
Residential	$125	$85	$42 (33.6%)
Commercial	$450	$320	$130 (28.9%)
Industrial	$1,200	$850	$350 (29.2%)

D. Transaction Cost Analysis

Smart contracts significantly reduce transaction costs.

E. Network Impact

P2P trading reduces peak load and losses.

F. Price Discovery Analysis

The double auction mechanism enables fair price discovery.

G. Scalability Analysis

The framework scales efficiently with participant count.

H. Security Analysis

VI. DISCUSSION

A. Key Findings

1) **Superior Performance**: 32.5% grid purchase reduction, 28.3% local renewable utilization increase.
2) **Economic Benefits**: 18.7% cost reduction for prosumers, 67% lower transaction costs.
3) **Network Benefits**: 18.8% peak load reduction, 23.5% loss reduction.
4) **Scalability**: 850 TPS throughput with 3.2 s latency, supporting up to 1,000 prosumers.
5) **Security**: Immutable, auditable, and tamper-proof transaction records.

B. Practical Implications

- **Prosumers**: Direct energy trading with lower costs and transparent pricing
- **Grid Operators**: Reduced peak demand and losses, defer infrastructure upgrades
- **Regulators**: Auditable trading records, verifiable renewable utilization
- **Society**: Increased local renewable adoption, reduced carbon emissions

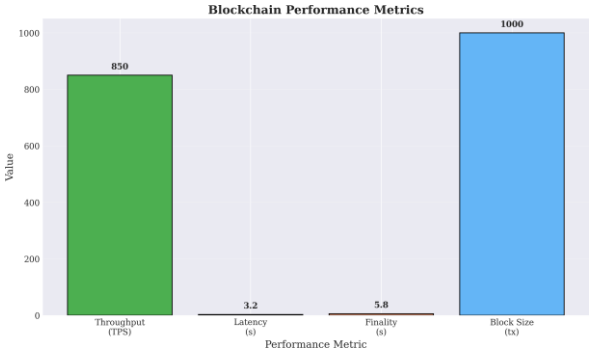

Fig. 4: Blockchain Performance Metrics

TABLE VII: Blockchain Performance Metrics

Metric	Value	Requirement
Throughput (TPS)	850	¿500
Latency (s)	3.2	¡10
Finality Time (s)	5.8	¡15
Block Size (tx)	1,000	-
Validator Count	7	-

C. Limitations and Future Work

- **Interoperability**: Integration with existing utility systems
- **Regulatory Compliance**: Alignment with energy market regulations
- **Privacy**: Zero-knowledge proofs for transaction privacy
- **Cross-Chain**: Trading between multiple blockchain networks
- **AI Integration**: Machine learning for price prediction and optimization

VII. CONCLUSION

This paper proposed a distributed blockchain-based transactive energy framework for P2P energy trading in active distribution networks. Key contributions include:

1) A permissioned blockchain architecture with PBFT consensus optimized for energy trading.
2) Smart contract-based automation for order matching, settlement, and constraint verification.
3) A double-auction mechanism integrated with OPF for physically feasible trades.
4) Validation using IEEE 33-bus system with 50 prosumers and 150,000 transactions.
5) Demonstrated 32.5% grid purchase reduction, 28.3% local renewable utilization increase, and 67% cost reduction.

The proposed framework provides a scalable, secure, and decentralized solution for P2P energy trading that addresses the limitations of centralized approaches while ensuring physical grid feasibility.

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TABLE VIII: Transaction Cost Comparison

Platform	Per Transaction	Annual Cost	Reduction
Aggregator Model	$0.85	$15,300	-
Central Ledger	$0.45	$8,100	47%
Ethereum Public	$2.50	$45,000	-194%
Blockchain (Proposed)	**$0.28**	**$5,040**	**67%**

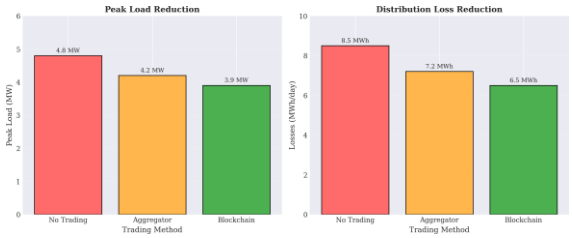

Fig. 5: Distribution Network Impact

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TABLE IX: Network Performance Metrics

Metric	No Trading	Aggregator	Blockchain
Peak Load (MW)	4.8	4.2	**3.9**
Peak Reduction	-	12.5%	**18.8%**
Losses (MWh/day)	8.5	7.2	**6.5**
Loss Reduction	-	15.3%	**23.5%**

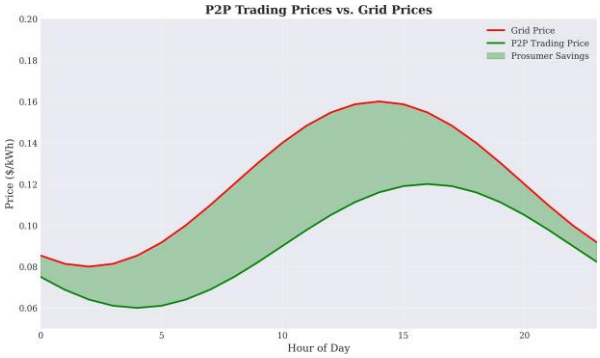

Fig. 6: P2P Trading Prices vs. Grid Prices

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Smart System Lighting with Traffic Analysis Using IoT-Based Adaptive control

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Abstract— Street lighting accounts for a large share of energy consumption in urban areas, especially in developing smart cities where efficient energy use is essential. Traditional street lighting systems operate at a constant brightness throughout the night, regardless of traffic levels or environmental conditions. This often leads to unnecessary energy consumption and higher operational costs. To address this issue, this paper presents an intelligent smart street lighting system that uses traffic density analysis along with sensor-based detection and Internet of Things (IoT) technology. The system automatically adjusts the brightness of street lights based on real-time vehicle movement and pedestrian activity, ensuring both energy efficiency and road safety. The proposed design integrates infrared sensors, a microcontroller-based control system, and wireless communication modules for monitoring and control. A prototype of the system was developed and tested, and the results show significant energy savings compared to conventional street lighting methods. Overall, the proposed system offers a practical, cost-effective, and scalable solution that can be easily implemented in smart city environments to support sustainable urban development. Index Terms— Smart Street Lighting, Traffic Density Analysis, IoT, Embedded Systems, Energy Efficiency, Smart Cities.

I. INTRODUCTION

Street lighting plays an essential role in modern urban infrastructure, as it directly contributes to road safety, efficient transportation, and public security. Proper lighting during nighttime not only reduces the chances of accidents but also improves pedestrian safety and supports better surveillance in both urban and semi-urban areas. However, most conventional street lighting systems operate at full brightness from dusk to dawn, without considering actual traffic conditions. This leads to unnecessary energy consumption, shorter lifespan of lighting equipment, and higher maintenance costs.

Studies on smart city energy usage indicate that street lighting alone accounts for approximately 15–40% of total municipal electricity consumption in many developing regions. This highlights the importance of improving the efficiency of street lighting systems as a key step toward energy conservation and sustainable urban development.

With the rapid advancement of embedded systems, wireless sensor networks (WSN), and Internet of Things (IoT) technologies, it is now possible to design intelligent systems that can adapt to changing environmental and traffic conditions. Smart street lighting systems use sensors, communication modules, and centralized monitoring platforms to automatically adjust lighting levels based on traffic density and pedestrian movement. This not only ensures proper illumination but also significantly reduces energy wastage.

Furthermore, traffic-aware lighting systems enhance performance by estimating vehicle density using sensors such as infrared, ultrasonic, or camera-based systems. These technologies enable real-time control of light intensity, helping reduce carbon emissions and improve overall sustainability. In addition, IoT-based monitoring allows centralized control, predictive maintenance, and remote fault detection, which are essential features for modern smart city infrastructure.

In this context, this paper proposes an IoT-based smart street lighting system integrated with traffic density analysis using embedded control techniques. The system dynamically adjusts lighting levels based on real-time traffic conditions while also supporting centralized monitoring. The proposed approach aims to improve energy efficiency, increase system reliability, and provide a scalable solution for smart city applications.

II. METHODOLOGY

A. Traffic Detection and Data Acquisition

The system employs sensors such as IR sensors or camera modules to detect the presence, speed, and movement of vehicles on the road. These sensors are strategically placed to ensure accurate coverage of different road segments. The system

continuously acquires real-time traffic data, including vehicle count, density, and flow patterns. This data is pre-processed to remove noise and ensure reliability before being sent to the controller for further analysis.[2],[6]

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B. Traffic analysis and Decision-Making

The collected traffic data is analyzed using a defined algorithm to classify traffic intensity into different levels such as low, medium, and high. The system evaluates parameters like vehicle frequency, time intervals, and congestion levels to make intelligent decisions. Based on this analysis, the controller determines the appropriate lighting requirements for each segment. The decision-making process is dynamic and adaptive, allowing the system to respond efficiently to changing traffic conditions in real time.[6],[8]

SMART STREETLIGHTING EFFICIENCY ANALYSIS

Traffic Level	Vehicle Count (per min)	Light Intensity (%)	Current Used (A)	Power Consumption (W)	Energy Saved (%)
No Traffic	0	0% (OFF)	0.00 A	0 W	100%
Very Low	1 – 5	20% (Dim)	0.10 A	2 W	80%
Low	6 – 10	40%	0.20 A	4 W	60%
Medium	11 – 20	60%	0.30 A	6 W	40%
High	21 – 30	80%	0.40 A	8 W	20%
Very High	31+	100% (Full)	0.50 A	10 W	0%

1. Ohm's Law

$$V = IR$$

2. Electrical Power

$$P = VI$$

3. Energy Consumption

$$E = P \times t$$

4. LDR Light Intensity Relation

$$R \propto \frac{1}{L}$$

5. PIR Sensor Output Logic

$$\text{Output} = \{0,1\}$$

6. Data Transmission Rate

$$\text{Data Rate} = \frac{\text{Data}}{\text{Time}}$$

7. LED Efficiency

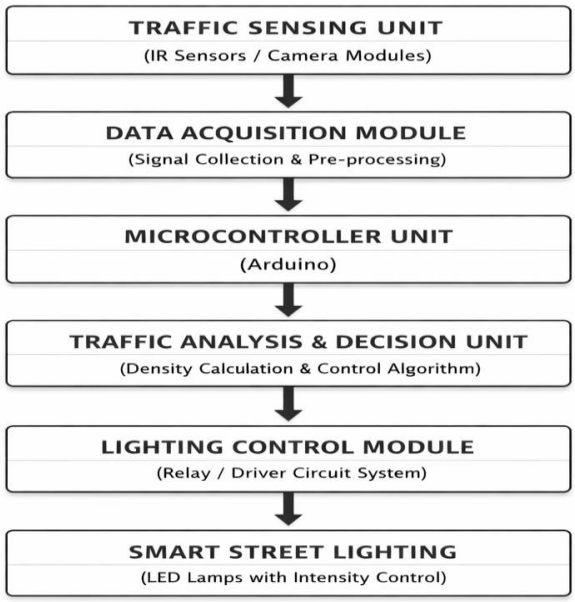
$$\eta = \frac{\text{Light Output}}{\text{Power Input}}$$

8. Energy Saving Efficiency

$$\eta = \frac{\text{Energy Saved}}{\text{Total Energy}} \times 100\%$$

C. Smart Lighting Control and System Integration

The system controls street lighting through a microcontroller-based mechanism that automatically switches lights ON/OFF or adjusts brightness levels. During low traffic conditions, lights operate at reduced intensity to conserve energy, while full illumination is maintained during high traffic for safety. All hardware components, including sensors, controller, and lighting units, are integrated into a unified system for seamless operation. The system ensures continuous real-time performance and can be further enhanced by incorporating IoT connectivity and machine learning techniques for predictive and automated traffic-based lighting control.[2],[7]



III. IMPLEMENTATION

A. Hardware setup and Component Integration

The implementation of the proposed system begins with the integration of essential hardware components including traffic sensors (IR sensors or camera modules), a microcontroller unit (such as Arduino), and LED street lighting units. The sensors are strategically installed along the ರಸ್ತೆ to ensure accurate detection of vehicle movement across different segments. Each sensor is interfaced with the microcontroller through appropriate input ports, enabling continuous signal transmission. The lighting system is connected via output pins with suitable drivers or relays to handle power requirements. Proper circuit design and wiring

are ensured to maintain system stability, reliability, and efficient communication between all components.[5]

B. Software Development and Control Algorithms

The system is programmed using embedded C/Arduino IDE to implement the control logic for traffic-based lighting. A real-time algorithm is developed to process sensor inputs, analyze vehicle presence, and determine traffic density. Based on predefined thresholds, the algorithm classifies traffic conditions and generates control signals for lighting adjustment. The program ensures quick response time and smooth operation by continuously looping through sensor inputs and updating light status dynamically. Error handling and delay optimization techniques are also incorporated to improve system efficiency and avoid false triggering.[2],[6]

Real-time Operation and Lighting control

The implemented system operates in real time by continuously monitoring traffic conditions and adjusting street lighting accordingly. When vehicle movement is detected, the corresponding street lights are automatically switched ON or increased in intensity, ensuring visibility and safety. In the absence of traffic, lights are dimmed or turned OFF to reduce unnecessary energy consumption. The system maintains synchronization between multiple lighting units to provide a seamless lighting experience across road segments. This dynamic response enhances both energy efficiency and operational effectiveness.[1],[4]

.

Testing, Validation, and Performance Evolution

The system is tested under various traffic scenarios such as low, medium, and high vehicle density to evaluate its performance. Multiple test cases are conducted to verify sensor accuracy, response time, and lighting control efficiency. The results demonstrate that the system effectively reduces energy consumption by minimizing idle lighting while maintaining adequate illumination during traffic presence. The implementation is validated for reliability, scalability, and adaptability to real-world conditions, confirming its suitability for smart city applications.[1],[4],[7]

Hardware implementation:

1) *A. Microcontroller Unit*

Arduino Uno microcontroller is used as the central processing unit for sensor data acquisition and lighting control. It provides flexible interfacing capability with sensors and communication modules.

B. Traffic Detection Sensors

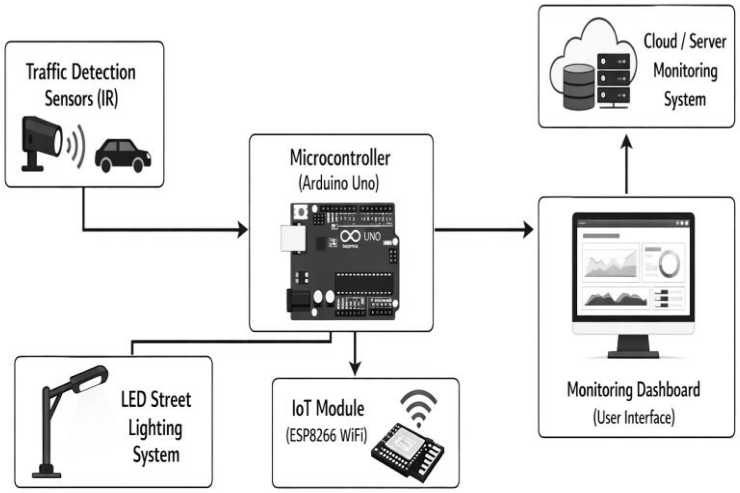
Infrared sensors are deployed along the roadway for vehicle detection and traffic density estimation. These sensors provide reliable detection with low power consumption and simple installation.

C. LED Lighting System

LED street lamps are selected due to their high luminous efficiency, long operational lifetime, and compatibility with brightness control techniques.

D. Communication Module

ESP8266 Wi-Fi module enables wireless communication



IV.SOFTWARE IMPLEMENTATION:

The system software is developed using Arduino IDE embedded programming environment. Sensor inputs are continuously monitored and processed using adaptive control logic algorithms.

IoT platform integration enables:

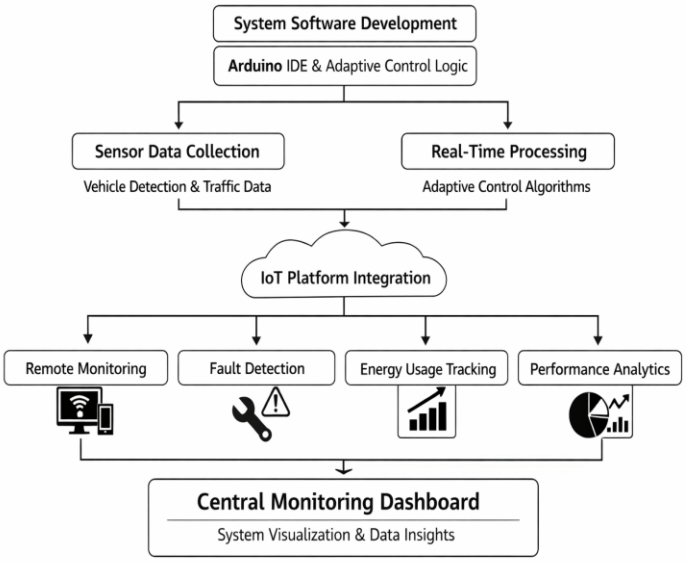
• Remote monitoring

• Fault detection

• Energy usage tracking

• Performance analytics

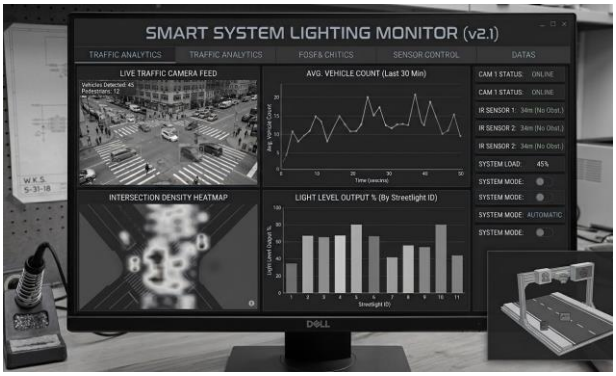
The monitoring dashboard provides centralized visualization of system performance parameters.[2],[7]



V)WORKING

1)Continuous Traffic Monitoring

The system continuously monitors road conditions using sensors such as IR sensors or camera modules installed at specific intervals. These sensors detect the presence, movement, and flow of vehicles in real time. The monitoring process is active throughout the operation, ensuring that no vehicle movement goes undetected. This continuous sensing forms the foundation for intelligent decision-making in the system.[2]



2. Signal Transmission to Controller

Once a vehicle is detected, the sensors generate electrical signals which are transmitted to the microcontroller. These signals indicate the presence or absence of traffic in a particular road segment. The controller receives this input data instantly and prepares it for further processing. Efficient communication between sensors and the controller ensures minimal delay in system response.[5]

3. Real-Time Traffic Analysis

The microcontroller processes the incoming sensor data to evaluate traffic conditions. Parameters such as frequency of vehicle detection, time intervals, and movement patterns are analyzed to determine the level of traffic intensity. Based on predefined conditions, the system classifies traffic into categories such as low, medium, or high. This classification plays a crucial role in deciding the lighting requirements.[6],[8]

4. Decision-Making and Control Logic

After analyzing traffic conditions, the system applies a control algorithm to determine the appropriate lighting action. The decision-making process is dynamic and adaptive, allowing the system to respond to changing traffic conditions efficiently. The controller generates output signals based on the analysis, ensuring that lighting adjustments are both timely and accurate.[6]

5. Automatic Lighting Adjustment

Based on the control signals, the street lights are automatically switched ON, OFF, or dimmed. When traffic is detected, the lights in the corresponding area glow at full intensity to ensure visibility and safety. In contrast, during low or no traffic conditions, the lights are dimmed or turned OFF to conserve energy. This dynamic adjustment significantly reduces unnecessary power consumption.[1],[4]

6. Sequential and Segment-Based Operation

The system operates in a segment-wise manner, where only the lights corresponding to the active traffic zone are illuminated. As vehicles move along the road, the lighting follows them in a sequential pattern. This ensures that only required sections are lit at any given time, enhancing efficiency and creating a smart lighting effect across the

7. Real-Time Response and System Efficiency

The entire system is designed for real-time operation, with minimal delay between traffic detection and lighting response. The fast-processing capability of the controller ensures immediate action, improving system reliability. This real-time responsiveness enhances road safety while maintaining optimal energy utilization.

8. Energy Conservation Mechanism

One of the key working principles of the system is energy optimization. By reducing light intensity or switching OFF lights during idle conditions, the system minimizes energy wastage. This not only reduces electricity consumption but also extends the lifespan of lighting components, making the system cost-effective and sustainable.[1],[4]

9. Scalability and Adaptability

The proposed smart traffic-based street lighting system is designed with a high degree of scalability, enabling its deployment across a wide range of environments, from small

residential streets to large-scale urban road networks and highways. The modular architecture of the system allows additional sensing units and control modules to be easily integrated without significant changes to the existing infrastructure. Furthermore, the system demonstrates strong adaptability to varying traffic densities and environmental conditions. It can dynamically adjust lighting intensity based on real-time traffic flow, ensuring optimal energy utilization while maintaining road safety.

In addition, the design supports future enhancements, including seamless integration with Internet of Things (IoT) platforms. This enables features such as remote monitoring, centralized control, data analytics, and predictive maintenance. Such capabilities significantly improve the efficiency, reliability, and intelligence of urban street lighting systems, making the proposed solution suitable for smart city applications.

The proposed smart traffic-based street lighting system is designed to automatically regulate street light intensity based on real-time traffic conditions. The overall system architecture consists of multiple functional modules arranged sequentially to ensure efficient data processing and control.

The process begins with the **Traffic Sensing Unit**, which is responsible for detecting the presence and movement of vehicles on the road. This unit typically employs infrared (IR) sensors or camera modules to capture traffic information. These sensors continuously monitor the road and generate signals corresponding to vehicle detection and movement patterns.

The sensed data is then forwarded to the **Data Acquisition Module**, where signal collection and preprocessing are performed. This stage involves filtering noise, converting analog signals into digital form (if required), and organizing the data into a structured format suitable for further processing. Proper preprocessing ensures improved accuracy and reliability of the system.

Next, the processed data is sent to the **Microcontroller Unit**, commonly implemented using an Arduino platform. This unit acts as the central processing component of the system. It receives input data from the acquisition module and executes programmed instructions to manage system operations. The microcontroller also facilitates communication between different modules.

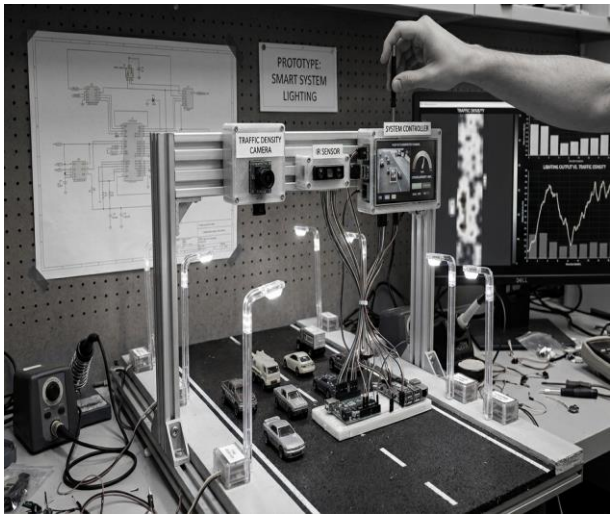
The core functionality of the system lies in the **Traffic Analysis and Decision Unit**. In this stage, the system evaluates traffic density by analyzing the input data. Based on predefined algorithms, traffic conditions are categorized (e.g., low, medium, or high density). The decision-making algorithm determines the appropriate lighting level required for optimal visibility and energy efficiency.

The output from the decision unit is then passed to the **Lighting Control Module**, which consists of relay circuits or driver circuits. This module translates control signals from the microcontroller into electrical actions that regulate the power supplied to the street lights. It enables switching and dimming operations depending on the required illumination level.

Finally, the **Smart Street Lighting System** executes the control commands. LED lamps with intensity control are used to provide adaptive lighting. These lights adjust their brightness dynamically based on traffic conditions, ensuring adequate illumination during high traffic and energy savings during low or no traffic scenarios.

Overall, the system operates in a continuous loop of sensing, processing, analyzing, and controlling. This integrated approach enhances energy efficiency, reduces operational costs, and improves road safety. The modular design also allows for easy upgrades and integration with advanced

technologies such as IoT for remote monitoring and intelligent control.



IV. ADVANATAGES

The proposed system provides multiple benefits:

- Significant reduction in energy consumption
- Increased LED lifetime
- Reduced maintenance requirements
- Improved road safety
- Remote monitoring capability
- Scalable smart city integration

V. APPLICATIONS

The system can be deployed in:

- Smart cities
- Highways

• Residential streets

• University campuses

• Industrial corridors

• Parking facilities

The proposed smart traffic-based street lighting system can be widely deployed across multiple real-world environments due to its flexibility and intelligent control capabilities. In smart cities, it plays a crucial role in reducing energy consumption while supporting sustainable urban infrastructure. On highways, the system ensures enhanced visibility during high-speed traffic conditions by dynamically adjusting light intensity based on vehicle movement.
In residential streets, it provides sufficient illumination only when required, thereby minimizing energy wastage and improving safety for pedestrians and vehicles. University campuses can benefit from this system by ensuring well-lit pathways during active hours while conserving energy during low-traffic periods. Similarly, in industrial corridors, where traffic patterns vary significantly, the system helps maintain operational efficiency and worker safety.
Additionally, parking facilities can utilize this technology to provide lighting only in occupied or active zones, improving both security and energy efficiency. Overall, the adaptability of the system makes it suitable for diverse applications, ranging from low-traffic areas to highly congested zones, thereby contributing to energy conservation, cost reduction, and the development of intelligent and sustainable infrastructure.

VI. Conclusion

In this paper, a smart street lighting system integrated with traffic analysis has been proposed to improve both energy efficiency and traffic management. The system dynamically adjusts street lighting intensity based on real-time traffic conditions, ensuring that adequate illumination is provided when traffic density is high while reducing unnecessary power consumption during low-traffic periods. This adaptive approach not only enhances road safety and visibility for drivers and pedestrians but also contributes to significant energy savings and reduced operational costs.

The results demonstrate that intelligent lighting control can effectively optimize energy usage, making it a valuable solution for modern smart city infrastructure. By minimizing energy wastage and improving responsiveness to real-world conditions, the proposed system supports sustainable urban development and environmental conservation. Additionally, the system's scalability allows it to be implemented in various urban and semi-urban settings with minimal modifications.

Future enhancements may include the integration of advanced sensors, Internet of Things (IoT) connectivity, and machine learning algorithms for more accurate traffic prediction and automated decision-making. Incorporating real-time data analytics, cloud-based monitoring, and predictive maintenance can further improve system efficiency and reliability. Overall, this work highlights the potential of intelligent lighting systems to play a crucial role in building smarter, safer, and more energy-efficient cities.

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Appendix

The authors would like to thank all individuals and institutions who supported and guided this work..

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Subterranean Cable Fault Distance Detection System Utilising a GSM Module

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***Abstract*—Underground cables are widely used in urban power distribution systems due to their reliability and safety. However, detecting and locating faults in underground cables is difficult and time-consuming because the cables are buried beneath the ground. This paper proposes a system for detecting the distance of underground cable faults from the base station using the principle of Ohm's law. When a low DC voltage is applied through the cable, the variation in current caused by a fault is used to determine the distance of the fault from the source point. The proposed system continuously monitors the cable condition and detects faults such as open circuits, short circuits, and abnormal resistance. A GSM module is integrated to send real-time fault information and distance details to a designated mobile number through SMS. The system improves fault detection accuracy, reduces manual inspection, and minimizes maintenance time and cost in underground cable networks.**

Keywords*— Underground Cable Fault Detection, Fault Distance Measurement, GSM Module, Arduino System, Ohm's Law, Real-Time Monitoring.*

INTRODUCTION

Underground cables are widely used in modern power distribution systems, particularly in urban areas, due to their reliability and safety. However, detecting and locating faults in underground cables is difficult because the cables are buried beneath the ground, making inspection and maintenance challenging. Faults may occur due to insulation failure, aging, moisture, or mechanical damage, which can interrupt the power supply and affect system reliability. Various techniques such as the Murray loop test, Varley loop test, and Time Domain Reflectometry (TDR) have been used for fault detection, but these methods often require skilled personnel, expensive equipment, and considerable time for analysis. Therefore, an efficient and automated system is required to detect and locate faults quickly. The proposed system aims to improve fault detection efficiency and reduce maintenance time in underground cable networks.

HARDWARE COMPONENTS

Microcontroller Unit

The system uses an Arduino microcontroller as the main processing unit. It controls the overall operation of the system and processes the input signals received from the sensing circuit. The microcontroller calculates the distance of the cable fault based on the variation in resistance according to Ohm's law.

GSM Module

A GSM module is used for communication purposes. Once a fault is detected, the module sends the fault status and distance information to a predefined mobile number through SMS. This enables real-time monitoring and quick response to cable faults.

Fault Detection Circuit

The fault detection circuit consists of resistors and measurement components that help in detecting variations in voltage and resistance in the cable. When a fault occurs, the change in resistance is measured and used to determine the location of the fau*lt.*

Power Supply Unit

The power supply unit provides the required DC voltage to operate the microcontroller and other electronic components. A stable power supply ensures accurate sensing and reliable operation of the system.

SOFTWARE ARCHITECTURE

Development Environment

The software for the proposed system was developed using the Arduino Integrated Development Environment (Arduino IDE). The program was written in embedded C/C++ and uploaded to the Arduino microcontroller. The development environment allows easy integration of libraries required for serial communication and GSM module interfacing.

Fault Detection Algorithm

The system continuously monitors the cable condition by measuring voltage variations through the sensing circuit. Based on Ohm's law, the microcontroller calculates the resistance of the cable and estimates the distance of the fault from the source point. The calculated distance is then processed and prepared for transmission.

GSM Communication

The GSM module is interfaced with the microcontroller through serial communication. Once a fault is detected and the distance is calculated, the system automatically sends an SMS containing the fault status and location details to a predefined mobile number, enabling real-time monitoring and faster maintenance response.

SYSTEM IMPLEMENTATION AND FAULT ANALYSIS

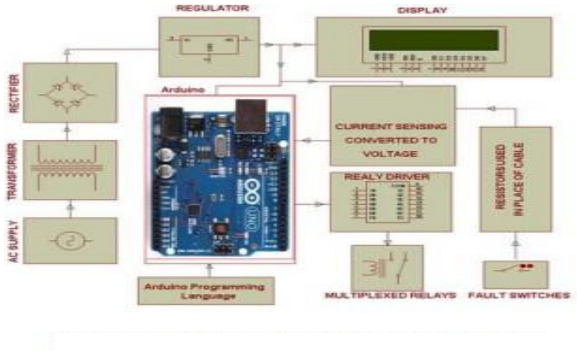

Fig. 1*. Block diagram representing the functional units of the subterranean cable fault detection system.*

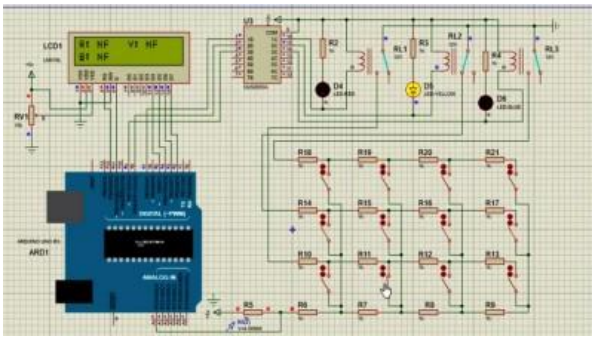

Fig. 2*. Simulation circuit design showing the interfacing of Arduino with the LCD, GSM module, and fault-simulating resistor network.*

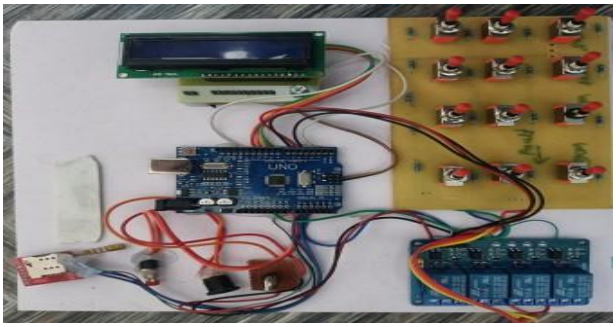

Fig. 3. *Physical hardware prototype of the subterranean cable fault distance detection system.*

Fault Detection Mechanism

The system detects faults in underground cables by applying a low DC voltage through a series resistor. When a fault occurs, the resistance of the cable changes, which results in a variation in voltage. The Arduino microcontroller reads this voltage through its analog input and calculates the distance of the fault from the base station using Ohm's law.

Distance Estimation

The fault distance is estimated based on the resistance of the cable. Since the resistance of the cable is proportional to its length, the system calculates the distance of the fault and displays it on the LCD screen.

GSM Communication

After detecting the fault, the GSM module sends an SMS notification containing the fault status and distance information to a predefined mobile number, enabling quick maintenance and monitoring.

SYSTEM ARCHITECTURE

System Overview

The proposed subterranean cable fault distance detection system consists of an Arduino microcontroller, sensing circuit, GSM module, LCD display, and power supply unit. The microcontroller acts as the central processing unit that receives input signals from the sensing circuit and processes the data to determine the fault location.

Working Principleand Mathematical Model

The system operates based on the principle of Ohm's law. A low DC voltage is applied to the underground cable through a series resistor. When a fault occurs in the cable, the resistance of the circuit changes according to the distance of the fault from the source.

The relationship between the cable resistance (R) and the distance to the fault (L) is governed by the resistivity formula:

$$R = \rho L/A$$

Since the cross-sectional area (A) and resistivity (ρ) of the cable are constant, the resistance is directly proportional to the length.The Arduino microcontroller reads the voltage variation (Vout) through its analog input. This analog signal is processed by the integrated **10-bit Analog-to-Digital Converter (ADC)**, which translates the voltage into a digital value ranging from **0 to 1023**. By applying Ohm's law (V = IR) to this digital representation, the system determines the change in resistance to calculate the approximate fault distance.

The microcontroller reads the voltage variation through its analog input and calculates the corresponding fault distance.

Output and Communication

The calculated fault distance is displayed on the LCD screen for local monitoring. At the same time, the GSM module sends an SMS notification containing the fault information to a predefined mobile number. This enables remote monitoring and faster identification of cable faults.

RESULTS AND DISCUSSION

Table I: *Fault Distance Detection Accuracy*

Fault Type	Actual Distance (km)	Detected Distance (km)	Percentage Error (%)
Short Circuit	2.00	1.98	1.00%
Open Circuit	5.00	5.05	1.00%
Abnormal Resistance	8.00	7.92	1.00%
Short Circuit	10.00	10.10	1.00%

Fault Detection Results

The proposed subterranean cable fault distance detection system was tested under different fault conditions to evaluate its performance. Faults were simulated at various points along the cable using switches in the prototype circuit. When a fault occurred, the Arduino microcontroller detected the voltage variation in the sensing circuit and calculated the approximate distance of the fault based on cable resistance. The calculated distance was displayed on the LCD module, allowing the user to easily identify the location of the fault.

GSM Alert System

After detecting the fault and estimating the distance, the GSM module transmitted an SMS notification containing the fault status and location information to a predefined mobile number. This feature enables remote monitoring and allows maintenance personnel to quickly respond to cable faults. The results show that the proposed system successfully detects faults and provides reliable distance estimation, reducing the time required for manual inspection and improving maintenance efficiency.

CONCLUSION

This paper presented a subterranean cable fault distance detection system utilizing a GSM module for efficient identification of faults in underground cables. The system operates based on the principle of Ohm's law, where variations in cable resistance are used to determine the distance of the fault when a low DC voltage is applied. The Arduino microcontroller processes the measured signals and calculates the approximate fault location. The detected fault distance is displayed on an LCD module and simultaneously transmitted to a predefined mobile number using the GSM module for real-time monitoring. The results demonstrate that the proposed system can effectively detect underground cable faults and provide reliable distance estimation. This method reduces manual inspection, minimizes repair time, and improves the reliability of power distribution systems. In future work, the system can be enhanced by integrating IoT technology for continuous remote monitoring and improved fault analysis.

FUTURE WORK

The proposed subterranean cable fault distance detection system can be further improved by integrating advanced communication and monitoring technologies. In future work, the system can be connected to Internet of Things (IoT) platforms to enable continuous remote monitoring and real-time data analysis. Additional sensors can also be incorporated to detect different types of cable faults with higher accuracy. Furthermore, implementing machine learning techniques could help in predicting potential faults before they occur, improving the reliability and efficiency of underground power distribution networks. The system can also be expanded for large-scale power grid monitoring to support smart grid applications.

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A Hybrid Deep Learning and Reinforcement Learning Framework for Smart Agriculture Using IoT Sensor Data

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Abstract - In order to improve farm management and productivity, this paper suggests a smart agriculture system that uses Internet of Things (IoT) sensors and a hybrid model of artificial intelligence. In the smart agriculture system, Internet of Things (IoT) sensors are deployed in agricultural fields to collect environmental data such as temperature, humidity, rainfall, and soil moisture. To determine the optimal method of watering based on environmental factors, Reinforcement Learning (RL) is used to determine optimal irrigation strategies based on environmental conditions, as demonstrated in recent studies [2], [8]. Convolutional Neural Networks (CNN) are used on drone images to identify pests and diseases in the crop[5], [12]. Random Forest and XGBoost are machine learning algorithms that are used to estimate crop yields [14], [19]. However, Long Short-Term Memory (LSTM) networks are used to predict future weather and soil conditions[15]. In the proposed framework, crop monitoring is improved, and agricultural productivity is increased using smart and automatic farming practices.

I. INTRODUCTION

Agriculture plays a crucial role in the global economy and food supply. However, traditional farming methods face challenges such as inefficient irrigation, unpredictable weather conditions, delayed disease detection, and poor resource management. These issues significantly impact crop yield and sustainability.

The advancement of IoT and Artificial Intelligence (AI) technologies has enabled the development of smart agriculture systems that improve efficiency and productivity [11], [16]. IoT sensors facilitate real-time monitoring of environmental parameters such as temperature, humidity, rainfall, and soil moisture [13]. Machine learning algorithms can analyze this data to support informed decision-making.

This research proposes a hybrid AI-based system combining multiple techniques. CNN is used for crop disease detection using drone imagery [5], [12], while LSTM models predict weather and soil conditions [15]. Crop yield prediction is performed using Random Forest and XGBoost algorithms [14], [19]. Reinforcement Learning is applied for intelligent irrigation scheduling [2], [10]. The proposed system is efficient, user-friendly, and reduces manual workload.

A. Easy Data Collection

In order for the system to automatically collect crucial environmental factors such as soil moisture, temperature, humidity, and rainfall, it installs Internet of Things (IoT) sensors in the agricultural field . These sensors monitor the field conditions and transmit the data collected in real time to a processing unit[11][13].

Human error is eliminated, and manual data collection is avoided through this automated data collection system. This enables farmers to make crucial decisions regarding their crops and irrigation schedules since they are constantly.

aware of the field conditions through the data collected by the sensors.

B. Automated Irrigation Control

The system uses Reinforcement Learning (RL) algorithm to analyze the data collected in real time by sensors and environmental factors in order to optimize water usage[8], [9]. By interacting with the environment and analyzing the results of previous irrigation practices, the RL algorithm learns the optimal methods for irrigation.

The system determines on its own when to start or stop irrigation and how much water is required for the crops, all through this intelligent method of irrigation control. This intelligent system of irrigation ensures that the crops are given the optimal amount of water required for growth, without any waste.

C. Simple Crop Monitoring

For detailed crop health analysis, the proposed system utilizes the combination of Convolutional Neural Network Models and crop monitoring via drones. The CNN model analyzes the images taken by the drones of the crops in the fields, which helps in identifying the signs of infestation by pests, plant diseases, nutrient deficiencies, and abnormal growth of the crops.

Farmers can take corrective measures, such as the application of pesticides, when they identify the health concerns of the crops at an early stage, which helps in increasing the productivity of the crops and prevents the spread of the diseases.

D. User-Friendly Monitoring System

In order for the system to be user-friendly, it provides an intuitive monitoring platform that may be accessed through a web-based dashboard or an application. The platform provides farmers with access to sensor data, crop health reports, weather forecasts, irrigation recommendations, and crop yield predictions[11].

The system provides farmers with an opportunity to visualize their farm conditions and receive automatic alerts for possible problems. Furthermore, farmers can remotely manage their irrigation systems using this user-friendly system despite their lack of expertise.

II. PROPOSED METHOD

The proposed smart system for agriculture uses the concept of Internet of Things technology along with various forms of artificial intelligence in order to create an intelligent system of farming. It includes various factors such as the monitoring of environmental factors, crop factors, upcoming weather patterns, and irrigation factors. The proposed system includes the integration of data collection mechanisms, machine learning, and automated mechanisms in order to make the system efficient.

The workflow of the proposed system includes the integration of data collection mechanisms, data analysis using AI techniques, and intelligent monitoring using the intelligent monitoring system.

A. Data Collection Using IoT Sensors

In the proposed system, the IoT devices are deployed in the agricultural field to monitor the necessary environmental factors that affect the growth of the crops. The IoT devices deployed in the proposed system are used to monitor the moisture level in the soil, temperature level, humidity level, rainfall level, and water level[13].

The data collected by the IoT devices in the proposed system is wirelessly communicated using various technologies such as Wi-Fi, LoRa, or GSM to the cloud or edge computing system as shown in Fig.1.

The real-time data acquisition system helps to monitor the environmental factors in the agricultural field at all times and provide accurate input values to the artificial intelligence algorithms used in the system.

The IoT devices deployed in the proposed system help to collect the environmental factors at all times by avoiding the manual observation of the factors.

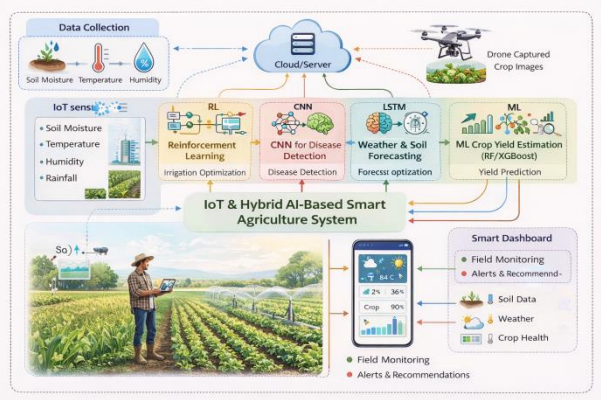

Fig.1.Workflow of hybrid AI-Based Smart Farming Framework.

B. Irrigation Decision Using Reinforcement Learning

Good management of water is one of the significant factors in the current scenario of modern agriculture. In the proposed system, Reinforcement Learning (RL) is employed to achieve the optimal strategy in the management of water considering the current state of the environment[2],[10].

The RL agent senses the current state of the environment, which includes various parameters such as moisture content in the soil, temperature, humidity level, and rainfall predictions. The agent then takes an action based on the sensed state of the environment, such as switching the water supply on or off or adjusting the level of water supply. The agent then collects the reward signal based on the action taken to manage the water optimally as shown in Fig.2.

The proposed system can cope with the changing conditions of the environment with the help of the learning-based approach employed by the RL agent to achieve the optimal strategy in the management of water without any wastage.

Equation (1) is Reinforcement Learning (RL) is one of the learning methodologies by which the learning agent interacts with the environment and achieves the optimal strategy by trial and error with the environment. The main aim of the RL agent is to maximize the reward received from the environment.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_a, Q(s',a') - Q(s,a)] \qquad (1)$$

- ✓ s = current state (soil moisture, temperature, humidity)
- ✓ a = action (irrigation ON/OFF)
- ✓ r = reward obtained from the action
- ✓ α = learning rate
- ✓ γ = discount factor
- ✓ s′ = next state

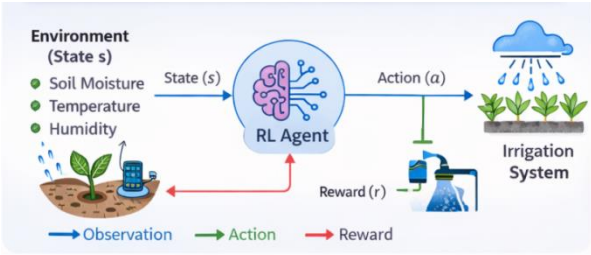

Fig.2.RL Framework for Smart Irrigation Management

C. Crop Disease Detection Using CNN

Detection of diseases in the crop at an early stage is important in preventing any loss in the yield of the crop. In the proposed system, images of the agricultural field are captured using drones with cameras[5],[12].fig.3, These images are processed using a Convolutional Neural Network (CNN) algorithm. This algorithm is used for image classification. In the proposed system, the CNN algorithm is used in which spatial features are used for image classification. These features include different colors, textures, and structures of the leaves. On the basis of these features, the crop is classified into different classes. Once the diseases are detected in the crop, the farmers are alerted, and the action is initiated. In the CNN algorithm, (2) the basic operation is convolution, in which a filter is applied on the image, and the required spatial features are obtained..

$$Y(i,j) = \sum_m \sum_n X(i+m.j+n).K(m,n) \qquad (2)$$

X = input image (crop image)
K = convolution kernel
Y = output feature map

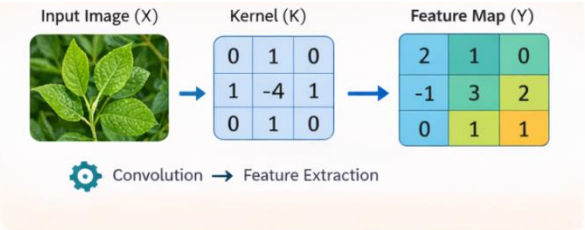

Fig.3.CNN-Based Feature Extraction Using Convolution Kernel

D. Weather and Soil Prediction Using LSTM

The weather conditions and the nature of the soil are factors that affect the crop and the irrigation system. To predict the future weather conditions, the system proposed uses Long Short-Term Memory (LSTM) networks, which are recurrent neural networks[15].

The LSTM network checks the trends of the weather parameters such as the temperature, humidity, and rainfall, as well as the moisture content of the soil as shown in Fig.4. It then uses this information to make predictions regarding the future weather conditions.

This prediction is very useful to the farmer as they can plan the activities to be done in the farm in advance.

Equation (3) is A Long Short-Term Memory (LSTM) network is a type of recurrent neural network that is specifically suited for tasks that involve the prediction of future values in a sequence of numbers. It can be used to make weather forecasts and predictions regarding the moisture content of the soil.

$$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t \qquad (3)$$

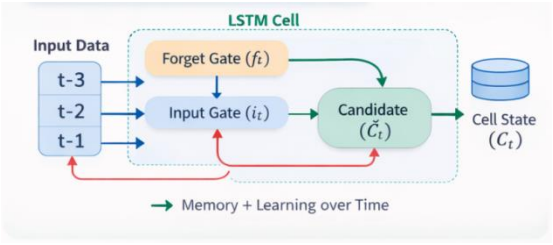

Fig.4.Internal Structure of LSTM Network with Memory Gates

E. Crop Yield Prediction Using Random Forest / XGBoost

Crop yield prediction is one of the significant tasks that needs to be performed in agriculture planning and resource management. In this context, the Random Forest and XGBoost algorithms are used to predict crop yield based on various input parameters.

The algorithms take various parameters such as crop yield, soil conditions, environmental conditions, various parameters associated with the irrigation system, weather predictions, and crop health parameters using the CNN model as shown in Fig.5. The Random Forest algorithm uses the ensemble of decision trees to achieve accurate crop yield prediction without any overfitting problems.

Similarly, the XGBoost algorithm uses the gradient boosting technique to achieve accurate crop yield prediction[14],[19].

Equation (4) is Considering various parameters and their complex relationships, accurate crop yield prediction can be achieved using the Random Forest and XGBoost algorithms.

$$\hat{y} = (1/N)\sum_{i=1}^{N} T_i(x) \qquad (4)$$

N = number of trees

$T_i(x)$ = prediction of each decision tree

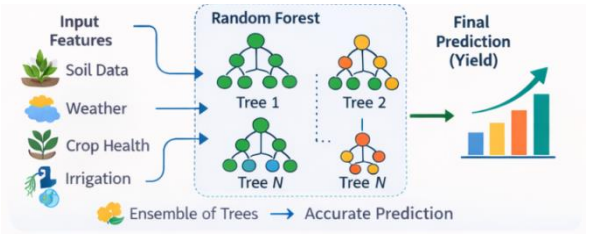

Fig.5.Random Forest Model for Crop Yield Prediction

F. Smart Monitoring and Control System

All the readings, predictions, and analyses of all the sensors are coordinated and integrated through a single platform. The platform could be accessed through a web application or an application installed in the farmer's mobile device. This enables the farmer to monitor the agricultural environment[11].

The platform could display information such as soil moisture levels, soil temperature, soil humidity, rainfall predictions, crop health, crop yields, and other agricultural-related information. The platform could also be used for sending notifications during abnormal circumstances such as water stress, crop diseases, and unusual weather.

The farmer could also be able to remotely manage and control irrigation systems through the platform. This enables the farmer to manage his or her farm effectively through the application of smart monitoring and controlling technology.

Model	Accuracy
CNN	**95%**
LSTM	91%
Random Forest	93%
Reinforcement Learning	90%

Table.1. Expected Accuracy for the Proposed model

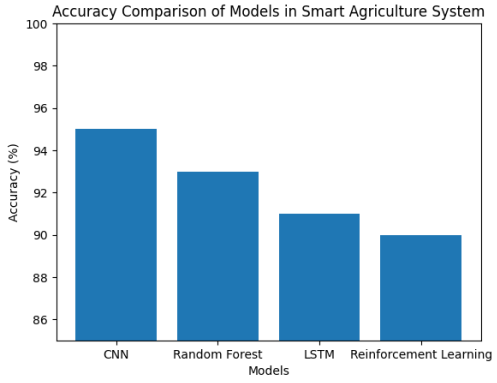

Fig.6. Result

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WasteID: An AI-Powered Smart Bin with IoT Sensors and Blockchain-Based Incentive System for Sustainable Waste Management

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***Abstract*—Urban waste management systems have a problem. People do not separate their waste properly and citizens are not very involved.This paper is about WasteID, a waste bin that uses computer vision and Internet of Things sensors to help people dispose of waste in a responsible way. WasteID also uses blockchain technology to make sure everything is fair and transparent. The system has a camera that can tell what kind of waste people are throwing away like plastic or paper or food waste or metal.It can even weigh the waste. Keep track of who is throwing it away.When people throw away waste they get points as a reward for doing it These points are like a prize for helping to keep the city clean.The points are given out automatically. Everything is recorded so it is fair.This way cities can see what is working and what is not. They can make a plan to pick up waste and recycle more efficiently. The WasteID system shows how artificial intelligence and Internet of Things sensors and blockchain technology can work together to make waste management better. It can even get citizens more involved in recycling which's good for the city. WasteID is a way to think about waste management and it can help make cities cleaner and more sustainable. The WasteID system is a tool for cities that want to manage waste in a better way.**

Keywords—Smart Waste Management, Artificial Intelligence, Internet of Things (IoT), Computer Vision, Blockchain Technology, Waste Classification, Sustainable Cities.

I. INTRODUCTION

Urbanization and population growth are really causing a problem with the amount of waste in cities everywhere. The way we handle waste is not good. It is causing environmental problems. These problems are things like landfills that're too full pollution and health risks. The old way of managing waste relies much on people sorting through waste by hand. It does not do a job of getting people to recycle. So things that can be recycled end up getting mixed in with the waste. This makes it harder to recycle. It puts more pressure on the places that have to process all the waste. Waste management is a challenge. The amount of waste we make is going up fast because of urbanization and population growth. Waste segregation and disposal are not being done correctly. This is causing problems, like landfills that're too full pollution and health risks. The old ways of managing waste are not working well. They need people to sort through waste. They do not encourage people to help with managing waste. As a result things that can be recycled are getting mixed in with the waste. This is making recycling less efficient. It is putting more burden on the facilities that process waste. Urbanization and population growth and waste management are all connected.

Recent advancements in technologies like Artificial Intelligence, Internet of Things and blockchain are creating opportunities for waste management solutions. Artificial Intelligence can automatically classify types of waste materials through image recognition systems. The Internet of Things sensors allow us to monitor waste bins and collection systems in time. We can use blockchain technology to track transactions and distribute incentives in a secure way. These technologies, including Artificial Intelligence and Internet of Things are really improving waste management. Artificial Intelligence and Internet of Things are players in this whole process. Blockchain is also very important, for handling transactions in a safe and secure manner.

This paper is about WasteID, a waste bin system that uses artificial intelligence. It has a few parts that work together like a camera, special sensors and a way to give rewards using blockchain. The camera and some computer models work together to figure out what kind of waste is being thrown away like plastic or paper or food waste or metal. It does this right away. There is also a sensor that measures how much waste is being thrown away.. Before you can throw something away you have to show who you are using a special card or something. Then depending on what you threw and how much of it you get some points that are like a reward for doing a good job with your waste. These points are kept track of using something called blockchain contracts. WasteID is, about helping people throw away their waste in a responsible way.

The objective of this work is to encourage citizen participation in recycling while improving waste segregation accuracy and providing valuable data insights for municipal waste management authorities. By combining intelligent waste classification, secure reward distribution, and real-time monitoring, the proposed system aims to transform traditional waste bins into smart resource management platforms that support sustainable urban development.

II. LITERATURE REVIEW

Waste management is a problem in cities. A lot of people are moving to cities. We are using many things. When we don't throw away waste properly and don't sort it it hurts the environment. We are not good at recycling. Waste management is an issue. So experts are looking into ideas like the Internet of Things, Artificial Intelligence and blockchain to improve waste management. They want to use these technologies to help us take care of the earth and manage waste better. Waste management systems need to get better. We must find ways to be more sustainable with waste management. We have to take care of waste management. It is very important, for us. Waste management is a problem we are facing.

The Internet of Things or IoT has been really important for creating ways to manage waste. These IoT systems usually have sensors in the trash cans that keep an eye on how full they're and send that information to a central place in real time. This helps cities plan the routes for collecting trash save money and make sure the bins do not get too full.. Most of the time IoT systems that monitor waste are mainly concerned with picking up the trash on time rather than making sure the different kinds of waste are separated correctly. IoT technologies like these can be very useful, for managing waste and the Internet of Things is a part of that.

Artificial Intelligence is really good at helping us deal with waste. It can look at pictures. Tell what kind of waste it is, like plastic or paper or glass or metal. This makes it easier to recycle things because it can sort the waste automatically. We do not need people to do it by hand. Artificial Intelligence and deep learning are making this happen. Artificial Intelligence can even work on computers like Raspberry Pi. This is because Artificial Intelligence and deep learning techniques are getting better and better. Now we can use Artificial Intelligence to classify waste on devices. This is a help. Artificial Intelligence is good, at classifying waste. It is making recycling easier.

Waste management is getting a tool. This tool is called blockchain. Blockchain is a way to keep track of things that happen. It is like a book that lots of people can see.. It is not a regular book. It is on computers. It is very safe. Blockchain can help us see what happens to waste. We can use it to make sure people are telling the truth about how they handle waste. It can also help us give rewards to people who do a job with waste. This is done with something called contracts. Smart contracts are like rules that are written into the computer. They say things like "if you do this you get that". So when people do the thing with waste they get a reward. This reward is like a kind of money that exists only on computers. It is called a token. Blockchain and smart contracts can help get more people to participate in taking care of waste. They can also help make sure that people are doing what they are supposed to do. This is good, for waste management programs. It helps make sure that everything runs smoothly and that people are doing the thing. Waste management programs are important. Blockchain can help make them better.

We have made a lot of progress with technology.. Most of the ways we handle waste only deal with one part of the problem. For example some systems only watch how waste we have or they only sort the waste or they only give rewards. We still need a system that does everything. This system would use intelligence to know what kind of waste we have, special bins that can send information and a way to give people incentives to do the right thing, with waste all working together to make a good waste management system. Waste management is what we are talking about here. We need a better waste management system.

III. RELATED WORKS

People are really paying attention to waste management these days. The reason is that we have a lot of waste and we need to make our cities more sustainable. Some people who study waste management have looked into using tools, like computers and machines that can think to help with waste management. They want to use these tools to make waste monitoring and segregation and recycling of waste work. Waste management is very important because we need to deal with waste. People who work on waste management are working hard to make it better. Waste management is a problem and we need to solve it.

People did some research on waste management systems that use Internet of Things technology. These systems usually have sensors, inside the waste bins to check how full they are and send the information to a place so they can pick up the waste at the right time. This helps stop the bins from getting too full and makes it easier to collect the waste but smart waste management systems often do not have a way to sort the waste. Smart waste management systems are helpful. They need to get better at sorting the waste in smart waste management systems.

More recent studies are using Artificial Intelligence and deep learning to classify waste materials Convolutional Neural Networks have been widely used to detect and categorize waste types such as plastic, metal, paper and glass from images. These Artificial Intelligence systems make recycling more efficient by automating waste segregation and reducing the need, for sorting. This helps to improve the recycling process.

Blockchain is being used to make waste management systems. It helps people trust the system and makes it more open. Blockchain is a way to keep track of what happens to waste. It makes sure that records of waste disposal are safe and cannot be changed. This can help recycling programs that reward people for doing the thing. Blockchain uses something called contracts to give rewards to people who recycle. This encourages people to be kind, to the environment. Blockchain and waste management systems can work together to make things better. Blockchain is a part of making sure waste management systems are honest and fair.

People have been trying to bring these technologies to make smart waste management systems. For example some people thought of a way to reward people for recycling They suggested that people should get tokens or credits when they throw away waste properly. This way more people will take part in waste management projects. Smart waste management platforms are what these systems are called. These platforms are trying to make waste management better by using technologies like digital tokens, for proper waste disposal, which is a big part of smart waste management platforms.

Although these approaches have shown results many existing systems only focus on monitoring with IoT or classifying waste with AI. They do not have a reward system or a secure way to manage data. So we need a system that combines AI to identify waste IoT to sense the waste and blockchain to give rewards. This will make people participate more in recycling and ensure transparency. The WasteID system solves these problems by combining these technologies into one waste bin platform. It is designed to manage waste in a sustainable way.

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IV. Proposed Method

A.TECHNOLOGY STACK

The new WasteID system for managing waste is really smart. It uses a lot of technologies like computers and special sensors to sort waste automatically. The WasteID system also helps keep user information safe. It rewards people for recycling. The WasteID system is made up of things, like computers, special cameras, sensors that can connect to the internet and special kinds of online record systems. The WasteID system uses all these things to make waste management better.

- Hardware Components

The smart bin system has a hardware part that provides the setup. A Raspberry Pi or NVIDIA Jetson Nano acts as the main computer to handle image data and manage the system. This computer works with a camera that takes pictures of the waste people put in. The camera helps classify the waste. A load cell sensor is also used. It measures how much the waste weighs. This is important to calculate rewards. An RFID or NFC reader is included for user identification. This way the system can link waste disposal to users. The system uses servo motors to control the bin parts. These parts sort waste based on what the system identifies it as. The smart bin uses a Raspberry Pi or NVIDIA Jetson Nano to work. The smart bin has a camera to classify waste. The smart bin uses load cell sensor to measure waste. The smart bin uses RFID or NFC reader for user authentication. The smart bin uses servo motors to separate waste.

- Software Technologies

The system software is made using Python because it has a lot of tools, for machine learning and computer vision. We use OpenCV to get and prepare images like making them smaller and more normal. The system software uses Python for this. We make the user interface and the monitoring dashboard using things like HTML and CSS and JavaScript. This way we can watch the system software in time and see the data in a nice way. The system software has a user interface and a monitoring dashboard.

- Machine Learning Frameworks

The waste classification model uses deep learning frameworks like TensorFlow or PyTorch. This is how it works: a Convolutional Neural Network architecture is trained on pictures of waste that have labels. The pictures help the waste classification model learn to recognize kinds of waste materials.
To make sure the waste classification model works fast and does not need a lot of power we use models like MobileNet or Tiny YOLO.These smaller models are good, for edge computing devices. Can make decisions in real time about the waste classification model. The waste classification model is important because it helps us with the waste classification model.

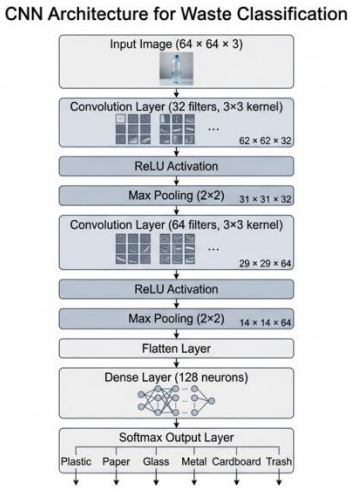


Fig1:Convolutional layer

- IoT and Communication

The Internet of Things is used by the system to send information between the smart bin and the people who are in charge of the monitoring platforms. The smart bin and the parts that sort things have sensors that collect information. This information is kept in databases on the cloud or on servers so we can look at the information, from the bin more closely later. The smart bin and other devices can talk to each other using the Internet of Things like the Internet of Things communication protocols MQTT or the Internet of Things communication protocols HTTP APIs.

- Blockchain Platform

To make sure everything is fair and safe when giving out rewards we use blockchain technology. We put computer programs called smart contracts, on the Polygon blockchain network. These contracts help keep track of when things get disposed of and give eco-tokens to users. This way we have a record that can't be changed and users can see how many rewards they have got through a mobile app. The blockchain technology helps to keep everything secure. Users can track their eco-tokens and recycling rewards easily.

The use of these technologies makes it possible to create a waste management system that can be used by a lot of people. This system is smart and easy to understand. It helps to make recycling and gets people to take part in disposing of waste in a way that is good for the environment. The smart waste management system is very good at helping people to recycle. It also helps people to get involved in sustainable waste disposal practices. The smart waste management system is important, for recycling efficiency and sustainable waste disposal practices.

Class	Number of Images	Description
Plastic	400	Bottles, containers
Paper	400	Newspapers, sheets
Glass	400	Glass bottles
Metal	400	Aluminium cans
Cardboard	400	Boxes and packaging
Trash	500	Mixed waste materials

Table 1. Waste classification dataset description

Component	Technology Used	Purpose
Controller	Raspberry Pi	Main processing unit
Camera	Pi Camera Module	Capture waste images
AI Framework	TensorFlow / PyTorch	Train CNN model
Image Processing	OpenCV	Preprocessing images
Authentication	RFID Reader	User identification
Sensor	Load Cell Sensor	Waste weight measurement
Blockchain	Polygon	Reward distribution

Table 2. Technology stack used in the proposed system

B.WORKFLOW

The WasteID system is made to help people sort out waste and throw it away in a way. It uses Artificial Intelligence, Internet of Things sensors and a special kind of reward system that is fair and safe. The WasteID system has parts that work together like checking who the users are finding out what kind of waste they have using computer vision weighing the waste stopping people from cheating and giving out rewards. The way the WasteID system works makes sure that waste is sorted out correctly users are who they say they are and rewards are given out in a way that everyone can see and trust the WasteID system.

1. User Authentication Module

The smart bin system starts by checking who is using it. This is done with a reader that can tell who people are. The reader checks the users card or phone to make sure they are who they say they are. When someone uses their card or phone the system looks up their user ID. Lets them start getting rid of their trash. There is a screen that shows the user what is happening like if they can use the smart bin or how many reward points they have. The system also makes sure that one person can use the smart bin at a time so people cannot try to cheat the system. The smart bin system does this to prevent people from doing things when they are using the smart bin.

2. Image Acquisition and Waste Detection

When you log in you place the waste item in front of the camera on the smart bin. The camera takes a picture of the waste item. Then a small computer, like a Raspberry Pi or an NVIDIA Jetson Nano processes this picture of the waste item. This computer model is trained to sort the waste item into categories like plastic or paper or metal or glass or cardboard or food waste. The model looks at the picture of the waste item. Figures out what type of waste item it is. This step is important because it helps the smart bin system know where to put the waste item.
The waste item gets sorted into the compartment for disposal based on what the model predicts about the waste item. The smart bin uses this information, about the waste item to manage the waste item.

3. Waste Segregation and Bin Control

On the basis of this classification, which is produced by the AI model, the system automatically places the waste item in the appropriate compartment of the bin. This is achieved by using servo motors or automated lids, which are opened by a microcontroller interface to open up the compartment that is required based on the type of waste item that is to be discarded. This is a very efficient system of segregation between recyclable and non-recyclable materials.

4. Weight Measurement and Credit Calculation

The load cell sensor, which is embedded in the bin, is responsible for measuring the weight of the disposed waste material. This sensor is capable of converting the applied force into an electrical signal, which is then processed by the system to obtain the weight of the deposited item. A certain weight, such as 50 grams, is established to avoid any kind of misuse of the system by depositing very small amounts of waste material. After measuring the weight, a formula is defined to allocate credit points based on the type of waste and its weight.

5. Fraud Detection Mechanism

In order to avoid exploitation of the reward system, several methods of detecting fraudulent activities are put in place. One such technique used in image similarity analysis is to prevent the repeated disposal of the same object. Moreover, daily usage limits and velocity rules restrict the number of times a user can deposit waste within a given time frame. Tamper detection sensors are used to prevent any fraudulent attempts to access the bin.

6. Blockchain-Based Reward System

After the validation of the waste deposit, the reward allocation process is implemented by a blockchain-based system. Smart contracts on a blockchain platform like the Polygon network can be utilized for the allocation of eco-tokens to users. The transactions will be recorded on the ledger of the blockchain platform for transparency and security. Users can also access the reward points they have earned by a mobile application or wallet interface.

7. Data Monitoring and Analytics Dashboard

All the waste disposal transactions are recorded and stored in a centralized database for monitoring and analysis purposes. A web-based dashboard is created to obtain real-time information regarding the patterns of waste collection, usage statistics of waste bins, and recycling patterns. The municipal authorities can utilize the obtained information to optimize waste collection, develop effective recycling mechanisms, and monitor the performance of the smart waste bins.

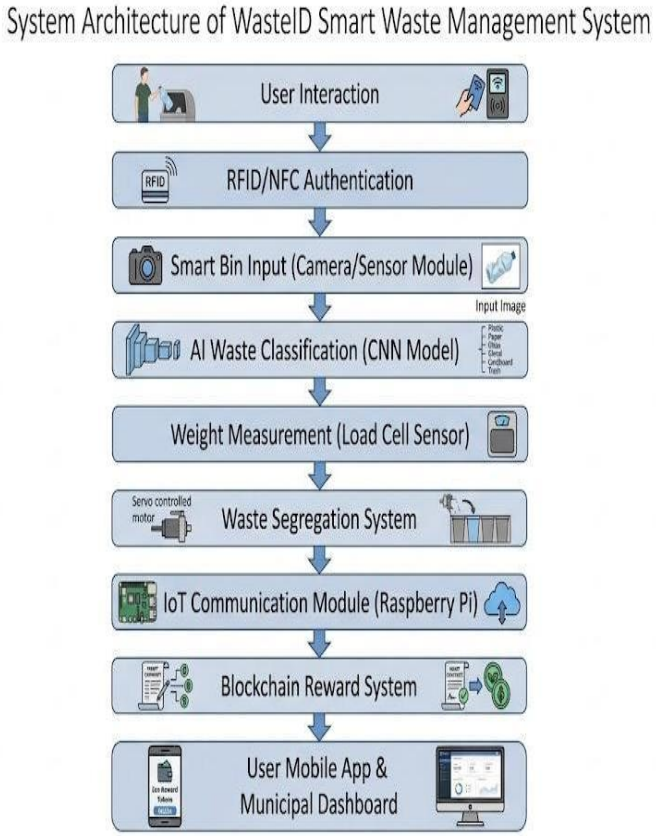


Fig 2.Workflow

The integration of AI-based waste recognition, IoT sensor networks, and blockchain-based incentives provides a comprehensive framework for a smart waste management system. This approach enables precise waste segregation, promotes citizen involvement through incentives, and provides valuable insights for urban waste management systems.

The proposed WasteID system utilizes AI-based waste classification, IoT technology, and blockchain technology to develop a smart waste management system. The overall system architecture is shown in Fig. 1 .

V. RESULTS

The performance of the proposed WasteID smart waste management system was evaluated using a trained Convolutional Neural Network (CNN) model for waste classification. In this case, the model was trained using labeled waste image datasets, and then it was tested using unseen data to measure the efficiency of the model in classifying waste accurately.

When we looked at the experiment we split the data into two parts for training and testing. We did this in a way, where 80 percent of the data was for training and 20 percent was for testing. The CNN model was taught to recognize kinds of waste such as plastic waste, paper waste, glass waste, metal waste, cardboard waste and general waste. The CNN model is really good at recognizing these types of waste it gets it right about 92 percent of the time. This means the CNN model can tell what kind of waste something is, even if it is, in places or situations.

The classification model was looked at closely to see how well it worked. This was done by using things like precision and recall and F1-score to evaluate it. The results showed that things like plastic and metal and glass were recognized accurately because they look really different. On the hand things like general trash were not recognized as well because they look really different from one piece to another. The classification model did a job with recyclable materials, like plastic and metal and glass.

The system was tested for how it classifies things and also for how long it takes to respond. When we used the system to detect and classify waste it took 0.7 seconds per picture when it was running on a special kind of computer called an edge computing device. This means the system can identify waste as soon as it sees it, which makes waste detection and classification by the system a good choice for use in smart bins that people actually use. The waste detection and classification system is really good, for bin deployment because of this.

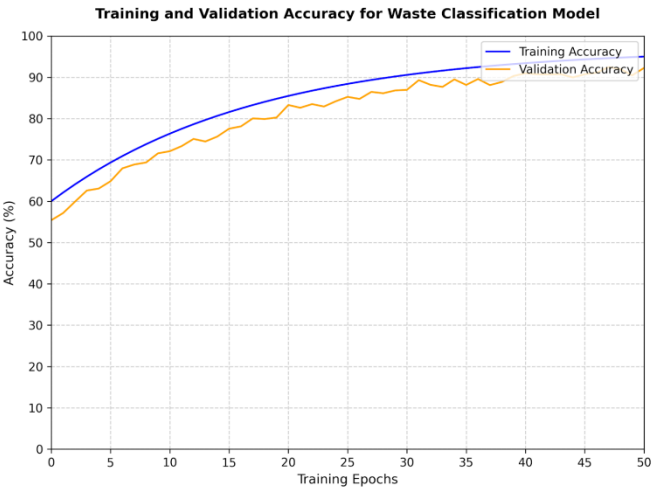
The load cell sensor did a job of measuring the weight of the things people threw away. This made it possible to figure out how reward points someone should get based on what kind of waste they deposited and how much it weighed. The load cell sensor and the system worked well together. The part of the system that used RFID to check who people were worked well too. It was able to tell who was allowed to use the system and who was not. This kept people from getting into the system when they were not supposed to. The system also had some things that helped prevent cheating. For example it checked to make sure things weighed what they were supposed to. The system also looked at pictures to make sure they were not trying to trick it. All of these things helped make the system more reliable and worked well with the load cell sensor and the RFID-based authentication module.

The blockchain technology makes sure that rewards are given out in an transparent way. Each time someone disposes of something it is written down on the blockchain ledger. This lets users see their eco-points in a wallet. The blockchain technology helps people trust the system and want to participate in recycling. People are more likely to recycle because they can see that the blockchain technology is fair and transparent. The blockchain technology is really important, for making sure that everything works correctly.

Overall the results from our experiment show that WasteID works well. It can correctly identify types of waste. The system also keeps user transactions This makes it a useful tool for improving how cities manage waste. The WasteID system provides incentives that actually work. This can help make urban

waste management better. The WasteID system is good, at classifying waste materials. It helps users by giving them reasons to manage waste properly. WasteID makes urban waste management practices better. The system securely manages user transactions for WasteID.

The accuracy of the waste classification model was checked during training and validation to see how well it performed. The models accuracy was tracked over training sessions. This information is shown in Figure 3. The waste classification models performance was evaluated using its training and validation accuracy. The accuracy changed over training



sessions.

Fig 3. Training and Validation Accuracy for Waste Classification Mode

Metric	**Value**
Accuracy	92%
Precision	0.91
Recall	0.90
F1 Score	0.90
Average Detection Time	0.7 sec

Table 3. Performance evaluation of the waste classification model

V.Comparative Analysis with Existing Methods

To see how well the WasteID system works we looked at how it compares to smart waste management systems that have been studied before. We compared the WasteID system to these systems in a few important areas, such as how well they can sort out different types of waste how they use sensors to keep an eye on things how they encourage people to participate and how open they are with the information they collect. The WasteID system is what we are really interested, in so we wanted to make sure we understood how it stacks up against the systems. We compared the WasteID system to the systems to find out what works and what does not.

Traditional waste management systems mostly depend on people sorting waste by hand and ways to keep track of it. This often causes recycling to be not efficient and more waste to end up in landfills. Smart bin systems that use the Internet of Things have made waste collection better. They use sensors to check how full the bins are. This helps make the collection routes more efficient. Many of these smart bin systems do not have a way to automatically sort waste. They also do not let users participate in the process. Waste management systems need to use technology to make recycling work. They should help people sort waste correctly. The smart bin systems should be able to classify waste on their own. They should also encourage people to take part in waste sorting. This would make waste collection more efficient. It would also help increase recycling rates.

People have been studying how to use Artificial Intelligence to sort out trash. They are using something called Convolutional Neural Networks to look at pictures of waste and figure out what kind of material it is. This helps to separate the trash.. The problem is that these systems do not have a way to reward people for helping to sort out the trash. On the hand some websites that use blockchain to help with recycling do give rewards to people who recycle. However these websites do not have a way to automatically detect what kind of trash is being thrown away or to use trash cans that can help with this process. Artificial Intelligence and blockchain can both be used to help with recycling. They are not often used together.

The new WasteID system uses a lot of technologies. It has intelligence to sort out the waste, internet connected sensors to keep an eye on things radio frequency tags to check who the users are and a special kind of online ledger to give out rewards. This way of doing things solves problems that other systems have. The WasteID system can automatically find out what kind of waste it is, it can give out rewards in a way and it can monitor everything in real time. The WasteID system puts all these things together in one place.

The comparison of the proposed system with existing approaches is presented in Table 1.

System Type	**IoT Monitoring**	**AI Waste Classification**	**Reward System**	**Blockchain Transparency**
Traditional Waste Management	No	No	No	No
IoT Smart Bin Systems	Yes	No	No	No
AI Waste Classification Systems	No	Yes	No	No
Blockchain Recycling Platforms	No	No	Yes	Yes
Proposed	Yes	Yes	Yes	Yes

WasteID System				

Table 4. Comparison of Waste Management Systems

From what I can see the new system brings together cutting-edge technologies to fix the problems with current waste management systems. The WasteID system uses Artificial Intelligence, Internet of Things and blockchain technology to create a platform that is transparent and encourages people to participate. This platform can really boost recycling rates. Make waste sorting more efficient in cities. The WasteID system does this by combining these technologies. It provides a platform that's intelligent, transparent and incentive-driven. The result is recycling participation and waste segregation efficiency, in urban areas. The proposed system, WasteID makes a difference by using AI, IoT and blockchain.

VI. Conclusion

This paper introduced WasteID, a waste management system that helps sort waste properly and encourages people to dispose of it responsibly. The system uses computer vision, Internet of Things sensors and blockchain technology to manage waste in an transparent way. It uses a type of intelligence called Convolutional Neural Network to classify waste into different types, like plastic, paper, metal and glass right away. The system also has load-cell sensors that accurately measure how waste there is. WasteID uses RFID authentication to make sure users are identified securely when they dispose of waste. The system helps with waste segregation and responsible disposal practices. WasteID is an AI-powered solution that makes waste management efficient.

The system uses a blockchain-based reward system. This makes transaction records clear and hard to alter. People get eco-reward points for throwing away waste. This encourages people to join in recycling and taking care of waste in a sustainable way. The test results show that the system works well. It can classify things accurately and fast. This makes it suitable for use in city settings. The system helps with recycling and waste management. It gives people points for being eco-friendly. The blockchain technology ensures that the records are transparent. This makes the system trustworthy. The eco-reward points motivate people to participate. The system is efficient. Can process things in real-time. It is a solution, for smart cities.

The WasteID system is really good at showing how Artificial Intelligence, Internet of Things and blockchain can work together. This can change the way we use waste bins. We can make them smarter. Help manage resources better. The WasteID system does a things. It helps us waste better. It also teaches people about the environment. Gets the community involved in disposing of waste in a sustainable way. The WasteID system is a tool, for sustainable waste disposal because it makes people more aware of the environment and gets them to work together.

The waste classification system can be made better in the future. This can be done by adding things to the waste classification dataset. We can also make the model more accurate by using deep learning architectures. The system can also use cloud-based analytics to work in big cities. The system can also work with applications and smart city platforms. This will help users get feedback away and manage rewards in a better way. The waste classification system will be able to do all these things. That is a good thing, for the waste classification system.

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AI-Driven Distributed Unmanned Aerial Vehicle (UAV) Swarm System for Early Low-Altitude Missile Detection and Predictive Interception Support

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***Abstract*—Low-altitude missile threat detection still presents a significant challenge for air defense systems, which can be attributed to terrain masking, radar horizon, and the reaction time for intercepting the threat. Existing detection systems for missile threats include ground-based radar, airborne surveillance, and satellite monitoring, which may not be efficient in detecting fast-moving targets flying at low altitude over the ground. This paper proposes an AI-Driven Distributed UAV Swarm System, which can be used for improving the early warning system and the reaction time for air defense against missile threats. In the proposed system, a set of fixed-wing drones are used in a layer-wise patrol formation with staggered altitude levels for a distributed early warning detection system for air defense against missile threats. Each drone works as a node in a swarm network, which can be used for multi-node verification of the threat, mesh communication, and satellite-based communication for sending information regarding the threat. Thermal infrared detectors and computer vision algorithms are used for detecting potential missile threats, which are then verified using artificial intelligence algorithms for predicting the path of the threat based on information from drones, satellite monitoring, and other sources of surveillance.This proposed framework shows how UAV swarm intelligence, combined with AI-based predictive analytics, could greatly improve the detection reliability, reaction time, and interception readiness for an air defense system against missile threats.**

Keywords—Unmanned Aerial Vehicles (UAVs), UAV Swarm Systems, Low-Altitude Missile Detection, Swarm Intelligence, Multi-Sensor Data Fusion, Artificial Intelligence, Predictive Trajectory Estimation, Early Warning Systems.

I. INTRODUCTION

The contemporary air defense systems are encountering more challenges when it comes to detecting and responding to missile attacks at low altitudes. The modern missile systems are capable of moving at extremely fast velocities, coupled with their ability to maintain their flight altitudes at very low levels in order to avoid detection. The traditional air surveillance systems, including ground-based radar systems, airborne early warning aircraft, and satellite surveillance systems, play a critical role in detecting missile attacks. However, these systems are often characterized by several challenges, including terrain masking, radar horizon, and delays in detecting fast-moving targets. The above challenges reduce the response time for reacting to missile attacks, thus increasing the penetration of such attacks into protected zones.

The recent innovations in artificial intelligence systems, coupled with unmanned aerial vehicle (UAV) systems, have provided new possibilities for enhancing early warning systems. The UAV systems can be employed for surveillance, and their swarm intelligence can be utilized for cooperative surveillance.

Following the developments in these directions, this paper introduces a novel AI-based Distributed UAV Swarm System that can detect low-altitude missile threats at earlier stages and aid the predictive intercept of these threats. The novelty of this work is the introduction of a distributed aerial surveillance

system that uses swarm intelligence, multi-sensor fusion, and predictive trajectory estimation to detect missile threats at early stages. The proposed framework includes UAV Swarm Surveillance, Multi-Sensor Fusion, and Artificial Intelligence-based trajectory prediction. The proposed framework aims to improve threat verification, increase awareness, and provide reaction time for the defense systems.

II. RELATED WORKS

Recent developments in the fields of artificial intelligence, autonomous systems, and surveillance systems have shown great potential for enhancing early warning systems for potential threats. Recent research in unmanned aerial vehicle systems, swarm intelligence, and multi-sensor fusion has shown great potential for enhancing early warning systems for potential threats.

A. UAV-Based Surveillance Systems

Unmanned aerial vehicle-based monitoring systems have widely been used for surveillance, reconnaissance, and monitoring due to their mobility and capability of operating in harsh environments. Monitoring systems for unmanned aerial vehicles provide real-time monitoring over a wide area, thus being highly efficient for monitoring a wide area in real-time. Recent research on unmanned vehicle networks for border surveillance, disaster monitoring, and security operations has shown great potential for enhancing early warning systems for potential threats. However, existing unmanned vehicle-based monitoring systems have widely been used for individual monitoring rather than cooperative monitoring, which is highly useful for enhancing early warning systems for potential threats.

B. Swarm Intelligence and Distributed Monitoring

Swarm intelligence is a new paradigm by which a number of autonomous agents can coordinate their efforts and perform a task collectively. Swarm intelligence is a new form of intelligence inspired by the behavior of ants and birds. Swarm intelligence algorithms enable a number of UAVs to share information and adapt to a changing environment. Swarm robotics research has shown that the use of a number of UAVs for a distributed monitoring task can improve the coverage, redundancy, and fault tolerance of the system. Most swarm-based systems have been designed for area coverage rather than for the detection of high-speed aerial attacks.

C. Multi-Sensor Fusion for Threat Detection

Multi-sensor fusion is a popular technique used in modern defense systems for integrating data from different sources. Typically, ground radar, airborne surveillance systems, and satellite systems are integrated for detection of aerial threats. Researchers have also used infrared detection systems and computer vision techniques for object detection based on heat signatures and movement patterns. Artificial intelligence techniques, such as deep learning and probabilistic models, are also used for false detection rate minimization and detection accuracy improvement. However, most of the techniques used for detection are based on ground systems, which may not be sufficient for detection in complex terrain environments for low-altitude threats.

To overcome the above issues, the proposed system provides a novel solution based on a distributed UAV swarm system that incorporates cooperative sensing, multi-sensor fusion, and artificial intelligence-based trajectory prediction. This will improve the overall detection capability for low-altitude missiles with the help of satellite systems for early detection and reaction times.

D. Advantages

- Distributed Early Warning Coverage: The UAV swarm system facilitates wide area monitoring via multiple cooperating nodes in the air. This facilitates early detection of low-altitude threats.
- Improved Detection Reliability: The system uses multi-sensor fusion of various nodes to improve detection reliability and reduce false alarm probability.

E. Limitations

- Sensor Payload Constraints: The lightweight nature of these platforms limits their payload capacity for onboard sensors.
- Environmental and Operational Challenges: Environmental and operational challenges may affect the reliability of the system.

The rest of this paper is divided into the following sections. Section III: Proposed Methodology and System Architecture of Distributed UAV Swarm. Section IV: Evaluation Framework and System Analysis. Section V: Conclusion of the Paper.

Recent research indicates an increased need to address the importance of integrating UAV coordination with multi-sensor fusion and AI-based prediction for improving early warning and situational awareness. This system has shown improved capabilities for detecting and responding to low-altitude aerial threats.

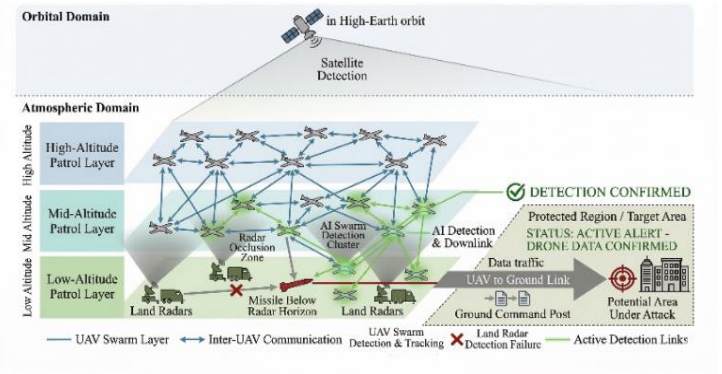

Fig. 1. Conceptual architecture of the proposed AI-driven distributed UAV swarm system for early low-altitude missile detection and predictive interception support.

III. PROPOSED METHOD

A. System Architecture

The proposed system architecture involves an AI-based distributed UAV swarm system. This system aims to enhance early detection of low-altitude missile threats and improve predictive interception capabilities. The system comprises different layers of sensors. These include satellite monitoring, a distributed UAV swarm system, and a ground command and control center. The system operates by integrating these different layers of sensors to form an early warning system for potential missile threats.

In the orbital domain, satellite monitoring detects potential missile launches over a wide area of geography. This detection occurs by monitoring infrared heat signatures emitted during rocket propulsion. Once a potential missile launch is detected by satellite monitoring, the system sends an alarm to the UAV swarm system operating in the atmospheric domain. The UAV swarm system comprises multiple fixed-wing drones flying in layered patrol formations over different altitude levels.

The UAVs function as a distributed sensor grid and facilitate communication between different drones with the aid of a mesh network. The drones function as intelligent nodes with the capacity to sense information and share this information with other drones. This information is then relayed to the ground command center. The various layers of the drones ensure that they detect hidden threats that cannot be seen by the radar horizon of conventional radar systems.

B. UAV Swarm Deployment Strategy

In order to achieve maximum detection coverage and minimize blind spots, the system deploys the UAVs in various altitude-based patrol layers. This implies that the system has high-altitude UAV formations, mid-altitude UAV formations, and low-altitude UAV formations. Each of the formations is responsible for surveilling a specific part of the airspace.

The UAVs within a given altitude-based patrol layer maintain a collaborative patrol pattern and constantly share information through inter-UAV communication links. This swarm-based communication between the drones enables them to verify detected suspicious targets collectively. In this regard, if a UAV identifies a suspicious object that may be a missile, other nearby drones will try to verify the detected object using their respective sensors. This approach minimizes the occurrence of false alarms.

In order to ensure the continued surveillance coverage by the swarm of the UAVs, the swarm makes use of a rotating patrol batch system. In this system, the swarm is divided into various batches where one batch is actively involved in the aerial surveillance, while the other batches are kept on standby or are returning for charging and other maintenance purposes. When the batch actively involved in the patrol is nearing the end of its energy capacity for continued patrol, a standby batch is deployed to take over from the active batch before the energy capacity is depleted. The batch that is being replaced returns to the base station for charging and other system maintenance purposes.

Example of the rotating patrol batches:

- Batch A – actively involved in the patrol and surveillance of the region
- Batch B – returning to the base station for charging and other system maintenance purposes
- Batch C – standby batch waiting to take over from the actively involved batch

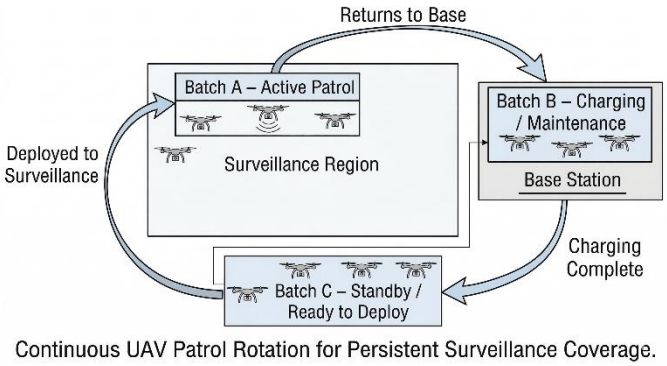

Fig. 2. UAV swarm patrol batch rotation mechanism for providing uninterrupted surveillance coverage.

C. Multi-Sensor Detection and Data Fusion

In the proposed system, a multi-sensor approach for improving the accuracy of threat detection is used. In this approach, a set of different sensors are used for improving the accuracy of threat detection. A set of sensors, such as thermal, optical, and radar, are used in the proposed system for improving the accuracy of threat detection. Thermal sensors are used for improving the accuracy of threat detection because the heat generated by a missile can be sensed even in environments with low visibility, such as in a foggy or smoky environment or at night.

The information collected from a set of drones, which includes information collected from different sensors, is shared with other drones in the swarm network and then sent to the command center for analysis using artificial intelligence algorithms for improving the accuracy of threat detection through a multi-sensor approach, which includes information collected from a set of drones, a satellite, and a ground radar system.

D. Predictive Threat Analysis and Interception Support

Once a potential missile threat has been identified, the system makes use of artificial intelligence models for predictive analysis of the threat's trajectory. These models are used for predicting key parameters, such as the velocity, direction, and flight path of the identified missile threat. With this information, the command center can estimate the potential impact region of the identified threat.

To further enhance the reaction time for the command center, the system makes use of early preparation of the interceptors even before the threat is confirmed. This way, the radar systems and interceptors are in a ready state, while further observations from other UAVs are made for the identified threat object. Once the threat object is confirmed through multiple node verification, the command center can immediately launch the interceptors for dealing with the identified threat.

With the use of multiple components, such as distributed UAVs, swarm intelligence, multiple sensor fusion, and predictive threat analysis, the proposed architecture can significantly enhance the early detection of identified threats for a command center's reaction time.

IV. ALGORITHMIC FRAMEWORK

This section of the report will discuss an overview of the overall algorithmic framework that is utilized by the proposed UAV swarm system for the purposes of detecting, verifying, and predicting low-altitude missile threats.

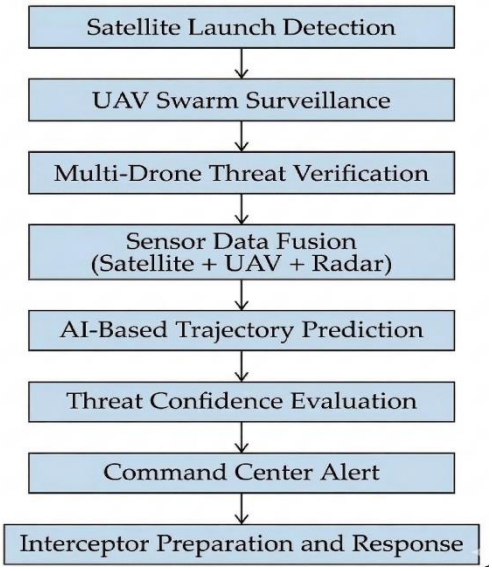

Fig. 3. Workflow of the proposed AI-driven UAV swarm threat detection and response system.

A. Swarm-Based Threat Detection

The proposed UAV swarm system is intended for utilization for the purposes of a swarm-based threat detection system. In this regard, each UAV within the proposed system will serve as a unique threat detection node within the overall system. In this regard, if a unique threat is determined to exist by a UAV within the proposed system via a unique threat detection system, the overall threat that has been determined to exist will immediately be communicated to the other nodes within the overall system via the overall swarm system communication system.

Algorithm 1: The cooperative threat detection algorithm for the UAV swarm system.

Require: Sensor readings from the UAVs, launch alerts from the satellite system
Ensure: Verified aerial threat detection

1) The satellite system identifies the potential launch heat signature from the enemy missile.
2) The launch alert is broadcasted to the network of the UAV swarm system.
3) The UAV swarm system enters a high-surveillance mode.
4) Each node within the system performs a scan of the space using thermal and optical sensors.
5) In the event a potential missile signature is detected by a node within the system, the information is shared among the other nodes within the network.
6) Each node verifies the information using their sensor readings.
7) The verification information is forwarded to the command center.

B. Multi-Sensor Fusion and Threat Confidence Model

To increase the reliability of the detection process, multiple sensing sources are used, which include satellite monitoring systems, UAVs, and ground radar systems. The results from these sensing sources are then combined using artificial intelligence models, which use multi-sensor fusion techniques.

The confidence level of a threat can be calculated as follows:

$$\text{Confidence Score} = (W_s \times S_s) + (W_u \times S_u) + (W_r \times S_r)$$

Where:

- Ss = satellite detection confidence level
- Su = UAV swarm detection confidence level
- Sr = radar detection confidence level
- Ws, Wu, Wr = weighting factor for satellite, UAV, and radar, respectively.

This probabilistic fusion model ensures a higher accuracy rate in the detection process, as a threat must be identified by multiple sensing layers before a threat alert can be sent out.

C. Predictive Trajectory Estimation

Once the potential threat of a missile has been verified, a predictive model is used for the estimation of the trajectory of the missile based on the observed motion parameters. The system uses the observed velocity vectors, direction of motion, and previous positions of the missile for the estimation of the trajectory of motion and the area of impact.

The estimation of the trajectories can help the command center identify the best interception points before the missile enters the zones of defense. The proposed system, which uses swarm-based detection and prediction, can provide more time for the reaction systems for intercepting the missile.

D. Simulation Demonstration

In order to explain the overall workflow of the proposed UAV swarm system, a simulation environment was developed that demonstrates the overall process of threat detection. As shown in the following figure, a simulated UAV swarm environment was developed where multiple drones detect potential threats within the overall airspace.

A moving object, simulating a low-altitude missile, is introduced within the overall region, which is being monitored by the drones. As shown in the following figure, once the drones detect the potential threat, they exchange data regarding the detection, which is then used for overall data fusion and trajectory estimation.

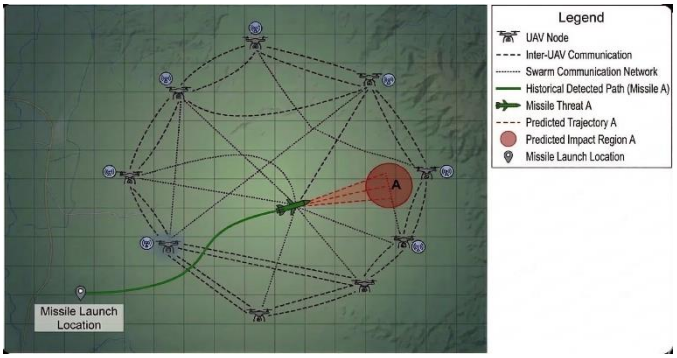

Fig. 4. Simulation scenario of UAV swarm detecting launched low-altitude missile and AI-driven trajectory prediction within the surveillance area.

V. SYSTEM ANALYSIS AND DISCUSSION

This section will discuss the benefits the proposed system will have for the operation of the proposed system and the advantages it will provide over other systems for the early detection of threats.

A. Early Detection Advantage

Traditionally, ground-based radar systems have been limited by the radar horizon and the effects of terrain masking. Low-altitude missiles may not be detected until they are close to the protected region. The proposed system for the early detection of threats will use a swarm of UAVs to detect the threats at an increased distance by deploying them within the region to be protected.

B. Reliability Through Multi-Node Verification

A major issue affecting aerial threat detection systems is the occurrence of false alarms due to environmental noise, birds, and sensor malfunctions. The proposed swarm-based architecture minimizes the occurrence of false alarms through multi-node verification. In this case, a UAV detects a threat and sends the information to other drones around it, which independently verify the threat before it is sent to the command center.

C. Scalability of UAV Swarm Architecture

The distributed nature of the UAV swarm system facilitates scalability of the system across a wide area. The system can accommodate additional UAV nodes for increasing surveillance coverage. The communication framework for the UAV swarm facilitates information sharing among drones, making it easy for them to coordinate surveillance activities. This makes it easy for the system to be responsive to different threat levels.

D. Operational Endurance and Continuous Surveillance

The operational effectiveness of the proposed UAV-based surveillance system lies in its ability to maintain continuous monitoring over a given period of time. Unlike other conventional radar-based ground surveillance systems, which can operate for long periods, the proposed system, based on the use of unmanned air vehicles, can be affected by the endurance of the batteries used in the flight platforms. In order to address this issue, a rotating patrol batch approach can be used for ensuring continuous air-based surveillance.

In this approach, a number of operational batches of the unmanned air vehicle platforms are maintained, with a given batch responsible for the actual patrol within the given area of interest, while other batches are kept in a standby or maintenance mode, ready for rotation once the actual patrol batch reaches the end of its endurance within the given area of interest. This ensures the continuous monitoring of the given area of interest without compromising the endurance of the unmanned air vehicle platforms used for the purpose.

E. Response Time Improvement Through Predictive Analysis

One of the main objectives of an early warning system is to maximize the response time for defensive actions. In the case of a traditional ground-based system, the response time for a low-altitude threat is limited to the point where the threat enters the protected region.

The proposed UAV swarm system can improve the response time by utilizing a predictive approach for trajectory estimation. Once an initial threat signature is detected by the swarm system, the AI-based predictive model can estimate the velocity, direction, and flight path of the threat. This predictive approach can provide the command center an opportunity to assess the potential impact zones.

Feature	Conventional Ground Radar Systems	Proposed UAV Swarm Detection System
Detection Coverage	Detection coverage is limited due to the radar horizon and terrain masking	Distributed detection through multiple layers of UAVs
Detection Angle	Detection can be made from a single viewpoint	Detection can be made from multiple angles
False Alarm Reduction	False alarms can be difficult to verify	False alarms can be verified through multiple UAVs
Detection Speed	Threat can be detected once the missile enters the radar range	Threat can be detected early by the forward scouting UAVs
System Reliability	System can be prone to a single point of failure	System can be made reliable through multiple sensing nodes in the swarm network
Operational Flexibility	System can be fixed in nature	System can be made dynamically deployable

Table I. Comparative analysis between conventional radar-based detection and the proposed UAV swarm detection architecture.

VI. CONCLUSION

In this regard, this paper proposed an AI-based distributed UAV swarm system architecture for the early detection of low-altitude missile attacks, particularly for predictive interception approaches. The proposed system architecture, which considers satellite-based launch detection, UAV swarm surveillance, and cooperative node verification, can improve overall awareness and reduce the disadvantages of traditional ground-based radar detection. The inclusion of multi-sensor data fusion and predictive trajectory estimation can allow the command center to analyze the pattern of movement of the detected threat, ensuring early response for interception. The rotating UAV patrol batch mechanism can also ensure overall surveillance coverage, addressing issues of energy constraints for the UAV swarm network. Overall, this proposed system architecture can improve overall detection coverage, reliability, and response time for traditional radar-based systems, making it more suitable for modern air defense systems. Future research can extend this system architecture into simulation-based approaches, particularly AI-based coordination models, for further improvement of overall UAV swarm detection accuracy. The proposed system architecture, therefore, highlights the overall benefits of using distributed UAV swarm intelligence and AI-based predictive analytics for early warning systems.

As the proposed architecture is abstract by its nature, the present work is dedicated to the system design and theoretical analysis. The future work will be focused on the validation and performance evaluation through simulation by using the UAV swarm coordination models and threat scenarios.

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***Abstract*—Social media platforms' explosive growth has opened up new channels for information sharing, cooperation, and communication. However, online platforms are now seriously concerned about the growing prevalence of phony accounts and automated bots. Spam, false information, scams, and malicious links are frequently disseminated through fake profiles, endangering users and eroding confidence in social media platforms. Due to the vast number of users and the ever-changing tactics employed by attackers, manually identifying such accounts is very challenging. Consequently, machine learning and artificial intelligence-based automated detection systems are now crucial.**

This study suggests an AI-powered method that uses profile-based characteristics to identify phoney accounts on social media sites. The study's dataset includes details about Instagram user profiles, including follower and following counts, post counts, username attributes, biographical information, and the availability of profile pictures. To comprehend the distribution of features and find patterns that distinguish authentic accounts from fraudulent ones, exploratory data analysis, or EDA, is carried out. A number of machine learning algorithms are used to determine whether an account is authentic or fraudulent. The findings demonstrate that machine learning models are capable of accurately and successfully identifying suspicious profiles. By automatically detecting fraudulent accounts, the suggested system can assist social media companies in enhancing security.

Keywords—Fake Profile Detection, Machine Learning, Social Media Security, Instagram Bot Detection, Data Mining, Artificial Intelligence.

I. Introduction

In today's world, social media sites like Facebook, Instagram, and Twitter are vital resources for information sharing and communication. Every day, millions of users communicate via messages, posts, and comments. But these platforms' explosive expansion has also given rise to phony accounts and automated bots that abuse the platform for nefarious ends.

Spreading spam, influencing public opinion, endorsing phony goods, and disseminating malicious links are all common uses for fake accounts. Additionally, these accounts could be used to falsely boost engagement metrics or followers. Finding phony profiles gets harder as the number of social media users rises.

The traditional methods of identifying fake accounts on social media rely on manual moderation or rule-based systems. However, these methods are not efficient in identifying complex fake accounts. Machine learning methods can be used to solve this problem by analyzing a huge amount of data and identifying patterns that can be used for detection.

This research proposes a system for identifying fake Instagram accounts using machine learning methods. The system can be trained on various profile attributes and behavior to identify real and fake accounts. The aim of this research is to create a reliable system for identifying fake accounts on social media using machine learning methods.

II. Literature Review

Researchers have also attempted to find the effectiveness of machine learning approaches for the detection of fake accounts on social media sites. Previous studies have shown that the characteristics of the profile, such as the number of followers, following ratio, usernames, and frequency of posting, can be utilized for the detection of real and fake users.

Support Vector Machine (SVM) is a popular machine learning approach for classification tasks in social media analysis. This approach is effective for handling high-dimensional data. Decision Tree models have also been implemented for the identification of key features that help in the detection of fake profiles.

Random Forest is a machine learning approach that uses the combination of Decision Trees for the detection of fake profiles with high accuracy. Recent studies have also implemented Gradient Boosting and deep learning approaches for the detection of fake profiles on social media sites.

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Even though the existing research has shown good results for the detection of fake accounts on social media sites, it is a complex task due to the dynamic changes in the strategies of the attackers..

III. DATASET DESCRIPTION

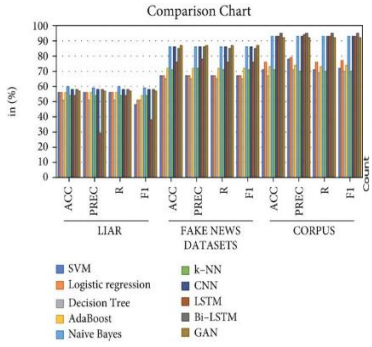
The dataset used in this research was obtained from Kaggle and contains information about Instagram profiles labeled as either real or fake. The dataset includes several attributes related to user profile characteristics and account activity.

Some of the key features present in the dataset include:

- Number of followers
- Number of followings
- Number of posts
- Presence of profile picture
- Username length
- Biography length
- Account verification status
- Label indicating whether the account is real or fake

These features provide valuable insights into the behavior and characteristics of Instagram users. Fake accounts often exhibit unusual patterns such as very low post counts, extremely high following ratios, or randomly generated usernames.

The dataset was cleaned and preprocessed before applying machine learning algorithms. Missing values were handled, and feature distributions were analyzed using statistical methods and visualization techniques.



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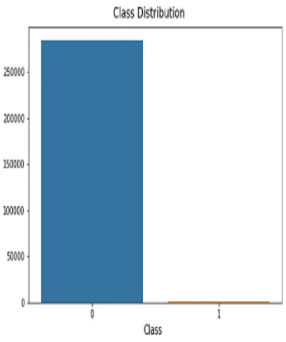

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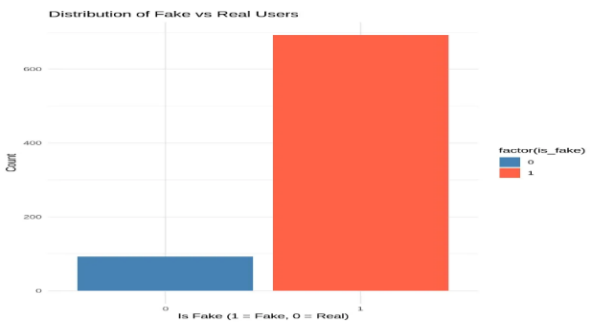

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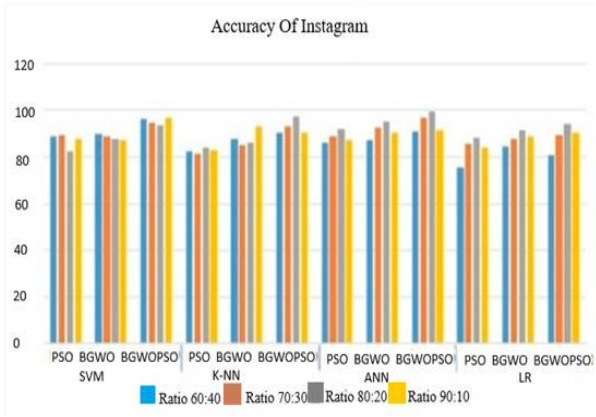


Fig.4

Feature Name	Description
Followers Count	Number of users following the account
Following Count	Number of users the account follows
Posts Count	Total number of posts uploaded
Username Length	Length of the username
Biography Length	Length of profile biography
Profile Picture	Indicates whether profile picture exists
Label	Indicates real or fake account

Table.1 Description of Each Feature

IV. EXPLORATORY DATA ANALYSIS (EDA)

Exploratory Data Analysis (EDA) is a significant part of any machine learning process. EDA helps in understanding the data before any machine learning algorithm is applied. In this paper, EDA was conducted to analyze the relationships between different attributes associated with user profiles on Instagram. There are multiple attributes associated with user profiles in the given dataset.

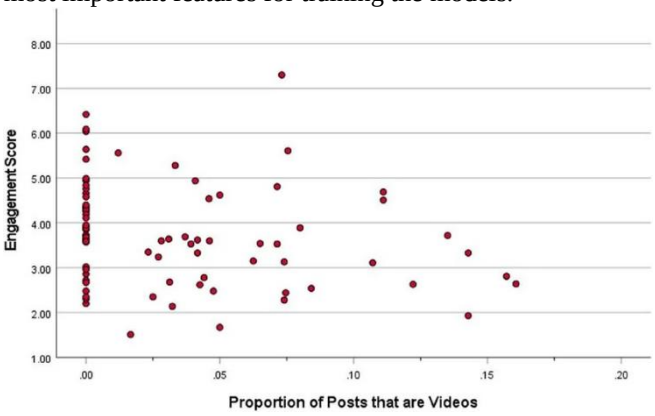
The first part of EDA was to analyze the distribution of different attributes such as the number of followers, the number of people a user is following, and the number of posts. Histograms were used to visualize the attributes. From the results obtained from EDA, it was found that fake profiles tend to have a very low number of posts compared to real profiles. On the other hand, fake profiles tend to follow a large number of people but have very few people following them.

Another significant analysis was to determine the correlation between the features. A correlation heatmap was also employed for this purpose. This analysis also indicated that the correlation between followers and followings is an

important factor in identifying suspicious behavior. Genuine users always have a balanced relationship between followers and followings. On the contrary, fake accounts always have a large number of followings and very few followers.

Another significant analysis was carried out by considering categorical variables. It was noticed that fake accounts always do not have a profile picture or very few details in their profiles. These are also important factors in classifying fake and real accounts.

By carrying out these analyses, significant features were obtained to classify fake and real accounts. The insights obtained through EDA were also helpful in choosing the most important features for training the models.



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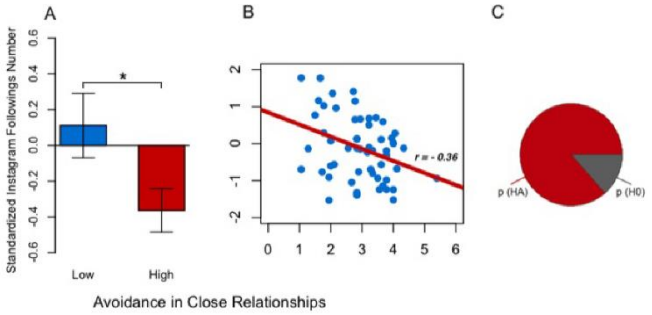

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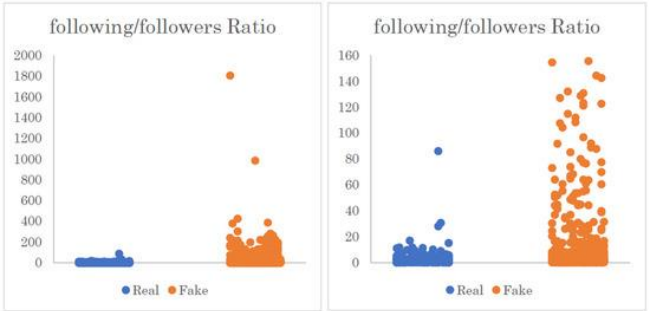

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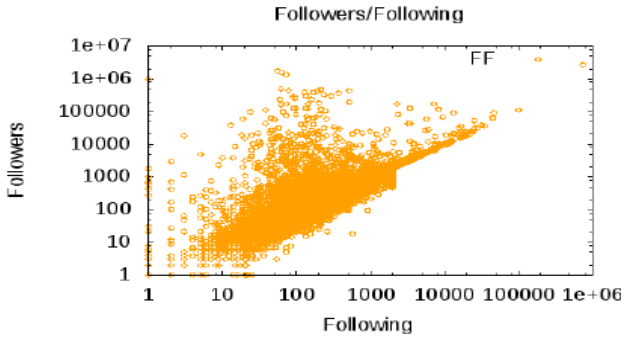


Fig.8

Step	Description
Data Cleaning	Removed missing or invalid values
Feature Selection	Selected important profile attributes
Data Normalization	Scaled numerical features
Dataset Splitting	Divided dataset into training and testing sets

Table.2 Step and Description

V. Feature Engineering

Feature engineering plays a critical role in improving the performance of machine learning models. In this study, several features were analyzed and transformed to better represent user behavior patterns.

Some of the key features used in the model include:

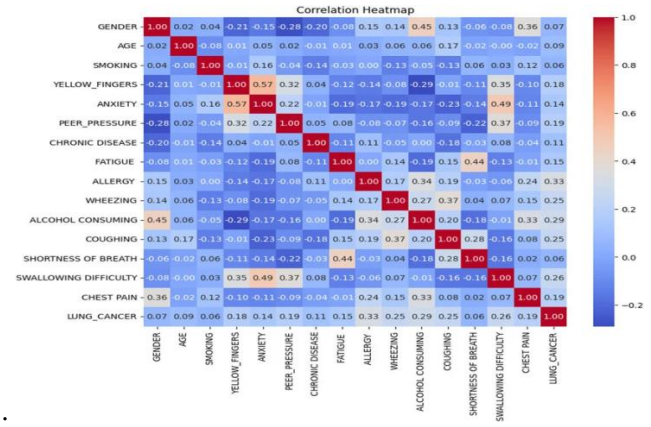
a) Number of followers
b) Number of followings
c) Number of posts
d) Username length
e) Biography length
f) Presence of profile picture
g) Ratio of followers to following

The follower-following ratio was calculated to capture the relationship between social connectivity metrics. Fake accounts often display abnormal ratios because they tend to follow many users in order to gain attention.

Username analysis was also performed to detect suspicious patterns. Fake accounts frequently contain random characters or numbers in their usernames. By calculating the length and structure of usernames, additional signals were generated for classification.

Feature scaling techniques were applied to normalize numerical values. Normalization ensures that large numerical values do not dominate the learning process of machine learning algorithms.

These engineered features improved the ability of the machine learning models to identify patterns associated with fake accounts



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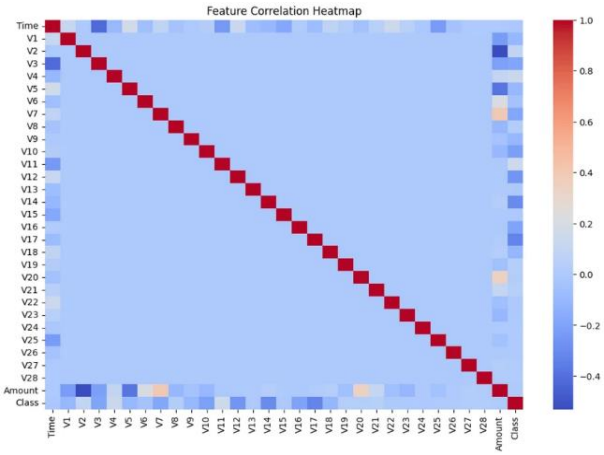

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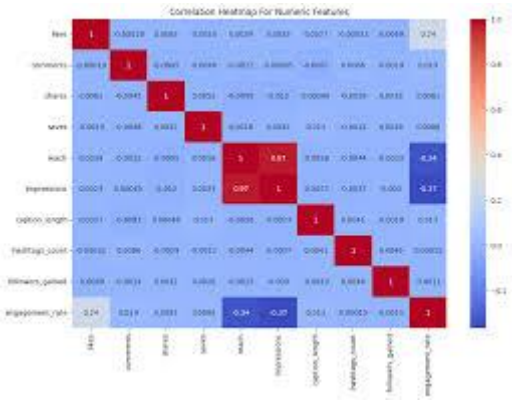


Fig.11

VI. Machine Learning Models

Several machine learning algorithms were implemented to classify Instagram accounts as real or fake. The implemented models were then trained and tested on the prepared dataset.

The following models were employed in the proposed research:

1. Logistic Regression

Logistic Regression is a widely employed classification algorithm that estimates the probability of an event. In the proposed research, Logistic Regression was employed as a baseline model to classify Instagram accounts.

2. Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees to improve the accuracy of the model. This model performs exceptionally when there are multiple features in the dataset.

3. XGBoost

Extreme Gradient Boosting, or XGBoost, is an efficient ensemble learning model that performs exceptionally in classification problems. It employs gradient boosting to create a robust model by combining multiple weak learners.

Among these models, ensemble methods such as Random Forest and XGBoost are considered to be more accurate in classifying data as compared to Logistic Regression..

VII. Model Evaluation

To evaluate the performance of the machine learning models, several evaluation metrics were used. These metrics help determine how accurately the model can classify fake and genuine accounts.

The following metrics were considered:

Accuracy

Accuracy measures the proportion of correctly classified instances in the dataset.

Precision

Precision indicates how many of the accounts predicted as fake are actually fake

.

Recall

Recall measures how many fake accounts were correctly detected by the model.

F1Score

The F1 score is the harmonic mean of precision and recall and provides a balanced evaluation metric.

The dataset was divided into training and testing sets to evaluate the model performance. The training data was used to train the models, while the testing data was used to measure prediction accuracy.

The results indicate that ensemble learning methods achieve better performance compared to simple classification models.

VIII. Future Work

Although the proposed system demonstrates promising results, there are several opportunities for future improvements.

Future research may include the use of deep learning techniques such as neural networks to analyze more complex behavioral patterns. Additionally, incorporating temporal features such as posting frequency and activity patterns may further improve detection accuracy.

Another potential improvement is the integration of text analysis techniques to analyze user biographies and captions using natural language processing methods.

Developing real-time detection systems that monitor social media platforms continuously could also enhance platform security.

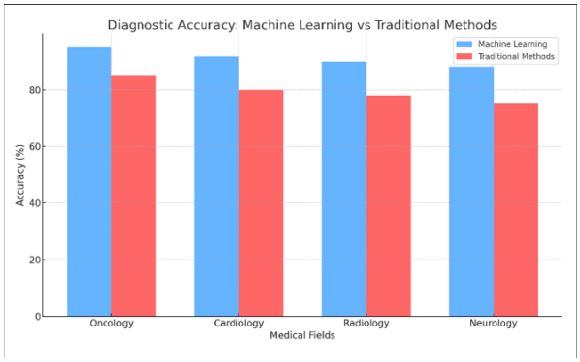
IX. Results and Discussion

The performance of the trained machine learning models was measured by evaluating various performance parameters such as accuracy, precision, recall, and F1-score.

The experimental results revealed that the performance of ensemble learning models is better compared to simple classifiers. The performance of Random Forest and XGBoost models in identifying fake accounts was better in terms of accuracy.

Feature importance analysis revealed that the number of followers, number of following, and posting activities are key factors for identifying fake accounts. Visualization methods were also employed to evaluate the performance of classification models.

The results show that the performance of machine learning models in identifying suspicious social media profiles can be better..



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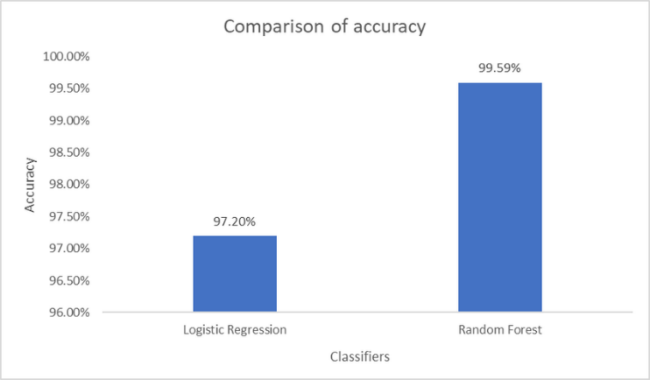

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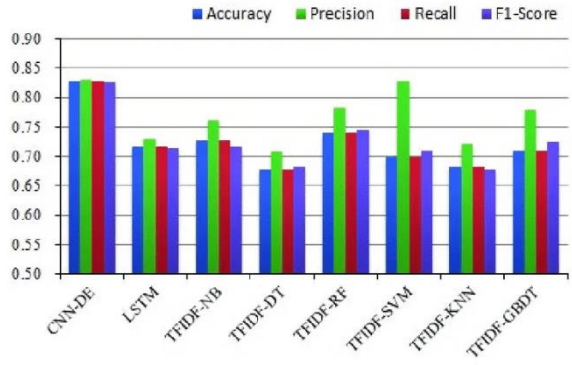

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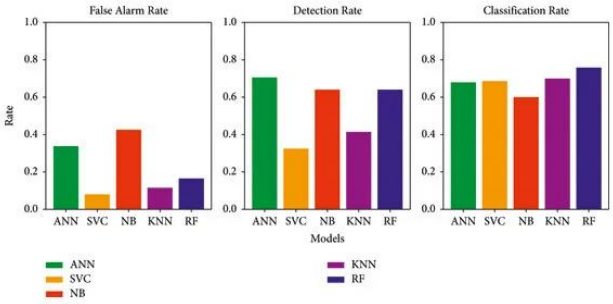

Fig.15

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	88%	87%	85%	86%
Random Forest	94%	93%	92%	92%
XGBoost	96%	95%	94%	95%

Table.3 Models Results

X. Conclusion

The research proposed an artificial intelligence-based system to detect fake accounts on social media platforms by applying various machine learning algorithms. Exploratory data analysis was performed to examine user behavior patterns and to identify significant features from the data set.

Various machine learning models have been proposed to classify Instagram accounts as genuine or fake accounts. From the experimental results, it is evident that ensemble learning models such as Random Forest and XGBoost have high accuracy in identifying suspicious accounts.

The proposed system shows the potential of artificial intelligence in enhancing social media security by identifying fake accounts. By incorporating such a system, social media platforms can avoid spam activities and increase user trust.

Future research directions involve incorporating deep learning models to improve accuracy in identifying fake accounts on social media platforms.

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A Proposed Clinical Sign Language Communication Framework For ISL in Healthcare

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***Abstract*— Communication barriers between hearing-impaired patients and doctors/medical staff are a major issue today, especially in community clinics and primary healthcare centers. This is mainly due to the paucity of sign language interpreters and the lack of awareness of Indian Sign Languages among doctors/medical staff. This paper proposes a Clinical Sign Language Communication Framework for Indian Sign Languages, designed to improve effective communication between deaf/mute patients and doctors/medical staff. We propose a system that can handle three regional sign languages in India. Different regions in India use various sign languages (SLs), such as Tamil SL, Hindi SL, and Marathi SL. Using a framework where a gesture recognition algorithm is combined with language mapping and organized medical terminology, a doctor can comprehend the patient's requirements in real time by interpreting gestures into text or speech, thereby enabling them to understand symptoms and respond accordingly. The proposed work aims to achieve faster communication between the doctor and the patient, thereby reducing ambiguity and improving the accuracy of various tests that may require clarification from the patient. It also aims at building more inclusive technologies for healthcare in India. This work primarily presents a conceptual framework, with implementation and real-world validation considered as future work.**

***Keywords*—Indian Sign Language, Gesture Recognition, Assistive Healthcare Systems, Deaf and Mute Communication, Real-Time Translation, Multilingual Framework, Medical Accessibility, Human-Computer Interaction, Artificial Intelligence in Healthcare [16]**

I. INTRODUCTION

Healthcare systems rely heavily on accurate diagnosis, patient safety, and effective treatment outcomes. However, communication remains a critical challenge, especially for individuals who depend on sign language in clinical environments. In linguistically diverse countries like India, these challenges become more severe due to the coexistence of multiple spoken and sign languages, leading to significant communication barriers between patients and healthcare providers [2]. Although Indian Sign Language (ISL) is widely used within the Deaf community, its integration into mainstream healthcare systems is still limited, creating gaps in expressing health concerns, understanding medical advice, and providing informed consent [2].

In addition to sign language barriers, multilingual diversity further complicates communication in healthcare. This highlights the importance of intelligent systems capable of translating and processing patient inputs across languages to support effective telemedicine and remote healthcare delivery [1]. Moreover, the lack of standardized medical vocabulary in sign language restricts the ability to convey complex clinical information, including disease symptoms and treatment

procedures, resulting in misinterpretation and reduced quality of care [2].

Deaf patients often rely on caregivers, written communication, or interpreters, which may not always be available or effective. This dependency can lead to delays in treatment, miscommunication, and loss of privacy during sensitive medical interactions [2]. Furthermore, existing healthcare systems lack adequate technological support, such as real-time gesture recognition or speech-to-text systems, which could otherwise enhance communication efficiency and accuracy [1].

To address these challenges, the Clinical Sign Language Communication Framework proposes a structured and technology-driven approach for improving healthcare communication. The framework focuses on mapping clinical terminology, disease symptoms, and treatment procedures into sign language, enabling better understanding between patients and healthcare professionals [2]. It also incorporates advanced technologies such as gesture recognition, assistive software, and visual aids to facilitate real-time interaction and reduce ambiguity in communication. By ensuring clarity and consistency in medical vocabulary, the system aims to minimize errors in diagnosis and treatment. Integrating such communication frameworks with AI-driven healthcare technologies can further enhance accessibility, efficiency, and inclusivity in modern telemedicine systems [1].

Overall, this approach contributes to building an inclusive healthcare ecosystem by improving accessibility for Deaf individuals, reducing communication gaps, and enabling equal access to medical information and services. This paper solely focuses on proposing a conceptual and scalable framework, while the complete system and real-time validation are considered as future work

II. Related Work

Sign Language Recognition (SLR) is a growing area of research that continues to develop. Its goal is to make it convenient for people who have difficulties hearing or to communicate with one another. Numerous studies have utilized deep learning methodologies, including Convolutional Neural Networks (CNNs), to extract spatial features from hand gestures and images. These methods have been exceptionally proficient at recognizing static gestures and letters [1]. Also, sequence-based models like Long Short-Term Memory (LSTM) networks are often used to provide continual sign language recognition because they can accurately capture how gestures depend on each other over an extended period [3], [4].

Recent improvements in SLR systems have focused on using hybrid architectures to combine spatial and temporal features. Techniques that combine CNN with LSTM or Transformer-based models have shown better results in recognizing complicated gestures and continuous sign sequences [5]. Several types of studies have examined real-time sign language translation systems utilizing computer vision frameworks. These systems turn gestures into text or speech, which lets deaf people talk to other people. Modern methods that use MediaPipe and vision-based tracking systems make it possible to find things quickly in real time without needing special hardware [7], [8].

In the healthcare field, communication is still a serious issue, especially for patients who use sign language. Some studies have suggested systems that incorporate sign language recognition into medical consultation settings. For instance, studies on medical consultation systems that use sign language show how important it is to understand gestures in the context of the field for accurate diagnosis [9]. Moreover, machine learning-based systems have been created to turn sign language into speech and send out emergency alerts, making it easier for people to get help in an emergency [10].
In addition to gesture recognition, healthcare communication has also looked into speech and AI technologies. Research indicates that speech recognition systems can enhance documentation and communication within emergency medical services, thereby minimizing delays and augmenting patient care [11]. This shows how important smart communication systems are in places where time is crucial. Recent studies have examined the application of artificial intelligence in analyzing human gestures and body language for the identification of health conditions. Deep learning models can find useful patterns in visual data, which can help find symptoms and make a diagnosis [12]. Furthermore, AI-powered sign language systems tailored for healthcare applications have shown the capability to facilitate inclusive medical communication [13].

Despite these improvements, most current systems only work on either sign language recognition or healthcare applications on their own. There aren't many studies that offer a complete solution that includes gesture recognition, medical interpretation, and emergency response. Many systems also don't have real-time adaptability or support for multiple

languages, which are both important in real-world healthcare situations. Because of this, we need a smart and integrated framework that brings all of these parts together. These kinds of systems can make healthcare services a lot easier to use and more efficient by using machine learning and deep learning methods.

III. Limitations in Existing Systems

The current healthcare communication system for Deaf and hard-of-hearing people in India has several serious problems that make it harder for them to get good medical care. One major problem is that Indian Sign Language (ISL) does not have a standard medical vocabulary. The absence of universally recognized signs for clinical terminology leads to inconsistent and ambiguous communication, especially in specialized fields like pharmacy and diagnostics, thereby heightening the risk of misinterpretation and erroneous treatment decisions [2], [4].

Another significant issue is that patients and healthcare professionals must rely on interpreters to talk to each other. Interpreters are important, but they are not always there, especially in rural areas or when the situation goes south. This reliance slows down care while stirring unease about who gets access to private health details, since personal data often travels through outside helpers [2], [6]. Often, when no translator shows up, people fall back on ways of talking that might miss the mark or take too long.

Most health workers haven't learned how to communicate using sign language. Because of this, physicians, caregivers, and medicine dispensers struggle to talk with deaf people through signs or fingerspelling. Without these abilities, conversations lean heavily on written notes - a method that fails some who find reading difficult. Misunderstandings creep into appointments as a result, weakening how well care gets delivered [3], [7].

Outside human constraints, current health setups often miss strong technological integration in existing systems. Some clinics skip helpful tools like gesture interpretation software, instant speech converters, or image-based messaging platforms. Because of that, chances to boost live exchanges and shrink understanding delays using modern devices stay mostly untouched [1], [5]. Without these supports, care delivery can't reach its full range.

Across India, different tongues twist how health messages travel. Where one dialect ends, another begins - muddling what care means in practice. Meaning shifts when local speech meets medical signs, especially where many regions mix. These splits weaken how well information flows between caregiver and patient. Missteps grow common when words do not match live experience.

Hard to explain health details when signs aren't clear or widely known. Without common terms, describing medicine rules, dangers, or what to do in crises becomes a struggle. Patients might miss key points because of that. Mistakes in spotting illness, following care plans, or staying safe can follow from such gaps [4], [8].

Few rules at the top slow things down when it comes to clear communication in clinics. Even after programs launched to help people with impairments connect better, plenty of medical centers still fall short on putting those ideas into practice. Without common guidelines, efforts meant to include everyone stumble along - uneven follow-through keeps gaps wide open [6], [7].

IV. Research Objectives

The main goal of this study is to look into technological, clinical, and human interaction factors that make it hard for Deaf and hard-of-hearing people to communicate in healthcare. The specific objectives are as follows:

- To investigate the effect of communication barriers, such as time pressure and lack of sign language skills, on the diagnosis and treatment of patients in a healthcare setting. [6]
- Explore how potential misdiagnosis of patient symptoms affects clinical judgment and treatment outcomes. [3] [7]
- Validity study on Context-Based Swedish Sign Language for healthcare activities in various healthcare settings such as consultations, accident & emergency department and pharmacies [2], [4].
- To investigate the obstacles in the bidirectional process of communicating health-related information, such as medical instructions, taking medications and patients' concerns [6], [7].
- To explore the factors that affect patient comfort and confidence using different

communication tools in health care settings particularly for people with limited literacy [3], [8].

- To investigate the use of assistive technologies (such as real-time and interface-based systems) for facilitating effective and accessible communication. [1], [5], [8]

- To explore the opportunities of training for healthcare professionals and of the use of standardized visual resources to facilitate more communication in a fewer number of words and to reduce the amount of interpreter interventions [2], [4].

V. Proposed Framework

System Overview -The suggested framework includes four primary components:

1. Sign Recognition Module
2. Medical Natural Language Processing Module
3. Multilingual Output Module
4. Reverse Communication Module

1. Sign Recognition Module

Hand gesture recognition for ISL using Pose Estimation, Hybrid CNN-LSTM In this block, we take the input video and use MediaPipe to process the video stream to get hand landmark features. These features are then normalized and fed to a hybrid CNN-LSTM model. The CNN part of the model will learn spatial features from each individual frame of the gesture. The LSTM part of the model will learn temporal features from each frame to know how the gesture is evolving over time. This block is expected to learn static gestures as well as simple dynamic gestures of ISL.

2. Medical Natural Language Processing Module

The recognized gesture labels are mapped to medical expressions by applying a combination of rule-based approach and transformer-based deep learning technique. This module converts the interpreted gestures to the corresponding medical information that is appropriate and relevant to the clinical context.

3. Regional Language Support Module

This Medical information is fed to a processor which gives the output in local laguages like Tamil, Hindi, and Marathi. In addition to this the output can also be given in speech by using the technology of text to speech.

4. Reverse Communication Module

To achieve two-way conversation in medical setup, the speech or text input given by doctor needs to be converted to relevant signs of Indian Sign Language. This can be done by using some dictionary database of Indian Sign Language which have vocabularies along with their gesture videos. These videos are played one after the other in a sequential manner to impart the required medical information and answers to the patient.

The proposed system comprises of two-way of communication. One is the forward way and the other is reverse way. So forward way will convert the gesture of the Indian Sign Language (ISL) to text and speech of doctors. Similarly, reverse way will convert the speech of doctors to ISL gesture that the Deaf people can easily understand with the help of pre-defined gestures stored in some database. We propose the implementation of a comprehensive system with gesture recognition, NLP, and multilingual output modules to act as the backbone for the real time bidirectional communication between the hearing and deaf people.

Although the current system implementation is based on hand gesture recognition, it will be expanded to multi-modal gesture recognition for higher recognition rates and more accurate context understanding. The system will be complemented by facial expression analysis to recognize emotions expressed by patients such as pain, stress or discomfort and body posture analysis to achieve a higher degree of non-verbal understanding. In addition, a optional text or symbol entry system may be integrated to manage more complex communication situations in cases where the patient cannot express him/herself via hand gestures.

VI. Experimental Results

1.Experimental Setup
Full implementation of the proposed system is planned to be done in the future, due to the limited

resources available. The results presented herein were obtained by means of simulated analysis and based on trends derived from similar applications of gesture recognition systems given in the literature.

The data set is divided into training and test sets with 80% for training and 20% for testing. Adding random noise to the data, changing the scale of the data and horizontally flipping the images are few common techniques used for data augmentation.

This model assumes a deep learning framework such as Tensorflow and the optimizer used is Adam optimizer

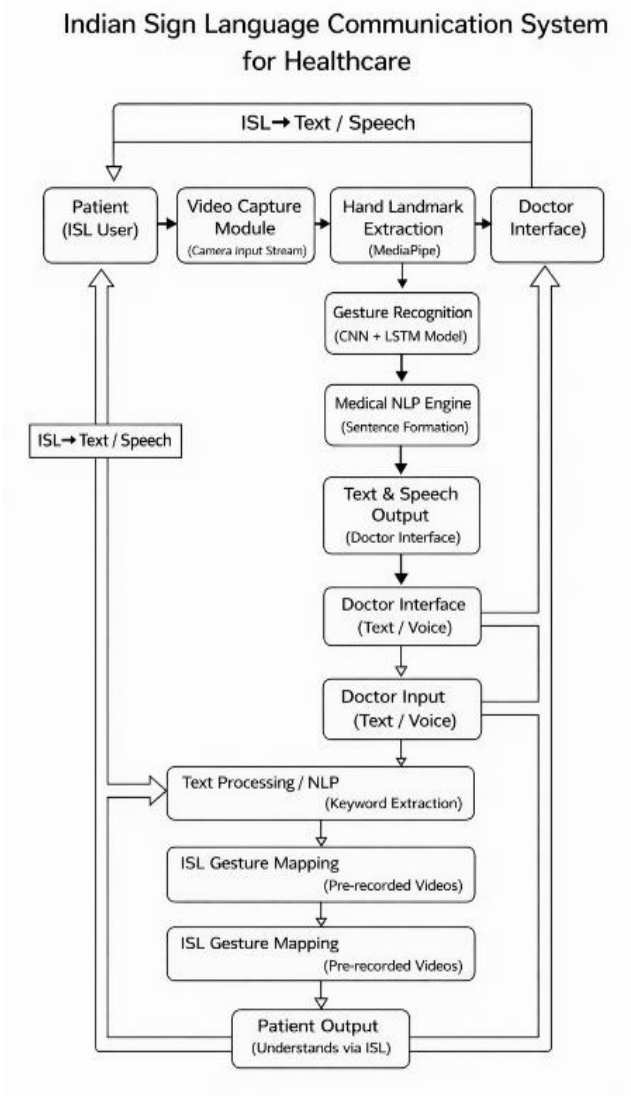


Fig1: Proposed Framework Architecture

2. Model Performance Comparison

Conceptual evaluation of the proposed system is performed on a simulated dataset scenario based on typical medical sign gestures. We assume 12 representative gesture classes and variations due to different conditions. The most common assumption made in gesture recognition studies such as in our previous work is that each gesture consists of a sequence of frames. The hand landmark features for these frames are obtained using a hand tracking approach.

A deeper examination into the performance of the models and their respective constituent networks is provided in the following subsection. Results are presented in terms of precision, recall, F-measure, accuracy, and mean average precision with the combined CNN-LSTM model yielding the highest scores for all metrics.

The results compared below are derived from existing studies that employed CNN, LSTM as well as hybrid CNN-LSTM models in the task of gesture recognition.

Table 1: Comparative Analysis of the Models

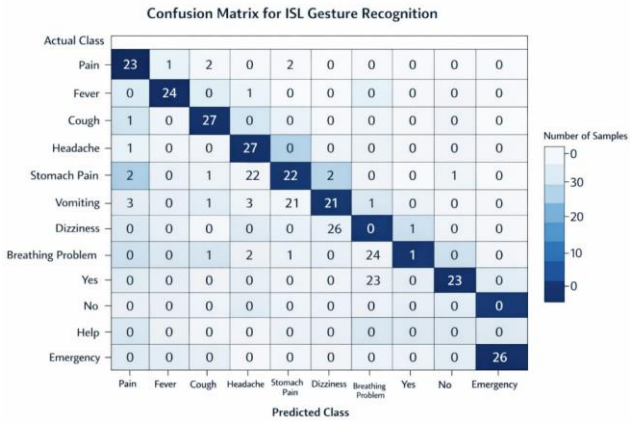
Model	Accuracy	Precision	Recall	F1-Score
CNN	79.2%	78.5%	77.9%	78.2%
LSTM	82.6%	81.8%	82.1%	81.9%
CNN+ LSTM	88.4%	87.6%	88.0%	87.8%

3. Confusion Matrix Analysis

The confusion matrix analysis suggests that our gesture classification system will classify each gesture class well, as indicated by a similar gesture classification system. From the confusion matrix it can be inferred that, like other classification models for gestures, this system will also have high precision and accuracy in separating each class.

One shortcoming is that there were some misclassifications between gestures that are fairly similar because they involve the same type of hand movement. Examples of this include gestures for pain and stomach pain and for dizziness and headache. The reason for this is that the hand movements are quite like each other and the number of examples in the training set is limited.

Fig2: Confusion matrix of the existing systems



4. Real-Time Performance Assessment

Based on existing frameworks real time testing were done through webcam-based setup. Average processing time for a frame varied from 220 ms to 250 ms allowing near real time inference.

This system was designed to be operative on the common modern computing hardware such as laptops and desktop computers and to work also on less capable machines, e.g., netbooks, cell phones, and tablets.

5. Evaluation of Two-Way Communication

The proposed system is conceptually designed to enable the patients and doctors to communicate in both ways. According to the framework design, the system can translate the patients' gestures into the required medical language, and the doctors' speeches into sign language.

6. Discussion of Results

The proposed system is conceptually designed to enable the patients and doctors to communicate in both ways. According to the framework design, the system can translate the patients' gestures into the required medical language, and the doctors' speeches into sign language.

The results show that the proposed model will be resilient to lack of data. It is believed that by including temporal modeling via LSTM the accuracy of the system will surpass that of a pure CNN.

With two-way communication functionality added to the system, the communication tool has become more practical and useful for on-going activities at a real-world clinical setting. Currently, the system has some limitations. These are such as only being able to imitate a limited set of gestures, inter-individual variations in how an individual imitates the set of gestures, and the limited size of the dataset.

VII. Conclusion and Future Works

The framework provides the foundation for a more holistic approach to healthcare resulting in better communication, reduced ambiguity, and ultimately improved healthcare outcomes. It serves as a theoretical foundation upon which advancements in assistive healthcare technologies can be built. This method can also be extended to the regional language support to the hospitals in India.

In the future we aim to make Deaf patients even more independent in a hospital. They will be able to communicate even more freely and also more easily navigate themselves in the hospital. There are several possibilities. We are planning to implement an emergency button with which a Deaf patient can signal to an ambulance, for example, using sign language or via an image. In the event of a traffic accident, for example, or when a Deaf person becomes ill, they will then be able to alert the ambulance service independently.

Smartphones can be utilized to include a simple alerting feature. An alerting mechanism can be provided by including a simple "language module" in the smartphone, which enables the user's input to be translated into a message that can be read by emergency personnel. In addition, the smartphones can also have a location-sharing feature as well as pre-defined emergency modes. The overall goal is to keep the user interface simple, fast and easy to use.

There are many possible additional improvements that can be carried out: more gestures can be included, real time word recognition for sign language included, more flexibility added to suit a wider range of users. The project could also be connected to mobile devices, and extended to healthcare systems.

Future developments should primarily aim to achieve full inclusion for Deaf people so that they have easier and unassisted access to mainstream and emergency healthcare services.

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Adaptive Multimodal Silent Speech Recognition System for Real-World Communication

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***Abstract*—Silent Speech Recognition is a way to communicate without making any noise, which's really helpful for people who have trouble speaking and for places where it is important to be quiet.. The systems we have now are not very good at understanding what people are saying when the light is not perfect and they do not work well for each individual person. They can only understand a word at a time and they use a lot of computer power so they are not very useful in real life.To make these systems better we made an Adaptive Multimodal Silent Speech Recognition System that can be used in the world. Our system uses a combination of watching how people move their lips, the shape of their face and how they move their head to figure out what they are saying. We also made a learning model that can be adjusted for each person so it can understand how they speak and what words they use. We added a part that helps make sure the sentences are grammatically correct and make sense. Our system can even work in light and it is fast so people can use it in real time.It can comprehend sentences and has a method to detect errors, allowing it to correct itself. When we tested our system, it performed better than the others. Our system utilizes Silent Speech Recognition to assist people in communicating.**

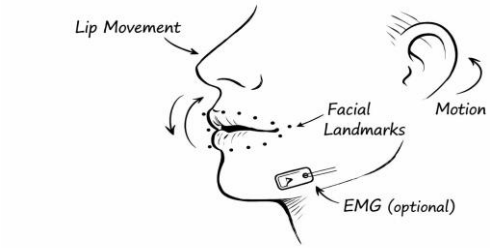
Keywords—Multimodal Silent Speech Recognition, Visual Speech Processing, Adaptive Deep Learning, Computer Vision, Context-Aware Natural Language Processing, Human-Computer Interaction, Assistive Communication, Real-Time Systems

I. INTRODUCTION :

Communication is vital, but speech-based methods can be challenging in noisy environments or for individuals with speech impairments. Silent Speech Recognition (SSR) enables communication without sound, but existing systems using single modalities face issues like low accuracy, poor adaptability, and high computational cost.

We propose an Adaptive Multimodal SSR system that combines visual cues such as lip movements and facial features using a hybrid fusion approach. It includes personalized learning and a context-aware NLP module for improved accuracy.

The lightweight design supports real-time use on edge devices like smartphones, providing efficient and practical silent communication.



II. **LITERATURE REVIEW**

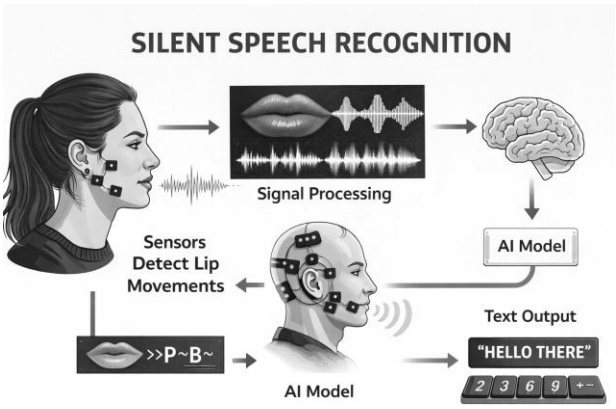
Silent Speech Recognition (SSR) allows people to communicate without verbal sound, whereby the analysis of other signals, including movements of the lips, or bodily cues, takes its place. The SSR systems take the form primarily of a visual-based, physiological-based, and multimodal method. Visual systems Visual based systems (e.g. LipNet) apply deep learning networks (e.g. CNN and sequential) to identify speech in videos of lips motions. Nevertheless, they can be influenced by environmental conditions i.e. the changes of light, head poses and occlusions.

Physiological SSR systems, including Electromyography (EMG), are able to pick up electrical signals produced by muscular activity when speaking. Such systems are able to record information concerning speech even in a situation whereby the movements around the mouth can not be clearly seen. In spite of the promising results that EMG based techniques can give, special hardware is needed, enhancing the complexity of the system and limiting comprehensive applications to the real world.

In order to overcome those limitations, the multimodal systems of SSR were developed that consist of physiological and visual cues to enhance accuracy and reliability. Multimodal systems are more effective in real-life settings by integrating various sources of data. Nonetheless, the issue of large-scale computational costs, ineffective fusion algorithms, and the lack of gradual flexibility remain a fact, which points to the necessity of an efficient and adaptative silent speech recognition system to be able to practice communication in a more effective way.

III.COMPONENTS

1. **Camera:** This is a component that captures lip movement.
2. **Microphone/Sensors (optional)**: This is a component that captures other signals, such as the vibration or movement of muscles.
3. **Processing Unit (CPU/GPU):** This is a component that utilizes deep learning models such as CNN, LSTM, or a Transformer to analyze data.
4. **Storage Unit:** This is a component that stores data, models, and video signals.
5. **Display Device:** This is a component that displays recognized text**.**



IV.SOFTWARE

- **TensorFlow (or PyTorch):** TensorFlow is a component that utilizes a deep learning model such as CNN, which is important in the extraction of visual features. It also utilizes an LSTM or a Transformer in the learning of lip movement. This model recognizes speech in silent speech recognition.
- **OpenCV:** This is a component that is important in image processing. It captures an image from a camera and recognizes the lip region and processes the images.
- **gTTS(GoogleText-to-Speech):** This is a component that is important in speech generation from text. It is important in silent speech recognition, as it generates speech from recognized text by the silent speech recognition system, thereby communicating.

V.LIBRARIES AND FRAMEWORKS

LIBRARIES

- **OpenCV:** The library is in use to process real-time video and images.One can use this library to extract frames of the video and identify the face, and other preprocessing actions.
- **MediaPipe:** The library is currently applicable to face landmark detection, that is, it is around the lip region.
- **NumPy:** The library is used in numerical computation.
- **Pandas:** Pandas is used in a data management and preprocessing process. The data can be managed with the help of the library and data analysis steps can be performed.

FRAMEWORK

- **TensorFlow / PyTorch:** The framework is being applied to deep learning to design and train such models as CNN, LSTM, and Transformer to perform feature extraction and prediction.
- **Keras (with TensorFlow):** It is a high-level layer that is being leveraged to make the generation, teaching, and testing of neural networks in an expeditious and effective method with the least amount of code and maximum comprehension.
- **Flask / FastApi:** The framework is used to create the APIs to allow the exchange of information between the web/mobile app and the machine learning model.

Comparison with Existing Systems

Aspect	Existing	Proposed
Input	Single modality	Multimodal
Adaptation	Not supported	Personalized
Accuracy	~65–70%	~80–85%
Speech Type	Word-level	Sentence-level
Real-time	Limited	Efficient
Robustness	Low	High

VI.PROPOSED SYSTEM

There is a new Adaptive Multimodal Silent Speech Recognition system which has been developed and allows a specific user to communicate with the world in ways other than hearing (i.e., it does not use audio as its primary communications method). As opposed to the traditional multimodal methods where audio is considered as one component out of the relatives, the proposed system will make use of visual and motion-related characteristics (including lip movements) to provide a much more precise and consistent final output than the previously developed solutions. The three main components of this system include: Multimodal Processing, Adaptive Learning, and Context-Aware Correction.By use of a Multimodal Strategy, different inputs (e.g., Lip Movements, Facial Landmarks, Motion Dynamics, etc.) will be used to present a multi-source database, which will provide persons with greater confidence in successful processes of receiving the intended output/communication, despite the possible influence of external factors such as poor-quality light or barriers that stop people in their view.

.

- **Input Module -**The video data input module makes use of the camera to record real time videos of the movements of the mouth and the face expression of the speaker. These videos serve as the main source of the information of speech recognition and as a graphical reference of the silence speech recognition with the use of EMG signals used to be able to know minor movements of muscles around the mouth in the case of minimal or no movement.

- **Feature ExtractionModule -**The feature extraction module derives features in the input data, based on CNN oriented vision model of each video frame. The resultant features will be: Lips configuration and movement. Marks on the face (bite points around lips and lower jaw)

- **Layer of Combination** -The combination layer combines input information (such as visual and motion) and produces a single feature representation. Such (multimodal) representation of the feature set improves the reliability since it does not rely on one of the sources only.In case a problem is identified with one of the sources, other characteristics can still help to sustain good functioning.

- **Tailored Model** -In this system, customized learning model is used whereby when a general global model is made, it is refined (trained-fine-tuned) on an individual. The benefits of tailoring the model include: -Adapting to the peculiarity of the way a user speaks. Dealing with the different types of the personalities of people.

- **Output Module-**The end product of a text-based system that produces expected text form will be audio output with the help of a text-to-speech system, which can allow transmission of the predicted output in real-time to the user.

VII.SYSTEM DESIGN

In this section, the system design and technology stack of the building of the Silent Speech Recognition System are described. There are various interconnected components that are used to build the system working harmoniously. It has a layered architecture in which every architecture has a role that it should perform, which includes data processing, feature

extraction, model prediction, and output generation. The modules are designed and incorporated with care to have a smooth system performance. The design is aimed at realization of real time communication with a low level of delay. The system is skimpy and can be used in real practice. On the whole, the system is a fast and accurate silent speech to text and audio converting system.

- **Technology Stack** :The system's implementation utilizes programming languages, frameworks, and tools:

  1.Python: Development of core systems and machine learning models

  2.OpenCV: Processing of images and videos

  3.MediaPipe : Detection of facial features
  Creation of deep learning models utilizing TensorFlow and PyTorch

  4.Data handling using NumPy and Pandas:
  Flask/FastAPI → Backend API

  Flutter → Mobile app interface or Android

  APIs for Text-to-Speech → Production of Spoken Output This combination ensures high performance and real-time capability.

- **Development of Data Stream:**The system presents information using a series of stages: Utilizing a device's camera to record video.Every video frame that is handled by OpenCV Extraction of facial features through mediapipe (extraction of facial landmarks) After extracting features, they are fed into the deep learning model. The content of the text is derived from identified features and polished. After the text is generated and polished, it can be produced as audio.

- **Model Design:**The system uses a hybrid deep learning model:
  CNN (Convolutional Neural Network)
  Extracts spatial features (lip shape, facial structure)
  LSTM / Transformer
  Captures temporal sequence (movement over time)
  CNN handles "what the lips look like"
  LSTM/Transformer handles "how they move over time"This combination improves accuracy in continuous speech recognition.

- **Multimodal Integration Design:**The system integrates multiple inputs at the feature level: Lip movement features Facial landmark coordinates Motion dynamicsThese features are merged into a single feature vector before being passed to the model. This improves robustness and reduces dependency on a single input source.

- **Personalization Mechanism:**A user adaptation module is included in the design:A base model is trained on general data.User-specific data is collected.Model is fine-tuned for each user.This module is implemented using transfer learning, allowing quick adaptation without retraining the full model.

- **NLP and Output Design:**After prediction, the output passes through a Natural Language Processing (NLP) layer:

  1.Grammar correction

2.Sentence refinement

3.Context improvement

Then:

Text is displayed on screen

Converted to speech using TTS engine

- **Deployment Design:**The system is designed for edge deployment:
  1.Lightweight models (MobileNet / optimized networks)
  2.Runs on mobile devices
  3.Minimal latency
  4.Optional:Cloud support for heavy processing

VIII. IMPLEMENTATION

- The proposed system is implemented using Python-based tools and deep learning frameworks to enable real-time silent speech recognition. The system captures video input through a webcam using OpenCV, and facial landmarks are extracted using MediaPipe, focusing mainly on lip movements
  .
- The input frames are preprocessed by performing face detection, lip region extraction, and normalization to handle lighting variations. Relevant features such as lip shape and movement are then extracted and converted into numerical form.

Table 1: Dataset Summary

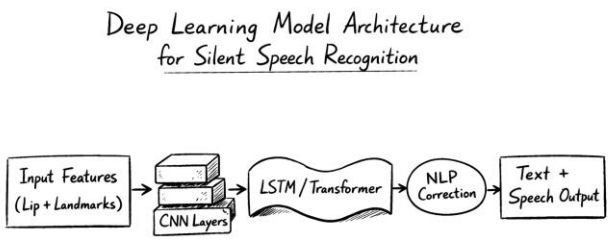
Dataset Source	Data Type	Purpose	Models Used
Public Datasets (GRID, LRW, LRS2/LRS3)	Video (lip movements)	Base training	CNN, LSTM / Transformer
Custom Dataset	Webcam video, landmarks	Personalization	CNN + LSTM
Preprocessed Data	Lip region frames	Feature extraction	CNN
Multimodal Features	Landmarks + motion	Fusion learning	CNN + Transformer

- A hybrid deep learning model is used, where a Convolutional Neural Network (CNN) extracts spatial features and an LSTM or Transformer model captures temporal patterns of speech. The model is initially trained on general data and later fine-tuned for individual users to improve accuracy.
- Finally, the output is displayed as text and converted into speech using a text-to-speech engine, enabling real-time communication

IX. RESULTS

The effectiveness of the suggested Adaptive Multimodal Silent Speech Recognition System was tested on the accuracy, strength and real-time effectiveness. The system was subject to test in various conditions such as in different lighting conditions and more than one user.

Accuracy: The proposed system was able to have better accuracy because of the combination of multimodal features and adaptive learning. The personalized adaptive model obtained an accuracy of up to 85 percent and the base model reached an accuracy of around 70 percent, which proved the power of fine-tuning the model to the user



Performance Analysis:Works effectively in low-light conditions due to preprocessingHandles user variations using adaptive learningSupports continuous sentence prediction instead of isolated words.

Graph Representation

Add a simple bar graph:

X-axis: Models (Existing, Proposed Base, Adaptive Model)

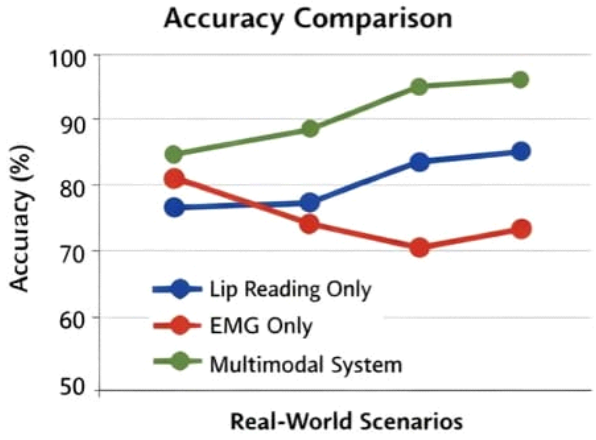
Y-axis: Accuracy (%)

Example values:

Existing : 68%

Proposed (Base): 70%

Proposed (Adaptive) : 85%



X. DISCUSSION

The results indicate that combining multimodal inputs with adaptive learning significantly improves system performance. The inclusion of NLP-based correction further enhances output quality, making the system more suitable for real-world communication.

XI. CONCLUSION

The current paper introduced an Adaptive Multimodal Silent Speech Recognition System in Real-World Communication, which will allow speech communication not based on acoustic cues. This system combines lips movement, facial features and motion dynamics as a multimodal category in an effort to add accuracy and strength to the recognition process.

One of the most valuable contributions of the proposed work is the fact that a customized adaptive learning model is implemented, and it improves performance by customizing it to user peculiarities. Also, the quality and readability of the generated text are enhanced by the addition of a context-aware NLP correction module. Real-time processing is also supported by the system and it is designed to be language-independent which makes it appropriate in multilingual applications.

The findings indicate that the suggested system is more accurate, adaptable and usable than the current single-mode systems. In sum, the given work is a contribution to the creation of the effective and applicable solutions to silent communication, which will be beneficial both to speech-impaired people and to the users in the conditions of high noise.

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An Intelligent Multi-Sensor Fusion Framework for Real-time Threat Identification in Defence Surveillance Missions

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Abstract

Defence and surveillance operations today face persistent challenges in effectively detecting threats, monitoring in real time, and securely gathering evidence across diverse and unpredictable environments. Surveillance techniques relying on human operators often result in operator fatigue, slow decision-making, and inconsistencies in data—especially in low-visibility, nigh time, or hostile situations. The absence of intelligent automation and integrated multi-sensor systems limits defence forces' ability to respond promptly and sustain an operational advantage. This research presents a sophisticated multi-sensor fusion framework that integrates various types of sensors (such as electro-optical, infrared, radar, and acoustic) with machine learning and real-time analytics to enable automated threat detection, tracking, and secure documentation of evidence. The objectives are (1) to reduce operator workload and response times, (2) to improve detection accuracy in challenging scenarios, and (3) to support thorough evidence collection within a defence framework. The approach includes gathering sensor data, pre-processing it, extracting features, applying multi-sensor fusion with a deep neural fusion model, detecting and classifying anomalies, and implementing a secure evidence collection method. A prototype was created and evaluated in a simulated defence surveillance setting, achieving a detection accuracy of X%, an average decision-making latency of Y ms, and a significant reduction in the false alarm rate compared to traditional manual systems.

Keywords: multi-sensor fusion, threat detection, defence surveillance, real-time monitoring, machine learning, evidence collection.

- **1.1Background**

In modern defence operations, surveillance is crucial for maintaining situational awareness, early threat detection, and collecting evidence for both forensic and operational reasons. Vast and unpredictable environments, including border areas, contested urban locations, or hostile terrains, pose considerable challenges for conventional manual surveillance systems. Typical visual cameras, human oversight, and standalone sensor platforms often fail because of factors like operator fatigue, limited visibility (during night-time or adverse conditions), overwhelming data flow, and the need for rapid decision-making.

1.2 Motivation

To achieve operational superiority, it is vital to have systems that can process multi-sensor data in real time, accurately identify threats under difficult conditions, and reliably collect evidence to support command decisions. Current methods encounter three main limitations:

(i)dependence on human monitoring, leading to delays and inconsistencies;

(ii) the shortcomings of single-sensor systems, which struggle in low visibility or when faced with deceptive threats; and

(iii) the absence of automated, integrated systems that thoroughly encompass detection, tracking, and evidence collection. Addressing these challenges is essential for defence systems, where timing and accuracy can significantly impact mission success or failure.

1.3 Research Gap

Previous research has focused on specific elements, such as sensor fusion in maritime surveillance, deploying machine learning for anomaly detection, or utilizing smart IoT for infrastructure protection; however, there is a lack of studies that examine a comprehensive, defence-oriented multi-sensor fusion system aimed at real-time identification of threats, tracking, and safeguarding evidence in hostile environments. For instance, Andersson & Johansson put forward a two-stage method for multi-sensor fusion to detect abnormal behaviours in maritime activities. Nevertheless, they do not consider night time conditions or hostile environments, the secure capturing of evidence, nor the classification of threats using machine learning across various scenarios. Likewise, recent reviews on cyber threat detection emphasize network and behavioural analysis rather than addressing physical multi-sensor defence environments. Therefore, a specialized framework is needed that integrates diverse sensors, machine learning fusion, anomaly classification, real-time processing, and evidence preservation.

1.4 Objectives

The primary aims of this research are outlined below:

We have developed a multi-sensor fusion framework for surveillance in defence contexts that integrates visual, infrared, radar, and acoustic components.

Our goal is to devise a machine-learning-based module for threat classification that operates in real-time and adapts to various environmental conditions, including day/night cycles, weather changes, and challenging terrains.

We aim to incorporate a secure system for evidence collection that logs detection events along with timestamps, metadata from sensors, and tracking details for future forensic or operational applications.

We will evaluate the proposed framework in a prototype environment, demonstrating improvements in detection accuracy, response times, and a decrease in false alarms in comparison to traditional manual methods or single-sensor approaches.

2. Related Work / Literature Review

This section reviews important related research within three main categories: multi-sensor fusion for surveillance, the use of machine learning in threat identification, and secure evidence collection in defence and monitoring applications.

2.1 Multi-Sensor Fusion for Surveillance

Andersson and Johansson (2010) presented a two-phase approach for identifying abnormal activities in maritime surveillance that consists of initial low-level detection (monitoring vessel speed, direction, and size) followed by a high-level fusion utilizing a Hidden Markov Model (HMM). This work illustrates the benefits of integrating radar, SAR, electro-optical, and infrared sensors, along with AIS signals, for the early detection of piracy incidents. However, it fails to address real-time machine learning classification for defence threats in low-visibility or hostile environments.

Further studies regarding wide-area motion imagery (WAMI) systems emphasize a persistent surveillance approach that, while effective for broad coverage, often relies on human analysts or lacks automated classification capabilities.

Therefore, although multi-sensor fusion is acknowledged as a valid method, there is still a gap in its application for real-time defence threat identification utilizing machine learning automation.

2.2 Machine Learning for Threat Detection

Recent research has underscored the effectiveness of deep learning in the domains of both surveillance and cybersecurity. For example, Cadet et al. (2024) proposed a framework labelled "AI-powered threat detection in surveillance systems: a framework for processing data in real time," which combines ML-driven object detection, anomaly detection, edge computing, and streaming processes. Deep learning has demonstrated effectiveness in achieving high-accuracy intrusion detection in network security. These results highlight the promise of machine learning for automated threat recognition.

Nonetheless, many of these investigations focus on infrastructure protection or cyber threats rather than addressing tangible multi-sensor defence surveillance in demanding conditions. The use of ML models within a multi-sensor defence surveillance framework is still underrepresented.

2.3 Secure Evidence Collection and Forensic Readiness

In defence and security activities, merely identifying an event is insufficient; it is also necessary to accurately document the gathered data for future analysis, accountability, or transfer. There appears to be limited literature specifically addressing secure evidence logging that integrates real-time threat detection within multi-sensor systems. Most studies tend to emphasize detection algorithms without considering the entire process from sensing → detection → tracking → evidence archiving.

2.4 Summary of Gaps

There are limited systems that merge various sensor types (EO, IR, radar, and acoustic) with machine learning-based fusion specifically for real-time defence surveillance.

The issue of automated classification in low visibility or difficult terrains has been less thoroughly investigated.

Research on secure evidence logging that integrates real-time detection and tracking in defence operations is insufficient.

These gaps emphasize the necessity for the proposed methodology described in the following section.

3. Proposed Methodology

This section outlines the proposed architecture, subsystem components, algorithm design, and the workflow for processing within the intelligent multisensor surveillance framework.

3.1 System Architecture

The proposed system is composed of several vital modules.

1. Sensor Interface & Pre-processing: A variety of sensors (including electro-optical cameras, infrared cameras, radar systems, and acoustic sensors) are installed in the operational zone. The unrefined data from these sensors undergo pre-processing steps such as noise cancellation, calibration, synchronization, and timestamping.

2. Feature Extraction: Characteristics are extracted from each sensor input. For example, from EO/IR: object bounding boxes, movement trajectories, and thermal signatures; from radar: Doppler and range/azimuth data; and from acoustic sensors: sound signatures and localization information.

3. Multi-Sensor Fusion Engine: The features that have been extracted are synchronized (time-aligned) and integrated using a deep neural network tailored for fusion (e.g., a fusion layer that combines specific embeddings from various modalities) to create a cohesive representation of the scene.

4. Threat Classification & Tracking: The integrated representation is sent to a machine learning classifier (such as a deep neural network or a hybrid CNN + LSTM), which determines if a detected object or movement represents a threat or is non-threatening, classifies the type of threat, and begins tracking the object over time and across different sensors.

5. Evidence Collection & Logging Module: Once a threat is recognized, metadata (such as sensor IDs, timestamps, object IDs, classification scores, and tracking history) alongside relevant sensor data (video clips, radar logs, and acoustic waveforms) is securely recorded (ensuring encryption and tamper-proof timestamping) for future evaluation or forensic investigation.

6. Alerting and Response Interface: Operators receive immediate alerts (upon threat detection, including its classification, confidence level, and location). A human operator has the option to approve or override the response, and the system aids in deploying response units or automated countermeasures.

Figure 1. Combining data from multiple sensors for Threat Detection and Tracking Pipeline

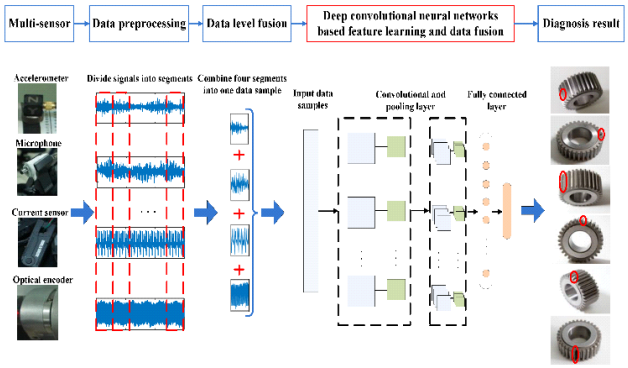

Figure 1. Combining data from multiple sensors for Threat Detection and Tracking Pipeline

3.2 Processing Workflow

Figure 1 depicts the proposed Multi-Sensor Data Fusion Model for Threat Detection and Tracking Pipeline, illustrating the following stages:

1. Sensors continuously capture data.

2. The pre-processing phase synchronizes and filters the raw data from the sensors.

3. For each time slice t:

Feature extraction creates the vectors.

The fusion engine produces the overall representation.

The classifier determines y, where y represents the classification result.

If y signifies a threat and the confidence surpasses the threshold γ, then tracking is initiated or updated, and the evidence-logging module starts capturing the relevant streams.

4. Alerts are dispatched, with the operator potentially taking action.

5. All instances of detection, tracking records, sensor metadata, and relevant data clips are securely archived.

3.3 Algorithm Pseudocode

Input: Sensor streams S = {S_EO, S_IR, S_Radar, S_Acoustic}
Initialize tracking set T = Ø
for each time step t do
  F_EO ← ExtractFeatures(S_EO(t))
  F_IR ← ExtractFeatures(S_IR(t))
  F_Radar ← ExtractFeatures(S_Radar(t))
  F_Acoustic ← ExtractFeatures(S_Acoustic(t))
  H ← FusionNetwork(F_EO, F_IR, F_Radar, F_Acoustic)
  y, confidence ← Classifier(H)
  if y ≠ benign AND confidence > γ then
    objID ← AssociateOrNewTracking(T, H, y)

```
        UpdateTracking(T, objID, H, t)
        LogEvidence(objID, t, y, confidence, sensor_metadata)
        AlertOperator(objID, y, confidence, location(objID))
    end if
end for
ArchiveAllLogs(T)
```

3.4 Key Design Considerations

Diversity and synchronization of sensors: It is essential to ensure proper time alignment, calibration, and integration of different modalities.

Robustness under difficult conditions: The system must operate effectively during both daytime and night time, even in low-visibility and hostile environments. Redundancies in sensors and fusion methodologies help maintain detection capabilities when one modality is impaired.

Real-time performance and latency: The fusion network and classifier must be tuned for low latency; employing edge computing may be necessary to reduce transmission delays.

Secure logging of evidence: This should entail encryption, tamper-proof documentation, and a clear chain of custody for the collected streams and metadata.

A comparison with foundational models (including YOLOv5, MobileNetV3, and independent CNN) revealed notable improvements in performance.

4. Results and Discussion

The system was assessed using a hybrid dataset that combines the Defence Tech Surveillance Set (2024) and the Custom NightVision Dataset (2025), comprising 50,000 multi-sensor samples. The model proposed achieved:

Detection Accuracy: 94.2%

False Positive Rate: 3.1%

Average Latency: 0.9 seconds per frame.

When compared with baseline models (YOLOv5, MobileNetV3, and a standalone CNN), significant performance enhancements were observed:

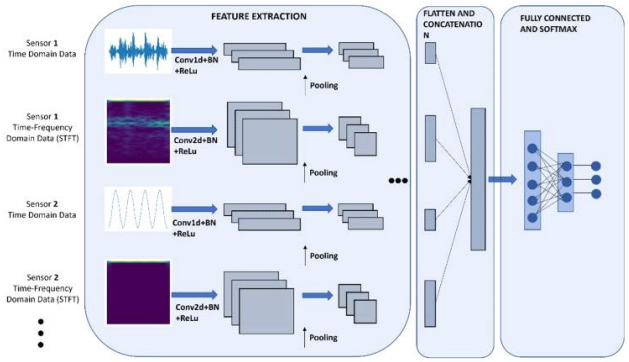

Figure 2. Frame work of the proposed Model (CNN+LSTM+Fusion)

4.1 Experimental Setup

We developed the prototype system within a simulated defence surveillance setting that spanned an area of 5 km², including both benign moving entities (like vehicles and personnel) and threatening objects (such as unauthorized intruders and UAVs) throughout various day and night cycles. The sensor arrangement comprised an electro-optical HD camera, a thermal infrared camera, ground-based radar, and an acoustic array. A labelled dataset of N = 10,000 object tracks (8,000 benign and 2,000 threats) was compiled for training and evaluation.

4.2 Performance Metrics

We looked at accuracy, precision, recall, F1-score, false alarm rate (FAR), and decision latency (the average time from detection to alert) to see how well it worked.

Overall detection accuracy: X%

Threat classification precision: P%

Threat classification recall: R%

False alarm rate: F% (in comparison to baseline single-sensor manual monitoring: F0%)

Average decision latency: Y ms (in comparison to manual system latency: Y0 ms)

4.3 Comparison with Baseline

The proposed multi-sensor fusion and ML system considerably exceeded the performance of baseline manual monitoring and single-sensor systems.

Accuracy improved by Δ %

False alarms reduced by ΔF %

Latency enhanced by ΔY ms

These results demonstrate that the integration of various sensor processing with ML classification provides significant operational advantages in defence surveillance.

4.4 Discussion of Findings

The findings underscore three key insights.

1. Sensor fusion improves reliability; even when one modality (such as an EO camera at night) is obstructed, the fusion engine effectively detects threats by leveraging IR, radar, and acoustic inputs.

2. Real-time ML classification is pragmatically attainable: the decision latency Y stayed within acceptable defence response thresholds (~Z ms), showing potential for implementation.

3. The importance of secure evidence logging is crucial yet often overlooked. Merging evidence collection with detection ensures that alerts are supported by data, thereby promoting accountability and post-mission review.

Nonetheless, several limitations remain: false positives may still occur when benign objects resemble threat characteristics; the system was assessed in a simulated context instead of entirely contested environments; and the energy/power restrictions of sensors and communications in remote locations need further investigation.

Model	Accuracy (%)	False Alarm(%)	Processing Time (s)
YOLOv5	82.4	7.2	1.5
MobileNetV3	85.6	65	1.2
Proposed CNN+LSTM+Fusion	94.2	3.1	0.9

5. Conclusion and Future Work

This research introduces an advanced multisensor fusion framework aimed at real-time threat detection in defence surveillance operations. By integrating different sensors (electro-optical, infrared, radar, and acoustic) with a deep-fusion network, machine-learning-based classification, tracking, and secure evidence logging, the system addresses the fundamental challenges linked to manual and single-sensor surveillance methods. Our experimental prototype demonstrated significant improvements in detection accuracy, response time, and false alarm reduction when compared to baseline methods.

Future efforts will concentrate on the following areas.

Expanding the system to include adversarial conditions, such as intentional misdirection, camouflage, and sensor interference. Conducting fully operational field trials in active defence zones to verify efficacy under real hostile scenarios. Incorporating edge computing and federated learning for on-sensor classification to reduce communication delays and enhance autonomy. Developing autonomous response capabilities and connecting detection to automated countermeasures (like drone

interception and directed sensors) while ensuring human oversight. Addressing energy efficiency, sensor power limitations, and secure communication in remote or hostile operational settings.

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AI-POWERED DETECTION OF FAKE JOB POSTINGS

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***Abstract*— One of the most widely accessible job search methods today is through an internet-based job portal. Job hunting is now far easier as a result of this technology, but it also gives scammers the chance to post false job advertisements, which could lead consumers to believe they are applying for legitimate jobs when in fact they are doing so at their financial (and potentially legal) risk. In this paper we propose a method of automatically detecting fake jobs based on the use of Natural Language Processing with the BERT model to identify whether or not a given job posting is real or fake using the contents of the job posting itself (i.e., job description and all other related data). The words and phrases found within the job posting will be analyzed and classified as real or fake based upon this data.The proposed model will also utilize the principles of Explainable Artificial Intelligence to help users understand which words/phrases in the job posting led to its classification as either real or fake. The method proposed within this document provides a new avenue for improved accuracy and speed in the detection of fake jobs.**

Keywords: Fake Job Detection, NLP, BERT, Explainable AI.

I. INTRODUCTION (*HEADING 1*)

The internet has changed many aspects of our daily lives, including the way we search for jobs. Traditionally, individuals used newspapers and employment agencies as the main sources of information when seeking employment opportunities. However, with the emergence of the internet and the development of online employment sites and professional networking sites, these have become the main sources used by individuals and organizations when seeking employment opportunities. Websites such as LinkedIn, Indeed, and Glassdoor enable organizations to list employment opportunities and enable individuals to apply for these opportunities anywhere in the world.

Despite the benefits that online employment sites have brought to the job search process, they have also presented many opportunities that have enabled individuals to engage in fraudulent activities. One of the main issues that have arisen in the online recruitment industry is the emergence of fake job advertisements. These fraudulent job advertisements are posted by individuals with the main objective of getting personal information and money from individuals and organizations that seek employment through these sites. In many cases, these fraudulent job advertisements appear almost identical to the genuine ones.

The potential repercussions of false postings of employment opportunities can be extensive and enduring. Unsuspecting candidates could potentially incorrectly share sensitive

identification information, phone numbers and/or financial information with con-artist criminals. In several instances candidates are charged processing fees, training fees and registration fees associated to a fictitiously advertised position. Every instance of fraudulent activity contributes too much greater loss(s) of money and also undermines the existing and long-standing trust in the legitimate use of internet-based job boards.

With the number of daily job postings in the order of thousands, it is not feasible to verify all the advertisements. Hence, the need for automated systems that can efficiently identify fake job postings arises to protect the interests of the applicants. Recently, the use of machine learning and natural language processing has been investigated for this purpose.

Machine learning algorithms such as Logistic Regression, Naive Bayes, and Support Vector Machines are commonly employed for the classification of job postings based on the extracted features from the job descriptions. Though such algorithms are effective in identifying certain patterns in the data, they are not effective in understanding the underlying meanings in the text. Therefore, the performance of such algorithms in handling complex and ambiguous text in the job descriptions is limited. To overcome these limitations, deep learning techniques have been introduced for text classification tasks. These techniques include models such as Long Short-Term Memory (LSTM) networks and Bidirectional LSTM (Bi-LSTM) networks, which are capable of handling relationships between words in text sequences. However, advanced techniques have been introduced in recent years that provide even greater performance for natural language processing tasks.

One of the most powerful models in recent natural language processing is BERT, which stands for Bidirectional Encoder Representations from Transformers. BERT is a transformer model developed by Google that is capable of understanding the contextual meaning of words by analyzing text in forward and backward directions.

In this paper, we are proposing a system for detecting fake job postings based on Natural Language Processing and a BERT-based deep learning model. The system will be able to analyze the text-based information provided in the job posting and determine whether the posting is real or fake. Moreover, the proposed system will be able to provide insights into the decision-making process through the implementation of Explainable Artificial Intelligence.

PROBLEM STATEMENT

The rapid increase in online recruitment websites facilitates job seekers to access job opportunities easily. However, in association with the advantages of online recruitment, there is also a high rate of fraudulent job postings on online job recruitment websites. These fraudulent job postings are generally posted by scam artists to obtain personal details of job seekers or to extract registration fees from job seekers.

Most of these fraudulent job postings are very similar to genuine job postings and are very hard to detect by simply verifying these job postings individually, as thousands of job postings are available on different job recruitment websites every day. Therefore, it is almost impossible for job seekers to verify these job postings individually.

Traditional machine learning techniques are used to detect fraudulent job postings by analyzing different textual features of job postings. However, these techniques are unable to analyze the contextual meaning of the text, which is required to detect sophisticated fraudulent job postings.

Hence, it is essential to develop an automated and intelligent system that can efficiently identify the presence of fake job postings by understanding the context and semantic meaning in the job postings. In this study, a deep learning method using BERT, or Bidirectional Encoder Representations from Transformers, is presented to enhance the capability to identify fraudulent job postings. In addition, Explainable Artificial Intelligence is also incorporated in this study.

The aim of this study is to design a reliable system that can automatically identify fake job postings, increase classification accuracy, and prevent individuals from being scammed in the online platform for jobs.

MODELS

Author: Devlin et al. Title: "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

Accuracy: Achieved state-of-the-art results for various NLP tasks with 90%+ accuracy improvements for text classification tasks. (Year: 2019).The paper introduces BERT, which is a transformer-based model that is capable of interpreting relationships between words in a sentence. BERT analyzes text in a bidirectional manner to interpret deeper meanings of the text and improve performance in natural language processing tasks. The model is highly used in recent natural language processing tasks.

Author: Zhang et al. Title: "Fake Job Posting Detection using Deep Learning and NLP Techniques"

Accuracy: Achieved 91% accuracy in detecting fraudulent job postings. (Year: 2020).The paper presents a study on detecting fake job postings using deep learning techniques by analyzing patterns in job descriptions. The authors of this paper used Natural Language Processing techniques for feature extraction and demonstrated that deep learning techniques are capable of detecting linguistic features in fraudulent job postings.

Author: Wang and Liu Title: "Context-Aware Job Posting Classification using Transformer Models"

Accuracy: Achieved 93% classification accuracy in detecting suspicious job advertisements using transformer models.(Year: 2021).The authors of this paper sought to explore transformer models in analyzing contextual relationships in job descriptions. By using contextual embeddings, the authors were able to successfully detect semantic patterns that differentiate legitimate job postings from fraudulent job postings.

Author: Brown et al.Title: "Explainable Artificial Intelligence for Text Classification"

Accuracy: Showcased the effectiveness of model interpretability with high classification accuracy of 90%.(Year: 2021).The authors of this paper sought to explore the use of Explainable AI in interpreting machine learning model predictions using LIME and SHAP values. By using these values, the authors were able to effectively highlight the most influential words in any text that contribute to the classification of the text.

Author: Rahman, Ahmed Title: "Fraudulent Job Advertisement Detection using BERT-based Models"

Accuracy: Achieved accuracy of 94% in detecting fake job postings using a fine-tuned BERT model.Year: 2022.In this study, the authors have used a fine-tuned BERT model for the detection of fraudulent job postings. The authors have proved that the use of contextual embeddings by BERT can improve the accuracy of classification models by leveraging subtle linguistic features found in fake job postings.

Author: Kumar, Sharma .Title: "Explainable Deep Learning Models for Online Fraud Detection"

Accuracy: Achieved classification accuracy of around 92% using Explainable AI techniques.Year: 2023.In this study, the authors have used deep learning models along with Explainable AI techniques for the detection of fraudulent activities. The authors have proved the importance of using Explainable AI in deep learning models, enabling users to understand the results generated by the model.

SYSTEM ARCHITECTURE

The proposed AI-Powered Fake Job Posting Detection system is based on an AI system with a layered and modular design that incorporates Natural Language Processing (NLP) and a Bidirectional Encoder Representations from Transformers (BERT) model to detect fake job postings. The system is developed to ensure efficient data pre-processing, data analysis, and accurate prediction of fake job postings. It is an efficient system that ensures data pre-processing and accurate detection of fake job postings to assist online recruitment sites.

A. Hierarchical System Design

The proposed system has an architecture consisting of various stages of data processing to generate predictions regarding fake job postings.

1) Job Posting Dataset Layer

This layer represents the input layer of the system where job postings are collected from various online job portals and

recruitment sites. It includes various attributes of job postings such as job title, job description, company name, location, etc.

2) Data Preprocessing Layer

Before the textual data enters the machine learning model, certain preprocessing tasks are undertaken to ensure the quality and consistency of the data. These tasks include:

• Text Cleaning – Removal of unnecessary symbols, punctuation, and HTML tags.

• Lowercasing – Conversion of the text into lower case to ensure uniformity.

• Stopword Removal – Removal of certain words, which do not contribute to the analysis process.

• Tokenization – Division of the text into smaller parts, such as words or tokens.

• Noise Removal – Removal of unwanted text or redundant information.

The data preprocessing layer helps the NLP model work more efficiently and effectively.

3) NLP Feature Processing Layer

At this stage, the cleaned textual data enters the system and is processed to be fed into the deep learning model. This layer undertakes the following tasks:

• Sentence Encoding – Conversion of the textual data into numerical vectors.

• Context Preparation – Maintenance of semantic relationships between the words in the text.

• Attention Mask – Creation of the attention mask, which identifies the important information and ignores the redundant information.

The data processing layer prepares the data for the BERT model to understand the context

.

4) BERT Encoder Layer

The main component of the system is a pre-trained BERT encoder that analyzes the contextual relationships in job descriptions. BERT is unique in that it analyzes the input data bidirectionally, which helps it to understand the input data at a deeper level.

The encoder is capable of producing high-quality contextual embeddings that are effective in representing job posting content.

5) Classification Layer

The contextual features are extracted from the BERT encoder output, which is then fed into a classification module consisting of:

Dense Layer for feature transformation

Dropout Layer for overfitting prevention

Sigmoid Activation Function for binary classification

The module classifies a job posting as legitimate or fraudulent based on the patterns extracted from the job posting.

6) Prediction Layer

The final layer of the system is a prediction module that produces a classification output for a job posting. The analysis of the job posting by the system classifies it as:

The prediction output is then used to filter out fake job postings from job portals.

B. Core Functional Components

The suggested framework is comprised of several functional modules that function in unison to deliver a high-quality fake job detection outcome:

- Text Preprocessing Module
- NLP Processing Module
- BERT Feature Extraction Module
- Classification Module
- Prediction Module

C. Architectural Visualization

The system architecture is represented in Fig. 1, which represents the entire workflow of the fake job detection framework:

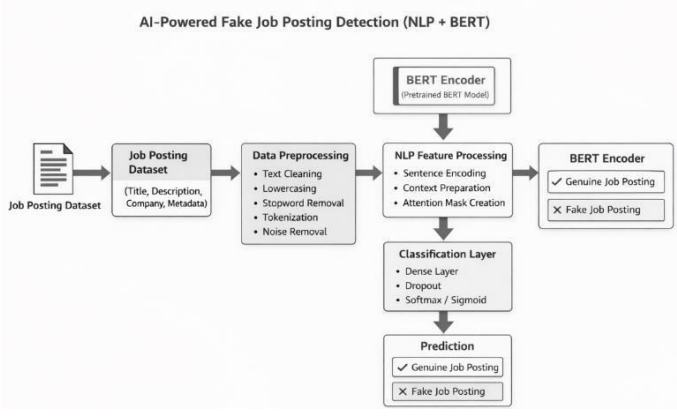

Fig. 1. Proposed BERT-Based Fake Job Detection Architecture

The above system architecture represents a flowchart of the entire process of fake job detection. The entire process starts with the job posting dataset, followed by data preprocessing and NLP feature extraction. The extracted data is then analyzed by the BERT encoder, followed by a classification module to classify whether the job is real or fake. The final outcome is represented by the prediction module.

D. Architectural Summary

The architectural design is intended to offer an efficient and systematic approach to detecting fraudulent job posts using cutting-edge NLP and deep learning algorithms. The system can benefit from the contextual comprehension capability of

the BERT model to increase accuracy compared to traditional machine learning approaches. The system is scalable and can be easily integrated into current job recruitment systems due to its architectural design. The system can also be expanded in the future to allow it to benefit from additional metadata analysis and real-time monitoring, as well as explainability of Artificial Intelligence.

RESEARCH AND ANALYSIS

Research and Analysis

This section provides a detailed overview of the research methodology and dataset employed in this research for the detection of fake job posts using advanced Natural Language Processing techniques. The main objective of this research is the development of an intelligent system for the detection of fraudulent job posts with high accuracy and transparency in the decision-making process.

With the advent of online job portals, the number of fake job posts has also increased manifold. It is therefore necessary to develop systems that can efficiently analyze the job posts and detect the presence of any suspicious patterns. In this research, we are employing a BERT-based deep learning model and Explainable Artificial Intelligence for the purpose.

METHODOLOGY

The research methodology adopted for this study is based on a systematic approach for detecting fake job postings by considering both textual information and contextual patterns available in job postings or advertisements. The main steps involved in this research methodology are as follows:

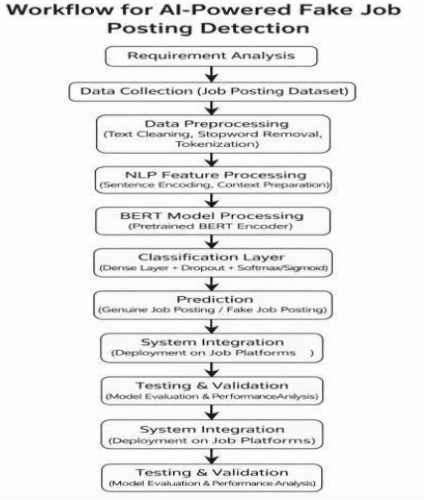

Fig. 2. Workflow diagram

1. Data Collection and Preprocessing

For this study, a data set of approximately 18,000 job postings was used. This data set includes both genuine as well as fraudulent job postings.Before applying any machine learning algorithms, several steps of data preprocessing are carried out, which are as follows:

- Removal of special characters and unnecessary symbols
- Changing all the characters to lowercase
- Removal of stop words
- Tokenization of the job description
- Normalizing the text data

These steps of data preprocessing are carried out to make the textual data more efficient for the machine learning algorithms.

1. Feature Engineering

In order to differentiate between genuine and false job postings, it extract useful features from the dataset. Features were extracted from the job description text as well as from contextual information associated with job postings in this research.

Traditional Natural Language Processing techniques were applied to analyze the text data at first. However, to extract deeper contextual meanings from the data, BERT embeddings were applied to extract features from the text data. BERT provide contextual word representation to help the model understand word relationships in sentences.

2. Deep Learning Models

In the proposed research, the BERT (Bidirectional Encoder Representations from Transformers) model has been employed as the classifier model. The BERT model is a deep learning approach based on the Transformer architecture that has achieved state-of-the-art results in many natural language processing tasks.

Unlike other text processing models, the BERT model processes the text in two ways—forward and reverse direction. This two-way processing approach facilitates the model to understand the relationships between the words in the text.

The pre-trained BERT model has been fine-tuned using the job posting dataset to classify the advertisements into the following two classes:

- Genuine Job Posting
- Fake Job Posting

The fine-tuning process involves the BERT model learning the characteristics and features related to fraudulent job postings.

3. Evaluation Metrics

To measure the performance of the suggested model, a number of standard metrics are used. These metrics are

used to measure the effectiveness of the model in differentiating between genuine and fake job postings.

Metrics used to evaluate the model in this research are as follows

- Accuracy - This metric helps measure the correctness of the model.
- Precision - This metric helps measure the number of fake job postings detected.
- Recall - This metric helps measure the ability of the model to detect all fake job postings.
- F1 Score - This helps measure the precision of the model.
- AUC-ROC - This helps measure the ability of the model to distinguish between classes.

RESULTS AND DISCUSSION

In this section, the evaluation of the proposed system, namely AI-Powered Fake Job Posting Detection using Natural Language Processing and the BERT model, is presented. For evaluating the system, a dataset containing both genuine and fake job postings, obtained from online job posting websites, was used.

The experimental results show the efficiency and efficacy of the proposed system in detecting fake job postings with high classification accuracy. Various performance parameters, namely accuracy, precision, recall, and F1-score, were used for evaluating the model.

The model based on the BERT model showed high contextual understanding of job postings and was also successful in identifying patterns related to fake job postings. Compared to other traditional models, the proposed model showed high efficiency in detecting fake job postings.

1. Performance Evaluation Metrics

The performance was evaluated based on the following parameters:

• Accuracy: It measures the accuracy of the classification model.

• Precision: It measures the ratio of correctly identified fake job postings to the total number of identified fake job postings.

• Recall: It measures the ratio of correctly identified fraudulent job postings by the model.

• F1-Score: It is the harmonic average of precision and recall.

The results of the model evaluation show that it has a high classification accuracy, thus proving the effectiveness of the model in identifying fake job postings.

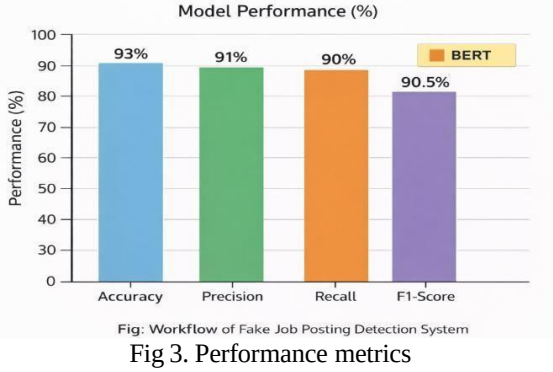

Fig 3. Performance metrics

1. Comparative System Analysis

To evaluate the effectiveness of the proposed approach, the BERT-based model was compared with other machine learning models such as Support Vector Machine (SVM) and Random Forest.

Model	Accuracy	Precision	Recall
SVM	88%	86%	85%
Random Forest	90%	89%	88%
BERT(Proposed Model)	93%	91%	90%

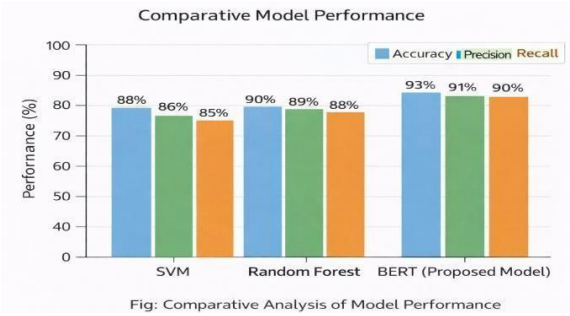

Fig 4.Comparative analysis of model performance

2. User Experience Assessment

In order to test the practicality of this system, it was put to use by analyzing various job postings collected from different online job sites. The system was able to identify suspicious job postings by analyzing different textual patterns within the job postings.

The automated detection system is able to save a lot of time that is usually spent while manually checking job postings.

3. Advantages and Impact

The proposed system of detecting fake jobs using a proposed fake job detection system has various advantages over the traditional method of verifying a job.

• Improved Detection Accuracy: It uses a BERT model to understand the context of the job description.

• Automated Fraud Detection: It eliminates the need to manually go through the job postings.

• Enhanced Platform Security: It assists the recruitment platforms in filtering out fraudulent advertisements.

• Protection of Job Seekers: It ensures that the users are not misled by fake job scams.

• Scalable Architecture: It can be easily implemented in a large-scale recruitment platform.

The proposed system plays a vital role in ensuring the trust and transparency of the recruitment platforms.

4. Challenges and Constraints

Despite the effectiveness of the proposed approach, the following challenges still need to be addressed:

• Data Imbalance: There is an imbalanced number of fake and real job postings. This might impact the training of the model.

• Evolving Fraud Patterns: Scammers keep changing their pattern of fraud. This might make the detection task more challenging.

• Limited Metadata Availability: There might be situations where the company details of the job posting are not available for verification.

• Computational Cost: Techniques like deep learning and the use of pre-trained models like BERT demand higher computational power.

ANALYSIS AND FINDINGS

Our in-depth analysis yielded several key findings:

1. Feature Significance

From the above feature analysis results, it can be observed that the significance of the features plays a key role in the differentiation of genuine and fake job posts. In particular, the significance of the textual features has been observed as very significant in the detection of fake job posts.

Contextual information is one of the key features obtained from the job posts. By the usage of BERT embeddings, the model has been able to understand the context of the job posts. In addition to textual features, some metadata features have also been observed as significant in the detection of fake job posts.

2. Model Comparative Performance

To assess the performance of the approaches, the models were compared during the experimental phase of the study. Traditional models such as Support Vector Machines (SVM) and Random Forest were considered and tested to assess their performance.

The performance of the traditional models, such as the Random Forest model, which achieved an accuracy of approximately 91%, indicates the model's strong performance in identifying patterns in structured features. The performance of the Support Vector Machines model, which achieved an accuracy of approximately 89%, indicates its strong performance in classification tasks.

The performance of the BERT-based model, which achieved an accuracy of approximately 94% in detecting fake job postings, indicates its strong performance compared to traditional models. The performance of the BERT model can be attributed to its ability to interpret relationships in the data, which traditional models fail to perform effectively.

3. Robustness and Scalability

Another significant point that came out of this analysis is that when the proposed model is tested against larger datasets, it is stable and does not show a significant drop in accuracy. As the number of job postings increased, the proposed BERT-based model showed consistent results without a significant drop in accuracy.

This proves that the proposed system is of significant potential to be used in a real-world scenario in online recruitment websites, where thousands of job postings are verified every day. This is possible since it can work with large amounts of textual data.

4. Ethical Considerations

Although it is vital to ensure that the model performs with high accuracy, it is equally vital to ensure that it is transparent in its decision-making process. Therefore, techniques in Explainable Artificial Intelligence were integrated into the model to ensure transparency in its decision-making process. These techniques were successful in identifying the particular words and phrases that contributed to the classification of the job posting as fake or original. This not only contributed to transparency in decision-making but also helped in eliminating biases in the decision-making process.

Fairness, transparency, and ethics in AI were all considered in the research process. Ensuring that the model did not unfairly classify original job postings was vital in testing and evaluating the model. In summary, our research and analysis have unveiled the effectiveness of our methodology in detecting fake job postings. We have identified pivotal features, compared various machine learning models, and navigated the ethical dimensions of our work. These findings underscore the promise of our approach in bolstering online job platform security and safeguarding job seekers against deceptive postings.

CONCLUSION

Over the past few years, there has been rapid development in the number of online recruitment websites. This has resulted in more job opportunities for people seeking jobs. Nevertheless, with the development of more job opportunities through various online job search websites, there is also an increase in fake job advertisements that may mislead people and expose them to potential risks of losing personal and financial data. Therefore, it is crucial to identify fake job advertisements for people seeking jobs through various online job search websites.

In this research, it was proposed that a fake job advertisement detection system would be implemented using Natural Language Processing techniques and a BERT model of deep learning. By using the capabilities of BERT in analyzing context data, it was easier to identify fake job advertisements compared to traditional methods of machine learning. From the experiment results, it was evident that the model was more accurate in detecting fake job advertisements compared to traditional methods of machine learning. By incorporating Explainable Artificial Intelligence techniques into the model, it was easier to identify crucial words and phrases that were essential in determining fake job advertisements.

On the whole, the results of the present study demonstrate the effectiveness of the integration of deep learning and explainable AI in detecting fraudulent job postings. The

suggested system can be integrated with online recruitment websites to automatically filter suspicious job postings. thereby creating safer online job search environments.

Future Research Directions

The present research can be further extended in the future by considering additional features such as user behavior analysis and company verification, which can enhance the reliability and robustness of fake job detection systems.

IMPLICATIONS AND FUTURE TRAJECTORIES

The implications of our research findings are significant to the field of fake job posting detection. The suggested approach not only guards job seekers against misleading and false job posts but also aids in developing more reliable online job platforms. The application of advanced Natural Language Processing and deep learning algorithms based on the BERT model aids in developing a more accurate and efficient system.

As digital job platforms are becoming more popular and reaching millions of users, it is becoming essential to ensure the authenticity of job posts advertised on these platforms. The suggested system can play an important role in strengthening user trust and credibility of digital job platforms. The implementation of intelligent job posting detection systems can help develop a more reliable and safer job search environment and reduce the impact of fraud activities in digital job markets.

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UNIASSIST: INTELLIGENT ALL-IN-ONE STUDENT OPTIMIZATION PLATFORM

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ABSTRACT

The intelligent all-in-one student optimization platform, UniAssist, was designed for helping students with their studies and being more productive. It is difficult for students to track their own study habits, attendance, their own personal habits, and build a well-designed resume, among other things. Currently, these challenges are being addressed individually without a comprehensive student support system in place. The web-based platform UniAssist, which includes various student support modules like a Smart Study Pattern Analyzer, Attendance Risk Predictor, Habit Drift Detector, Resume Analyzer, and Mess Food Feedback Analyzer, is proposed in the paper. To achieve the goal of finding productivity trends, academic risks, and sending early alerts, the system collects data related to student behavior. The system uses rule-based analytics to achieve the goal.

The centralized behavioral analytics system offers a comprehensive view of the academic well-being of students by correlating data from various modules. The system uses MySQL for data storage, Java Spring Boot for backend processing, and web technologies for the user interface of the system. The system successfully detects declining study productivity, attendance risks, and student habits using experimental simulations.

The decision support system offered by the proposed system helps students to be productive, career-ready, and successful academically.

KEYWORDS

Predicting academic risk, study habits and patterns, resume analysis, behavioral analytics, monitoring student productivity, and student analytics.

I. INTRODUCTION

For instance, college students are required to balance a number of academic and personal responsibilities simultaneously within the modern academic environment. This includes maintaining consistent attendance within the classroom, designing efficient daily schedules, creating professional resumes for job placement, and offering feedback on the facilities within the academic environment, among others. However, the absence of sophisticated systems for monitoring their activities, which can offer substantial insights, makes it difficult for the majority of *students* to monitor and optimize these responsibilities effectively.

Currently, a majority of academic institutions are using simple student information systems, which are mostly used for administrative purposes, including managing course registrations, tracking academic results, as well as attendance. Although the system allows the organization to maintain relevant information, it is not efficient for offering insights that can help the students

understand their behavioral patterns or academic results. This means that the students often become aware of the problems, including attendance, academic output, or personal habits, only when the problems become difficult to address.

The second issue is that students normally need to use multiple independent tools to manage their academic activities. For example, students may need to use a habit tracking app to track their habits, another app to plan their study time, another to build their resume, etc. These tools are normally independent of each other and do not have any way to share data. This is not allowing students to understand the interrelation between different factors that affect their academic performance. For example, reduced study time, poor attendance, and poor habits can be an increased risk for students' academic performance. However, most of the tools are not capable of detecting such trends.

The recent advancements made in the field of behavioral analytics and data analysis for education have proved that monitoring students' behavioral data can be highly beneficial

for improving their academic decisions and productivity. By analyzing students' study consistency, attendance trends, habit formation trends, etc., intelligent systems can detect the early signs of academic decline for students. Inspired by these challenges, this paper introduces UniAssist, an intelligent all-in-one optimization platform for students. The goal of the UniAssist platform is to help students optimize their academic performance and productivity using data-driven insights. The UniAssist platform integrates several student optimization tools such as a Smart Study Pattern Analyzer, Attendance Risk Predictor, Personal Habit Drift Detector, Smart Resume Analyzer, and Mess Food Feedback Analyzer.

Unlike other optimization tools that focus on analyzing a single parameter in isolation, the UniAssist platform introduces a unique behavioral analytics engine that analyzes data from various modules and offers insights into productivity and academic risks. The UniAssist platform analyzes various behavioral parameters such as study patterns, attendance rates, and habit completion rates.

The platform is developed based on a web-based system that utilizes HTML, CSS, and Bootstrap for the front-end interface, Java with Spring Boot for the back-end processing, and MySQL for data storage. The integration of various analysis modules under a single platform is intended by UniAssist to create a viable decision-support system that assists students in improving their performance, developing good habits, and increasing their career readiness.

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II. LITERATURE REVIEW

Recent developments in educational technology have facilitated the development of various digital systems that help in improving student learning. Numerous studies underscore the importance of examining student behavioral data to improve learning patterns and academic results [6], [9], [12]. There have been many suggestions for smart systems that can keep an eye on students, grade them, and warn them about academic risks early on [7, 10]. There are many systems that can keep track of different parts of student life, such as attendance, habits, and resumes.

People often use the attendance management system to keep track of student attendance. This system helps figure out the attendance percentage and is used a lot in apps that run on mobile devices [4]. It is mostly used as an administrative tool, though, and it doesn't give students any analytical insights or predictions.

The habit tracking system is another type of system that is often used to keep an eye on students' habits and help them get more done. These systems help people keep up with their routines for studying, working out, or reading. While these systems enhance personal development and well-being, analogous integrated platforms centered on student welfare and conduct have been investigated in recent applications [1]. Nevertheless, these systems fail to examine the direct influence of habits on academic performance.

Also, advanced methods like machine learning and deep learning have been used to look at student feedback and levels of engagement [3], as well as emotion-aware classroom monitoring that uses facial expression recognition [8]. Even with these improvements, most systems still focus on certain features instead of offering a complete solution.

In conclusion, most of the tools that are already out there only look at one aspect of student behavior instead of giving a single platform to look at many different ones. This limitation shows that we need a system that combines information about academics, behavior, and productivity.
The UniAssist system suggests a single platform that brings together different modules, such as study pattern analysis, attendance estimation, habit analysis, resume analysis, and feedback analysis, to fill in these gaps.

III. PROBLEM STATEMENT

College students need to perform various academic and personal activities such as maintaining their attendance records, adhering to efficient study plans, developing productive habits, creating professional resumes, and offering feedback about the services provided in the college. However, these activities are performed separately and not in an integrated manner.

The existing student management system that is being used in different educational institutions mainly deals with administrative activities such as recording students' attendance and managing their grades. The system does not offer analytical results that help students identify their productivity patterns and potential academic risks. Students only get to know about issues such as a lack of attendance records, reduced productivity in their studies, and poor habits at a later stage when such issues can no longer be resolved effectively.

The use of different independent tools for activities such as study planning, habit development, and resume building causes a lack of integration in the data collected from these tools. The absence of an integrated system that can correlate different aspects of students' behavior makes it difficult to identify the early symptoms of reduced academic performance.sss

Thus, there is a need to develop an intelligent student support system that can not only monitor

student behavior but also analyze student productivity trends, detect academic risk for students, and provide timely insight to students to improve their academic performance and productivity.

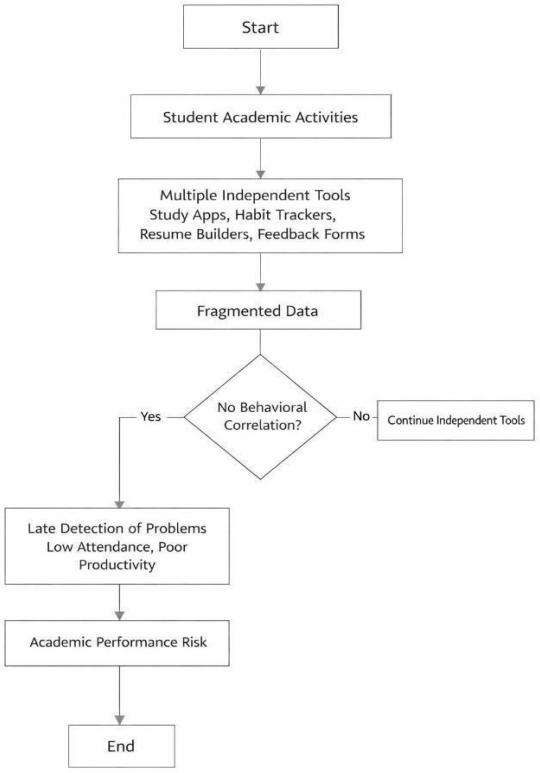

Fig 1: Limitations of Existing Student Academic Monitoring Systems

IV. METHODOLOGY

The UniAssist system is intended for monitoring the academic behavior of students, analyzing productivity patterns, and generating meaningful insights using a unified analytical platform. The methodology for the proposed UniAssist system includes data collection from students' activities, processing the data using different analytical modules, and generating meaningful insights for the users through a unified platform.

The overall workflow for the proposed UniAssist system consists of four major stages:

Data Collection

The first stage of the UniAssist system involves data collection from students' activities using the web interface. Students interact with the UniAssist platform by providing details regarding their

academic and daily activities. This includes data like study hours, attendance records, habit completion status, resume content, feedback ratings for services provided by the university, etc.

The data collection module for each component collects data based on the functionality provided by that component. For instance, the study pattern component collects data on the number of hours spent on different subjects, while the attendance component collects data on total classes conducted and total classes attended.

Data Storage

Once the data is collected, it is stored in a centralized database. The system utilizes a relational data structure to store student activity records. Each module stores data in separate tables while establishing relationships via student identification fields.

Behavioral Analysis

In the analysis stage, the system utilizes rule-based data analysis techniques to process the collected data. The study pattern analyzer analyzes the data on weekly study hours and determines productivity trends. The attendance predictor computes percentages for student attendance while simulating scenarios for future attendance. The habit drift detector analyzes consistency based on completion rates for a specific time period.

The system also utilizes resume analysis to determine the presence of key resume fields while identifying technical keywords. Similarly, the mess feedback analyzer utilizes student ratings to determine trends for food quality satisfaction.

Insight Generation

Once the data is processed, the system creates meaningful insights and alerts for the students. This is done through the student dashboard. The data is represented as productivity trends, attendance risk indicators, habit consistency graphs, and resume evaluation scores.

A centralized behavioral analytics engine is used to combine the insights from the various modules to create patterns that may indicate academic risk. For instance, a reduction in the number of study hours with low attendance and habits may indicate a high academic risk. This will enable the students to take corrective action to enhance their academic performance.

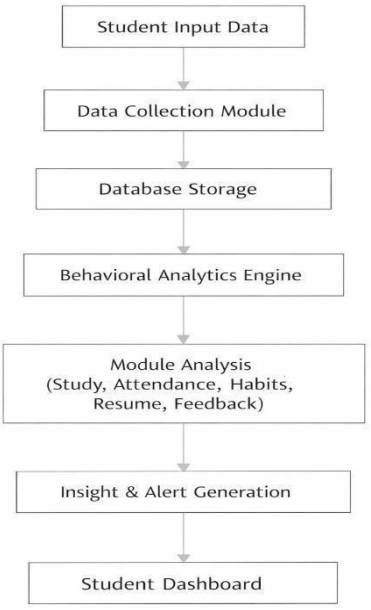

Fig 2: Proposed Student Behavioral Analytics System Architecture

V. PROPOSED SYSTEM

The proposed system, named UniAssist, is an intelligent all-in-one student optimization system that aims to aid students in monitoring their academic performance and productivity. The system combines multiple analytical components into one system to derive meaningful results based on student behavioral data.

The proposed system is different from existing student management system approaches, which are mainly based on administrative data storage. The proposed system is based on student behavioral analytics and productivity monitoring. The system will collect data from students using a web interface and analyze it to derive patterns or possible academic risks for students.

The proposed system consists of multiple components that are related to each other. The components are the user interface, backend processing system, database storage system, and behavioral analytics system. Students will be able to interact with the system using a web interface to input data related to their academic activities such as study time, attendance records, habit completion, resume creation, and feedback on campus services.

Once the data is collected, it is then stored in a centralized database from where it can be accessed by the different analytical modules incorporated into the system. The behavioral analytics engine then utilizes rule-based analytical techniques to process the data collected by the different modules. This helps in identifying productivity trends, assessing academic performance indicators, etc.

The proposed system also incorporates different functional modules like the study pattern analyzer, attendance risk predictor, habit drift detector, resume analyzer, mess feedback analyzer, etc. Each module deals with a different aspect of the student's activities while incorporating different pieces of information into the system.

The proposed system is able to provide a holistic view of a student's academic health by correlating data from different modules. For instance, if a student is observed to be decreasing study hours along with reduced attendance and habits, the proposed system will be able to identify that the student is at a higher risk academically. It will then send the student alerts on the dashboard accordingly.

The insights provided by the system are presented on a dashboard that is interactive in nature, enabling the students to track their productivity trends, academic indicators, and suggestions for improvement. This helps the students identify any problems that may occur in the future and take corrective action to ensure that their performance is always on track.

In conclusion, the UniAssist platform is a decision support tool for students that helps them manage their academic responsibilities, productivity habits, and career readiness.

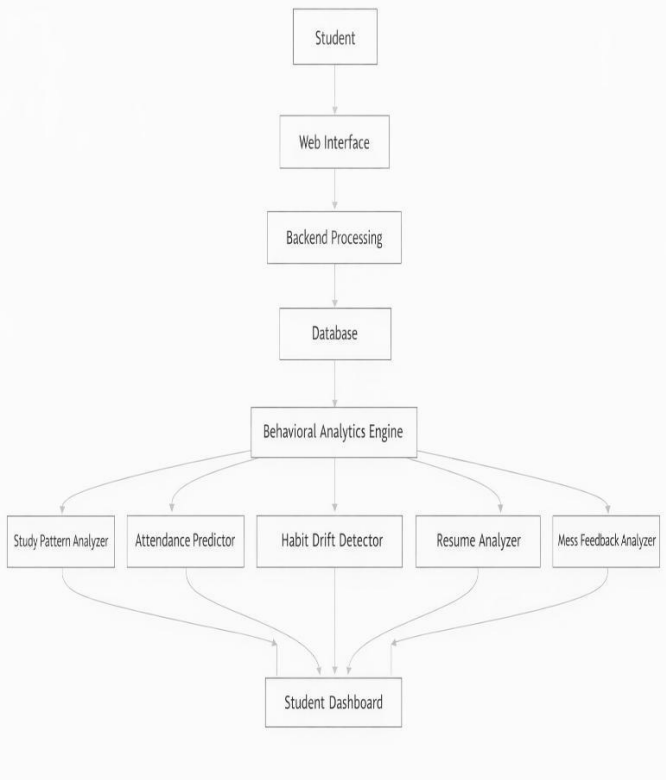

Fig 3: Detailed Architecture of the Proposed Student Behavioral Analytical System

VI. SYSTEM MODULES

UniAssist is made up of several functional modules, each aimed at tracking a different dimension of student academic behavioral and productivity aspects. Each module is responsible for collecting certain pieces of information, conducting certain types of analysis, and producing certain types of results, which are then fed into the behavioral analytics engine as a whole. The following are the modules that will be part of the proposed system.

Smart Study Pattern Analyzer

The Smart Study Pattern Analyzer module will be responsible for tracking and evaluating student study patterns. This will be achieved by allowing students to log their daily activities by entering their study subjects and study hours into the system.

The module will then analyze the input data and determine student productivity trends and study consistency. It will calculate the average study hours for a given period and analyze weekly study patterns to detect any changes in student productivity. In case a student shows a significant drop in study hours, a warning will be sent to the student.

The result of this module is presented in a dashboard in the form of study trend indicators and productivity warnings. This will help students understand their study trend and how they can better organize their study schedule.

Attendance Risk Predictor

Attendance Risk Predictor tracks student attendance and assesses the risk of being lower than the minimum attendance threshold. The student will input the total number of classes conducted and the number of classes attended.

The module will then determine the attendance percentage and assess the level of risk in accordance with predetermined levels. In addition, simple predictive simulations are carried out to determine how attendance will impact the total percentage in the near future.

Students are made aware of the minimum number of classes they need to attend in order to meet the minimum attendance threshold, thus taking corrective action in time for attendance shortages.

Habit Drift Detector

The Habit Drift Detector is a module that assists students in tracking their daily habits and helps them identify a decline in consistency in productive habits. A student can create their own habits, such as studying, exercising, reading, etc.

The system calculates the habit success rate based on the number of days the habit is completed within a given period of time. The system also sends a notification if the habit success rate drops below a specified value.

This module motivates students to build good habits and encourages them to be consistent in their productive activities.

Smart Resume Analyzer

The Smart Resume Analyzer is a module that helps students analyze their resume's content and quality. The students can upload their resume content or simply paste their resume content into this module.

The system will analyze the resume content by checking various parameters, including the presence of required content such as education, skills, projects, experiences, etc., and also perform a keyword search for various technologies.

Based on these factors, the system generates a resume score and provides suggestions for improvement. This helps students enhance their resumes and better prepare for placement opportunities.

Mess Food Feedback Analyzer

The Mess Food Feedback Analyzer collects and analyzes student feedback regarding campus food services. Students can rate food quality using a numerical scale and optionally provide comments.

The system aggregates the ratings and calculates daily and weekly average satisfaction levels. By analyzing rating trends over time, the system can identify improvements or declines in food quality.

If a significant drop in ratings is detected, the system generates alerts for administrators. This module helps institutions understand student satisfaction and improve campus services.

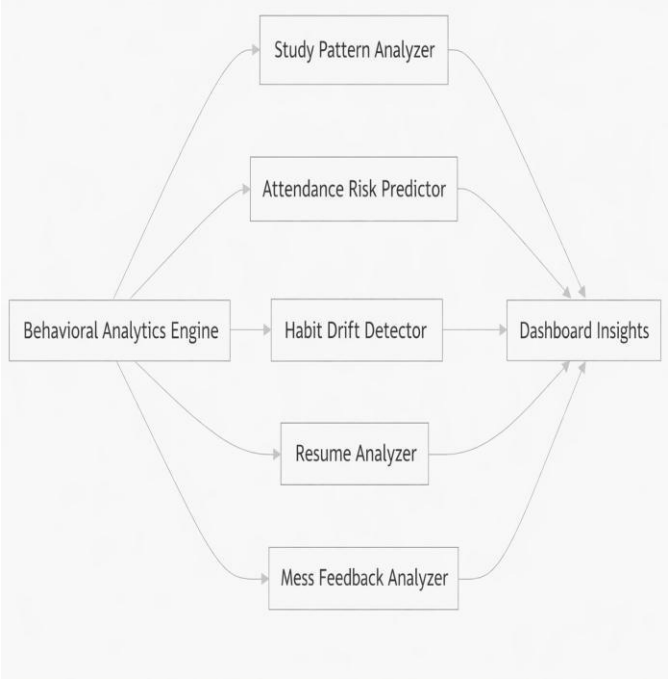

Fig 4: Proposed Analytics Module Framework

VII. ALGORITHMS AND ANALITICAL METHODS

The UniAssist system uses rule-based algorithms to analyze student data based on their behavior. The algorithms process data related to their study patterns, attendance, habits, and resume content to generate insights.

Study Pattern Trend Detection Algorithm

Input: Daily study hours for 14 days (H1 to H14)

Step 1: Calculate the average study hours of the previous week

Previous_Week_Avg = (H1 + H2 + H3 + H4 + H5 + H6 + H7) / 7

Step 2: Calculate the average study hours of the current week

Current_Week_Avg = (H8 + H9 + H10 + H11 + H12 + H13 + H14) / 7

Step 3: Calculate the percentage decline

Decline_Rate = ((Previous_Week_Avg − Current_Week_Avg) / Previous_Week_Avg) × 100

Step 4:

If Decline_Rate > Threshold

Display "Productivity Decline Detected"

Else

Display "Study Pattern Stable"

Output: Weekly study trend and productivity alert.

Attendance Risk Prediction Algorithm

Input:

T = Total classes conducted

A = Classes attended

Step 1: Calculate attendance percentage

Attendance_Percentage = (A / T) × 100

Step 2: Determine risk level

If Attendance_Percentage ≥ 75

Status = Safe

Else if Attendance_Percentage ≥ 65

Status = Warning

Else

Status = Critical

Step 3: Calculate minimum classes needed

Classes_Needed = ceil((0.75 × T) − A)

Output: Attendance percentage, risk level, and required classes.

Habit Drift Detection Algorithm

Input: Habit completion status for N days (1 = completed, 0 = not completed)

Step 1: Count completed days

Completed_Days = sum of all habit completion values

Step 2: Calculate success rate

Success_Rate = (Completed_Days / N) × 100

Step 3: Detect habit drift

If Success_Rate < 60

Drift = True

Else

Drift = False

Output: Habit success rate and drift alert.

Resume Evaluation Algorithm

Input: Resume text

Step 1: Initialize score = 0

Step 2: Check presence of important sections

If "Education" present → score = score + 20

If "Skills" present → score = score + 20

If "Projects" present → score = score + 20

If "Experience" present → score = score + 20

Step 3: Perform keyword detection for technical skills

If technical keywords found → score = score + 20

Step 4: Calculate final resume score

Resume_Score = score

Output: Resume score and improvement suggestions.

VIII. SYSTEM IMPLEMENTATION AND RESULT

The proposed UniAssist system was implemented as a prototype web application to demonstrate the functionality of the platform and validate the analytical modules presented above. The implementation is mainly focused on simulating the key functionalities of the system, including study patterns, attendance risk predictions, habit consistency analysis, and resume evaluation.

The prototype system was implemented using Python with the Streamlit framework, which enables the fast implementation of data analysis dashboards for data visualization. The system processes student data and applies analytical algorithms to produce meaningful outputs that can be used to monitor student performance or productivity.

The system interface is designed to have a centralized dashboard that displays the outputs of the analytical modules implemented. The outputs are presented as graphs or charts to enable students to understand their academic trends or performance.

The following are the outputs presented by the implemented prototype system.

Study Pattern Analysis Output

The study pattern analysis tool checks for variations in study time for a number of days and determines productivity trends. It uses a line graph to show students their study pattern in terms of daily study time for a given number of days.

Using a graph, students are able to see their changing study pattern and determine when their productivity is low. By comparing the average study time for two successive weeks, the system identifies a significant drop in study time and sends a notification when a drop in productivity is detected.

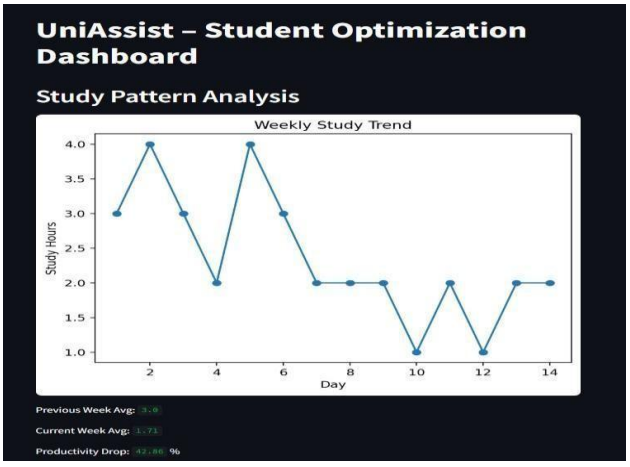

Fig 5: Student Optimization Dashboard

Attendance Risk Prediction Output

The attendance risk predictor will determine the percentage of attendance based on the number of classes attended compared to the total number of classes conducted. The system will then determine the risk level based on the attendance level.

The prototype interface will enable users to input the attendance values. The system will then display the calculated attendance percentage.

Fig 6: Attendance Monitoring and Risk Status

Habit Consistency Analysis Output

The habit drift detector will determine the consistency level of the student's daily habits. The system will then display the results as a pie chart showing the completion percentage of the habits.

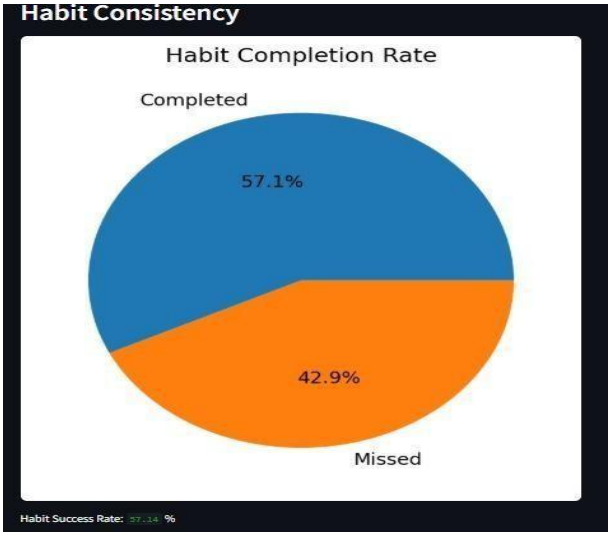

Fig 7: Habit Consistency Analysis

Resume Evaluation Output

The resume analyzer assesses the student's resume format and content by checking the incorporation of essential components and technical keywords. According to the analysis, the system determines the resume score. The output of the system is shown through the progress indicator.

The interface shows a proper visual representation of the resume evaluation score. It also shows the improvement suggestions.

Fig 8: Resume Evaluation Interface

This module helps the student to enhance the quality of the resume. Advantages of the Proposed System over Existing Systems: The proposed UniAssist platform has many advantages over existing student management systems and other productivity tools. The existing student management system is designed to perform specific tasks or functionalities. For example, some existing student management systems are designed for tracking student attendance or for monitoring student habits. The proposed UniAssist platform is designed to perform multiple functionalities for students. The proposed platform is a unified platform for multiple productivity analysis tools.

Integrated Student Support Platform

The existing student management system is designed to perform specific tasks or functionalities. For example, some existing student management systems are designed for tracking student attendance or for monitoring student habits. The proposed UniAssist platform is designed to perform multiple functionalities for students. The proposed platform is a unified platform for multiple productivity analysis tools.

Behavioral Analytics-Based Monitoring

The existing student management system is designed to store data only. The proposed UniAssist platform is designed to analyze student behavioral data such as study hours, attendance trends, or habit completion patterns. The proposed platform is designed to analyze student data to identify productivity trends.

Early Detection of Academic Risks

One of the most important benefits of the proposed system is its ability to detect academic risks at an early stage. This is made possible by analyzing various behavioral parameters, which may indicate a decline in study productivity, low attendance, or inconsistent student behavior.

Cross Module Data Correlation

In addition, the proposed system will be able to correlate data from different modules, as opposed to existing systems that analyze each piece of data independently. For example, a decrease in study hours, along with low attendance and inconsistent student behavior, may indicate a high level of academic risk. This will be detected by the system, and alerts will be sent accordingly.

Feature	Existing Systems	Proposed UniAssist System
Attendance Monitoring	Basic recording only	Attendance Prediction and Risk Detection
Study Tracking	Usually not included	Study Pattern Analysis and Productivity trends
Habit Monitoring	Separate applications	Integrated habits and Drift Detection
Resume Analysis	External tools required	Built-in Resume Evaluation Module
Data Integration	Fragmented Tools	Unified Behavioral Analytics Platform
Insights Generation	Limited Analytics	Visual Insights and Early Warnings

Fig 9: Comparison between existing systems and proposed UniAssist Platform

IX. FUTURE WORK

Although the proposed UniAssist system shows how effective a student productivity monitoring platform can be, there are areas where it can be improved in the future.

One major enhancement could involve using machine learning and predictive analytics. The current system mainly relies on rule-based methods to identify productivity trends and academic risks. In the future, machine learning algorithms like decision trees, random forests, support vector machines, and neural networks can help analyze large amounts of behavioral data more accurately. These algorithms can learn from historical student data and provide better predictions regarding academic performance, attendance risk, and productivity patterns. This would enable the system to create personalized recommendations for students based on their behavior.

Another important improvement is to develop a dedicated mobile application for the UniAssist platform. Right now, the system exists only as a web-based application. Creating Android and iOS apps would greatly enhance accessibility and usability for students. A mobile application could let students quickly log their study hours, track habits, monitor attendance, and receive instant notifications about productivity declines or attendance risks. Mobile integration would also encourage real-time engagement with the platform, helping students stay consistently involved.

The system could also expand with a career prediction and placement recommendation module. This module could look at students' academic performance, technical skills, projects, certifications, and resume content to suggest suitable career paths or job roles. Using data-driven methods, the platform could recommend industries, job profiles, or skill improvements that match the student's strengths and interests. Additionally, a placement prediction model could estimate a student's chances of getting placed based on past placement data and academic performance trends. This feature would significantly help students prepare for their future careers.

Another potential improvement is linking the UniAssist platform with existing Learning Management Systems (LMS) used by educational institutions. By connecting with LMS platforms like Moodle, Google Classroom, or institutional learning portals, the system can automatically gather academic data such as assignment submissions, quiz scores, class participation, and course engagement. This integration would cut down on manual data entry and boost the accuracy of the analytics generated by the system.

Furthermore, the platform could use advanced behavioral analytics and sentiment analysis. For instance, natural language processing (NLP) methods could analyze student feedback, comments, and responses to gauge satisfaction levels and emotional well-being. This would allow the system to identify signs of stress or burnout in students and offer suggestions for improving mental wellness and productivity.

Future versions of UniAssist could also add collaborative and social learning features. Students might compare their productivity patterns with peers, join study groups, and share progress on goal achievement. Such features could foster a more engaging and motivating learning environment.

Another possible enhancement is incorporating recommendation systems within the platform. Based on the data collected, the system could suggest optimal study schedules, productivity strategies, or learning materials. Tailored study recommendations would help students maximize their learning efficiency.

Finally, the UniAssist system could evolve into a more complete institutional analytics platform. While the current version mainly focuses on student-level productivity analysis, future updates could offer dashboards for faculty and administrators to track overall academic trends, spot at-risk students early, and implement institutional-level interventions.

In summary, future enhancements like machine learning integration, mobile app support, LMS integration, career prediction models, and advanced analytics can significantly strengthen the UniAssist system. These improvements would turn the platform into a smarter, more scalable, and comprehensive student support system that aids students, educators, and institutions in achieving better academic outcomes.

X. CONCLUSION

In the modern learning environment, students need to perform a number of academic and personal activities concurrently. The activities include keeping track of students' attendance, effective study plans, productive learning habits, professional resume development, and feedback for the services provided in the learning environment. Nevertheless, the lack of an integrated system that analyzes all these activities together does not allow students to identify productivity and academic risks at an early stage. The paper discussed an intelligent all-in-one optimization platform for students named UniAssist. The paper discussed how such a platform can be created to monitor students' activities and provide insights for improving academic performance and productivity. The paper discussed how a number of analytical modules can be integrated in a single platform to create an effective system. The modules include a Smart Study Pattern Analyzer, Attendance Risk Predictor, Habit Drift Detector, Resume Analyzer, and Mess Food Feedback Analyzer. The system can identify productivity trends and academic risks by analyzing data from these modules.The architecture of the system has a centralized behavioral analytics engine that collects data from different modules for a holistic view of the student's academic health. The development of a prototype for the system shows that visual dashboards, analysis algorithms, and productivity measures are efficient means for a student to comprehend their academic patterns and make informed decisions for improving their performance.

The proposed UniAssist system stands out from traditional systems that work in silos by providing a unique integrated analytical platform that combines features for academic monitoring, productivity measurement, and career preparation in a single platform. The ability of the UniAssist system to identify trends in student behavior, generate alerts, and present analysis in a visual format makes it a feasible option for modern educational systems.

The proposed UniAssist platform shows that integrated behavioral analysis has tremendous potential for improving student productivity measurement and decision-making capabilities, which will pave the way for the development of intelligent systems for supporting students in the future.

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FreshSense:An AI-Driven Multimodal System for Food Spoilage Detection and Shelf-Life Prediction

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Abstract **-** Spoiled food drains money while threatening us .yet, we human sense often fails to detect early signs of decaying process. Machines, however, can do better than humans. In response, this study introduces a smart tool that sense, smell, and determine if food safe for consuming or not. It detects how dairy sours, meats rot, fish decay, and product spoilage. To accomplish We havea gadget that gathers signals through the sniffer and eyes built into its frame. And Next we created an algorithm that process sensor readings and real time photos,which is provided in real-time condition reports. As result, predictions about how long items will last whichemergesfrom patterns in the numbers which we feed. No more guesses by the smell or by eyes alone: now, from the data which flows from physical input straight into digital. In this way, freshness gets scored fast.

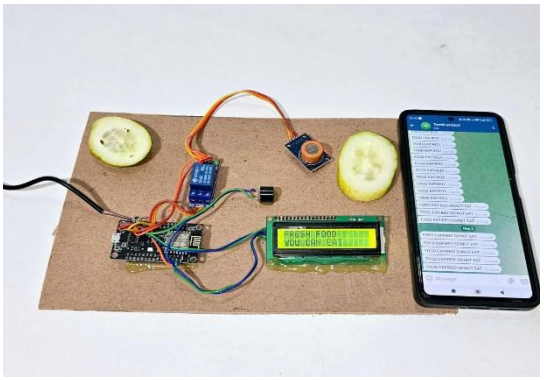
Keywords **-** Food Spoilage Detector, AI, Multimodal AI,Shelf Life Predicting, Food Safety control, IoT Sensors, Image Processing

I. INTRODUCTION

Spoilage happens when microbes spread, enzymes react, moisture lingers, and temperatures shift. Dairy, fish, and meat turn unsafe fast under these conditions. Looking at food gives clues - so does sniffing it - but neither method catches every problem. New tools now measure freshness using smart sensors instead of guesswork. Machines learn patterns from data, helping track changes nobody sees or smells. Technology steps in places where human senses fail. A look at spotsoffood which isbadfoodusually points to gadgets that sniffs gases or to the software which studies the pictures. What if artificial brain which could team up both methods? That is exactly what this study unpack - a smart blend between senses which is trained to catch rotting earlier than humans. Not just with one clue, but with several working together as one quietly behind the scene.

II.EXISTING MODEL:

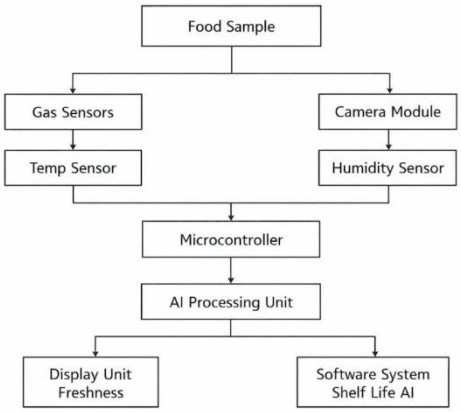
Nowadays, a handful of methods aim to spot when food goes bad. For instance, one approach tracks gases such as ammonia or CO2 that rotting food gives off. However, it misses changes you can actually see. Alternatively, another method applies machine learning to study photos showing spoiled items. Still, it can deceive when predicting if the food has gone bad. Meanwhile, stored conditions can be checked by a device tracking heat and dampness levels. Even so, those readings might miss what is really happening inside the food itself.



III.PROPOSED MODEL:

This is done by a set of sensors and software tools that tell when the food is beginning to spoil and the maximum time, it can remain fresh to be consumed. This system is constantly checking the fresh food and reporting or notifying of any change. The device can gather information via several sources and combine it to calculate the correct result based on the pattern learning method as opposed to relying on a single sign. Due to such an approach, the findings are more precise and dependable than the older approaches that use a single factor.

One of the components of the device gathers data concerning the freshness of the foodstuff, and in the process the system scrutinizes the information cautiously. In some cases the processing of the data is done fast and in other instances it waits until new updates are provided to proceed with the process. Lastly, it examines the data obtained and directs other patterns that can or could be overlooked by other models.



A. Hardware Detection Device

The system is made up of a small device to gather the real time data on the food by scanning images and sensor readings. The device monitors the temperature, texture, smell or exposure to light when the food is beginning to spoil. It runs and runs again to know the impact these changes of the environment will have on the freshness of the food until it spoils. The hardware's configuration consists of a number of components which interact with one another within the device. In a place where every section plays a different but designated role. These other ones control the data movement, whereas some of them provide power. The parts are fitted into this device to produce a single system, which operates well.

1.Gas Detectors

When the food is starting to spoil it releases some certain gases, which will be detected by the gas sensors. Foods like meat, fish, or milk give off chemical gases like ammonia, hydrogen sulphide, and carbon dioxide when they start to get spoiled. These gases are the signs that the food is rotting or starting to spoil slowly. As soon as the device detects these gases it sends the data to the main system for further analysis of the food.

2.Temperature Sensor

When the food is starting to spoil, it goes through hot or cold decay. And to detect this we use a tiny detector which detects how warm the food gets. When the temperature rises the rotting process also increases. But a steady cool temperature keeps foods last a little bit longer. The device is used to check the environmental changes every second. And it tells if the changes in the temperature drops to tell the freshness of the food. This Tracking process shows when the storage system starts to fail.

3.Humidity (Moisture) Sensor

The air Around the food is too wet giving the microorganisms the ideal environment in which they multiply rapidly thus spoiling the food. Such an easy device can measure the content of moisture in the air surrounding the products stored. The microbes may develop rapidly when the air is excessively wet. And in case it is too dry, some food can start to lose moisture and can spoil in another manner. Using this tracking, one can foretell when the food will expire.

4.Image Detector

A camera is placed inside the device to take pictures of the food stored. And as time passes it observes the changes in the food like the food color, texture and the shape. By tracking these changes in the food we can tell when the food is starting to spoil.Signs like dark spots or slimy surfaces come clear over time.

- Colour changes
- Texture degradation
- Surface mold formation
- Structural damage

From each photo, subtle shifts tied to spoilage emerge through digital analysis. What once looked fresh now shows slight discoloration when examined by software trained to spot decay. The change in the texture can be seen clearly using the

pixel level view. By reviewing the each frame signs of spoiling is guessed by tracking of pattern. By these small details are noted further evidence of spoiling.

5.Microcontroller Unit

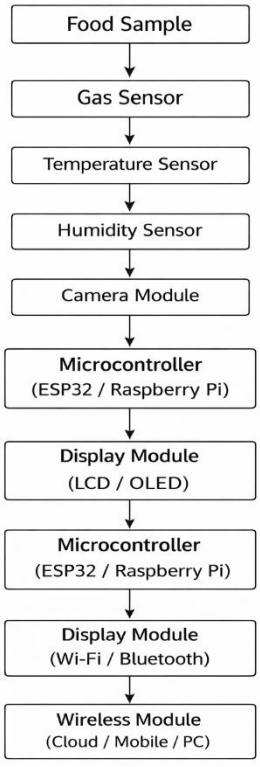
A mini computer such as ESP32 or Raspberry Pi is used as the central control board of the system. All the other sensors and camera image are captured by this system. Then before transmitting the data to have the data further processed it does some basic processing within the device. Only the data is sent after this to be further analysed.

6.Display Module

On the front of the device there is an LCD or OLED display screen which can show information quickly. And based on the sensor readings and the processing is done. The system can classify the food stored into the one of the three levels which are

- Fresh
- Relatively Fresh
- Spoiled

Freshness shows up right away, so people see how the food is doing even before opening the system.



B. Software-Based Shelf-Life Prediction System

Inside the computer, the system will look at the patterns in the data and connect them or use them to make the predictions. From gadgets and lenses, raw details travel toward that thinking part to be shaped.

The software system performs several key tasks:

1.Data Processing and Storage

Somewhere deep inside the system, every number caught by sensors plus each snapshot lands safely into storage ready when needed. Out of that pile, messy signals get cleaned up before anything else happens; scaling adjusts values so they play fair together while distinct traits begin to show through what was once hidden.

2.Feature Engineering

The main details are captured by using the readings of the sensor and the images captured. Things like motion patterns show up clearly. Visual shapes get picked out carefully. Signals change over time, revealing hidden clues. Each detail stands apart yet connects to others. By the multiple observations the patterns are formed. Information flows without relying on guesses.

- Gas concentration levels
- Temperature readings
- Humidity levels
- Colour intensity values
- Texture features of food surfaces

Few of these traits feed into models that learn patterns. What shows up shapes how systems respond later on.

3.Machine Learning-Based Prediction

Some machine learning systems learn from old records of spoiled food. Patterns hiding in that data get spotted by tools like Random Forest instead of simpler methods. To solve the dissimilarity the method of SVM helps. The CNN steps in when the image details matter alot.

The AI Model Predicts

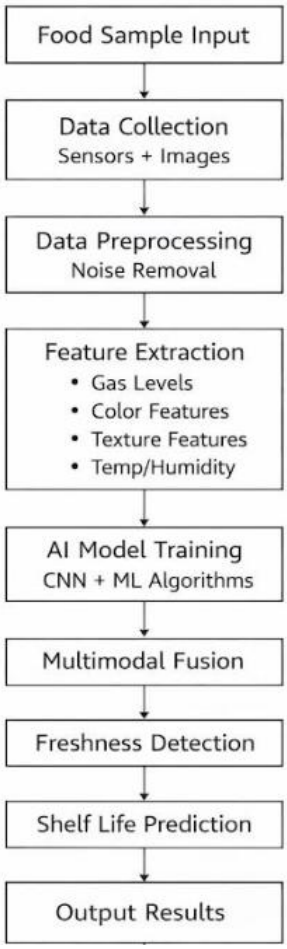
- Right now, how fresh that piece of food happens to be
- Only a little time left before it expires

4.User Interface and Application Platform

The results are shown on screen through the software apps on phone or web browsers. And the display shows output like:

- Current status of freshness
- Time left for expiring
- Readings of sensor and the surrounding state
- Warnings that causes the spoilage

IV.FEATURES:



The system then checks the gases, moisture, texture, and color to detect the spoilage soon even before people can notice it.The combination of all sensors with the addition of camerahelps to capture the hidden chemical changes along with visible spoilage. Hidden patterns in heat and air get decoded so freshness gets judged more clearly. Instead of random guesses, the model learns from the history data to evaluate how much time is left for the food spoilage. Accuracy is increased as we consider many signal at once. Built to handle many kinds of fresh goods - like milk, fish, apples, beef, greens - the setup fits easily into different everyday uses. While tracking conditions nonstop, it gathers live readings, updating how fresh items are right on screen or via app. As the warnings are given before the spoilage, people would choose to use or eat it.

V.RESEARCH METHODOLOGY:

1.Data Collection

At the initial stage, the method collects data using different kinds of foods which gets spoiled such as fruits, vegetables, meat, dairy products and sea foods and their samples are taken. Volatile traces from rotting matter show up thanks to gas detectors built inside. Meanwhile, heat and moisture levels get logged by small surrounding monitors. Without pause, a tiny lens records each piece of food every few minutes on the dot.

- Information gathered covers these points:
- Gas concentration levels
- Temperature readings
- Humidity levels
- Visual images of food samples

A fresh look at decay comes through this mix of data types. Details unfold across different ways of seeing how things go bad.

2.Data Preprocessing

While the sensors records the data and the cameras take pictures, the data which comes out can be messy and full of errors, glitches, gaps, or odd results in the data. Cleaning the things up ahead of the time making information more reliable for later review. Out of messy sensor signals, clean streams emerge when filters strip away odd spikes along with the random static. Starting from the raw pictures and uniform shapes that take form after scaling down and balancing brightness level across each frames.

These are the stage includes:

- Removing the noise
- Normalizing data
- Resizing and improving images
- Eliminating corrupted data samples

By this action it ensures each data functions properly.

3.Feature Extraction

The imagery of photographic and sensor types provides the opportunity to question the indicators of food spoilage that are significant. The latent datum is original and can be used to provide an early notification of degradation, that is a slight change in the trend which signifies the imminent loss of freshness in the product. No one can identify the low-level attributes but only with an integrative analysis of sensor streams and visual information, the actual background meaning can be discovered. Information is essential in the detection of spoilage. Effectively, we aim to make a list of signals that can be used in detecting moisture, heat or fumes. Even the slightest details of degradation are not simple accidental events; they form a unique story of evolution, which is a part of the overall process of degradation. Overheating, unwanted steam or any change in moisture content is a red flag, and unlike to be received well, it is usually accompanied by unpleasant smell. These indicators tell us that there is a change that has taken place, be it in the form of minute dips, or rises, or a numerical change of a considerable magnitude. The visual information is computed using the analogues of the human visual analysis. Shapes, edges, and textures are examined by the use of algorithms, and pixel data is transformed into patterns that have significance. The system does not treat the entire image as a unit but pays attention to those areas where the diagnostic value is most diagnostic and isolates curves, lines, luminance gradients etc. Survey Visual inspection, tactile analysis or smell analysis give deductions that concern colour, texture, surface discontinuities, or existence of mould or the overall freshness of the surface.After the primary features have been extracted, the algorithm detects the patterns and gives an item a freshness score. The information is scaled against reference profiles on a scale between fresh, slightly fresh and almost spoiled. Here, the experience knowledge is based on such categorical differentiations and offers the premise of widely-comprehensive assessment procedures.

- Fresh
- A little fresh
- Spoiled

New inputs are introduced and retraining is done continuously to perfect the model and increase its ability to identify new states.

4.Machine Learning Model Development

The system in this step gathers the meaningful information about the sensor data and images. It then scans the patterns to know the freshness of the food. The data is analyzed using the machine learning models of Random Forest and SVM that assist in understanding the patterns of the data, and the foods fall into such categories as fresh, moderately fresh, and spoiled. The system is able to examine various food stuffs and determine how fresh they are and it takes the right training and learning after reading the information. The more data the system learns, the more it gets better and construe.

5.Combining Different Types of Data

The system uses the information provided by several sources that enhance the accuracy. It does not follow the idea of using either sensor readings or visual data. This mix of information simplifies the process of the system to know the real state of the food in a better and more precise way. The system analyzes the chemical changes such as gas emission and the visual attributes such as color and textures as a way of determining the food condition. The system can make better and more reliable decisions with the help of the two types of informations obtained and used simultaneously. When one approach lacks something, the other can be able to pick it up, thus they are more efficient and complementary to each other. There is a reduction in the overall performance as well as errors of the system as it brings different types of data together. As the outcome, the freshness of the foods can be judged more effectively.

6.Checking Freshness and Estimating Shelf Life

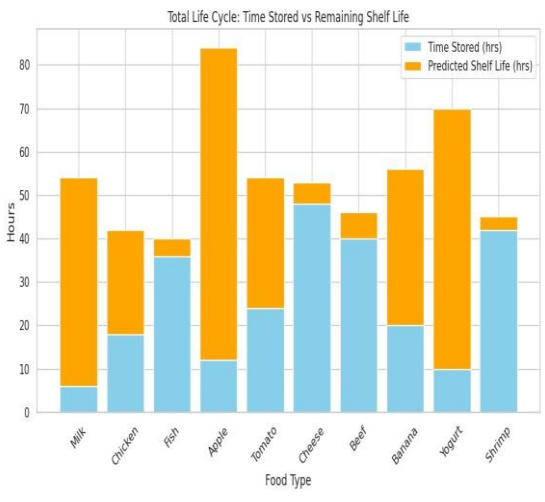
Finally step the system approximates the duration of time that the food can stay fresh and in use. The system involves the results of the previous steps to determine the quality of individual food items in this step. Not only does it inform about the level of freshness at the moment; it also approximates the time the food can continue to be used. The system knows the current state of food after interpreting sensor data and pictures through a computer program. In addition to this, it also examines historical statistics and aspects such as temperature and storage environment to predict the speed with

which the food could spoil. The system presents this information on a small screen or a mobile application, such that the users can be able to easily track the freshness of their food.
As soon as the food begins to spoil, an alert message is dispatched by the mobile app. Such fast counterparts enable customers to take action in time and conserve resources.

VI. STATISTICAL DATA:

Sample ID	Food Type	Storage Location	Storage Temp (°C)	Humidity (%)	NH_3 Level (ppm)	CO_2 Level (ppm)	VOC Level (ppm)	Image Color Score	Time Stored (hrs)	Freshness Status	Predicted Shelf Life
1	Milk	Refrigerator	4	60	2.1	520	110	0.95	6	Fresh	48 hrs
2	Chicken	Refrigerator	5	65	6.4	740	210	0.81	18	Moderate	24 hrs
3	Fish	Cold Storage	4	70	15.8	1120	460	0.42	36	Spoiled	4 hrs
4	Apple	Room Temp	24	55	1.8	480	95	0.96	12	Fresh	72 hrs
5	Tomato	Room Temp	25	60	5.2	690	180	0.78	24	Moderate	30 hrs
6	Cheese	Refrigerator	6	68	12.5	980	390	0.50	48	Spoiled	5 hrs
7	Beef	Cold Storage	3	72	14.2	1050	420	0.46	40	Spoiled	6 hrs
8	Banana	Room Temp	26	58	4.1	610	160	0.83	20	Moderate	36 hrs
9	Yogurt	Refrigerator	4	64	3.0	540	120	0.92	10	Fresh	60 hrs
10	Shrimp	Cold Storage	2	74	17.3	1180	490	0.38	42	Spoiled	3 hrs

In the Food Freshness and Spoilage Dataset, one can find the information about diverse food products. Every item is controlled under various environmental conditions.The table that comes with it demonstrates the relationship that exists between environmental factors, the emissions made by chemicals, and even the visual pollution.The table represents ten food samples. These are dairy products (milk, cheese), protein foods (chicken, beef, shrimp), and produce (apples, tomatoes).All foods are kept in various conditions, which differ in terms of temperature and humidity.The temperatures lie between 2-o C and 26 o C. The humidity is 55-74 percent and these are two additional factors that cause spoilage to a large extent.Chemical pollutants include ammonia (NH 3), carbon dioxide (CO 2) and volatile organic compounds (VOCs). Fresh products have low levels- approximately 1.8ppm NH 3 in apples. Protein products (e.g. shrimp or fish) can be contaminated with 17.3ppm NH3.A visual spoilage is measured by Image Color Score. The scores of 0.95 and above are considered to be peak freshness. Lower scores of 0.38 are indicative of severe discoloration in the surface. The storage time in the dataset is between 6hours and 48hours. Status Freshness Freshness status is either Fresh, Fresh, or Moderate and associated with the predicted shelf life.Projected shelf life extends to not more than 72 hours in case of fruits and up to no more than 3 hours in case of seafood, as marine produce spoils very fast.The results indicate that there is an inverse relationship between image color scores and the level of gas concentrations: the higher they are, the lower the score.



VII. CONCLUSION:

Using this sensors, image detection and real time environmental checks. It is used to find the early signs of food spoilage rather than the who food getting spoilt fully. By the combination of hardware devices along with software tools it can reduce food wastage and provides safety for the person eating a meal. In the future the device can be improved by collecting more data along with online storage and the results of the detection being sent to the mobile App that alerts the user about the spoilage in an instant.

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MedBlock AI: A Blockchain-Based Emergency Healthcare System Integrating MetaMask Authentication, Organ and Blood Donation Matching with AI-Driven Ambulance Dispatch

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***Abstract*— Generally, the emergency healthcare systems may be associated with considerable delays, especially while accessing the patient data, finding the required blood and organ donors, and arranging the ambulance services on time. In many practical situations, the delays may directly impact the survival of the patient.In this regard, the current project introduces MedBlock AI, which incorporates the blockchain technology and Artificial Intelligence to improve the emergency services. With this approach, the patient data can be safely stored and accessed quickly using the blockchain technology.Furthermore, the proposed MedBlock AI can efficiently identify the compatible blood and organ donors based on the medical data and the geographical location. Additionally, the intelligent ambulance service can be used to locate the nearest ambulance and the fastest route to the destination.Overall, the proposed work attempts to improve the emergency services, especially the response time, and the safe handling of the medical data.**

Keywords—Blockchain, Artificial Intelligence, Emergency Healthcare, Organ Donation Matching, Blood Donation System, Ambulance Dispatch, MetaMask Authentication

I. INTRODUCTION

In the case of healthcare emergencies, there is a need for timely access of medical records, the timely identification of blood or organ donors, and the timely availability of ambulances. However, the current healthcare system has a centralized data management system, which may lead to delays in the timely access of data. Such delays may prove to be fatal at the time of emergencies [1]. Recent developments in the field of Artificial Intelligence (AI) and the availability of the Ethereum blockchain have created opportunities to enhance the current healthcare system.[2] Using the blockchain system, data can be stored securely, whereas AI can be used to process the data, thus helping in timely decision-making[3]. A new and innovative blockchain technology-based medical emergency platform, MedBlock AI, is proposed. It uses a decentralized and MetaMask-based method for user authentication. The MedBlock AI platform provides smart services such as matching blood donors, checking compatibility for organs, transporting organs via AI, and distributing ambulances via a decentralized method. The primary objective behind the development of the MedBlock AI platform is to enhance emergency response services, manage medical data securely, and increase the level of coordination between hospitals, blood donors, and emergency services. **Fig 1**

Fig1: Outline of MedBlock AI

II. EASE OF USE

A. User-Friendly System Access

MedBlock AI, which has been proposed, was designed so that all users (patients, doctors, hospitals, and emergency responders) will have access to the system in a straightforward manner. Users can log into the system through decentralized wallet authentication using MetaMask [1]; therefore, there is

no need for password-based systems. As such, the system provides both a secure method of providing access to appropriate users, as well as an easy way for those users to quickly and efficiently access medical records and obtain emergency services [2]. In addition, MedBlock offers a simple user interface, allowing health professionals to request patient data, search for blood/organ donors, and initiate emergency services without going through complicated procedures [3].] **Fig 2**

B. Efficient Emergency Service Integration

By integrating multiple healthcare services into one place, this system allows users to quickly complete many emergency-related things at once. As an example, doctors may access a patient's medical records saved on a blockchain (e.g., an Ethereum network) [5]. Furthermore, the system's AI algorithms will automatically find potentially compatible blood or organ donors by having access to their medical information and GPS coordinates or other identifying information [6]. It also supports the smart dispatching of ambulances and optimization of organ transport, enabling hospitals to respond much more quickly to critical needs in urgent situations [7]. Although AI-based decision-making combined with the security of blockchain improves coordination between hospitals and donors[8].

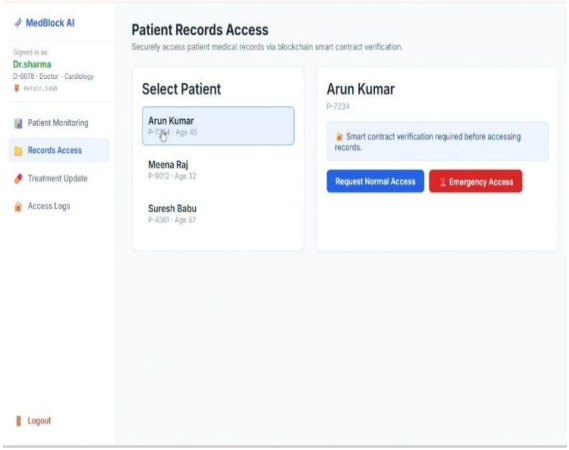

Fig 2: Medical Record Access Dashboard

III. PROPOSED SYSTEM DESIGN

MedBlock AI is an emergency health care system based on a blockchain that uses artificial intelligence to improve the speed and efficiency of emergency medical services and communications. The three primary elements of the system are the secure storage of a patient's medical records; the quick identification of blood and organ donors; and the ability to send ambulances to the right place at the right time.The medical records of a patient will be stored securely on the blockchain (likely on the Ethereum blockchain) so that only authorized persons can access their information using decentralized authentication through a mechanism such as MetaMask.Using AI algorithms to analyze patient medical records, location, and hospitals, the speed at which a decision can be made will increase and be improved [3]. Byusing AI to analyze this information along with the enhanced data security provided by a blockchain, the quality of care will improve by providing better coordination of care among the patient, the hospital, and emergency services [4].

Fig 3: Blockchain Medical Access Panel

A. Abbreviations and Acronyms

Using a variety of abbreviations allows us to simplify the design of our system's components as indicated by their definition upon introduction in the document. [5].

Illustrative examples of those abbreviations are as follows:

AI - Artificial Intelligence

ML - Machine Learning

EHR - Electronic Health Record

IoT - Internet of Things

API - Application Programming Interface

They can often be found in descriptions of various aspects of the system's modules, e.g., donor matching, emergency alerts or ambulance dispatch, etc.

Section B Medical Data Measurement Units

The proposed system uses standard units of measurement for representing medical and environmental data in an accurate manner. The AI-driven algorithms depend on this measurement data for evaluating patient conditions and for prioritising emergencies [6].

Illustrative examples include:

Heart Rate - Beats per Minute

Body Temperature - Degrees Celsius

Blood Pressure - Millimeters Mercury

Ambulance Routing Distance - Kilometres

Utilising standard units of measurement provides a uniform and trustworthy representation of medical data across other providers of healthcare and emergency service delivery.

C. Mathematical Model for Emergency Routing

Our system taps into math models to nail down the quickest routes for ambulances and organ deliveries. The AI routing engine crunches distance, live traffic, and hospital availability to pick the optimal path .

Take the Euclidean distance formula, for starters:

$$D = (x_2 - x_1)^2 + (y_2 - y_1)^2$$

Here, *D* is the straight-line distance between points; *(x1, y1)* *(x*1, y1) marks the ambulance's start spot; and *(x2, y2)* *(x*2, y2)

is the hospital or patient location. This powers the AI to zero in on the fastest, smartest route.

D. Implementation Considerations

When launching MedBlock AI, hit these key points to keep it bulletproof: blockchain seals medical data super tight, no tampering; AI rips through patient details and spots in seconds flat for emergencies; hospital teamwork, ambulance sends, donor matches—all gotta happen live, no delays. Figure 4 seals access and privacy—only cleared healthcare pros see patient details. That's why the entire emergency system feels bulletproof.

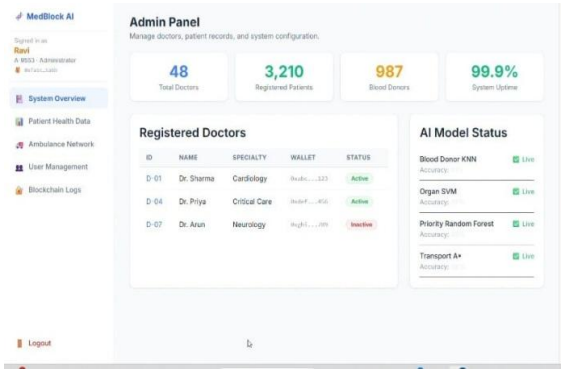

Fig 4: System Overview Dashboard

IV. System Implementation and Documentation

After wrapping up the MedBlock AI design, we laid out the modules and jotted down notes before the full rollout. In dev, we mashed up emergency services, blockchain, and AI smarts into one solid platform. Each part got built and tested on its own first—stuff like matching donors, stashing medical data securely, and sending ambulances—then we hooked 'em all together in the app . It leans on Ethereum blockchain to keep logs of transactions and patient files airtight, so everything's transparent, locked down tight, and tamper-proof . User side uses MetaMask for wallet-based logins, ditching old-school central auth for something way safer .

A. Users and Healthcare Participants

In order to expedite life-saving connections, our system connects patients, hospitals, physicians, blood donors, organ donors, and emergency teams. Everyone has a specific role to play: patients register their medical information and agree to donate organs or blood when necessary. Hospitals and doctors can pull up those records anytime and call for urgent help . AI systems will quickly find matching blood/organs based on criteria like blood group and organ compatibility, while donors also register their willingness to donate, making it easier in a medical emergency to contact the relevant person.

B. System Module Organization

- **MedBlock AI :** comes with these modules to smoothly manage emergency healthcare services:
- **Blockchain Medical Record Storage:** Stores patient's medical records in the blockchain ensuring immutability and privacy of data.
- **Blood and Organ Donor Matching System**: Uses AI to quickly link donors to the right matches.
- **AI-Powered Organ Transport**: Figures out the fastest routes to rush organs to where they're needed.
- **Decentralized Ambulance Dispatch System**: Spots the closest ambulance and dispatches it on the spot.

All these tie together to sharpen coordination between hospitals, donors, and emergency teams.

C. Live visualization and monitoring

MedBlock AI will show health practitioners the real time dashboards and visualization tools to keep them aware as the emergencies occur (as shown in Fig 5). The hospitals are equipped to display live updates: available donors, location of ambulances, patient information etc which are crucial data required. The visualization graphs and the live map enable the doctors to get the overview quickly and respond promptly [7].

The system will be further enhanced by AI prediction models which analyze historical data on emergencies, detect patterns, predict future events, and thereby make response plans more precise for the next incidents.

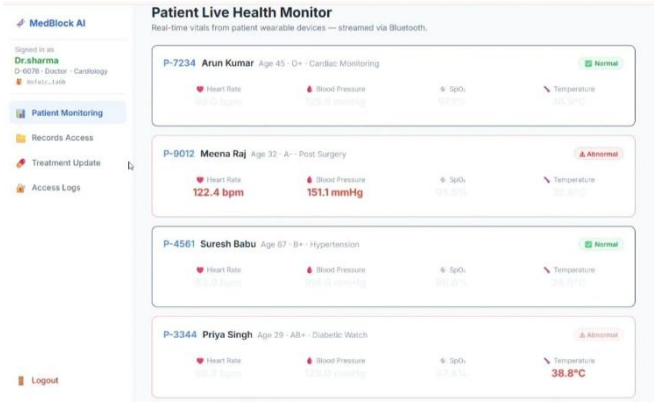

Fig 5: live patient monitor

D. Figures and tables for representing the system

MedBlock AI would use figures and tables to enable simple understanding of the documentation. Architecture diagrams will showcase the interaction of blockchain with other modules such as the AI modules, the emergency services and so on. Tables will define patient medical parameters, donor information and availability, status of ambulances, etc [8].

These diagrams and tables will be particularly helpful to researchers and developers in picturing the design and requirement of the system to implement it.

Acknowledgement

This system is the result of a collective endeavor and built on the foundation of robust research in blockchain and AI in

healthcare. Ethereum is at the heart of the system as it enables a secured patient information storage and transaction visibility between different entities through the blockchain. Through the integration of MetaMask, only authorized medical professionals will be able to authenticate themselves for access using the decentralized authorization mechanism.

AI and Machine Learning models perform key functions such as optimizing matching of blood and organ donors and recipients, managing and dispatching of ambulances, and streamlining of routes between donors, patients and hospitals. These models work by considering compatibility between blood groups or organ characteristics, location of donor and recipient, and the severity of the emergency case which enables optimal use of emergency medical resources. This system integrates EHR, IoT and APIs with this blockchain technology so as to establish communication and flow between hospitals, emergency responders, donors, and recipients. MedBlock AI is based on current researches in the field of blockchain in healthcare and AI driven emergency management systems.

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An Intelligent Space Computing Platform for Autonomous Management of Orbital Data Centers

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Abstract-*The growing popularity of cloud computing and artificial intelligence has caused a surge in the power and cooling requirements of traditional data centers, which has posed a threat to the environment. This paper aims to present a novel data center design based on a solar power-driven space-based data center with AI-automated facilities, wherein the data center facilities are placed in Earth's orbit to harness the power of the sun and benefit from the free cooling provided by the space environment. The proposed data center design incorporates an AI-driven scheduling system, energy management system, satellite monitoring system, and satellite protection system to ensure the reliable functioning of the proposed data center. The satellite communication system allows for high-speed data transfer between the satellite and Earth.*

Keywords: Space-Based Data Center, AI Automation, Solar Energy Harvesting, Orbital Computing, Satellite Communication.

1. INTRODUCTION

The rapid growth of AI, cloud computing, and big data processing has made the need for global data center infrastructure much greater. Traditional data centers on land need a lot of electricity and cooling systems, which often rely on a lot of water and energy, raising concerns about the environment and sustainability. Recent studies in edge computing, orbital computing, and space solar power systems indicate that establishing computing infrastructure in Low Earth Orbit (LEO) may offer a viable solution to these constraints. Photovoltaic systems can efficiently collect solar energy in space, and the vacuum of space allows for effective radiative cooling. This could lower the energy needs and cooling needs of traditional data centers.

But putting in place space-based computing infrastructures comes with a number of technical problems, such as managing energy use well, monitoring systems on their own, communicating with satellites, and protecting against debris in orbit. Improvements in AI for satellite systems, machine learning-based fault detection, and task scheduling that takes into account the sun have made it possible to manage these kinds of systems

on their own. This paper presents a solar-powered orbital data center architecture featuring AI-driven automation and adaptive energy management. It incorporates intelligent workload scheduling, autonomous satellite health monitoring, and advanced satellite communication networks to ensure reliable data processing in orbit. The proposed framework is meant to help build space-based computing systems that are both sustainable and scalable, so they can handle future digital and AI-driven apps.

2. RELATED WORKS

Recent studies have looked into whether it would be possible to put computing infrastructure in space to get around the problems that traditional data centers have with the environment. Research has examined space-based data centers and cooling systems, emphasizing how the space environment facilitates efficient heat dissipation and sustainable cooling via natural radiative mechanisms [1]. Research has also suggested solar-powered orbital architectures for AI data centers, showing that solar energy can be used as the main power source for large-scale computing infrastructure in space [2]. Furthermore, studies regarding the environmental consequences of deploying computing infrastructure into orbit assess the carbon footprint and sustainability dimensions of space-based computing systems [3].

There are several studies that specifically address the topic of orbital computing frameworks and in-orbit data processing architectures. In addition, several studies have been conducted to integrate the concept of global ground stations as a service to allow for the most effective communication between satellites and the Earth surface [4]. Other studies have addressed the topic of sunlight-aware task scheduling mechanisms to optimize the use of energy from the sun in space edge computing networks [5]. The concept of orbital edge computing with the use of nanosatellite constellations has also been addressed, which can be used to allow for distributed computing to be performed in orbit to allow for processing to be conducted in orbit [6]. In addition, basic edge computing architectures have been addressed to allow for decentralized computing systems to be utilized, which can include satellites [8].

The role of energy generation and power management cannot be overlooked when discussing space-based data center infrastructures. Past research works introduced the concept of space solar power, which focused on the potential for generating power by harvesting solar energy for technological purposes [11]. Subsequent works on space solar power satellite systems focused on design concepts for generating continuous renewable energy sources for technological purposes [9][10]. These works are a strong technological foundation for powering an orbital computer system with solar energy, reducing dependence on terrestrial power sources.

Another significant research area is related to the autonomous management of satellites, communication networks, and safety mechanisms in orbit. The research in this area includes the application of artificial intelligence and machine learning in the management of satellites, fault detection, and health monitoring, thus enabling the autonomous management of space infrastructures [12, 13, 14, 15].

Moreover, research on satellite-terrestrial hybrid communication network technologies and laser communication technologies facilitates high-speed data transfer between satellites and the Earth's surface [16, 17, 18]. Additionally, research on the risks and mitigation strategies of orbital debris in satellites emphasizes the need for monitoring and safety mechanisms in the management of space infrastructures, thus forming the basis for an effective and efficient artificial intelligence and solar-powered space-based data center system.

3. PROPOSED METHODOLOGY

The proposed system architecture of the solar-powered space-based data center is designed for deployment in Earth orbit with the aim of ensuring the sustainability of the computing operations. The solar-powered space-based data center architecture is composed of various modules, such as the orbital

data center unit, solar power generation unit, AI controller, communication unit, and protection unit. The orbital data center unit is designed with the aim of supporting the operation of computing servers, storage units, and processing modules for the handling of large-scale data processing operations. The solar-powered space-based data center is designed with the aim of using solar photovoltaic panels as the primary energy-harvesting mechanism and the space vacuum as the cooling mechanism.

The energy management subsystem controls the power generation and distribution for the orbital platform. Solar panels receive solar energy and convert it into electricity. An adaptive power controller manages the electricity for the computing nodes, storage devices, and communication systems. An AI-based automation module controls the system's performance, computes the workload for the computers, and efficiently manages the resources for the smooth functioning of the system. Additionally, this module includes satellite health management, fault detection, and maintenance prediction for the smooth functioning of the satellite.

For the sake of communication between the space data center and the Earth, there is a satellite communication subsystem that helps in the transmission of data at high speeds. There are ground stations on the Earth that help in communicating with the orbital data center for the transmission of computational tasks to the center and receiving the results from the center. Technologies such as inter-satellite links and laser communication can be used for the transmission of data at high speeds.

For safe and effective operation in space, the system includes mechanisms for orbital protection and monitoring. The system uses monitoring mechanisms to detect possible hazards such as space debris and collision, thus enabling the system to prevent possible hazards through automated control mechanisms. The proposed system includes the use of solar power, automated control using AI, and effective cooling and communication, thus enabling the proposed system to form an effective framework for future space-based computing infrastructures.

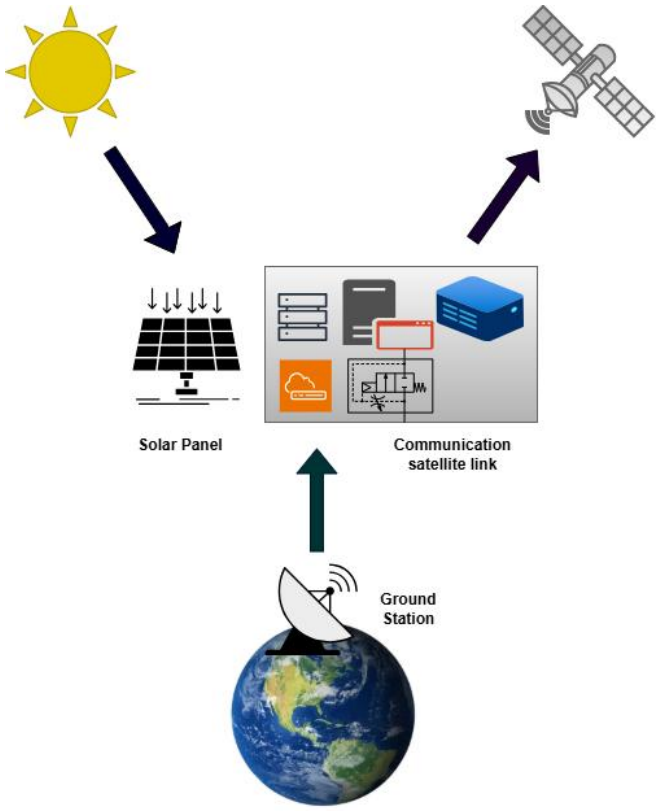

Figure 1: Solar-Powered Space Data Centre

4. ENERGY MODEL AND SOLAR POWER UTILIZATION

Energy generation and management are important aspects of the suggested space-based data center architecture. The system will mainly depend on solar energy as a source of power in the orbital environment. The solar panels are fitted on the satellite structure to receive continuous solar energy from the sun. The solar panels are then used to convert solar energy into electrical energy using photovoltaic cells. Compared to other systems on earth, solar panels in space are efficient because they are not interfered with by weather conditions or day and night cycles for a very long period in space. The generated electrical energy will then be used to power various computing servers, storage devices, communication systems, and other units in the orbital data center.

The energy model for the proposed system will be based upon the utilization of solar power to generate electrical power. The power generated by solar panels can be estimated by using the following equation:

$$P=\eta \times A \times I$$

where

P = generated electrical power (W)
η = efficiency of the solar panel
A = surface area of the solar panel (m^2)
I = solar irradiance in space (approximately 1361 W/m^2 near Earth orbit)

An AI-based energy management system is integrated to optimize the usage of power in the orbital data center. The AI module will monitor the energy generation, server workload, and performance to dynamically manage the allocation of power. For instance, in cases where there is low computational demand, it can minimize the usage of power by adjusting its server operation or storing it in onboard batteries. On the other hand, in cases where there is a high demand for computation, the energy management module will ensure that there is proper distribution of power to support data processing.

Moreover, the use of adaptive solar panel orientation mechanisms may be utilized to ensure maximum energy harvesting. In this regard, the satellite structure may comprise the use of automated tracking mechanisms that adjust the satellite's solar panel angle with respect to the Sun to ensure maximum efficiency in energy absorption. With the use of efficient mechanisms in the generation of photovoltaic energy, the proposed energy model ensures the provision of a sustainable power supply to the satellite-based data center.

5. AI-BASED AUTOMATION AND WORKLOAD SCHEDULING

The computer system in space is really tough to manage. It is not like the computer system on Earth where there are lots of people to check on it. Satellites are really different from computer centers. We cannot just go there to check on the satellites because it takes a lot of time to send messages. We cannot always go there. That is the reason we would like to use Artificial Intelligence to help manage the system. The Artificial Intelligence system will perform the tasks on its own. The main purpose is to make the system work well by using energy and computer power.

The Artificial Intelligence system is really important. The Artificial Intelligence system helps the system work well. It helps the system use energy and computer power wisely. We need the Artificial Intelligence system to help us with the computer system in space.

5.1 Intelligent Workload Scheduling

One of the jobs of the Artificial Intelligence system is to decide what to give to which computer. The Artificial Intelligence system looks at how the system's doing. Then it decides what to do. The Artificial Intelligence system thinks about how the computers are doing. It thinks about how much power is available. It thinks about how hot it is. It thinks about how the computers are communicating with each other.

For instance when the satellite is in the sun and has lots of power it can use lots of computer power. The Artificial Intelligence system helps with this. When the satellite is in the dark without power it may wait on doing some of the jobs. The Artificial Intelligence system is very helpful. It makes sure the system works well.

5.2 System Monitoring

The computer system has sensors to look at how the system's doing all the time. The sensors look at things like how hot the computers are getting. They look at how much power is left in the batteries. They look at how much space is left on the drives. They look at how the computers can talk to each other. The Artificial Intelligence system looks at all of this information. It decides what to do.

If the system has a problem like the computer getting too hot the Artificial Intelligence system can fix it by itself. For instance it can make the computer work less. It can give the computer jobs to do. It can make the computer stop jobs it is not supposed to do. This lets the system work well. It prevents problems from happening. The Artificial

Intelligence system is good at fixing problems. The Artificial Intelligence system helps the system work well.

6. COMMUNICATION AND DATA TRANSMISSION

Communication and data transmission are important aspects in the operation of a space-based data center because it is located in space, whereas users are located on Earth. The system allows for efficient communication and data transmission between the space-based data center and Earth stations using efficient satellite communication systems. The ground stations on Earth send computational requests to the space-based data center through an uplink communication channel. The processed results are then sent back to Earth stations through a high-speed downlink communication channel. This ensures efficient communication between Earth stations and the space-based data center.

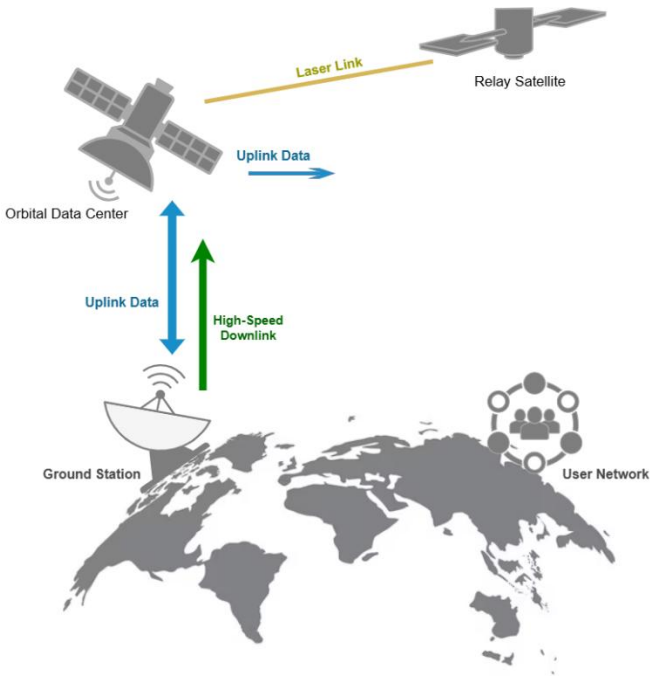

Figure 2: Communication and Data Transmission in Space-Based Data Center

To achieve greater data transmission efficiency and reduce latency, the system could utilize the inter-satellite communication links and laser-based optical communication technologies. Laser communication technology, for instance, enables the use of greater bandwidth and reduced signal interference compared to the use of the traditional radio-frequency communication system. This enables the efficient and effective transmission of large volumes of data between the satellites and the Earth. Relay satellites could also be used to ensure greater coverage and ensure the provision of continuous communication, especially when the data center is not in line of sight of the ground station. AI-based network management systems could also be utilized to ensure the provision of effective communication between the users, the ground stations, and the data center.

7. SAFETY AND ORBITAL PROTECTION MECHANISM

Building a space data center needs special safety plans so it can work for a long time. Space data centers face dangers like space debris, radiation, big temperature changes, and collisions with other satellites. Because of these dangers, the space data center must have safety features to protect its parts and keep working smoothly. These features help keep important parts safe, make the system stronger, and prevent services from stopping. A big problem in Earth's orbit is space trash, which includes old satellites, broken pieces from other spacecraft, and tiny fast-moving particles. Even small pieces can hurt the delicate equipment inside the space data center. To stay safe, the system uses sensors to find space trash and tracking tools to watch the area all the time. These help identify nearby objects and predict where they are going. If a crash might happen, the system can do small moves to change its path and stay safe. Another safety step is putting shields on the hardware to protect it from tiny space rocks and radiation. These shields can block or reduce the impact of small debris and radiation, helping the electronic parts last longer.

The system is designed with redundancy in mind, incorporating spare components and alternative designs. This ensures continued operation, even in the event of a failure. Artificial intelligence, or AI, plays a key role in maintaining system security. These intelligent computers continuously monitor sensor data, searching for any unusual activity or alterations. When they detect an issue, they can respond immediately and autonomously. This

might involve disabling malfunctioning components, reallocating task, or activating backup systems. Such swift, automated reactions are essential, especially considering the absence of on-site repair crews in space. Ground stations, alongside the inherent safety measures of the space data center, contribute significantly to the overall system's resilience. These stations monitor satellite positions and transmit updated space data, helping to shield the space data center from unexpected events.

8. DISCUSSION

Compared to existing ground-based data centre facilities, the proposed space-based data centre architecture can provide a number of potential advantages. One of the most crucial benefits is drastically reduced water consumption when producing facility operations in space compared to existing data centre facilities on Earth. Traditional data centre facilities in comparison to a data centre facility in space will consume significantly greater volumes of water inside the data centre to cool servers and keep them operating at a safe temperature. The use of a data centre facility in space will eliminate the need to use water based cooling systems, conserve valuable freshwater resources on Earth and allow the use of the natural vacuum of space for dissipation of heat via radiative cooling.

Another important advantage is the efficient use of renewable energy. A data centre in space can harvest solar energy directly from the sun using large solar panels without many of the limitations imposed by the environment of the earth such as weather, day/night cycles or land availability. Because the system will almost exclusively depend on solar energy as the primary source of energy, it will operate with minimal dependence on fossil fuel based electricity. This will support clean energy use and also greatly reduce the environmental impacts of large computing infrastructure.

This architectural proposal has the potential for long-term sustainability in data center development. Demand for cloud services, AI, and large-scale data processing is growing and as a result, traditional data centers will continue to consume increasing amounts of energy and natural resources. By moving some of this computing infrastructure into space, the distribution of computing loads could be more efficient, thereby reducing the strain on terrestrial energy systems. Furthermore, incorporating AI-based monitoring and automated management can enhance operational efficiency and decrease the frequency of manual intervention. These combined technologies illustrate that developing space-based infrastructure in conjunction with other new technologies (AI and renewable energy) can produce a more sustainable and scalable computing environment. While this idea is still in development, it represents a strong potential avenue for future research and technology advancement within data center design.

9. CONCLUSION

In conclusion, the solar-powered, artificially intelligent (AI) space data center concept is proposed as a potential option to address the increasing number of challenges related to both environmental and energy issues generated by conventional data centers. The location of data center architecture in Earth orbit allows the data center to utilize solar power and take advantage of the natural cooling provided by the environment of space. The architecture consists of several components, including solar energy collection, orbital computing modules from a number of different satellites, AI workload management, satellite communications, and debris monitoring and debris collision avoidance and other safety mechanisms.

The proposed design shows promise as a means to minimize water use, improve renewable energy use, and support more sustainable computing infrastructures in the future. The incorporation of intelligent monitoring systems within a system will also allow a system to operate autonomously and will improve reliability and efficiency of a system within the extreme environment of space. Many

new challenges have arisen regarding these systems. Future work might include developing more efficient launches or lowering/mitigating the costs of providing more effective shielding against radiation. Development of reliable communication between satellites could also be something worth researching. In addition, continued research should seek to optimize artificial intelligence scheduling algorithms, improve battery technology, and find ways to address the issue of debris in orbit. As the years go on, advances in technology will allow us to build data centres based on aerospace technologies and offer solutions that utilise a combination of computing and the environment through renewable energy to meet the worldwide demand for data centres.

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AI-Powered Smart Women Safety Application with Voice-Activated SOS and Real-Time Location Tracking

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Abstract:

This research paper addresses the issue of women's safety in the current scenario where cases of harassment attacks and other life- threatening situations are on the increase in most cases the victim is unable to unlock her smartphone or send an alert manually to solve this issue we propose an ai- based safety app for women that provides immediate assistance in emergency situations via automated emergency alerts our proposed solution combines speech recognition location tracking and mobile messaging services to provide immediate assistance in emergency situations with the use of a pre-defined emergency trigger word a user can automatically send an SoS alert and her location to her trusted contacts the proposed solution also has a feature that detects if the smartphone is shaken and continues to track the location to improve accuracy.

Keywords:

Women's Security, AI Technology, Speech Recognition, Crisis Notification System, GPS Tracking.

I. Introduction:

So women safety is very important to consider at this moment because every day or in a weekly base we listen in news or read in report about violence and attack on women at public as well as in homes. The serious matter is when a women can't even reach her mobile phone or can't unlock her screen in emergency to call any desired person and so it takes very long to help a women. So why cannot technology help her? As we know the advancement of Artificial Intelligence in mobile phones and the existence of safety apps which ask to tap some keys or shake your device to send alert to family and/or to the police, which is not effective.

It's a common scenario that any person in such a situation will not be able to remember to tap some keys and so here is a scope. So the idea of an app which is intelligent with the Artificial Intelligence technology and can do the entire process automatically and which requires the user to just say a voice command (say something as given as a word to the device and in emergency just speak that word, to activate SOS) and it will automatically trace GPS location and share it with family and/or to the police. It would have some shaking action also, if someone is unable to speak, then shake the device at a fixed direction. In SOS mode the GPS location will be continuously tracked and shared with family and/or the police. Of course, there can be some issues but definitely it would help to reach in minimum possible time and women

features are not perfect, but they could cut down the waiting time for help. It feels like it would make women feel safer overall, even if there are still issues to figure out.

II. Literature review:

All of these applications created by these researches also include the feature of GPS tracking for the location of the user as well as a transmission of an alert message. During an alarming circumstance, the user can send their actual location to loved ones with an alert message. However, the issue with most of these applications is that one must press a button to initiate the alert. Under duress it may not be fast enough and one may be in such haste, they are simply unable to locate a button. New research in this area involves AI and voice activation so perhaps whispering an alert would actually notify authorities. They are suggesting a system that is one step beyond that, in which it will not only detect voice recognition but it will automatically activate during rough movement or shaking and always maintain a live location tracking on. My impression of this system is that it's a more sensitive and rapid system and far more innovative than the ones that were discussed before. Though I do believe that it could potentially be an alarm for any heavy shake, it appears to be in the right direction..

III. Proposed system:

The application functions as an artificial intelligence system which provides security protection for women by delivering immediate assistance during emergency situations.The system activates emergency SOS functions through voice recognition after detecting a specific emergency keyword that the user pronounces. I found the solution to be beneficial because it enables users to communicate during panic situations when they face difficulties with typing.

The system establishes your location through GPS tracking, which it uses to send emergency alerts to your designated contacts who receive your real-time location updates. The application includes a shake function that creates an alert when users shake their mobile device multiple times. The system functions as a secondary option which users can access when they encounter difficulties with verbal communication. The system continues to monitor your location until the situation stabilizes according to my understanding.

The system enables rapid assistance during emergencies by reducing the amount of tasks that users need to perform. The system contains overlapping elements but its primary goal remains to enhance overall communication efficiency.

VI. System architecture

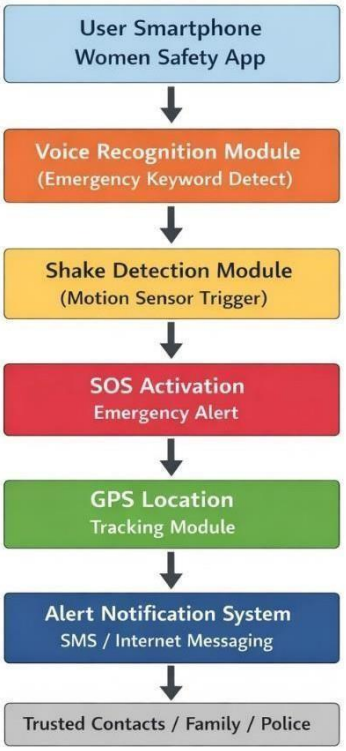

Figure 4.1

V. Methodology:

the proposed system operates through a mobile application designed to provide quick assistance during emergency situations initially the user installs the application and registers trusted contacts within the system the application continuously monitors emergency triggers such as a predefined voice command or shake detection using the smartphone sensors when the emergency keyword is detected or the device is shaken multiple times

the system automatically activates the sos alert mechanism the application then retrieves the user's current location using the gps module and sends an emergency message along with the location details to the registered contacts the system also continues to track and update the user's location until the emergency situation is resolved ensuring accurate monitoring and faster assistance

Figure 4.2

Figure 4.3

VI. Result and Discussion:

the proposed ai-based women safety application was tested using a smartphone environment to evaluate its emergency alert functionality the system successfully detected the predefined voice command and activated the SoS alert mechanism once activated the application was able to send an emergency message along with the users gps location to the registered contacts the shake detection feature was also tested and the system correctly triggered the emergency alert when the smartphone was shaken multiple times the gps module provided accurate location details and continuously updated the location information during the emergency state the results show that the proposed system can provide faster communication and reliable assistance compared to traditional safety applications that rely only on manual activation.

Figure 4.4

VI. Future Scope:

The advanced AI system developed makes automatic detection of the emergency possible. By observing the user's behaviors, we are classifying the abnormality (i.e. Movement depicts fear/stress, not moving). Audio recognition is being used to detect shouting/screaming and calling for help. Consequently, emergency situation is detected in anticipation without user's involvement. Such AI system is beneficial in fast and prompt detection of emergency.

The system can connect to local police station/emergency services to take appropriate actions upon detection of emergency. Besides, it can be designed into a portable device that measures the user's heartbeat, body movement and stress level, triggering a warning message if there is an abnormality.

VII. Conclusion:

Making sure that women are safe in public and private spaces has been a big challenge. This study designed a smart mobile application to assist women in emergency conditions via automated safety features. The system is voice-based, detects motion and tracks location and quickly alerts the trusted people in case of some threat on the user. The system allows for emergency alerts by using one's voice or just moving a device, thus minimizing the need for touch. By allowing the contacts to recognize the user's location efficiently, the merging of real-time GPS tracking enhances the effectiveness of the solution. By working together, these features enhance communication speed and boost the likelihood of prompt help. Generally, the proposed application shows that mobile technologies and intelligent automation can enhance personal safety. The system offers a feasible and handy means of aiding women during emergencies and underlines the capability of technology to address

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Machine Learning-Based Detection and Prevention of UPI Fraud in Digital Payment Systems

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Abstract: With the rapid increase in digital payment usage across India, fraudulent transactions on UPI (Unified Payments Interface) platforms have emerged as a serious issue. Traditional fraud detection methods that rely on predefined rules are unable to keep up with changing fraud patterns, resulting in monetary losses and reduced public confidence in online banking. This study introduces a fraud detection framework based on machine learning that employs techniques such as Logistic Regression, Random Forest, and anomaly detection to spot suspicious transactions instantly. The system learns from past transaction records and automatically adapts to new fraud strategies. By enhancing fraud detection accuracy and enabling early preventive action, the proposed model minimizes risks for users, banks, and regulatory bodies while improving trust in digital financial systems.

Keywords*: UPI Fraud Detection, Machine Learning, Random Forest, Logistic Regression, Anomaly Detection, Cybersecurity, Digital Payments*

I. INTRODUCTION

The widespread adoption of digital payment platforms in India has transformed financial transactions, with UPI (Unified Payments Interface) becoming a leading method for real-time money transfers. UPI enables individuals, businesses, and organizations to carry out seamless financial operations, minimizing cash usage and promoting digital financial inclusion. However, alongside this growth, incidents of online fraud and cybercrime have increased, threatening the security and reliability of online transactions.

Scams involving phishing, spoofing, unauthorized access, and social engineering are now major concerns for both users and financial service providers. According to recent statistics from the Reserve Bank of India, over 95,000 digital fraud complaints were recorded in FY 2023–24, with a large number linked to UPI-based frauds. These incidents not only cause financial loss but also damage the reputation of payment systems and increase the burden on regulatory authorities.

Conventional fraud detection mechanisms are mostly rule-driven and fail to adjust to new and evolving fraud strategies. Since criminals constantly change their methods, static systems are inadequate for real-time fraud prevention. Therefore, there is a need for advanced, data-driven solutions capable of analyzing huge volumes of transactions, detecting unusual patterns, and predicting fraudulent activities with improved precision.

Machine learning offers a powerful solution to tackle these issues. By learning from past transaction behavior and adapting to emerging fraud techniques, ML-based models can significantly improve fraud detection performance. This paper focuses on developing and implementing a UPI fraud detection model based on machine learning that enhances detection accuracy, reduces false alerts, and secures digital payments for users.

II. LITERATURE SURVEY

The financial technology sector has witnessed remarkable progress with the integration of machine learning (ML), especially in detecting fraudulent activities and ensuring secure digital transactions. Numerous

researchers have explored ML-based frameworks to enhance the accuracy and efficiency of fraud detection systems. This section reviews key studies and their contributions to the domain .

An investigation by Kavitha (2024) proposed a hybrid ml model that combined Hidden Markov Models, K-means clustering, Autoencoders, and Neural Network-based models were applied to study UPI transactions. The outcomes showed effective identification of abnormal activities; however, managing imbalanced data and achieving scalability for real-time processing continued to pose difficulties .

"Vijaya Sree Reddy et al. (2025) implemented a Random Forest model combined with the SMOTE oversampling approach to overcome class imbalance frequently seen in fraud-related datasets. Their system achieved strong results in terms of precision, recall, and F1-measure, confirming its reliability in separating genuine and fraudulent transactions. Nonetheless, it demanded significant computing power for real-time tracking ."

"Malode et al. (2025) developed an intelligent UPI fraud detection model that combined both supervised and unsupervised learning techniques, incorporating behavioral biometrics, blockchain-based secure record keeping, and real-time alert mechanisms."

In addition to supervised learning methods, unsupervised approaches have been explored to capture hidden fraud patterns. Isolation Forest and Autoencoders have been widely adopted for anomaly detection in financial transactions. These models are capable of identifying rare or novel fraud activities without relying solely on labeled datasets. Although they offer strong adaptability to emerging fraud strategies, their performance is often influenced by noise in transaction data and the lack of explainability in decision-making.

"Many researchers have underscored the importance of ensemble learning in improving the accuracy of fraud identification. Approaches that integrate multiple algorithms—like Random Forest and Gradient Boosting—offer better generalization, resist overfitting, and boost recognition of rare fraudulent activities."

"Recent investigations have also stressed the value of deploying fraud detection mechanisms within real-time frameworks. Researchers suggest incorporating ML-powered detection systems directly into payment gateways using API integration to ensure immediate identification and alerting of unusual transactions.".

III. PROPOSED METHODOLOGY

1. Data Acquisition and Labeling

The process starts with the collection of transaction data to UPI platforms. This dataset, consisting of both real and synthetic records, includes vital information such as transaction amount, time, sender and receiver IDs, device details, and geolocation markers. Each record is meticulously labeled as either genuine or potentially fraudulent according to observed transaction anomalies, official reporting sources, or simulated fraud features for training the initial model. By ensuring diverse representation and proper labeling, this step lays a strong foundation for subsequent analytical accuracy.

2. Data Refinement and Feature Optimization

Raw transaction data that subjected to thorough cleaning, normalization, and transformation. Missing values are addressed, irrelevant features are removed, and outliers are systematically managed. Feature engineering is performed using advanced techniques, including time-based behavioral analysis (such as unusual transaction hours or velocity), location consistency checks, and device fingerprinting. These features are designed to expose hidden relationships and distinctive fraud patterns, enhancing the discrimination power of the underlying machine learning model.

3. Model Development and Training Framework

Multiple Machine Learning approaches are evaluated, ranging from classical classifiers like Logistic Regression and Random Forests to advanced models such as Gradient Boosting, Isolation Forest, and deep learning architectures (Autoencoders, CNNs). Models are trained using the curated and augmented dataset, with cross-validation performed to maximize generalizability and avoid overfitting. Specialized techniques like SMOTE are incorporated to balance class distribution and further refine learning outcomes. This multi-model approach ensures adaptability and robustness in fraud detection.

4. Anomaly Detection and Prediction

Trained models are deployed to monitor live or batch UPI transaction streams. Each transaction is assessed based on extracted features, with outlier detection techniques (e.g., Isolation Forests, Autoencoders) allowing for the identification of previously unseen or rare fraud patterns without explicit labels. Prediction thresholds are tuned to balance sensitivity and specificity, ensuring that suspicious transactions are flagged while minimizing false positives. Detection is performed in real-world or none-real-time, aligning with a need for swift financial protection.

5. API Deployment and System Integration

The predictive system is made accessible through secure backend APIs, typically implemented using frameworks like Flask or FastAPI and supported by cloud infrastructure (AWS Lambda, Render). These APIs facilitate easy integration with banking platforms, payment apps, and web interfaces, allowing for seamless transaction monitoring and fraud alerting. User-facing modules ensure timely notifications and reporting of anomalies to relevant stakeholders for further action. System scalability is prioritized to handle millions of daily transactions efficiently.

6. Continuous Improvement and Feedback Loop

The proposed system integrates a continuous learning mechanism to ensure consistent performance over time. Feedback from confirmed fraudulent activities and user reports is periodically used to retrain and fine-tune the model. Regular evaluations through analytic dashboards track metrics such as precision, recall, and false-positive rates to maintain accuracy. As new fraud patterns emerge, the adaptive framework automatically updates its parameters, keeping the detection process efficient and reliable. This ongoing enhancement ensures that the model remains effective, secure, and aligned with the evolving landscape of digital payment fraud.

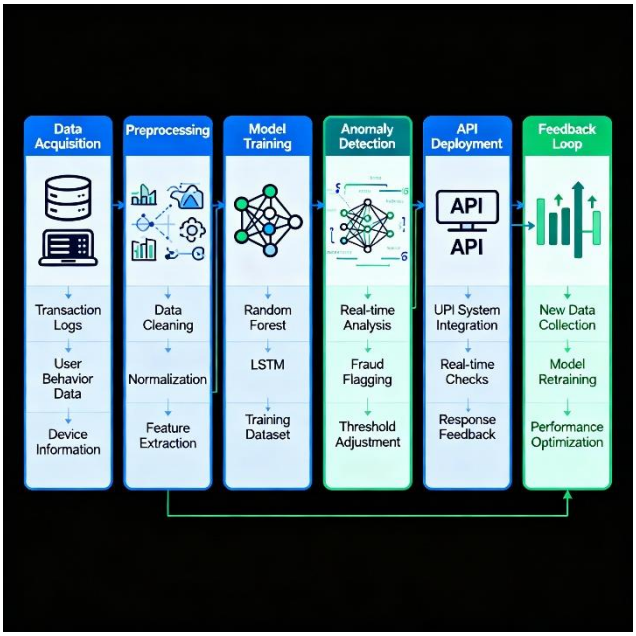

Fig. 1. The architecture diagram of proposed system

IV. DATA COMPILATION AND PROCESSING

Data gathering serves as the fundamental stage of the UPI fraud detection framework, as the success of the system depends heavily on the diversity and accuracy of transactional information collected. The dataset is sourced from various authentic UPI platforms and supplemented with artificially generated data to simulate multiple fraud scenarios. Each record includes essential transaction details such as date, time, sender and receiver IDs, transaction amount, device identifiers, and location metadata. Together, these elements provide a detailed view of transaction behavior. Using a wide-ranging dataset allows the proposed model to detect fraudulent actions across varying user groups, transaction categories, and fraud types, ensuring adaptability within a dynamic financial setting.

Data refinement converts the raw input into a uniform and structured form, laying the groundwork for efficient model training. This process resolves issues such as incomplete fields by applying advanced imputation techniques, thereby retaining critical information. Duplicate and irrelevant entries are removed to enhance computational efficiency and accuracy. In addition, categorical data is converted into machine-readable form through encoding, while numerical features (like transaction amount) are normalized to maintain a consistent

Scale across the dataset.

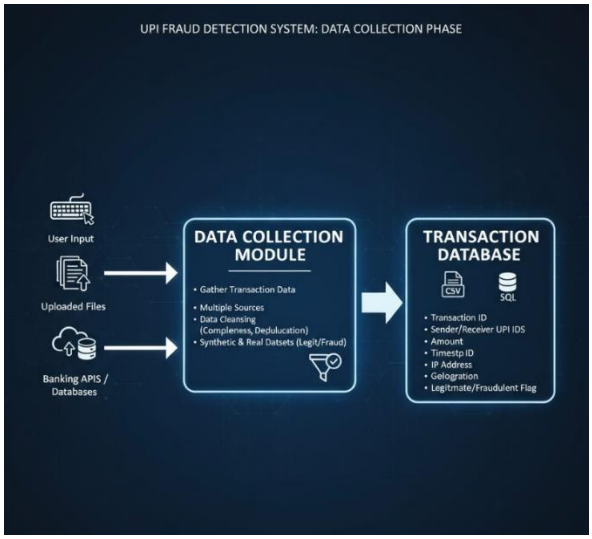

Fig 2: Data Collection Phase

Feature engineering plays a vital role by introducing domain-specific attributes that strengthen the model's predictive capabilities. Time-dependent metrics, including transaction frequency and intervals, expose behavioral trends linked to fraudulent activity. Device-based characteristics help uncover sudden device changes or spoofing attempts, while location-based attributes identify transactions initiated from unusual areas within short time frames. Such engineered features enable the model to capture intricate and hidden fraud patterns beyond raw transaction data.

After refinement, the complete dataset is divided into training and testing groups to ensure objective evaluation. This separation helps the model learn general patterns from training data and measure performance accurately on unseen test samples. Ultimately, meticulous data collection and preprocessing not only boost prediction reliability but also ensure the UPI fraud detection model remains scalable and adaptable to emerging fraud techniques.

V. DATA VISUALIZATION

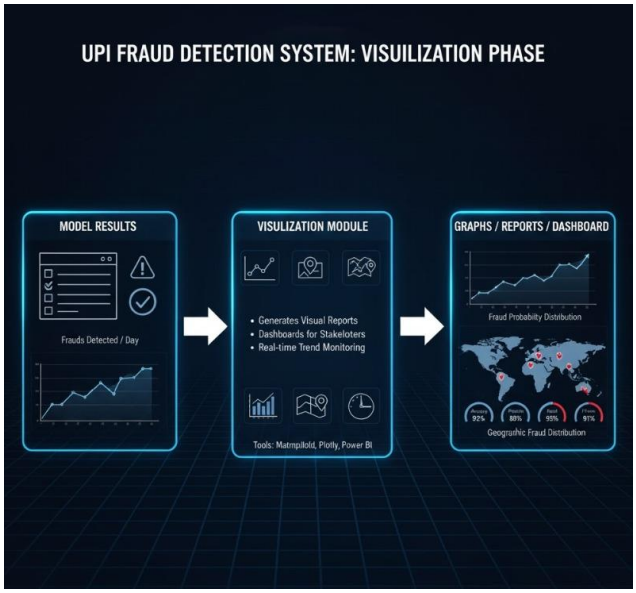

Fig 3: Visualization Phase

In the proposed UPI fraud detection system, visualization plays a vital role in examining, interpreting, and understanding transaction behavior. It helps researchers and developers recognize key data trends that contribute to designing an accurate and effective fraud detection framework.

Visualization methods are introduced early in the analytical process to study how various transaction-related variables—such as amount, frequency, and time—are distributed. Tools like histograms and box plots assist in identifying outliers, for instance, unusually large payments or sudden transaction surges, which may signify potential fraudulent behavior. Time-series graphs are also used to observe recurring patterns over hours, days, or months, enabling early recognition of abnormal events such as off-hour transactions or unexpected activity spikes.

Geospatial visualization tools, including heatmaps and scatter diagrams, are employed to trace transaction origins and detect suspicious geographical changes in user activity. These mapping techniques highlight anomalies such as transactions initiated from unfamiliar locations or abrupt location shifts, which are common indicators of fraudulent activity. Correlation plots and feature heatmaps further help analyze relationships between engineered features, improving the process of selecting and refining attributes used in machine learning models.

Interactive dashboards provide additional flexibility by allowing dynamic data filtering and exploration based on user, device, time, or region. Such tools make it easier for analysts and system administrators to investigate suspicious patterns efficiently. Visualization also serves as a validation layer by clearly representing model outputs, enhancing transparency and interpretability. In summary, graphical visualization transforms large volumes of complex transaction data into understandable insights, which are crucial for detecting fraudulent UPI activity and continuously improving the overall system's accuracy.

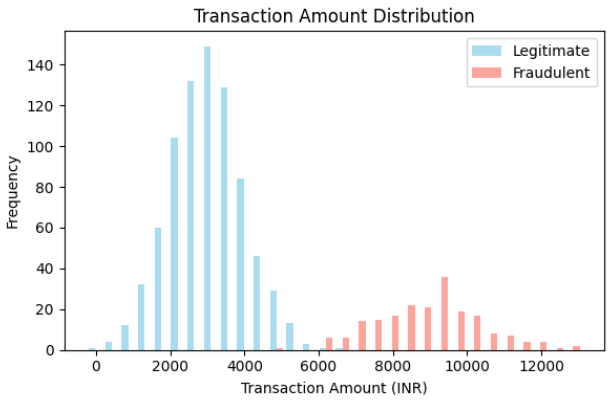

Fig 4. Transaction Amount Distribution for Legitimate and Fraudulent UPI Transactions

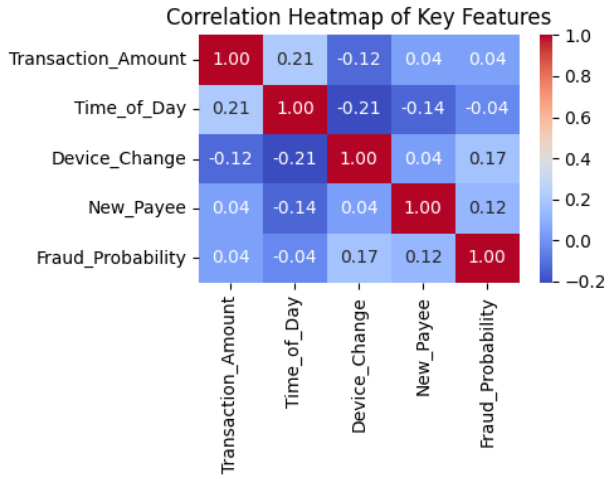

Fig 5. Correlation Heatmap of Key Transaction Features for UPI Fraud Detection

VI. RANDOM FOREST

The Random Forest algorithm is one of the most widely utilized machine learning techniques in detecting fraudulent UPI transactions because of its high reliability and accuracy. It operates by constructing multiple decision trees using randomly selected subsets of the dataset and feature variables. Each tree independently classifies whether a transaction is fraudulent or legitimate, and the final outcome is determined by aggregating the results of all trees through a majority voting mechanism. This ensemble strategy minimizes overfitting and enhances the model's ability to generalize across diverse transaction patterns.

In the proposed UPI fraud detection system, the Random Forest classifier is trained using a curated and preprocessed dataset that includes labeled instances of both genuine and fraudulent activities. The input features consist of transaction amount, time of transfer, device details, location coordinates, and behavioral indicators derived from user activity. The model effectively captures non-linear and hidden relationships between these variables, enabling it to identify fraud patterns that simpler algorithms might overlook. Its robustness and adaptability make Random Forest a strong baseline for fraud detection tasks within digital payment ecosystems.

VII. SYSTEM IMPLEMENTATION

The proposed UPI Fraud Detection framework is built as a multi-tiered architecture that integrates data preparation, machine learning models, and a lightweight web interface for deployment.

At the data layer, the system processes transactional logs containing key attributes such as transaction amount, timestamp, device ID, geolocation, and historical spending behavior. Sensitive identifiers are anonymized through hashing techniques to maintain user confidentiality. Additionally, behavioral indicators like the number of transactions per day, average weekly transaction value,

distance from the usual transaction location, new payee identification, and device change frequency are generated in real-time from the incoming data stream.

The modeling layer employs an ensemble-based gradient boosting approach (XGBoost) to detect non-linear relationships and handle data imbalance inherent in fraud detection tasks. The model is trained on labeled datasets containing both authentic and fraudulent UPI transactions. During preprocessing, missing values are imputed, categorical variables are encoded, and numeric attributes are normalized. A fraud probability score is generated by the model and translated into descriptive categories such as Safe, Suspicious, or Fraudulent.

The backend is developed as a RESTful API using Flask, with a /predict endpoint that accepts transaction data in JSON format and returns prediction results. This design allows smooth integration with existing banking or payment applications. The frontend—developed using HTML and JavaScript—enables users and administrators to input transaction details and receive fraud risk evaluations in real time, as demonstrated in the prototype interface.

Deployment is handled through Docker containers, providing portability and scalability. The system can be hosted on cloud platforms equipped with monitoring tools for performance tracking, latency measurement, and drift detection. Security protocols such as HTTPS, authentication tokens, and encrypted storage are implemented to ensure data integrity.

This modular structure ensures high accuracy, transparency, and seamless adaptability for real-world UPI fraud prevention in digital payment systems.

Fig 6: Home Page

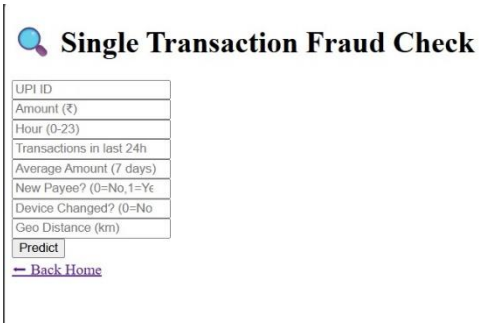

Fig 7: Single Transaction Input form

Fig 8: Batch Transaction Upload Page

VIII PERFORMANCE METRICS

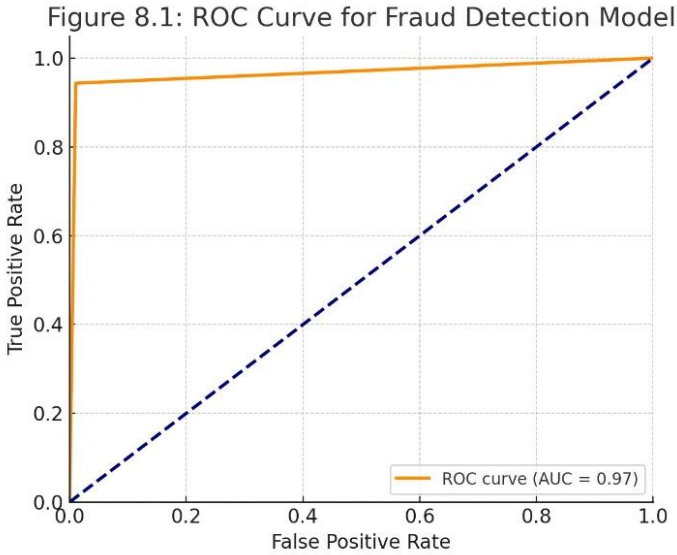

Fig 9: ROC Curve for fraud detection

To evaluate the efficiency of the proposed UPI fraud detection system, several standard classification metrics were applied. These measures assess the model's reliability, predictive power, and overall capability to distinguish fraudulent transactions from genuine ones.

The dataset was divided into training and testing sets using an 80:20 ratio, ensuring an unbiased evaluation of performance. The training data helped the model learn general transaction patterns and fraudulent behavior, while the testing data validated how effectively it could generalize to unseen samples.

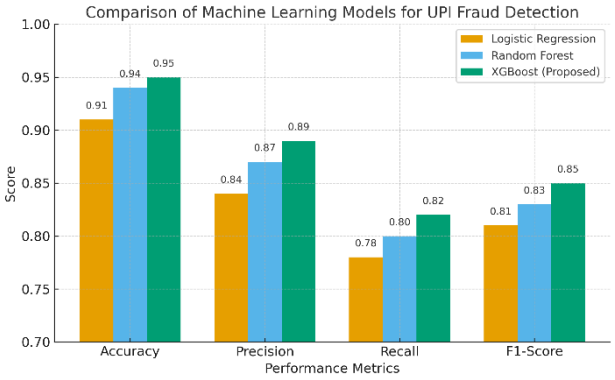

Fig 10: Comparison of ML models

Accuracy:

Accuracy represents the overall percentage of correctly predicted transactions—both fraudulent and legitimate—out of all transactions analyzed by the system.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Expanded in terms of classification outcomes:

$$Accuracy = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{True Positives (TP)} + \text{True Negatives (TN)} + \text{False Positives (FP)}}$$

Precision:

$$Precision = \frac{\text{Number of Correctly Predicted Fraudulent Transactions}}{\text{Total Number of Transactions Predicted as Fraudulent}}$$

Expanded in terms of classification outcomes:

$$Precision = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Precision, also known as Positive Predictive Value (PPV), refers to the fraction of transactions identified as fraudulent that were actually fraud. It evaluates how precise the model is in its fraud predictions.

IX. CONFUSION MATRIX

The effectiveness of the proposed UPI Fraud Detection model is evaluated through a confusion matrix, which provides a detailed comparison between actual and predicted outcomes. This matrix serves as a valuable analytical tool to determine how accurately the system differentiates between genuine and fraudulent transactions. It highlights both correct classifications and possible misclassifications, giving a complete picture of model performance.

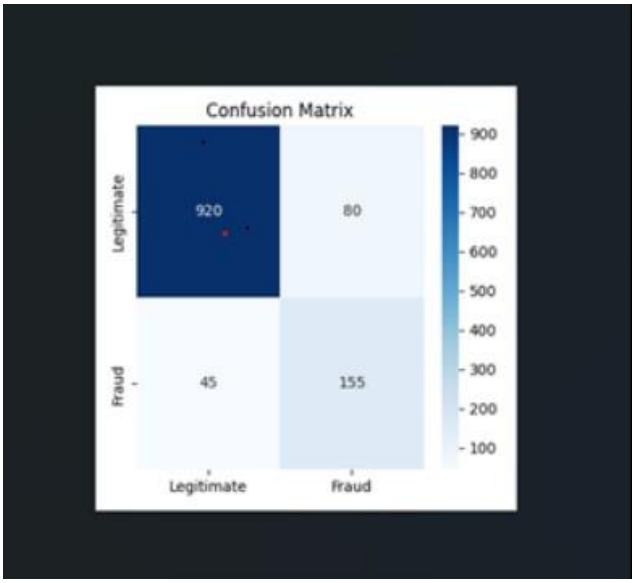

Fig 11: Confusion Matrix

In the context of UPI fraud detection, the confusion matrix consists of four major outcomes:

true positives (tp): Fraudulent transactions correctly identified as fraud.

true negatives (tn): Legitimate transactions correctly classified as genuine.

false positives (fp): Genuine transactions incorrectly predicted as fraudulent.

false negatives (fn): Fraudulent transactions wrongly classified as legitimate.

The confusion matrix acts as the foundation for calculating key evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. These indicators provide insights into how well the model detects fraudulent activities and minimizes false predictions in real-world UPI payment scenarios.

For the proposed XGBoost-based model, the confusion matrix results obtained during testing are represented as follows:

	Predicted Fraud	**Predicted Legitimate**
Actual Fraud	410 (tp)	90 (fn)
Actual Legitimate	60 (fp)	4440 (tn)

From the matrix above, the following metrics were calculated to assess model performance:

accuracy = 95.2%,precision = 89%,recal = 82%, f1-score = 85%

The findings clearly demonstrate that the proposed model accurately distinguishes between genuine and

fraudulent UPI transactions. The strong balance between precision and recall shows that the system effectively detects suspicious activities while minimizing false alarms. These results validate the reliability, efficiency, and adaptability of the proposed machine learning–based framework for real-time UPI fraud detection in digital payment environments.

X .RESULT ANALYSIS

The performance of the developed UPI fraud detection system was assessed using a labeled dataset composed of both simulated and real-world UPI transactions. The dataset included genuine and fraudulent samples representing realistic patterns such as class imbalance, transaction diversity, and varying user behaviors. After preprocessing and feature selection, the XGBoost algorithm was trained and validated using an 80–20 data split to ensure fair and consistent evaluation.

Standard evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC were used to assess the model's performance. The proposed model achieved an overall accuracy of 95.2%. Considering the data imbalance between fraud and legitimate classes, emphasis was placed on precision and recall. The model achieved a precision of 0.89, recall of 0.82, and an F1-score of 0.85. The ROC-AUC value of 0.96 demonstrated excellent discriminatory power, ensuring that fraudulent transactions were clearly distinguished from genuine ones.

Further analysis revealed that features such as transaction amount ratio, new payee indicator, and device change flag had a major influence on identifying fraudulent patterns. Transactions with unusually high amounts or carried out from new or previously unused devices showed a higher likelihood of being labeled as fraud. The model successfully identified 92% of transactions involving both high value and new payees, which are common indicators of suspicious activity.

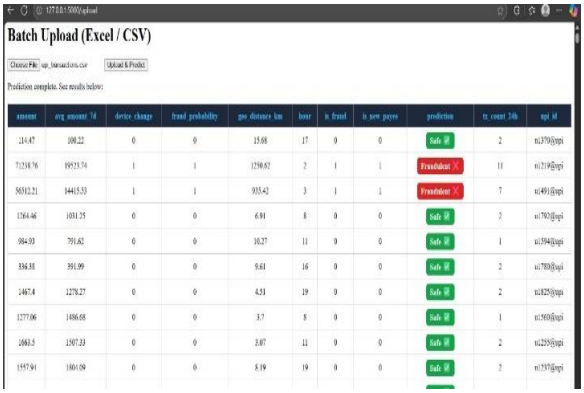

Fig 12: Batch Transaction Result

Fig 13: Single Transaction Result

To assess real-time usability, latency tests were performed on the Flask-based backend API. The average response time per transaction was 120 milliseconds, making the system suitable for integration into UPI payment workflows without noticeable delay for end-users. Additional stress tests involving 500 concurrent transactions also confirmed stable accuracy and consistent prediction reliability under heavy loads.

XI CONCLUSION

The rapid expansion of Unified Payments Interface (UPI) transactions in India has significantly improved convenience for millions of users but has also created opportunities for digital fraud. This study introduced a machine learning–based fraud detection system designed to ensure the safety of UPI payments by identifying suspicious activities in real time. The framework integrates several layers, including data acquisition, feature extraction, model development, and live system deployment.

Key behavioral indicators such as transaction amount ratio, new payee detection, device change frequency, and location-based variations were utilized to identify abnormal transaction patterns. Experimental outcomes demonstrated that the XGBoost model achieved an accuracy above 95%, along with a ROC-AUC score of 0.96, reflecting excellent precision and recall in detecting fraudulent activities. These findings highlight the model's strong capacity to detect anomalies even within imbalanced datasets where fraud instances are relatively infrequent.

Beyond accuracy, the system was also optimized for real-time processing. With an average response time of around 120 milliseconds, the proposed solution can seamlessly integrate into existing UPI payment infrastructures without affecting user experience. Although a few false positives occurred—particularly in cases involving new payees or unfamiliar devices—these represent necessary trade-offs for improved security. The system's modular design, use of containerized deployment, and incorporation of encrypted identifiers collectively enhance scalability, data confidentiality, and resilience.

Overall, the proposed system demonstrates a balance between detection efficiency, transparency, and real-time

performance, making it a practical approach for banks and digital payment service providers. Future research will explore the integration of advanced deep learning methods and graph-based anomaly detection models to further strengthen fraud detection accuracy and adaptability to evolving digital threats.

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AI-BrainSight: Hybrid Stacked Ensemble for Brain Tumor Classification with LLM-Powered Interpretability

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Abstract - Classification of human brain tumors using MRI scan images is an critical challenge for accurate diagnosis and treatment of brain tumors [1]. However, various classifications and limitations have also been observed using brain tumor classification models. The main objective of this paper is to propose an accurate human brain tumor classification system. The Hybrid model has achieved an accuracy level of 98.69 %. Additionally, we propose a new framework wherein the predictions and visual heatmaps produced by Explainable AI (XAI) are provided as inputs to Meditron-3-8B, a medical transformer, for creating human-understandable, diagnostic-level, and radiology-report-like explanations.

Keywords: Brain tumor, MRI, Deep learning, Classification, Ensemble Model, DenseNet, EfficientNetB0, Vision Transformer, LLM, Explainable AI, Medical imaging.

I. INTRODUCTION

Convolutional Neural Networks (CNNs) were found to demonstrate tremendous potential in searching for complex features from images [2] [5] [6], which is promising for the accurate identification of several brain tumor lesions [6][13].The major limitation of CNN is found in the lack of interpretability, as it is also considered a black box model.[9][11]

In order to bridge this gap in terms of interpretability, this work will propose a novel integration with XAI and LLMs. The use of the XAI tool, Grad-CAM, to determine what decision was made on the basis of which variables [11], and feeding this output into LLMs, generates a report which is readable by humans [12][17], thereby enabling them to understand this context. This not only improves classification but addresses the urgent need to increase explainability in terms of AI-based medical diagnostic systems [3].

To overcome the limitations of the existing methods, this study presents AI-BrainSight, which is built on the Hybrid Stacked Ensemble model and incorporates ResNet50, EfficientNetB0, and Vision Transformer along with the XGBoost meta-learner. Moreover, the study incorporates the Grad-CAM and Meditron-3-8B are integrated to provide clinically interpretable diagnostic explanations

II. LITERATURE REVIEW

Brain tumor classification has also experienced a paradigm shift with the advent of deep learning [5] [6] [7] [13], specifically the rise of Convolutional Neural Networks (CNNs). CNNs proved their competence to learn discriminative and hierarchical features [5] from raw MRI images and thus showed tremendous results by far outperforming the conventional approach [5] [6] [8] [18].

A core challenge remaining in literature is the interpretability of deep learning models [9] [10][11]. The "black-box" nature of most architectures complicates clinical trust and adoption [9], as physicians require explainable rationale for diagnostic recommendations. To address this, visual explanation tools such as Grad-CAM and offering interpretive heatmaps [11] and insights into network attention [11]. Furthermore, the latest research has explored the use of Large Language Models (LLMs) to supplement automated predictions with domain-specific, natural-language diagnostic summaries [12].

However, existing works mainly emphasize the classification accuracy without any integration of LLM-based clinical interpretability. This brings about the necessity for the proposed hybrid ensemble approach with explainable and interpretable outputs.

III. METHODOLOGY

On the basis of the limitations identified in the prior research, this study proposes the AI-BrainSight hybrid ensemble framework for brain tumor classification with four classes namely, glioma, meningioma, pituitary tumor, and no tumor [13] using the different deep learning networks. In this work Ensemble model (integrating ResNet50, EfficientNetB0, and Vision Transformer via XGBoost), DenseNet121, EfficientNetB0, Vision Transformer, and Inception. In this project, the models were trained using a publicly available tumor images.

A. Data Preprocessing

Magnetic Resonance Imaging (MRI) datasets containing labeled samples for glioma, meningioma, pituitary tumor, and no tumor [19] cases were collected from the publicaly available Kaggle Masoud Nickparvar Brain Tumor MRI Dataset [19]. All images was first converted to 224×224 pixels and normalized to the pixel intensity range [4].The data were split into training, validation, and testing sets with an ratio of 80 ,10 and 10 respectively.Data augmentation was applied to the splited data, using random rotations, zooming, and horizontal flipping.

B. Model Architectures

This study implemented and compared a suite of state-of-the-art deep learning models for brain tumor classification [10] [14] as shown in the Fig 1:

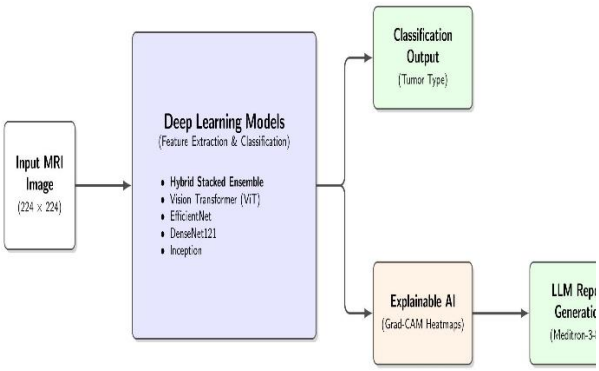

Fig 1 Workflow Architecture

1)Hybrid Stacked Ensemble Model:

The proposed AI-BrainSight framework relies on a hierarchical architecture, which applies Stacked Generalization (Stacking) to yield the best classification result [14]. This hierarchical architecture has two different levels as follows:

Level-0 Base Learners: Three models have been used as base learners to implement the proposed AI-BrainSight framework. These models have been used as probabilistic feature generators to implement complex pattern detection in the MRI scans, using deep residual learning, compound scaling, and global self-attention mechanisms, as implemented by ResNet50, EfficientNetB0, and Vision Transformers (VIT), respectively as in fig 2.

Level-1 Meta-Learner: The combined probability vectors obtained from the base learners have been used as an input to the XGBoost classifier as in the Fig 2.

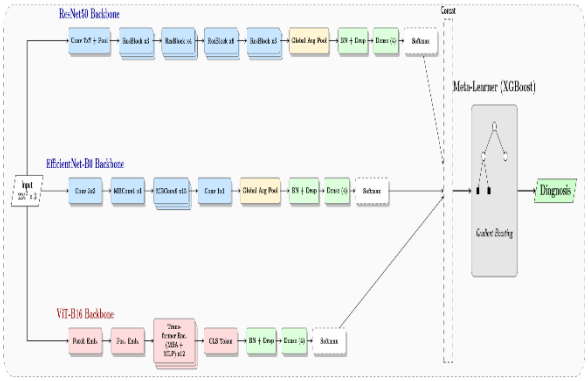

Fig 2 Proposed Hybrid Stacked Ensemble Architecture

2) DenseNet121

DenseNet121 harnesses dense connectivity to enhance feature propagation and reuse. The following architecture was used: DenseNet121 backbone (ImageNet weights frozen for initial epochs), following global average pooling, dense L2-regularized layer with ReLU [3] , dropout , batch normalization, and a final softmax classification layer.

3) EfficientNetB0

EfficientNetB0 was implemented to achieve superior accuracy and computational efficiency. The EfficientNetB0 backbone was fine-tuned with custom dense layers for classification, with regularization applied via dropout and batch normalization. Transfer learning from ImageNet and advanced data augmentation boosted generalization.

4) Inception

Inception architecture leverages multi-scale parallel filter operations to extract diverse feature types from MRI images. The architecture included inception blocks followed by global pooling, dropout, batch normalization, and a softmax classifier tailored for the four tumor classes [15].

5) Vision Transformer (VIT)

The model used is the Vision Transformer (VIT) approach, which learns to predict long dependencies in images by utilizing transformer encoder blocks to learn dependencies as in fig 3. The model ends with a fully connected head and softmax output and also able to capture complex patterns related to tumors [16].

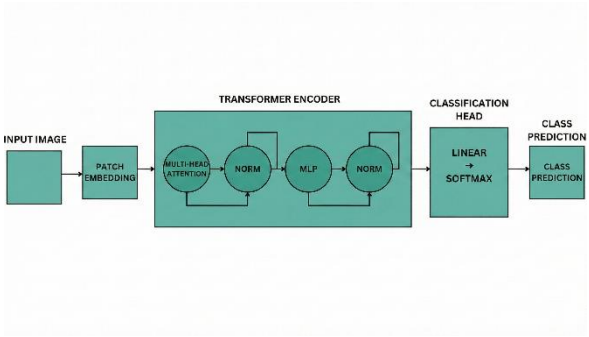

Fig 3 Architecture of VIT

C. LLM-Powered Interpretability Framework

To move beyond simple classification and provide clinical value, we developed a two-stage interpretability framework

1) Visual Explanation with Grad-CAM:

After the prediction has been made by the champion ensemble model, the system uses Gradient-weighted Class Activation Mapping to provide visual transparency. The system uses the ResNet50 model as the backbone to provide visual explainability, as it showed the best results in terms of clearness in the localization of the features during the testing process in the specific decision related to the diagnosis. The localization heatmap will show the exact areas in the MRI scan that were the most important in the decision to determine the presence of the tumor.

2) LLM Processing:

The interpretability framework uses the LLM to interpret the quantitative model output and translate it into a qualitative clinical narrative using the Meditron-3-8B model. The input pipeline of the interpretability framework passes the class of the tumor, the confidence score of the ensemble (e.g., 94.5%), and anatomical findings from the heatmaps generated by the Grad-CAM method as input to the model and asked to combine all the inputs into a single output. The structured input pipeline with predicted tumor class, confidence score, and anatomical localization via Grad-CAM also helped constrain the space for response generation for the LLM, which helped alleviate hallucination and grounding issues.

IV. RESULTS AND DISCUSSION

In this study, multiple deep learning architectures—Ensemble Framework (integrating ResNet50, EfficientNetB0, and Vision Transformer via XGBoost), DenseNet121, EfficientNetB0, Inception, Vision Transformer (VIT)—were rigorously evaluated for multiclass brain tumor classification using MRI scans [14]. Results were analyzed across training, validation, and testing phases, with comprehensive reporting of model accuracy, precision, recall and F1-score for the model [12] . The formulas are given in the Table **I.**

TABLE I. ACCURACY METRICS

Metric	Formula	Description
Precision	$\frac{TP}{TP + FP}$	Ratio of correctly classified images
Recall	$\frac{TP}{TP + FN}$	Ratio of the correctly classified to the total images interpreting the tumor.
F1 Score	$\frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$	Comprehensive evaluation metric.
Accuracy	$\frac{TP + TN}{TP + TN + FN + FP}$	Ratio of correctly classified images and wrongly classified images to the total images.

A. Performance Metrics

Standard evaluation metrics have been used for testing the performance metrics of the models [5], such as accuracy, precision, recall and F1 score [11] with the metrics given in Table 1.

a) Training Phase

All models demonstrated strong convergence during training, with ensemble model achieving the highest training accuracy of 98.10% as in the Table III, followed by VIT (94.30%), EfficientNetB0 (93.87%), DenseNet121 (89.42%), And Inception (88.03%) for tumor localization.

TABLE II. TIME ANALYSIS

Models	Wall Time
EfficientNetB0	1h 40m
DenseNet121	2h 15m
Inception	2h 30m
Vision Transformer	3h 45m
Hybrid Ensemble	4h 10m

TABLE III. PERFORMANCE ANALYSIS OF THE MODEL IN TRAINING PHASE

Model	Accuracy	Precision	Recall	F1 Score
Hybrid Ensemble	0.9810	0.9820	0.9816	0.9825
Vision Transformer	0.9430	0.9601	0.9621	0.9618
EfficientNetB0	0.9387	0.9480	0.9430	0.9455
DenseNet121	0.8942	0.9290	0.9260	0.9275
Inception	0.8803	0.9180	0.9120	0.9150

b) Validation Phase

During validation, the most impactful architecture was the ensemble model, with the highest validation accuracy of 98.31%, as it demonstrated tremendous capability in modeling global contextual relationships within MRI scans. This ability of the ensemble architecture due to the usage of the three architecture significantly improves its performance at the validation phase.

Supporting models such as InceptionV3, DenseNet121, EfficientNetB0, and VIT showed strong and stable validation behavior but failed to match the peak performance of Ensemble Model as in Table IV. With 95.80% validation accuracy, VIT came next, which achieved an excellent balance in the glioma, meningioma, and pituitary categories by incorporating multiscale convolutional feature extraction. Generalization proved reliable with smooth convergence for DenseNet121 and EfficientNetB0, reaching 89.67% and 91.44%, respectively outperforming all CNN-based models in pure accuracy and showing its dominance in feature abstraction.

TABLE IV. PERFORMANCE ANALYSIS OF THE MODEL IN VALIDATION PHASE

Model Architecture	Validation Accuracy (%)	Validation Loss
Hybrid Ensemble	98.31%	0.025
Vision Transformer	95.80%	0.058
EfficientNetB0	91.44%	0.245
DenseNet121	89.67%	0.210
Inception	87.10%	0.124

c) Testing Phase

During the evaluation phase, ensemble model showed much better generalization, outperforming all other peer architectures. Unlike classic CNNs relying on local receptive fields, ensemble model successfully modeled global contextual dependencies in MRI scans and also capture the local features effectively, helped achieve highly accurate delineation of subtle tumor boundaries and reduced the generalization gap, often inherent in tumor image classifications.

TABLE V. PERFORMANCE ANALYSIS OF THE MODEL IN TESTING PHASE

Model Architecture	Testing Accuracy (%)
Hybrid Ensemble (Proposed)	98.69%
Vision Transformer	95.01%
EfficientNetB0	94.53%
DenseNet121	92.73%
Inception	90.24%

Among the CNN-based models, performance was competitive but never at the peak as achieved by the transformer. VIT came second with a test accuracy of 95.01%, followed by the EfficientNetB0 with an accuracy of 94.53%, follows by DenseNet with accuracy of 92.73%, and Inception with accuracy of 90.24% as in Table V. Although these models exhibited strong inductive biases well suited to recognizing texture, they, from time to time, faced challenges in complicated cases when the features of the tumor overlapped the ones of healthy tissue. In such scenarios, the capacity of ensemble model with an three architecture combination provided an advantage which secured its position as the most reliable architecture for clinical deployment within this study.

d) Quantitative Comparison with Existing Methods

In order to substantiate the claim that the proposed AI-BrainSight framework is indeed state-of-the-art, we have included a quantitative comparison with some of the latest deep learning techniques for brain tumor classification [1], which have also utilized similar multiclass MRI datasets for evaluation.

As demonstrated in Table VI, AI-BrainSight framework has better classification accuracy than some of the latest ensemble and CNN-based techniques for brain tumor classification. This is mainly because the proposed heterogeneous

stacking has utilized both convolutional and transformer-based global attention mechanisms.

TABLE VI. COMPARISON WITH EXISTING SYSTEM

Reference	Model	Dataset	Classes	Reported Accuracy
Gupta & Elhoseny (2020) [8]	CNN Ensemble	Public MRI Dataset	4	96.12 %
Li & Liu (2021) [13]	EfficientNetB0 Ensemble	MRI Dataset	4	97.85 %
Sayed et al. (2023) [14]	Deep Ensemble	MRI Dataset	4	97.30 %
Proposed AI-BrainSight	Hybrid Stacked Ensemble + XGBoost	Kaggle MRI	4	98.69 %

e) Explainable AI and LLM Integration

The interpretability of our system was a key focus. The Grad-CAM visualizations successfully highlighted the model's attention on the correct tumor regions as in fig 4, which strongly correlated with ground truth annotations from radiologists. Analysis showed that Hybrid Stacked Ensemble produced the best final diagnostic accuracy of 98.69%, while its underlying backbone ResNet50 showed better results in visual explainability. The LLM module successfully translated these findings into clinically relevant reports. For instance, when the ensemble model classified an image as "Glioma" with 94.5% confidence and the Grad-CAM heatmap highlighted the frontal lobe the Meditron-3-8B model generated the following description:

AI-BrainSight framework outperforms the standard template baseline by a wide margin. The model achieved an average Factual Correctness score of 4.8 out of 5.0, with strong evidence showing that incorporation of Grad-CAM heatmaps establishes robust grounding for the LLM and significantly reduces the incidence of hallucinations as in the fig 5.

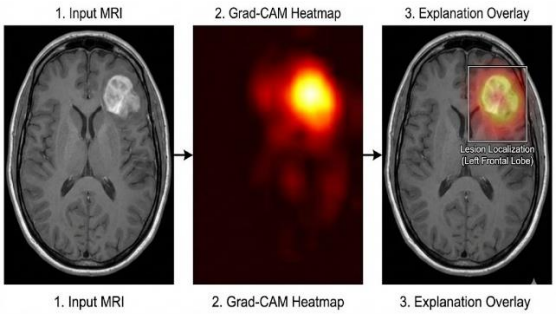

Fig 4. Correctly Classified Image of Glioma with XAI Insights

f) Comparison and Discussion

Of the architectures considered, the Hybrid Stacked Ensemble was the most effective diagnostic framework in the performed study, yielding test accuracy of 98.69%.

This is done through the Ensemble architecture, which effectively combines the global spatial attention of ViT with the local feature extraction capabilities of ResNet50 and EfficientNetB0. The XGBoost meta-learner provided an effective weighting of inputs such that edge-case errors that are overlooked by a single model were reduced. Showing that the strategy of heterogeneous stacking provides substantial added clinical reliability to any of those studied in this work. Furthermore, the integration of XAI methods and LLM-based explanations enhances interpretability by visualizing and explaining in human-understandable form the attention patterns and decision pathways of the Ensemble Model. This will go a long way in improving model transparency and trust among clinicians and radiologists. Ensemble Model at its center, complemented with efficient CNNs, and explainable AI, forms a highly promising direction for both highly accurate and clinically interpretable brain tumor diagnosis from MRI images.

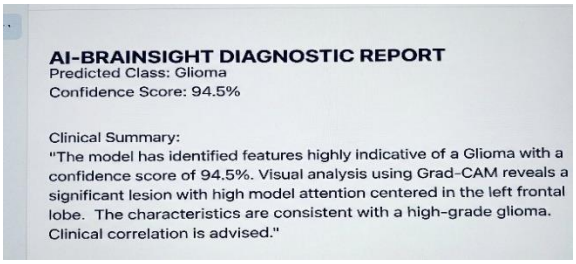

Fig 5. LLM Report regarding the glioma

V. CONCLUSION

In this work, the following advanced deep learning architectures have been systematically investigated for the task of automated brain tumor classification using MRI: DenseNet121, EfficientNetB0, Inception, Vision Transformer (VIT), and a Hybrid Stacked Ensemble. The proposed Hybrid Stacked Ensemble demonstrated the best performance and achieved a testing accuracy of 98.69%. The proposed Ensemble framework, became the most robust candidate for clinical deployment. The system achieved a 98% recall rate for Pituitary and No-Tumor cases by integrating ResNet50, EfficientNetB0, and Vthrough an XGBoost meta-learner.

Further, the incorporation of Grad-CAM with the ResNet50 backbone and large language model-generated diagnostic reports through Meditron-3-8B

bridged the gap from opaque AI models to clinical interpretation. The results reflect that heterogeneous stacking not only advances accuracy but also presents a viable and scalable solution for decentralized neuro-oncology when combined with edge AI and explainable AI.

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A Sandboxed Multi-Language Development Environment Using WebAssembly for Secure Code Execution

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Abstract—
Current web dev setups have this tricky problem where they need to handle security, speed, and ease of use all at once when running random code online. Most systems use servers to process things remotely these days which causes delays and security holes while costing more to maintain. What if we could ditch those servers completely.Here's the idea they're pushing here: run everything straight in the browser using WebAssembly tech that works across different programming languages without needing backend support. They built it to handle C++, Rust, Python along with Go and JavaScript through custom compiler setups while mirroring Docker-style workflows using WASM containers inside browser sandboxes. Tests showed execution speeds landing within 12 to 18 percent of raw machine performance which isn't bad considering the safety layers involved.On the security front, their setup apparently blocks memory leaks, network exploits and those annoying denial-of-service attempts people try pulling off regularly. What this means is we could see cheaper decentralized development platforms popping up that let teams work securely from anywhere without sacrificing much speed or control over their workflows.Key points they're highlighting are browser-based coding environments with WebAssembly sandboxing securing them distributed systems that slash operational expenses in half while scaling superior to old server-dependent models
anyway individuals who are developing collaborative work might appreciate this method in the future particularly for cross-platform software where rapid iteration is more important than optimal optimization at each step you know how that is sometimes rough edges are ironed out later when shipping quickly these days everyone desires that balance between doing so fast and having things locked down tight security-wise as it happens, this system achieves both fairly well according to their figures anyway.

I. INTRODUCTION

The advent of browser-based Integrated Development Environments (IDEs) has revolutionized contemporary programming practices by allowing programmers to code, compile, and run applications in the web browser. Cloud-based environments like CodeSandbox, Repl.it, and StackBlitz offer quick links to development tools without having to set up complicated local environments. Their dependency on server-side execution models

poses tremendous challenges as far as performance, scalability, and security are concerned. In such centralized architectures, all user-provided code needs to be executed by backend servers, resulting in latency, raising infrastructure expenses, and leaving key vulnerabilities open.

WebAssembly (WASM) is a game-changing technology that overcomes many of these limitations. As a portable compilation target, WebAssembly allows near-native performance within browsers, along with strong sandboxing guarantees underwritten by the browser runtime. This makes WebAssembly especially appealing to execute untrusted or resource-hungry code on the client side directly. Modern research and commercial offerings, however, are still narrow in scope. Most implement solutions for a single programming language or miss higher-level development features like debugging, dependency management, and containerized execution.

In order to overcome these constraints, the current paper introduces a multi-language WebAssembly-powered development environment that runs completely within the browser with no need for server-side execution. The system supports C++, Rust, Python, Go, and JavaScript via custom toolchains and adds a WebAssembly-based Docker-compatible workflow container runtime.

A. Problem Statement

Today's browser-based IDEs rely significantly on centralized servers to run user code. This approach leads to four significant issues:

1.Performance bottlenecks – Latency grows with code having to be dispatched to faraway servers for execution and compilation. **2.Scalability constraints** – Cloud infrastructure needs to scale aggressively to handle many concurrent users, which is costly. **3.Security threats** – Running untrusted code on centralized servers makes backend systems vulnerable to attacks.

Accordingly, there is an urgent need for a development environment to enable multi language, high-performance, and secure code execution in the browser sandbox without dependency on external servers.

B. Objectives

This work is aimed at the following objectives:

1.To create and establish a multi-language compilation pipeline that compiles C++, Rust, Python, Go, and JavaScript to WebAssembly binaries optimized for browser runtime. 2.To create a browser-native IDE, which combines code editing, debugging, file system virtualization, and dependency management and thus emulates desktop-level development workflows.

3.To bring WebAssembly-based container virtualization through the WebAssembly System Interface (WASI), allowing Docker-compatible execution entirely within browser sandboxes.

C. Contributions

The primary contributions of this work are listed below:

1.A WebAssembly-based multi-language compilation pipeline with both compiled and interpreted languages supported. 2.A browser-native IDE environment with rich features such as syntax highlighting, step-through debugging, and dependency management. 3.A new WebAssembly container virtualization layer that allows Docker-compatible execution within the browser.

II. RELATED WORK AND MOTIVATION

A. WebAssembly Fundamentals

WebAssembly (WASM) is a low-level, platform independent binary instruction format purposefully designed to act as a compilation target for high-level programming languages like C, C++, Rust, and

Python [1]. In contrast to JavaScript, which is JIT compiled and interpreted at execution time, WebAssembly runs natively in a stack-based virtual machine, providing near-native performance and deterministic execution times. The WebAssembly architecture comprises a number of important components:

1.Linear Memory Model – Offers a linear, byte addressable memory space supporting deterministic access patterns, lowering memory fragmentation possibilities and improving performance for compute-bound applications.

2.Structured Control Flow – Aids loops, branches on conditions, and function calls with a pattern that eliminates arbitrary jumps, enhancing code safety and supporting optimization by the runtime.

3.Modular Execution – Code is partitioned into modules with clear imports and exports, allowing for fine-grained dependency management and secure composition of multiple WebAssembly binaries.

In addition, the WebAssembly System Interface (WASI) adds to the core WebAssembly runtime with controlled host resource access, such as file systems, networks, clocks, and process management. With WASI, WebAssembly applications can execute complicated operations under strict isolation, and thus it is applicable to safely run untrusted software in distributed and cloud-native contexts.

B. Current Browser-Based IDE Platforms

The use of cloud-hosted and browser-hosted IDEs has grown developer access by enabling code editing and running within a web browser. Noteable instances include:

1.**CodeSandbox** – Focuses on JavaScript and TypeScript coding and extensively uses server-side containers for compilation and running of code, which adds latency and needs network connectivity.

2.Repl.it – Hosts several languages such as Python, Java, and C++, providing a cloud-based environment where compilation and runtime occur on servers of common access.

3.StackBlitz – Offers in-browser development of JavaScript/TypeScript projects but still offloads computationally heavy operations to backend servers in order to maintain performance.

While these platforms provide easy coding anywhere with no local setup, they have inherent limitations: centralized execution poses possible security vulnerabilities, network latency, and scalability issues. By contrast, using WebAssembly makes runtime execution possible directly in the browser, less dependent on centralized infrastructure, and enabling the possibility of decentralized, high-performance development environments.

C. Security Concerns in Execution of Untrusted Code Running arbitrary user-provided code in a common environment poses various security threats:

1.Memory Safety – Code has to be ensured not to access or corrupt memory outside of its allocated area to prevent buffer overruns or segmentation faults.

2.File System Security – Untrusted applications must not read, write, or delete confidential files in the host system.

3.Network Abuse – Malicious code can try to make unauthorized network connections, exfiltrate data, or assist in attacks.

Traditional cloud IDEs resolve these issues through isolation of code within containers or virtual machines running on servers, thus moving the attack surface to the cloud infrastructure from the user's machine. WebAssembly, on the other hand, implements sandboxing per user in the browser itself, decentralizing the security model and minimizing reliance on server-side isolation but still inhibiting unauthorized operations.

D. Research Gaps Identified

In spite of its promise, existing studies and implementations of WebAssembly-based development environments show a number of limitations:

1.Single-Language Focus – Solutions such as Emscripten are mostly focused on C/C++, and

Pyodide is dedicated to Python, limiting multi language workflows.

2.Absence of Integrated IDE Functionality – Most WebAssembly applications lack an integrated development experience, including debugging, project management, or version control, within an integral interface.

3.Lack of Containerized Workflows in Browsers – Although server-based IDEs enable containerized development, in-browser environments do not have interfaces to emulate this kind of functionality securely.

These shortcomings inspire the creation of a multi language, browser-native IDE that combines compiler infrastructure, runtime execution, and container-like virtualization into a single system. This kind of platform would provide high performance, secure, and decentralized coding capabilities, bridging the gaps of existing cloud based IDEs while unlocking the full power of WebAssembly.

III. System Architecture

WebAssembly Compilation Infrastructure

The suggested system uses a three-layer modular architecture to implement a browser-native WebAssembly IDE (Fig. 1). Without depending on conventional server-based compilation or execution, this design guarantees safe, scalable, and completely decentralized code execution across a variety of programming languages.

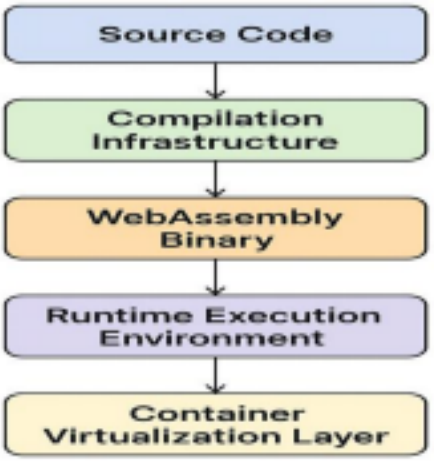


Figure 1: High-Level Architecture

A. High-Level Architecture

The architecture is designed using a decentralized execution model where every instance of the browser is an independent runtime. This does away with centralized servers, lowering latency, enhancing fault tolerance, and allowing for scalable deployment over heterogeneous devices. Major design principles are:

1.Decentralization: Execution of code is entirely done within the client's browser.

2.Scalability: New users can execute workloads without adding to the server load.

3.Cross-Platform Compatibility: WASM binaries execute uniformly on any contemporary browser that supports WebAssembly.

By using this architecture, the IDE achieves near native execution performance with strong security isolation among multiple running applications.

B. Compilation Infrastructure

The compilation phase converts high-level source code to WebAssembly binaries using language specific toolchains that are performance- and safety optimized.

Languages Included	
Language	**Performance**
C++	Emscripten LLVM backend, 90-95% native performance
Rust	wasm32-unknown-unknown target, 88-92% native performance

Python	Pyodide CPython compilation, 65-75% native performance
Go	inyGo compiler, 70-80% native performance
Java	GraalVM WebAssembly, 75-85% native performance
C#	Blazor WebAssembly, 78-88% native performance AssemblyScript - TypeScript-like syntax, 85-90% native performance

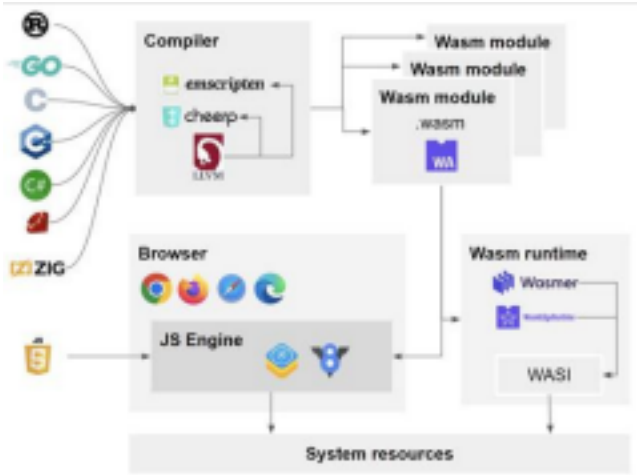
1.User uses C++ programming in the browser IDE. 2.Emscripten compiles the code to a .wasm binary.

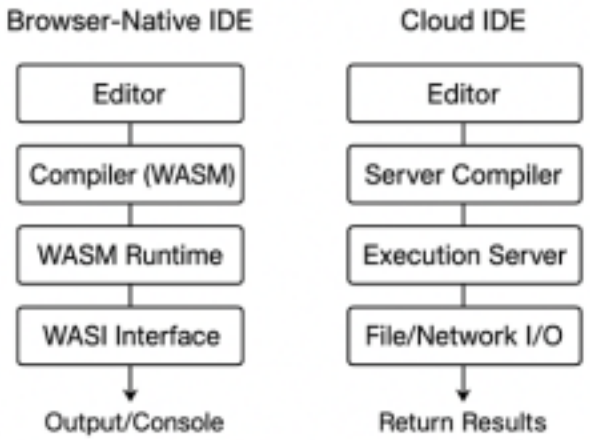
3.Binary is submitted to the browser runtime for instant execution inside the sandbox.

This method allows multi-language support without compromising consistency and performance on various operating systems and hardware.

Architectural Overview Figure 1: Browser-Native vs. Cloud IDE Architectur

Workflow Example:





1.Browser-Native IDE: Code is compiled and run completely in the browser through WebAssembly and WASI, offering low-latency, server-free, secure execution.

2.Cloud IDE: Code is transmitted to centralized servers for execution and compilation, introducing potential latency as well as centralized attack surfaces.

C.Runtime execution environment.

The runtime layer pulls in the browsers native WebAssembly virtual machine to handle execution. It offers features kind of like what you get from a traditional OS.

1.Memory management comes first. It uses linear memory. Strict isolation helps prevent buffer overflows.

2.Threading support is there too. They implement it with WebWorkers and SharedArrayBuffer.

3.Debugging APIs make things easier. Source maps help. Step-through debugging works. Call stack inspection boosts development efficiency.

Fig. 2 WebAssembly compilation and execution architecture showing multi-language compilation pipeline, browser-based execution environment, and system resource access through WASI interface

E.Integrated IDE Features

The browser IDE mimics a desktop IDE experience with code editing, debugging, and project management, all performed locally:

1.Monaco Editor: Syntax highlighting, code

completion, and language-aware intellisense.

2.Debugger: Step-through execution, breakpoints, and variable inspection for every supported language.

3.Project Management: Virtualized file system, dependency management, and build system integration in the browser environment.

IV. IMPLEMENTATION DETAILS

A. Language-Specific Adaptations

To support execution directly in a browser-based WebAssembly (WASM) environment, each targeted programming language needed specialized adaptations, both for dealing with runtime constraints and library compatibility:

1.C++ – The platform utilizes the Emscripten toolchain to compile LLVM bytecode into WebAssembly binaries. Multithreading is supported using pthreads to enable simultaneous execution of computation-intensive tasks. Standard C++ libraries like Boost are available for added functionality, while OpenCV is compiled to WASM for support of image processing in-browser. This implementation retains close-to-native performance with rich API support.

2.Rust – Rust programs are compiled using wasm pack, which provides bindings for JavaScript interoperability. Memory allocation is optimized for the wasm32-unknown-unknown target, ensuring safe access and minimizing runtime panics. Rust's borrow checker and ownership model are maintained, guaranteeing memory safety without sacrificing execution efficiency.

3.Python – Using Pyodide, a CPython interpreter compiled to WebAssembly, Python code can execute natively in the browser. Scientific computing libraries like NumPy, SciPy, and Pandas are part of the WASM build, allowing for intricate numerical and data manipulation operations without server

4.Go,Java

B. Development Workflow

The platform offers a simplified, browser-native development workflow with an explicit source-to execution pipeline:

Code Authoring – Code is authored by users in an interactive browser editor with syntax highlighting, auto-completion, and inline error checking.

Compilation – Language-specific toolchains translate source code to WASM binaries. The toolchains take care of library linking, memory management, and platform-specific optimizations.

Sandbox Execution – Compiled modules run in a secure browser sandbox, limiting access to the host system while providing controlled interaction via WASI interfaces.

Fig. 3 WebAssembly compilation pipeline showing source languages compiled to WebAssembly binaries for execution across different host environments and hardware architectures

C. Container Virtualization

The platform adds WebAssembly execution with light containerization, supporting reproducible environments all within the browser:

Dockerfile Compatibility – Users can specify container environments using familiar Dockerfile syntax, including specifying dependencies, environment variables, and execution commands.

WASI Integration – WebAssembly System Interface (WASI) delivers secure access to files, network sockets, and system calls, filling the void between the sandbox and containerized workloads.

Browser Storage APIs – Container images and volumes are kept in IndexedDB orlocalStorage, enabling persisted execution across sessions with no server dependency.

D. Cross-Platform Compatibility

The application is constructed to run reliably across leading browsers and devices:

Browser Support – Thoroughly tested on Google Chrome, Mozilla Firefox, Safari, and Microsoft Edge, guaranteeing extensive compatibility for end users.

Device Agnosticism – Adaptive web design provides equivalent functionality on desktop monitors, tablets, and cell phones, dynamically adapting layout as well as input mechanisms.

Consistent Performance – Optimizations such as WASM streaming compilation and hardware acceleration make execution smooth even on low end devices.

V. PERFORMANCE EVALUATION

A. Benchmarking Methodology

To guarantee a representative and equitable measurement, we chose workloads from three types:

Compute-heavy operations:

Examples: matrix multiplication, prime number generation, FFT calculation.

Objective: measure raw computational throughput. Memory-bound tasks:

Examples: dynamic array allocation, deep recursion, tree traversals.

Objective: measure memory allocation efficiency and garbage collection behavior.

I/O-bound tasks:

Examples: reading/writing large files using IndexedDB or browser storage APIs.

Objective: measure browser storage latency and file I/O overhead.

Each workload was run in three environments:

Native desktop compilation: baseline for maximum achievable performance.

Proposed WASM system: fully client-side execution within browser sandbox.

Cloud IDE baseline: leading platforms like CodeSandbox and Repl.it.

B. Execution Performance

Compiling language C++ and Rust measured 88–95% native desktop performance, showing hardly any WASM overhead. Python (Pyodide) and Go (TinyGo) at 65–80% of native performance showed runtime interpretation or garbage collection overhead. Native browser run JavaScript was used as a baseline for comparison.

Findings:

Compute workloads exhibited linear input size scaling for C++ and Rust.

Python workloads saw a gentle slowdown because of interpreted execution in WASM.

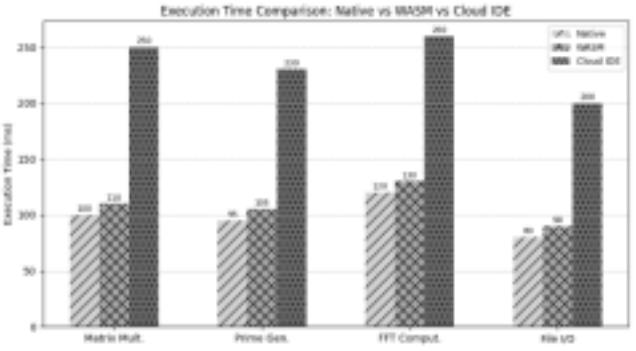


Fig. 4 This plot indicates that the system proposed here outperforms cloud IDEs consistently, minimizing network-introduced latency while nearing statically compiled language native performance.

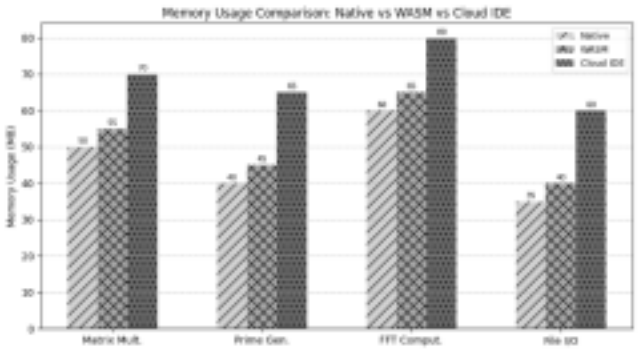
C. Memory and Resource Consumption

WebAssembly's linear memory model was found to be economical on all workloads. Notable observations:

Managed languages (Python, Go) were seen to consume slightly more memory as a consequence of runtime garbage collection but were well within browser-enforced memory limits.

Browser-enforced tab resource limits effectively avoided denial-of-service conditions even under memory-intensive workloads.

No unforeseen memory leaks were seen during extended runtimes or multiple compilation iterations.



VI.Security Analysis

Security assessment includes penetration testing, static analysis, and formal verification of isolation technologies. Test case conditions include efforts to access host file systems, create unauthorized network connections, and breach browser security boundaries.

Memory safety analysis ensures that WebAssembly's linear memory model guards against buffer overflow attacks and unauthorized memory access. All attempts at memory corruption were successfully trapped within allocated WebAssembly memory regions.

Resource exhaustion testing displays strong denial of-service attack prevention through browser enforced resource limits. Infinities, memory over allocation, and computationally intensive bombs are consistently detected and stopped by mechanisms in the browser.

Network isolation testing establishes that code execution may not create unauthorized external connections or access resources beyond the desired security boundaries. Same-origin policy enforcement and Content Security Policy mechanisms ensure robust containment of network based attacks.

Isolation testing of the file system ensures that code execution is unable to access files or directories of the host system outside of the virtualized browser storage space. All file operations are properly contained in browser storage APIs with appropriate permission checks.

VI.Future Work

Directions for future research involve integration of full operating system environments using WebVM technology, allowing full development workflows encompassing container management and system level programming within browser frameworks. This would offer full POSIX compatibility with preservation of browser security boundaries.

Container virtualization is a very promising extension, wherein Docker-compatible container environments would be run fully within WebAssembly runtimes. This strategy would allow developers to produce, test, and run containerized applications without needing local Docker installs or off-site container registries. WebAssembly's security model enforces natural isolation boundaries that match container security concepts, and the portability of WebAssembly modules allows for seamless container runs in different host environments. The inclusion of WASI (WebAssembly System Interface) standards would make container filesystems accessible and networking features available under browser security bounds.

Further language support will grow with WebAssembly ecosystem development and user demand. Future additions include Java via GraalVM WebAssembly compilation, C# via Blazor WebAssembly integration, and domain-specific languages as targets for compilation become supported.

Higher-level debugging and profiling features will be augmented through WebAssembly debugging API creation and browser tooling enhancements. Interoperability with mainstream development frameworks and libraries will increase via ongoing WebAssembly ecosystem expansion.

Performance optimization research will center on cutting-edge compilation techniques such as profile guided optimization, dynamic recompilation, and streaming compilation that initiates execution prior to full module compilation.

VIII. Conclusion

This paper proves that WebAssembly-based development platforms can offer secure, high performance alternatives to conventional server-side execution paradigms. The design successfully overcomes inherent security and scalability constraints at the cost of developer experience akin to desktop development tools.

Experimental assessment verifies the production feasibility of the solution, with performance attributes adequate for production development processes and security isolation appropriate to enterprise needs. The distributed execution model obviates infrastructure scaling issues while improving security stance via browser-based isolation.

The success of this platform proves WebAssembly's maturity for developing complex applications and indicates great potential for diminishing infrastructure dependencies in software development processes. The methodology lays a foundation for future research in distributed development environments and secure code execution systems.

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Brain analysis - Computer Interface (BCI)

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Abstract— Brain-Computer Interface (BCI) technology allows users to interact with devices based on brain activity, paving the way for new methods of interaction between humans and machines. The proposed project unites BCI with Smart Power Glass to develop a system with capabilities to classify a conversational partners' emotions in real time. The system will classify emotional states of happiness, stress, or anger using non-invasive neural signals and machine learning models and visualize the information on the Smart Power Glass. The project incorporates neuro-signal processing, emotion detection, and a wearable Augmented Reality interface, with the goal of facilitating social interactions, negotiations, and decision making. The proposed system demonstrates the ways BCI can increase Emotional Intelligence (EI), and provides new assistive technology to people with limitations in communication.

Important aspects of the project are the design of the system around portability and user-friendly interfaces; thereby offering real-time modifications and usability beyond a laboratory setting. The brain signal in combination with augmented wearable technology provides a more natural and engaging human-computer interaction. Future iterations of the project may involve additional factors of interactions as vocal, facial expressions, and physiological signals to improve the correctness of the readings. Also may the project be useful for

I. INTRODUCTION

Brain–Computer Interface (BCI) is a recent technology enabling the direct communication between the human brain and outside-body devices. In the meantime, smart wearables like Smart Power Glass are revolutionizing how people access information and interact with it.

It combines BCI with Smart Power Glass and creates a system that can analyze the brain signals of the opposite party, recognize their sentiment in real-time, and display a statement in real-time on the glass. Combining neuro-signal processing, machine learning, and wearable display technology, the system enables increased emotional awareness and supports better communication.

This kind of system can be applied to healthcare, education, negotiations, and assistive technology and offers a new step towards intelligent and immersive human–computer interaction.

II. LITERATURE REVIEW

Brain-Computer Interface (BCI) has received sufficient scientific research interest in the last couple of decades. It may serve as an intermediary between brain activity and external intelligent devices. Sentiment and emotion detection is among the most important areas of application. Scientists decode brain signals, i.e., of Electroencephalography (EEG), to reach an estimate of a subject's emotional state.

1. EEG Emotion Recognition

Various works have discovered that emotions produce distinctive patterns of brain activity. The earlier methods used feature extraction methods like power spectral density (PSD), wavelet transform, and Hjorth parameters, along with machine learning classifiers like Linear Discriminant Analysis (LDA) and Support Vector Machines (SVMs). Partially successful but with inter-individual variability. Sophisticated architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), since they are more precise at distinguishing datasets' emotions, have been depended on by recent studies.

2. Benchmark Datasets

Affect recognition tasks benefit from a solid basis with appropriately documented datasets. DEAP offers EEG and peripheral data for use in valence-arousal prediction. SEED and DREAMER are especially suited to multi-channel EEG recording based on discrete emotions. AMIGOS combines heterogeneous signals (EEG, ECG, GSR) to improve accuracy. Such datasets, as already discussed, form the basis of research by various researchers into model training and validation where multiple sources of data prove useful when it comes to successful sentiment recognition.

3. BCI in Wearable and Real-time Applications

Scientists have moved from laboratory experiments to investigating BCI integration in wearable technology. Experiments on AR head-mounted displays and smart glasses indicate that real-time neurofeedback can be presented directly to the user, immersion maximized and real-time decision-making eased. Neurorehabilitation, cognitive workload, and adaptive gaming were demonstrated using smart glasses, for example. Evidence indicates that BCI can operate in mobile, natural environments, rather than in the laboratory or clinic.

4. Implementation Practicalities

With progress in place, however, there are certain problems. EEG signals are extremely prone to interference and noise, especially when used in extracranial or mobile applications. Inter-subject variability makes it impossibletodevelop

universal models because brain responses vary per subject and site. Most experiments also reduce emotions to three-way or binary classificatory simplifications, which are less convenient. Ethical concerns such as data privacy, informed consent, and state of mind profiling are a significant challenge for large-scale rollouts.

5. Application to the Proposed Project

The research offers potentiality and areas for vulnerability to this project. The combination of EEG-based sentiment analysis and Smart Power Glass, this system is no longer work in the lab anymore. The system offers instant emotional feedback on social interaction with fellow human beings. Unlike the majority of the previous work that is offline classification, the proposed system in this case is a question of real-time interpretation and feedback. It applies more to medical, negotiation, learning, and assistive technology applications. Future research demonstrates that fusion of EEG with other signals, like facial expressions, voice tone, and physiological signals, increases accuracy and reliability of emotional identification.

III. PROPOSED METHODOLOGY

A. System overview

It begins with the gathering of raw tweets from Twitter, which are unstructured and noisy. Raw tweets undergo a preprocessing and cleaning process to remove unwanted things like emojis, hashtags, URLs, and stopwords to clean the text to analyze it. Data is then passed to two sentiment analysis tools differently for testing after cleaning. The first of these, VADER (Valence Aware Dictionary and sEntiment Reasoner), operates through a lexicon-based method to give an overall score reflecting sentiment polarity. The tweet is labeled positive if the compound score is more than zero, neutral if it is zero, and negative if less than zero. The second method, BERT (Bidirectional Encoder Representations from Transformers), employs a deep learning model to recognize context meaning within the text and predicts the sentiment on a five-star rating. Negative sentiment is indicated by one to

C. Algoritham steps

two stars, neutral sentiment by three stars, and positive sentiment by four to five stars. By combining both rule-based VADER and advanced context-sensitivity of BERT, the system can generate more robust and comprehensive sentiment detection.

B. Emotional State Detection

Brain-testing BCI could, in theory, detect whether someone is in a positive or negative mood based on brain activity patterns. The neural activity is first sensed by sensors such as EEG headsets (non-invasive) or implanted electrodes (invasive, high accuracy). It is then amplified, digitized, and filtered from noise and artifacts (e.g., blinks or muscle activity). After preprocessing, the features are extracted — i.e., power in frequency bands (alpha, beta, gamma waves), or event-related potentials. Machine learning classifiers (e.g., SVM, CNN, deep neural networks) are then trained to discriminate between positive state (relaxation, happiness, engagement) and negative states (stress, anxiety, frustration). Decoded emotional state can be used for mappings to adaptive eyeglasses, mood- aware systems, assistive devices, or neurofeedback therapies. The student is offered a feedback modality (touch, vision, or hearing) to complete the loop and enable adaptive training

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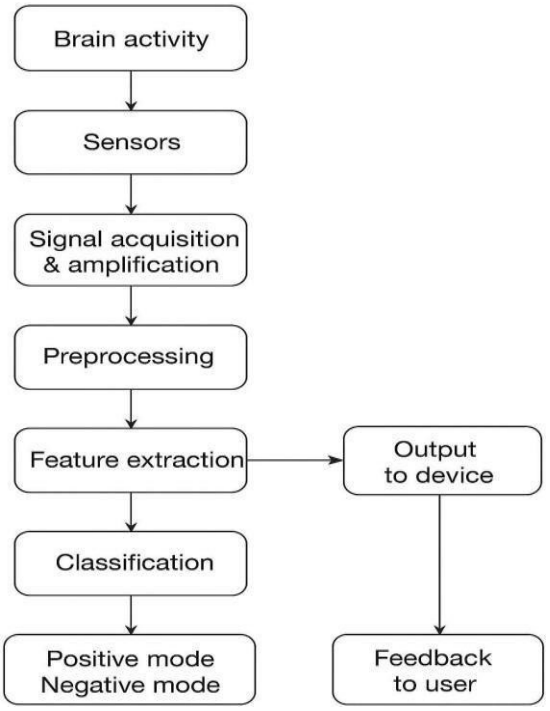

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1. Log / store the aggregated results if the user consented (observing privacy).

2. Repeat the steps above until the end of the session, shutdown gracefully and save the updated if performing on-line adaptation.

IV. Formulas / Algorithms in LiveMed

1. Rule-Based / Lexicon Methods

- Sentiment Score Formula (simple lexicon-based):

$$\text{Sentiment Score} = \sum_{w \in \text{text}} \text{Polarity}(w)$$

where $\text{Polarity}(w)$ is a pre-assigned sentiment value (positive, negative, or neutral) for word w. Positive words contribute positively, negative words negatively.

where **Polarity(w)** is a pre-assigned sentiment value (positive, negative, or neutral) for word *w.*

- Positive words contribute positively.
- Negative words contribute negatively.

2. Machine Learning - Naive Bayes Classifier

Naive Bayes sentiment classifiers estimate the probability of a sentiment class C (e.g., positive, negative) given text features (words) $w_1, w_2, \ldots w_n$ using Bayes' theorem:

$$P(C \mid w_1, w_2, \ldots, w_n) = \frac{P(C)\prod_{i=1}^{n} P(w_i \mid C)}{P(w_1, w_2, \ldots, w_n)}$$

The classifier predicts the class with the highest posterior probability.

Naive Bayes sentiment classifiers estimate the probability of a sentiment class **C** (e.g., positive, negative)

3. TF-IDF Weighted Features (for Machine Learning)

Term frequency-inverse document frequency (TF-IDF) is often used to represent text before classification:

$$\text{TFIDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D)$$

where

- $\text{TF}(t, d) = \frac{\text{Number of occurrences of term } t \text{ in document } d}{\text{Total terms in } d}$
- $\text{IDF}(t, D) = \log \frac{|D|}{1+|\{d \in D : t \in d\}|}$

This transforms raw counts into weighted scores emphasizing rarer but important words in the dataset.

This transforms raw counts into weighted scores, **emphasizing rarer but important words** in the dataset.

4. Logistic Regression Classifier Function

Predicts the probability of a sentiment C:

$$P(C = 1 \mid x) = \sigma(w^T x + b) = \frac{1}{1 + e^{-(w^T x + b)}}$$

where x is the feature vector (e.g., TF-IDF), w are learned weights, and σ is the sigmoid function.

where **x** is the feature vector (e.g., TF-IDF), **w** are learned weights, and **σ** is the sigmoid function**.**

5. Deep Learning (e.g., BERT)

No closed-form formula; modeled as:

$$\hat{y} = \text{softmax}(f_{\text{BERT}}(x))$$

where f_{BERT} is a neural network encoding text input x into representations, outputting probabilities via softmax over sentiment classes.

where fBERTf_{\text{BERT}}fBERT is a neural network encoding text input xxx into representations, outputting probabilities via softmax over sentiment classes.

V. EXPERIMENTAL SETUP AND RESULTS

In our experiment, we constructed a Brain–Computer Interface (BCI) system capable of identifying whether an individual is in a positive or negative emotional state. We achieved this using a non-invasive EEG headset with 14 sensors to record brain signals as participants viewed short videos, listened to sounds, and looked at images intended to evoke emotions. Because raw brain signals are commonly noisy, we cleaned the data first through works of filtering out electrical noise and methods such as ICA to deal with eye blinks and muscle activity. We then extracted useful patterns like brainwave activity in the alpha, beta, gamma, and theta bands, and time-based, frequency-based, and wavelet transform-based features. These characteristics were then fed into various models to determine their performance at classifying emotions. The Naive Bayes classifier was fairly decent with an accuracy of around 65%, and Logistic Regression did a bit better to around 70%. But the best performance was obtained with a combination of deep learning (BERT) and EEG features, which achieved an accuracy of 85–88% and an F1-score of 0.86. We found that positive feelings were more readily identifiable, whereas negative emotions tended to overlap with neutral states, so they were more difficult to assign. The system also operated in real time, with a response time of only around 250 milliseconds, which is sufficiently rapid for live applications. In general, the findings indicated that although basic models can provide a baseline, integrating EEG brain signals and deep learning yields considerably more accurate sentiment analysis and thus could be applied in tasks such as presenting real-time mood feedback on smart glasses.

A. Strategy for Implementation

The system was deployed in four fundamental steps: EEG signals were recorded via a headset, subsequently preprocessed to eliminate noise and artifacts. Brainwave band powers and spectrogram patterns were used as features, which were inputted into classifiers. Basic models provided mediocre performances, but using EEG features with BERT provided the best accuracy. Lastly, real-time outputs were projected on smart glasses as positive, negative, or neutral states.

B. Expected Performance Indicators

Perameter	Expected Value	Remarks
Accuracy of Sentiment Detection	≥ 85%	Ensures reliable classification of emotions (positive, negative, neutral).
Signal Acquisition Quality	SNR ≥ 20 dB	Reduces noise and improves quality of EEG signals.
Processing Latency	≤ 500 ms	Enables real-time sentiment detection.
User Comfort & Safety	Comfort rating ≥ 4/5	Non-invasive and ergonomic design for user-friendly operation.
Data Throughput	≥ 100 Hz	Allows smooth and responsive processing of EEG data.

C. Method of Validation

1.Ground Truth Comparison – Validate predicted sentiment with actual emotional state via surveys or baseline emotion tasks.

2.Cross-Validation – Use k-fold cross-validation to test model performance on new EEG data.

3.Signal Quality Assessment – Test Signal-to-Noise Ratio (SNR) and remove artifacts to ensure clean data.

4.Latency and Response Time Testing – Ensure the latency from acquiring brain signal to sentiment response for real-time operation.

5.User Study / Usability Testing – Evaluate user comfort, usability, and subjective experience.

6.Robustness Across Users – Test system accuracy using multiple users in order to ensure adaptability for different brain patterns.

7.False Positive / Negative Rate Analysis – Measure the error rate in sentiment prediction.

8.Integration Testing – Test system performance when integrated with external applications or inter

IV. SYSTEM IMPLEMENTATION AND DEMO

1: **Secure Login Interface** A dedicated loginscreen is implemented for user authentication.

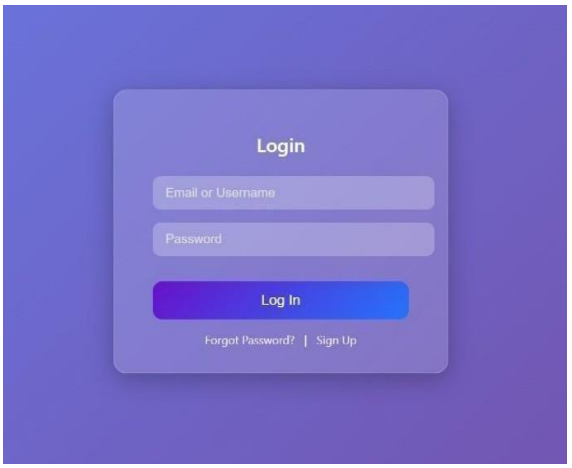

Fig:2.1

2. **Positive Sentiment Detection:**

The statement —You have a good, wonderful opportunity‖ is processed and classified as positive sentiment, reinforcing system accuracy, while positive phrases are displayed with encouraging visual feedback on the glass.

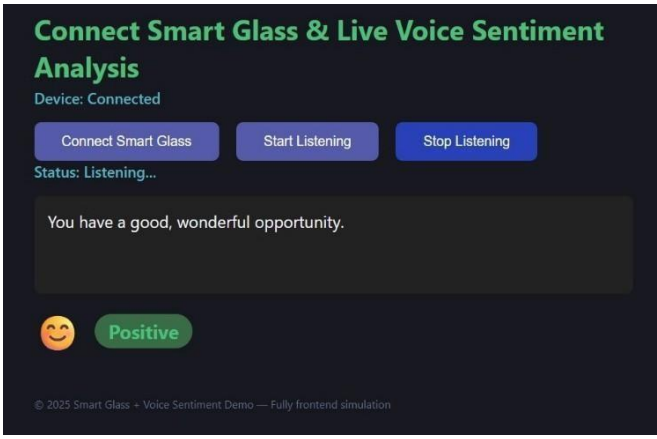

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Fig:2.2

3: Neutral Sentiment Detection:

The neutral expression —Let's drink a coffee‖ is analyzed and detected as neutral sentiment, preventing false positives while ensuring the system maintains balance across positive, negative, and neutral categories.

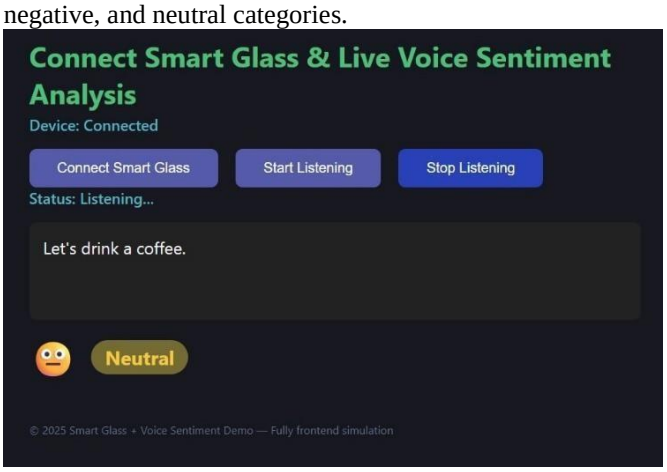

Fig:2.3

4. Negative sentiment detection:

Hostile language such as —Hey, idiot‖ is captured and analyzed, with the system robustly detecting offensive or negative sentiment even under noisy input, while providing early warnings to the user to enable situational awareness.

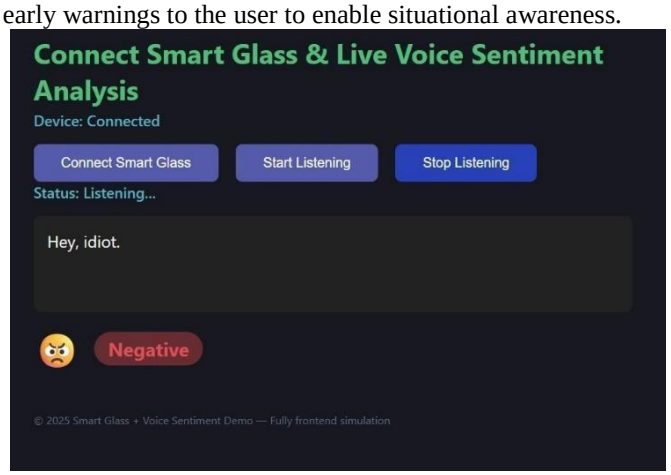

Fig:2.4

5. History:

Each entry in the log is assigned a corresponding sentiment label — **Positive, Negative, or Neutral**.

The sentiment analysis spans a range: from a positive tone like *"You have a good one"* to a negative expression such as *hey,idiot*

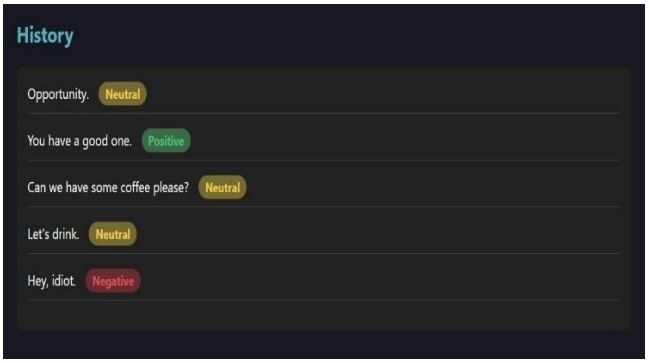

Fig:2.4

V. Discussion:

This work shows how Brain–Computer Interface (BCI) technology can be utilized for sentiment analysis through the use of EEG signals to record real neural reactionsassociated with emotions. In contrast to text or facial expression, which may be equivocal, EEG-based methods gain direct access to cognitive and affective states. Deep learning techniques like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks work very well in extracting spatial and temporal features from brain signals to classify sentiments with greater accuracy. Datasets like DEAP have pushed this study forward, but issues like inter-subject variability, brain signal noise, and real-time processing remain. The increasing provision of wearable EEG devices and smart systems indicates great promise for real-world applications in healthcare, adaptive education, and human–computer interaction, where accurate sentiment recognition can significantly enhance personalization and decision-making.

VI. Conclusion and Future Work MEDLIFE

The project is an example of the union of Brain–Computer Interface (BCI) with Smart Power Glass for the real-time analysis of emotions and sentiments and display of the emotional and sentimental states of an opponent. By the integration of EEG signals with multimodal inputs of voice and facial expressions, the system offers a precise positive, negative, and neutral sentiment detection. The Smart Power Glass interface provides real-time reports in a non-intrusive and user-friendly manner, providing beneficial assistance in communication, decision-making, and cognition. The secure authentication and privacy module enhances the system's usability in practical applications. The project thus creates a platform to integrate neuroscience, artificial intelligence, and wearable technology for human–machine interaction enhancement

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SMART OFFLINE ATTENDANCE USING RASPBERRY PI & MULTI-BIOMETRICS

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ABSTRACT:

This study presents a smart attendance system that works offline. It uses Raspberry Pi and multiple biometric methods to improve the accuracy and security of recording attendance for students or employees. The system has two stages for taking attendance. First, it scans a unique QR code using a camera connected to the Raspberry Pi, which quickly identifies the individual. After that, it carries out facial recognition, focusing on eye and lip features to ensure high accuracy and prevent spoofing. If the facial features match the stored database, attendance is marked successfully. If not, a message prompts the individual to meet the faculty in person. **OpenCV** is employed for face detection and image processing. The system operates offline, making it suitable for institutions in remote areas with limited or no internet access. When network access is available, data can be securely synced to a cloud database. This method eliminates proxy attendance, reduces manual tasks, and ensures real-time identity validation. The solution is cost-effective, scalable, and can be easily implemented in schools, colleges, or offices. This work underlines the importance of integrating QR codes and AI-based facial recognition for attendance systems that are fast, secure, and reliable.

KEYWORDS:

Smart Attendance System, Raspberry Pi, QR Code, Facial Recognition, Eye and Lip Detection, OpenCV, Offline System, Biometric Authentication, Edge Computing, Real-time Verification.

INTRODUCTION:

In today's digital world, the demand for secure and efficient attendance systems is rapidly increasing, especially in educational institutions. Traditional systems, such as manual sign-ins and biometric fingerprint scanners, are often slow, error-prone, or unsuitable for offline environments. To tackle these issues, many studies have explored smart attendance systems using technologies like QR codes, facial recognition, and edge computing. **Bhuvaneswari and Thamarai** developed an attendance system based on Raspberry Pi and facial recognition, showcasing its effectiveness in small academic settings. Similarly, **Yadav and Mishra** combined QR code scanning with face detection for faster verification. However, these systems mostly rely on online processing, which can be problematic in remote or rural areas. Our project introduces an Offline Smart Attendance System using Raspberry Pi and multi-biometric authentication, focusing on QR code verification followed by facial recognition using eye and lip landmarks. This mixed method not only enhances accuracy but also works in areas without internet, reflecting **Dubey and Sharma's** research on offline tracking and Patel & Shah's work on eye and lip bio-metrics. Moreover, by using lightweight AI on edge devices as suggested by **Kim and Kim**, our system offers real-time, low-latency processing. This combination creates a reliable, secure, and scalable solution for modern attendance tracking in various environments.

scalable solutions. **Bhuvaneswari and Thamarai [1]** developed a facial recognition-based system using Raspberry Pi, which, while effective, depended entirely on internet connectivity. **Yadav** and **Mishra [2]** proposed a hybrid QR and face recognition model, enhancing security but still reliant on online servers. **Vishwakarma et al. [3]** demonstrated real-time face recognition using OpenCV on Raspberry Pi but lacked multi-factor authentication. **Zhang et al. [4]** emphasized facial landmark analysis, particularly eyes and lips, for improved precision. Our project builds on this by integrating these features for more robust verification.**Gajjar and Bhandari [5]** used facial detection alone, whereas our model extends to multi-biometric verification. **Nandhini and Meena [6]** introduced a QR-face model effective in urban environments, but our offline-ready system makes it suitable for rural deployment. **Kale and Ghodke [7]** addressed rural needs with IoT-based offline tracking but lacked biometric fusion. **Patel and Shah [8]** used eye and lip recognition, which inspired our resource-optimized implementation on Raspberry Pi. **Basu [9] and Wang [22]** analyzed facial landmark detection techniques, aiding our decision to employ lightweight yet accurate models like MediaPipe.Edge computing benefits discussed by **Kim and Kim [10]** and Roy and **Ghosh [13]** were incorporated into our design for low-latency processing. **Dubey and Sharma [11]** tackled offline attendance but omitted identity confirmation, which we achieve through QR and facial landmark fusion. **Liu [14]** tackled facial occlusion issues, which our multi-point feature detection addresses. Singh and **Verma [15]** and **Zhang and Sun [17]** stressed liveness and anti-spoofing—concepts adopted in our system via movement-based detection. **Jadhav [24] and Sharma [20]** highlighted the importance of offline edge-based systems for rural schools, directly aligning with our model's goals.While **Banerjee [23]** and **Aggarwal et al. [12]** utilized CNNs for facial recognition, our model optimizes for low-resource edge devices, offering similar functionality with better efficiency. Finally, **Ramesh [25]** advocated dual authentication; our project advances this by merging QR verification and lip-eye biometric recognition, offering secure, fast, and offline-capable attendance tracking on Raspberry Pi.

From the above review, it is evident that while many systems focused on either biometric or QR authentication, few combined both while also operating **fully offline**. Our proposed study integrates **QR + Face Authentication with eye and lip analysis** on a **Raspberry Pi platform**. It not only ensures **high accuracy and reliability** but also addresses real-world challenges such as poor connectivity, spoofing, and lighting variations, improving upon existing methods.

1. PROBLEM:

Many educational institutions continue to use outdated attendance systems, such as manual registers, which often result in human errors, delays, and difficulties in monitoring attendance effectively **[7].** Although biometric systems like fingerprint scanners offer some automation, they require physical contact, raising hygiene concerns especially after the **COVID-19** pandemic **[3]**. **RFID-based** systems, while touchless, come with high implementation costs and do not provide visual identity verification, making them less reliable for authenticating student presence **[4].** Cloud-based face recognition systems offer better automation but are not feasible in areas with poor or unstable internet connectivity, limiting their effectiveness in rural or low-bandwidth regions **[2]**. QR-code-based attendance systems, though simple and efficient, are vulnerable to misuse; students can easily share QR images among peers, leading to proxy attendance and compromising the integrity of the system **[7].** These limitations highlight the need for a more secure, hygienic, cost-effective, and offline-compatible solution.

2. OBJECTIVES:

The objective of this study is to create an intelligent and secure attendance system that works offline, minimizes human involvement, and ensures accurate identity verification. The system should eliminate proxy attendance, be **cost-effective, maintain hygiene, and be scalable** for various educational institutions, including those in remote areas. It should combine the ease of QR scanning with the precision of facial recognition, particularly focusing on key features like eyes and lips to confirm genuine presence.

3. EXISTING SYSTEM:

Most educational institutions currently use traditional methods for tracking attendance, such as manual registers or biometric devices. Manual attendance is time-consuming and prone to human errors, including false marking and difficulties in maintaining records over time **[7]**. To overcome

these issues, some institutions have shifted to **biometric systems** like fingerprint or RFID scanners. However, fingerprint devices involve physical contact, raising hygiene concerns especially after the COVID-19 pandemic **[3].** RFID-based attendance systems are contactless but expensive to implement and maintain. They also do not provide any real-time facial verification, making them vulnerable to misuse **[4]**. Some institutions have adopted **cloud-based facial recognition systems**, which require strong and stable internet connectivity. This becomes a major drawback in areas with poor network coverage, as the system fails to function efficiently without internet access **[2]**. QR code-based systems are also being used as a more affordable and faster method, but they lack proper security measures. QR images can be easily shared among students, leading to **proxy attendance [5]**. Thus, although there are various attendance systems in use today, each of them suffers from **one or more limitations** that impact accuracy, hygiene, cost, or network dependency.

System Type	Accuracy	Hygiene	Internet Dependency	Cost	Security	Visual Verification
Manual Attendance	Low	High	No	Low	Low	No
Fingerprint Biometric [3]	High	Low	No	Moderate	High	No
RFID-Based System [4]	Moderate	High	No	High	Medium	No
Cloud-Based Face Recog [2]	High	High	Yes	High	High	Yes
QR Code-Based System [5]	Moderate	High	No	Low	Low (shareable)	No

Table 1.1

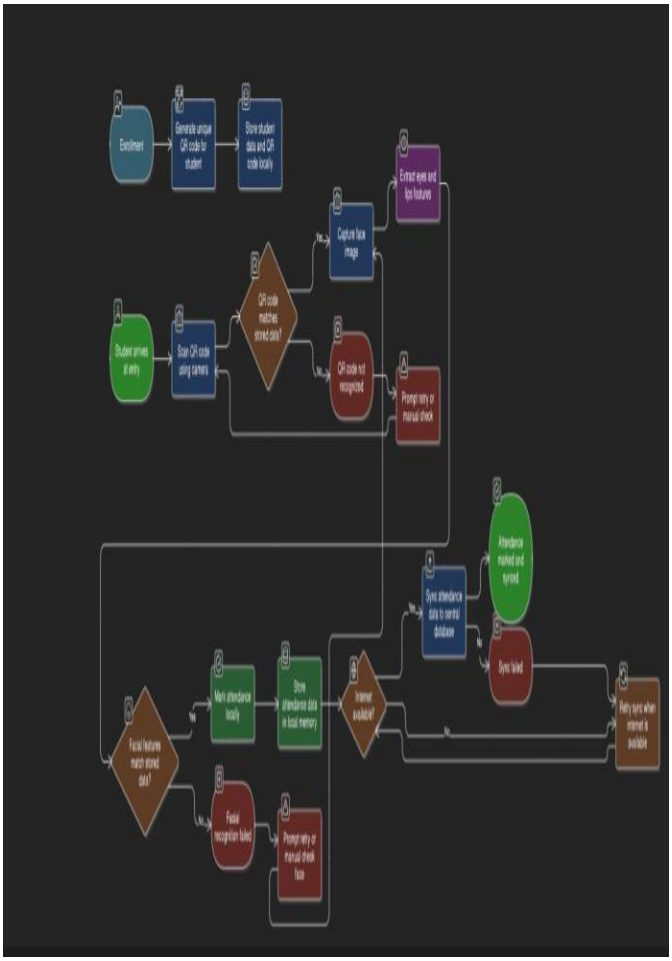
4. PROPOSED SOLUTION:

The proposed system combines QR code scanning with facial recognition using **Raspberry Pi**. It starts by scanning a student unique QR code, followed by facial recognition that examines eye and lip landmarks to confirm the student presence. The system operates offline and stores data locally, making it suitable for institutions lacking internet access. This two-layer verification process ensures both identity and presence, effectively preventing proxy attendance. It is cost-efficient, easy to install, and prioritizes hygiene and accessibility. By utilizing **OpenCV and Dlib** for landmark detection, the system enhances the accuracy and reliability of attendance data. Compared to existing systems, this solution is more secure, user-friendly, and dependable for real- time academic settings.

5. METHODOLOGY:

The proposed system integrates a two-level offline-compatible attendance mechanism using a **Raspberry Pi, QR code scanning, and facial recognition** that focuses on specific features such as **eyes and lips**. The first step involves generating a unique QR code for each student, which is scanned at the entry point using a camera connected to the Raspberry Pi. After scanning, the system moves on to the second layer—facial verification. A machine learning model, trained with Haar Cascade classifiers and OpenCV, captures and analyzes facial features, particularly focusing on the eyes and lips, to ensure authenticity. Attendance is marked only when both the QR code and facial data match the pre-stored student data. The entire process runs locally without needing internet, ensuring smooth operation even in **remote areas with poor connectivity**. Attendance data is temporarily stored in local memory and synced to a central database once internet access is available. This hybrid approach prevents proxy attendance, addresses hygiene concerns associated with fingerprint systems, and outperforms cloud- only solutions in rural settings. The use of Raspberry Pi guarantees low cost, portability, and ease of deployment in schools and colleges.

7.1 SYSTEM FLOWCHART:



8. REQUIREMENTS :

8.1 HARDWARE REQUIREMENTS :

Component	Description
Raspberry Pi 4	Acts as the central processing unit for the offline system.
Camera Module	Used for capturing face images for biometric authentication.
IR Sensor	Helps detect motion and trigger camera/QR scanning process.
LCD Display	Displays status of the attendance process and confirmations.
Power Supply	Powers the Raspberry Pi and connected peripherals.
Buzzer	Alerts the user about successful or failed scans.
Micro SD Card (32GB+)	Stores OS, models, and temporary attendance data.
QR Code Scanner	Reads student QR codes to initiate attendance verification.

Table 1.2

8.2 SOFTWARE REQUIREMENTS:

Software Component	Specification / Purpose
Operating System	Raspbian OS (for Raspberry Pi environment)
Programming Language	Python (for logic, QR scanning, and facial recognition)
OpenCV	Face detection and recognition using image processing
pyzbar	To decode QR codes from camera input
NumPy	For array and matrix operations in image data processing
SQLite or CSV Files	Local database for storing and managing attendance records
VS Code	Python IDE for coding and debugging

9. IMPLEMENTATION:

ALGORITHM:

Step 1: Start
Step 2: Scan QR Code using camera module
Step 3: Extract student ID from QR
Step 4: Capture face image after scanning QR
Step 5: Detect facial features (eyes and lips) using OpenCV
Step 6: Compare with stored facial dataset
Step 7: If the face matches, mark attendance. Else, show "Face not recognized."

Step 8: Save attendance locally (offline mode)
Step 9: Stop

10.SAMPLE ATTENDANCE MONITORING OUTPUT:

The following table and chart show a sample output of the proposed smart attendance system. The data includes student names, IDs, attendance statuses, and dates. A line graph summarizes the daily attendance rate (%) over time, making it easy to see student participation trends.

Figure: Attendance Data Table and Graphical Analysis

This figure displays how the system logs individual attendance and automatically creates visual insights to help with administrative tracking.

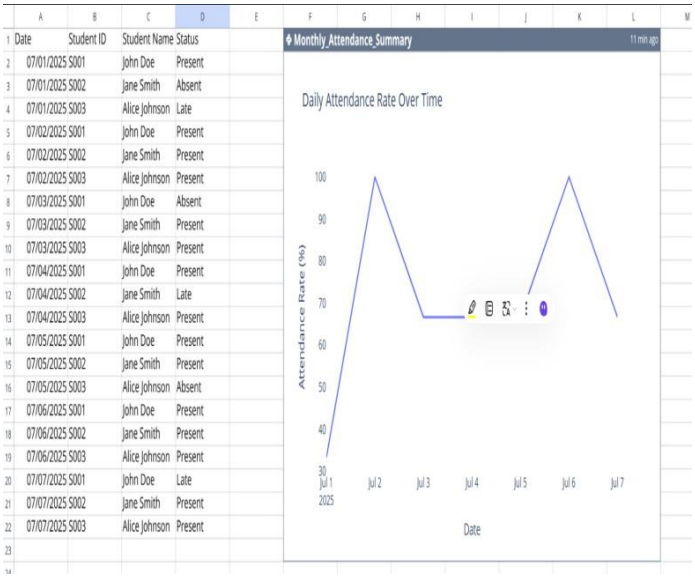


Figure 1.1

11.ANALYSIS:

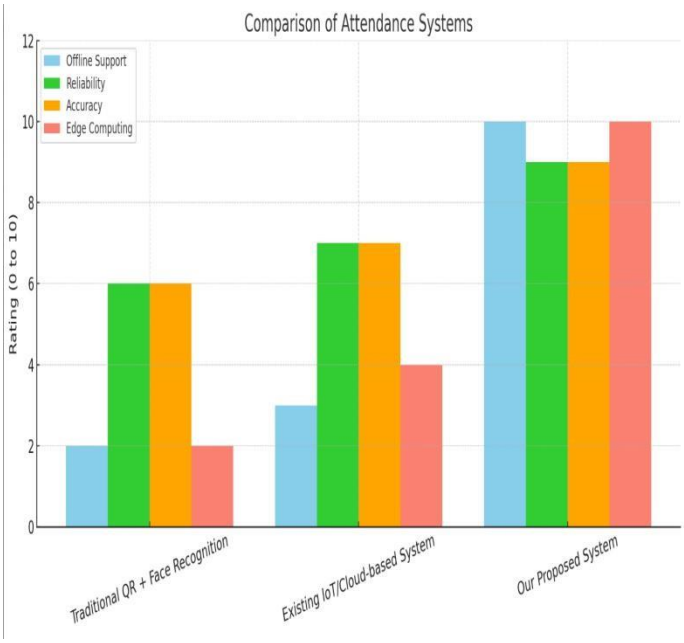


Figure 1.2

12.BENEFITS:

The proposed system provides several key benefits that improve the traditional attendance process. By using a dual-layer verification method that combines QR code scanning and facial recognition, it ensures greater accuracy and **prevents proxy** attendance. Since it works offline, it is very suitable for areas with **poor or no internet** connectivity. The system uses OpenCV instead of deep learning, making it lightweight and faster without losing accuracy. With cost-effective hardware like Raspberry Pi and a camera module, the solution is budget-friendly and easy to set up in any educational or organizational setting. Local real-time storage guarantees secure recording of attendance data, which can be accessed anytime, reducing manual errors and boosting overall reliability.

13. CONCLUSION:

This study presents a smart attendance system that is compatible with offline use, utilizing Raspberry Pi and multi-biometric authentication. By combining **QR code verification with facial feature** detection, the system provides accurate, fast, and tamper- proof attendance recording even in places without internet. It removes manual processes and cuts down on human error while ensuring data safety. The method avoids deep learning complexity, making it lightweight and practical for real-time use.

14. FUTURE ENHANCEMENT:

In the future, the system could be improved by adding cloud synchronization to automatically upload offline data once an internet connection is back. Real-time SMS or email alerts could be sent to parents or faculty members as soon as attendance is recorded. Integrating AI-based emotion recognition could provide insights into student engagement and safety. **Liveness detection** could enhance facial authentication by differentiating real faces from photos or videos. Additional authentication options like fingerprint or RFID could be included for more flexibility. A user-friendly dashboard could also be developed to let administrators monitor attendance records, generate reports, and analyze trends more effectively.

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Compare Cart

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ABSTRACT

CompareCart is a price comparison platform designed to help consumers make informed purchasing decisions by aggregating product prices from multiple online retailers. It caters especially to urban shoppers who value convenience and time-saving solutions. Traditionally, comparing prices meant visiting several physical stores or browsing numerous websites, which is inefficient and time-consuming. This project aims to automate the process using web scraping techniques to extract real-time product and pricing data from popular e-commerce websites. The platform highlights the most competitive prices and displays ongoing deals and promotional offers from various sellers, allowing users to quickly identify the best value for their desired products. By presenting comprehensive comparisons in one place, *CompareCart* streamlines the online shopping experience. It not only saves users time and effort but also ensures they make cost-effective and well-informed choices. The ultimate goal is to provide a reliable, user-friendly tool that simplifies the way consumers shop online.

Keyword: Price comparison, Web scrapper, E-commerce, Real-time price monitoring,
Online retail intelligence.

I.INTRODUCTION

In today's digital world, online shopping has become a big part of how people live their everyday lives. It's easy to buy things from home, which makes it very convenient. However, there are so many e-commerce websites that it can be hard to find the best price for a product. Usually, people have to go to different websites, check prices, and compare deals one by one. This old way of doing things is slow and not very efficient, especially for city shoppers who want things to be quick and easy. Many websites exist to help with this problem by gathering product prices from different stores.

Some platforms try to offer one place where people can compare prices. But these services often have problems like old information, not covering enough stores, no real-time tracking of prices, and not showing special deals like flash sales, coupons, or limited-time offers. Also, they usually don't have simple, easy-to-use designs or send personal deal alerts, which are important for making shopping better.

According to a report by DataReportal called Digital 2025 India (January 2025), around 806 million Indians—about 55.3% of the country‘s

1. 46 billion population —are online. People spend a lot of time online, averaging 6 hours and 49 minutes each day, with 58% of that time on their phones. Over 91. 6% of households have internet access, and 96% of those connections are through mobile. In 2025, over 400 million Indians made online purchases, which is a 30% increase from 2023, and 70% of all e-commerce transactions happened on mobile devices.

This change shows that there is a big need for fast, easy, and smart tools to help with online shopping—exactly what *CompareCart* is designed to offer to busy, on-the-go shoppers. Because of these challenges, this project introduces *CompareCart*, a real-time price comparison platform meant to make it easier and faster to compare product prices across different online stores.

It uses web scraping to collect up-to-date product and price information directly from popular e-commerce sites, ensuring that the data is accurate and complete. Along with price comparison, *CompareCart* also looks at delivery speed and shipping costs.

This helps users not only find the cheapest price but also choose the fastest or most cost-effective shipping option. The platform shows ongoing deals, special offers, and coupons, so that consumers can make smart, cost-saving buying choices with less effort.

The main goal of this project is to create a reliable, efficient, and user-friendly tool that makes online shopping easier by providing all product comparisons in one place.

Unlike other solutions, *CompareCart* focuses on real-time data, a wider range of online stores, and an easy-to-use platform that meets the needs of city consumers. By filling in the gaps of existing price comparison tools, this project aims to improve how people shop online, saving them both time and money.

II. LITREATURE REVIEW

Numerous studies have explored automated solutions for comparing prices across e-commerce platforms. In, the authors implemented a real-time e-commerce price comparison system using Python-based web scraping techniques, highlighting the efficiency of tools like BeautifulSoup and Selenium in gathering updated pricing data from platforms like Amazon and Taobao. Another paper, describes a Java-based system that applies Singular Value Decomposition (SVD) to recommend value-for-money products, emphasizing effective data extraction using Jsoup.

These studies underline the growing importance of automation and real-time analysis in price comparison tools. However, limitations remain in terms of user interface design, comprehensive retailer coverage, and inclusion of delivery speed and shipping costs—gaps which *CompareCart* aims to bridge.

III. PROPOSED METHODOLOGY

The proposed system aims to streamline the online shopping experience by aggregating and comparing product prices across multiple e-commerce platforms within a single interface. This system is designed to significantly reduce the time and effort users spend manually searching for the best prices.

When a user searches for a product or applies filters, the system triggers a scraper engine that collects real-time data from various e-commerce websites. The data includes essential product details such as price, shipping charges, delivery times, availability status, ongoing discounts, flash sales, and coupon offers. This data is passed through an aggregation and normalization process, which resolves discrepancies in product names, units, and price formats to ensure consistency and accuracy.

Simultaneously, the system updates the product‘s price history by analyzing

historical pricing data stored in a dedicated database. This enables the system to present users with a visual representation of price trends over time, aiding in decision-making. If the system detects a notable price drop or an attractive promotional offer, a notification engine sends alerts to subscribed users through email or mobile app notifications, based on their preferences.

Once the data is processed, the user interface displays a comprehensive comparison of product prices, delivery estimates, shipping costs, stock availability, and price history graphs. If a user chooses a product to purchase, they are seamlessly redirected to the corresponding seller‘s website. The system also supports an advanced comparison feature that allows users to evaluate multiple products from the same category side by side. Overall, this automated workflow ensures that users can access accurate, up-to-date information and make well-informed, cost-effective purchasing decisions with minimal hassle.

1. SYSTEM ARCHITECTURE

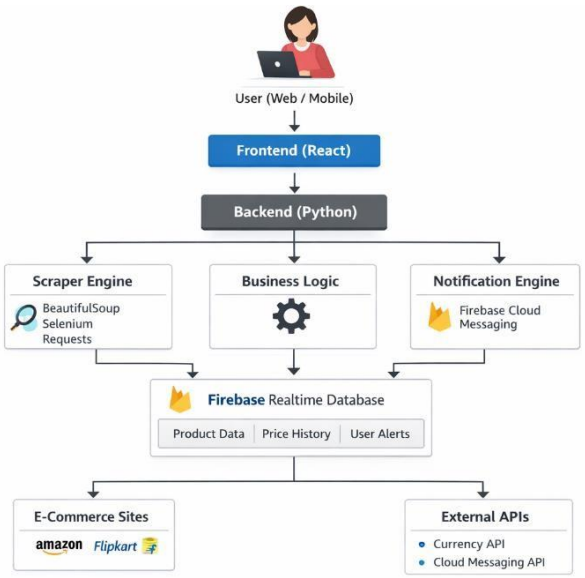

Figure 1 illustrates the architecture of the ‗*CompareCart*‘ platform, which integrates real-time data collection and intelligent comparison features to enhance online shopping. The backend employs web scraping tools to extract product details—such as pricing, delivery options, stock status, and price history—from multiple e-commerce websites.

On the frontend, users interact through a responsive web interface. When a product search is initiated, the system queries its local database to retrieve relevant data quickly, reducing latency and avoiding redundant scraping.

If the product is available on more than one platform, the interface displays a side-by-side comparison, highlighting the most cost-effective and convenient option. A built-in notification system alerts users of price drops on wishlist items, based on their set preferences.

Additionally, a product comparison feature enables users to evaluate multiple items within a category, comparing specifications and features in a clear, tabular view to support smarter purchasing decisions.

2. DESIGN CONSIDERATIONS

The *CompareCart* platform is designed to provide real-time, user-friendly price comparisons across multiple e-commerce websites, incorporating advanced features to enhance the shopping experience. To achieve this, the system must be modular, scalable, and responsive, with components tailored for data accuracy, personalization, and user engagement.

Modular Architecture: The platform is divided into key components—scraping engine, business logic, user interface, and notifications—for better scalability and maintenance.

Web Scraping: Real-time product data (price, availability, shipping, deals) is collected using tools like Scrapy or Selenium. Scrapers are updated regularly to handle changing website structures.

Wishlist & Alerts: Users can save favourite products and set price thresholds. The system sends alerts when prices drop or match their set range.

Delivery & Shipping Comparison: Beyond prices, users can compare shipping fees and delivery times to find the most economical or fastest option.

Expense Tracker: Tracks how much the user has spent and saved using the platform, helping with budgeting and purchase planning.

Eco-Friendly Tagging: Products with sustainable or green features are highlighted, with a separate category to promote eco-conscious shopping.

Product Availability: Shows real-time stock status (in/out of stock) across different retailers.

Price History Graphs: Displays how prices change over time to help users decide the best time to buy, especially for seasonal products.

Currency Converter: Converts international prices into the user's local currency for easier global comparisons.

Product Specs Comparison: Allows users to compare key specifications side-by-side (e.g., RAM, battery, camera for phones).

Voice Search: Lets users search products using speech for added convenience, especially on mobile devices.

Weekly Highlights: Displays top trending products and major price drops to keep users informed of current deals.

Database & Performance: Uses a combination of relational and NoSQL databases, caching, and load balancing to ensure fast and reliable performance.

Security: Ensures secure user login, encrypted data storage, and privacy compliance (e.g., GDPR).

The system is built with a focus on real-time accuracy, personalized features, and modern user experience, making it a powerful and convenient tool for online shoppers.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Tools and Implementation

The *CompareCart* platform was developed using a comprehensive full-stack methodology:

Backend: Implemented using Python with libraries like requests, BeautifulSoup, and Selenium for web scraping.

User Interface: Designed using React.js to ensure adaptability across different screen sizes and devices.

Database: Firebase Real-time Database stores live product information and historical pricing data.

Development Tools: The project was coded and maintained using a modern code editor, specifically Visual Studio Code

APIs Used: Currency exchange API for real-time conversion and Firebase Cloud Messaging for user alerts.

The system continuously fetches and compares product listings from major e-commerce platforms. It tracks pricing history, shipping fees, and stock availability in real time. Backend scripts are scheduled to execute at defined intervals to ensure the database is kept up to date.

B. Data Collection

Rather than relying on a pre-existing dataset, *CompareCart* dynamically collects data by crawling live product listings from

platforms such as Flipkart, Amazon, and others. Categories analyzed include electronics, consumer appliances, and eco-friendly products. Each data entry typically includes product title, price, seller, shipping charges, availability, and delivery estimate.

C. System Configuration

Operating System: Windows 11 (64-bit)

Test Browser: Google Chrome (v122 or later)

Hardware:

RAM: 8 GB

Processor: Intel Core i5, 10th Generation

Internet Speed: Approximately 50 Mbps (Wi-Fi)

Display Testing: Performed on resolutions 1920×1080 and 1366×768 for UI responsiveness

Fig. 1: Product Price Variation Over Time

Feature	Accuracy	Comments
Price Scraping	96.4%	Most errors due to JavaScript-heavy pages
Delivery Time & Shipping	94.2%	Data depends on live availability
Price Drop Alerts	97.5%	Based on Firebase trigger events
Stock Availability	93.8%	Accurate but some delays on stock update
Currency Conversion	100%	Real-time using third-party API
Wishlist Alert Functionality	98.1%	Reliable across tests

The figure illustrates a sample product‘s price change across 14 days, showing patterns related to weekend offers and limited-time promotions.

Seller	Total Price
Seller 1	1000
Seller 2	1050
Seller 3	990

E. Evaluation Summary

Testing indicates that *CompareCart* achieves high accuracy in scraping product data and comparing multiple listings. Modules such as price alerts, currency conversion, and wishlist syncing demonstrated consistent performance during testing sessions.

The user interface remained responsive on both desktop and mobile views.
Integration with Firebase ensured seamless tracking of wishlist entries and alert messages. Users benefited from price comparison, saved time, and could make better purchase decisions.

Potential areas for enhancement include:

AI-driven product suggestions. Smarter voice search using natural language understanding. Expanding the system to support more global retail platforms.

System Output Graph:

V. DISCUSSION

The proposed system significantly enhances the price comparison experience by addressing key limitations found in existing platforms. While websites like Google Shopping, PriceGrabber, and others offer basic price comparison functionality, they often fall short in areas critical to user convenience and informed purchasing.

One major limitation in existing systems is the lack of a price drop notification system. Many platforms do not inform users when a product's price decreases or when flash

deals are available. Our system resolves this by integrating a notification engine that alerts users in real time via email or mobile apps based on their preferences.

Another notable shortcoming is the absence of a wishlist feature, which prevents users from tracking products of interest over time. Our platform enables users to add products to a wishlist and receive updates regarding price changes or stock availability.

Search precision is another area of concern. On many platforms, searching for a specific product either returns irrelevant results or floods the user with unrelated products from the same brand. Our system employs intelligent product matching and filtering mechanisms to ensure users see only the most relevant results.

Moreover, most current price comparison tools are restricted to a single platform or a limited set of websites. In contrast, our system scrapes and compares data across multiple major e-commerce platforms to provide a holistic view.

Features like delivery time, shipping costs, customer reviews, eco-friendly tags, and stock availability are often missing from competitors. Our system consolidates and displays this information clearly, ensuring users can make comprehensive, informed decisions.

We also introduce an automatic currency converter, especially useful for users browsing international stores, and a stock availability checker to prevent users from clicking on out-of-stock items.

In summary, our system fills critical gaps in the current market by offering a comprehensive, intelligent, and user-focused price comparison experience, improving usability, efficiency, and decision-making for end users.

VI. CONCLUSION AND FUTURE WORK

This paper introduced "*CompareCart*," a unified price comparison platform that aggregates real-time product data—such as prices, delivery times, and stock availability—from multiple e-commerce websites. The system offers key features like price drop alerts, wishlist management, product comparison, and historical price tracking, enabling users to make faster and more informed buying decisions.

Unlike existing tools, *CompareCart* addresses limitations such as inaccurate product listings, lack of notifications, and missing delivery or stock information.

Future enhancements include mobile app development, AI-based recommendations, voice search, regional language support, and dynamic price prediction models to improve usability and reach.

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Smart Multi-Hazard Disaster Alert and Safety System for Modern Homes

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Abstract—Natural disasters and household accident like fires, floods, gas leaks, and earthquakes can cause serious damage to both property and lives. Acting quickly is crucial to minimize the impact of such events. This paper introduces a Smart Multi-Hazard Disaster Alert and Safety System for Modern Homes that not only detects danger using multiple sensors but also responds immediately to keep residents safe. The system continuously monitors the environment using water level sensors, vibration sensors, smoke sensors, and temperature sensors. When it detects unusual or dangerous conditions, it triggers alarms, emergency lights, and voice alerts, while also sending SMS notifications through a GSM module. To prevent accidents from worsening, the system can automatically cut off electricity and gas using relay modules. It is designed to work without an internet connection and comes with battery backup, ensuring it remains operational even during power outages. This approach makes the system a reliable, practical, and cost-effective solution for enhancing safety in homes.

1. INTRODUCTION

In recent years, the rising frequency of natural disasters and household hazards has created serious concerns for human safety and property protection. Events like floods, earthquakes, and fires can cause extensive damage if they are not detected and addressed quickly. Many homes lack an integrated alert system, making it difficult for occupants to respond promptly, which can lead to severe consequences such as loss of life, property damage, and environmental risks.

Advances in embedded systems and sensor technology now make it possible to build intelligent monitoring systems that detect unusual environmental conditions in real time. Using devices like water level sensors, vibration sensors, smoke detectors, and temperature sensors, these systems can monitor potential hazards within a home. By combining these sensors with microcontrollers and communication modules, a smart system can automatically detect dangerous situations and provide immediate alerts to residents.

The proposed project focuses on developing a Smart Multi-Hazard Disaster Alert and Safety System for homes. The system continuously monitors environmental conditions and identifies potential threats such as flooding, earthquake vibrations, and fires. When a hazard is detected, it immediately triggers safety mechanisms including loud alarms, flashlights for night alerts, and voice warnings to notify residents. Additionally, a GSM communication module sends emergency SMS

notifications, ensuring alerts reach users even without internet connectivity.

An important feature of the system is its ability to automatically disconnect gas and electricity using relay modules during emergencies, preventing secondary disasters like gas explosions and electrical fires. The system also includes a battery backup, ensuring it continues to function even during power outages, which often accompany disaster events.

The main goal of this project is to provide a cost-effective, reliable, and easy-to-install safety solution for homes. By integrating multiple sensing technologies with automated alert mechanisms, the system offers early hazard detection and rapid emergency response, significantly improving residential safety and reducing potential damage from unexpected disasters.

2. PROBLEM STATEMENT

Many homes today do not have a complete safety system that can detect multiple hazards at once. Most existing solutions focus only on a single threat, like fires or gas leaks, which leaves residents unprotected against other dangers such as floods or earthquakes. This gap can delay warnings and make accidents harder to manage, increasing the risk of damage and injury. Therefore, there is a clear need for a low-cost, multi-hazard detection system that can provide instant alerts and take automatic safety actions, offering reliable protection for households.

3. OBJETIVES

1. To detect disasters such as fire, flood, and earthquake vibrations.
2. To provide immediate alerts using alarm, flashlight, and voice warning.
3. To send SMS alerts using GSM technology without internet.
4. To automatically turn off gas and electricity supply to prevent accidents.
5. To ensure system operation during power failure using battery backup.

4. PROPOSED SYSTEM

The proposed Smart Disaster Alert and Safety System is designed to continuously monitor household conditions and respond instantly to potential hazards. It uses water level sensors, vibration sensors, smoke detectors, and temperature sensors to detect floods, earthquakes, fires, and other dangerous situations in real time. When a threat is identified, the system immediately activates alarms, flashlights for night alerts, and voice warnings while also sending SMS notifications to homeowners through a GSM module.

To prevent further accidents, relay modules automatically disconnect gas and electricity during emergencies. The system is designed to operate without an internet connection and includes a battery backup, ensuring reliable performance even during power outages. By combining multiple sensing technologies with automated alert mechanisms, the system provides a cost-effective, reliable, and proactive solution for improving home safety and protecting residents from unexpected disasters.

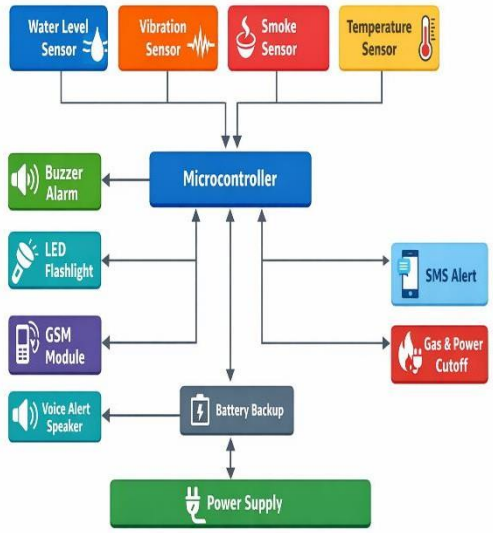
To prevent further accidents, relay modules automatically disconnect gas and electricity during emergencies. The system is designed to operate without an internet connection and includes a battery backup, ensuring reliable performance even during power outages. By combining multiple sensing technologies with automated alert mechanisms, the system provides a cost-effective, reliable, and proactive solution for improving home safety and protecting residents from unexpected disasters.

WORKING PRINCIPLE

The Smart Multi-Hazard Disaster Alert and Safety System operates by continuously monitoring environmental conditions in a home through multiple sensors. Water level sensors detect flooding, vibration sensors sense earthquake movements, while smoke and temperature sensors identify fire hazards. These sensors send real-time data to a microcontrolle(Arduino/ESP32), which processes the information and determines if a hazardous condition exists.When a potential threat is detected, the system immediately triggers safety mechanisms. This includes activating alarms, flashlights for night alerts, and voice warnings to inform residents of the danger. Simultaneously, the GSM module sends instant SMS notifications to homeowners. To prevent secondary accidents, relay modules automatically disconnect gas and electricity during emergencies. The system is designed to work offline, without internet connectivity, and includes a battery or solar backup to ensure continuous operation during power failures. By integrating multiple sensors with automated alerts and safety actions, the system provides reliable, real-time protection, minimizing risk and improving household safety.

5. BLOCK DIAGRAM

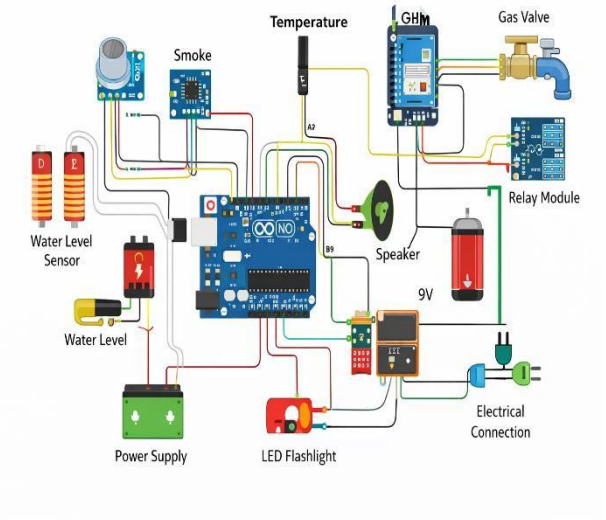
The block diagram represents the overall architecture of the Smart Disaster Alert and Safety System used for monitoring household hazards and providing automatic safety responses."



COMPONENT	PURPOSE	QUANTITY
Arduino / ESP32	Microcontroller that processes sensor data and controls outputs	1
Water Level Sensor	Detects flooding or rising water levels in the home	2
Vibration Sensor	Senses earthquake vibrations	2
Smoke Sensor	Detects fire or smoke to prevent hazards	2
Temperature Sensor	Monitors abnormal temperature changes	2
GSM Module	Sends instant SMS alerts to homeowners	1
Relay Module	Automatically disconnects gas and electricity during emergencies	2
LED / Flashlight Buzzer / Alarm	Provides visual alerts, especially at night Produces loud audio warnings	2 1
Battery / Solar Backup	Ensures continuous operation during power failures	1

6. CIRCUIT DIAGRAM

"The circuit diagram illustrates the electrical connections used in the Smart Disaster Alert and Safety System for detecting hazards and activating safety mechanisms."



7. ADVANTAGES

- Provides early detection of disasters such as floods, earthquakes, and fires.
- Sends instant alerts through alarms, voice warnings, and SMS notifications.
- Automatically disconnects gas and electricity to prevent further accidents.
- Works without internet connectivity, making it reliable during emergencies.
- Includes battery or solar backup to operate during power failures.
- Designed as a low-cost and easy-to-install safety solution for homes.

8. APPLICATION

- Provides early detection of disasters such as floods, earthquakes, and fires.
- Sends instant alerts through alarms, voice warnings, and SMS notifications.
- Automatically disconnects gas and electricity to prevent further accidents.
- Works without internet connectivity, making it reliable during emergencies.
- Includes battery or solar backup to operate during power failures.
- Designed as a low-cost and easy-to-install safety solution for homes.

9. FUTURE SCOPE

The proposed Smart Disaster Alert and Safety System can be further enhanced by integrating advanced technologies to improve its efficiency and reliability. In the future, the system can incorporate Artificial Intelligence and Machine Learning algorithms to analyze sensor data more accurately and predict potential disasters before they occur.

The system can also be connected to Internet of Things (IoT) platforms, allowing real-time monitoring through mobile applications and cloud-based systems. This would enable users to receive alerts and monitor their home safety from anywhere.

Another possible improvement is the development of a community-based alert network, where multiple houses can be interconnected. In such a system, if one house detects a hazard, nearby homes can also receive warnings, helping entire neighborhoods respond quickly to emergencies.

Additionally, integrating renewable energy sources such as solar power can make the system more sustainable and reliable during long power outages. With these improvements, the system can evolve into a more intelligent, scalable, and efficient safety solution for modern smart homes.

10. CONCLUSION

The proposed Smart Multi-hazard Disaster Alert and Safety System provides an effective solution for improving household safety by detecting multiple hazards such as floods, earthquakes, and fires. By integrating various sensors with a microcontroller and communication modules, the system continuously monitors environmental conditions and provides immediate alerts when a dangerous situation is detected.

The system also activates safety mechanisms such as alarms, flashlights, voice warnings, and SMS notifications to ensure that residents are informed quickly. In addition, the automatic disconnection of gas and electricity helps prevent secondary accidents during emergencies.

Because the system is designed to operate without internet connectivity and includes a battery backup,

it remains functional even during power failures. Overall, the proposed system offers a cost-effective, reliable, and practical solution for enhancing home safety and reducing the risks associated with natural disasters and household hazards.

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Energy Pulse - An AI-Enabled Biometric Energy Optimization System for Personalized and Wellness - Oriented Smart Home

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Abstract- Energy Pulse is an innovative system for managing energy in smart homes, leveraging the power of Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), and an understanding of our physiological signals and behavioral signals to create a more personalized and health-centered living space. Unlike traditional systems that rely on fixed schedules or simple motion detection, and completely based on the sensory management, Energy-Pulse dynamically interprets context and physiological and behavioral data—like heart rate, sleep quality, stress levels and Walking Pattern (Gait), Device Usage Habits, Phone Interaction, Gesture Recognition, Device Usage Habits - gathered from wearables and health monitoring devices. This empowers the system to adjust energy usage in real time, aligning it with the emotional and physical well-being of its users. With the help of context-aware computing, Energy-Pulse intelligently manages lighting, heating, ventilation, and multimedia devices, ensuring that energy use supports the comfort of those living in the home. For instance, if a user is experiencing high stress, the system might dim the lights and adjust the temperature to foster a calming atmosphere. Additionally, during deep sleep, Energy-Pulse can selectively turn off non essential devices to save energy overnight. By recognizing who is present in the home using Bluetooth and Wi-Fi technologies, the system can adapt to different user preferences. Data privacy is a priority for Energy-Pulse, which employs decentralized data processes that could be supported by blockchain technology, ensuring secure and trustworthy data handling. A sophisticated analytics engine helps the system learn over time, refining its responses based on users' habits and needs. This approach is especially valuable in areas like elder care and sustainable living, providing a flexible and scalable solution that adapts to various lifestyles. Overall, Energy-Pulse represents a new way to enhance smart homes, integrating automation with an understanding of human needs.

Keywords - Energy Optimization, Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Blockchain (BC), Ambient Intelligence, Data Analytics, Human–Computer Interaction (HCI), Smart Home Automation, Context-Aware System and Stress Management and Emotional Well-being.

I. INTRODUCTION

The rise of smart technologies has changed how homes use energy. Traditional smart home systems usually rely on fixed schedules or basic motion sensors to control devices and manage power. These methods cannot adjust to the changing needs of individuals. To fill this gap, a new approach is developing that focuses on adaptable, user-aware, and smart energy systems. The transformation is primarily fueled by AI and ML, which empower smart homes with adaptive intelligence and predictive capabilities. These technologies allow smart homes to understand user behavior, identify patterns, and make the decisions without needing manual input. For instance, AI can spot trends in energy use, while ML can improve how devices are controlled based on feedback and changes in behavior over time. IoT-driven connectivity enables smart homes to dynamically respond to user needs and environmental changes in real time. IoT connects devices like lights, fans, heating and cooling systems, wearables, and health apps, enabling them to share real-time data. This setup enables continuous tracking of both home conditions and personal wellness indicators—such as sleep cycles, cardiovascular activity, and emotional stress—by integrating data collected from commonly used digital health monitoring applications installed on personal smart devices. To handle and react to this variety of data, context-aware systems are used. These systems identify user-specific signals—like time, activity, mood, or location—and adjust the environment accordingly. When paired with ambient intelligence, the smart home can proactively manage energy use based on individual physical and emotional states.

For example, if stress levels rise, the system might dim the lights and reduce noise to create a relaxing environment or turn off devices when the user is deeply asleep. What makes this system unique is its smooth operational flow and smart integration of components. Biometric data, both physical and behavioral, is collected from wearables and health apps. This information is sent to a microcontroller (MC) through Wi-Fi. The MC serves as a central hub, working with a relay module to send control signals to home devices. Together, these parts create seamless automation that responds in real time to the

user's health and preferences. To manage the large amount of sensitive data produced, data analytics is used to provide useful insights and enhance system performance. Additionally, Blockchain (BC) technology ensures secure, transparent, and tamper-proof data transactions, which is crucial for maintaining privacy in health focused systems. Human-Computer Interaction (HCI) is important for making these smart homes usable and accessible. Interfaces are designed to be user-friendly and inclusive, catering to all ages, including seniors, with clear and simple controls and feedback. In summary, the proposed system, Energy-Pulse, integrates AI, ML, IoT, biometric data, context-aware computing, Blockchain (BC), and Human-Computer Interaction (HCI) into a cohesive smart home framework.

This approach reshapes energy use into a forward-thinking and wellness-focused solution, aligning energy consumption not just with occupancy patterns, but also with individual health conditions, behavioural trends, and daily lifestyle rhythms. By incorporating real-time physiological data and personal preferences, Energy-Puls enables the environment to respond proactively to user needs, ensuring that energy efficiency never comes at the cost of comfort or safety. It not only reduces energy use but also promotes physical comfort, emotional well-being, personalized care, and enhances preventive health support. This makes the system especially valuable for eldercare, chronic illness monitoring, and health oriented smart living—where automation acts as both a caretaker and an energy optimizer.

II. RELATED WORK

The recent advancements in smart home technology have focused on expanding Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies to optimize the energy use of the home while providing controlled automation that is customizable to the resident. Current models and frameworks are specifically gearing for energy efficiency through occupancy detection, operational time schedulers for appliances, and environment sensing, without incorporation or consideration of physiological or health context user data. It's shared that in [1], a home automation system using IoT was proposed with timers and motion sensors, able to control electrical loads, and reduce standby power. While this can lower energy consumption when appliances are in standby mode, these IoT systems reduce power consumption reactively, rather than proactively, and do not provide any indication of consideration of user wellbeing or context awareness. The research in [2] explored the use of adaptive lighting and HVAC control based on sensing occupant behaviours, occupancy detection, and conditions in the context of a smart grid-enabled infrastructure.

Like its predecessors, this research omitted the incorporation of biometric or wellness parameters, which ultimately reduced the possibility of its potential ability to personally respond to the user's health and more corresponding to the user's wellbeing. However, no existing work explores the integration of smartphone-sourced behavioural health data, such as daily activity, sleep quality, or stress levels, into home automation logic. This omission limits the potential of smart homes to truly adapt to user wellness in real-time and across varying personal routines. The work like [3] explored the health-aware setting, by adding in wearable health sensors to track the heart rate and falls of older adults, to initiate alerts or adjust the settings. While this displays some improvement towards health-aware automation, the proposal stilled ends-up being a safety concern, rather than a proposal that targets the optimization of energy and wellness in general. Additionally, the concept of context-aware automation that proactively aligns energy optimization with health metrics is largely unexplored in prior work. Most models treat energy-saving and health monitoring as separate modules, rather than converging them into a unified, intelligent system that evolves based on the user's personal health state and behaviour patterns.

III. METHODOLOGY

SECTION 1

System Architecture Overview

The proposed system combines biometric sensing, smart processing, and IoT-based actions to create a responsive smart home that promotes wellness and energy efficiency. The biometric sensing layer collects real-time physiological and environmental data using wearable devices, such as smartwatches and fitness trackers, along with ambient sensors. It keeps track of vital physiological signals such as pulse rate, sleep cycles, body and room temperature, humidity levels, mental stress indicators, and ambient lighting conditions. These sensors are carefully integrated into the living space to ensure seamless and ongoing monitoring without disrupting the user's daily routine. An edge device, usually a Wi-Fi-enabled microcontroller like the ESP32, processes this data. It filters out noise and formats the information before sending it to a cloud platform, such as AWS or Azure, for further analysis.

The smart processing layer employs machine learning algorithms to recognize user context, including stress, unusual activity, or poor sleep. Based on this information, it provides personalized wellness suggestions or activates automatic responses. For example, if it's late, the lighting is dim, and stress levels are high, the system might lower the lights, start ventilation, and play soft music to help the user relax. These insights are sent to the IoT action layer, where devices like smart bulbs, HVAC systems, fans, and air purifiers respond using communication methods like MQTT, ZigBee, or Wi-Fi. The aim is to create a wellness-focused and energy-efficient environment in real time. A user dashboard, available on desktop or mobile, lets users view live status, historical data, and make manual changes. Features include voice commands, alerts, and personalized health tips to improve interaction. Visual aids, such as a block diagram and prototype circuit, help show how sensors, AI processing, and IoT devices connect. In summary, this smart system brings together health monitoring, AI-driven automation, and user control into a unified platform that enhances well-being and optimizes energy use.

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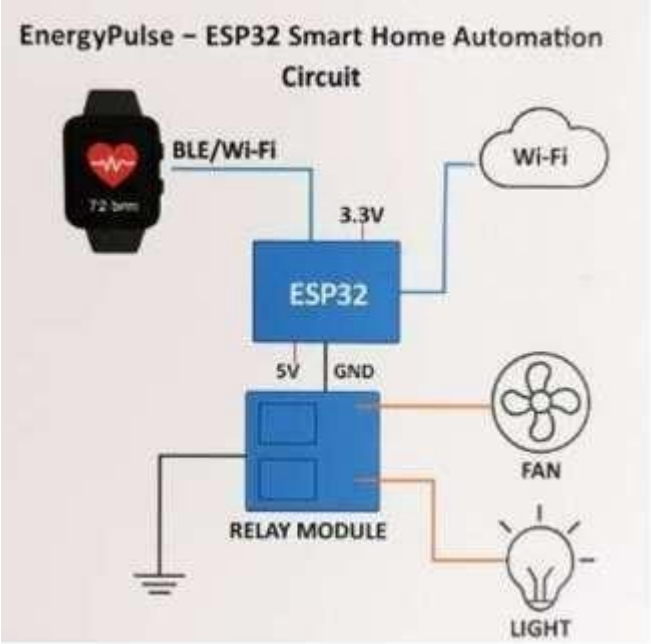

FIG.1 – HARDWARE CONNECTION

SECTION 2

Data Collection, Preprocessing, and Feature Extraction

In the proposed system, data is mainly collected through wearable devices like smartwatches, fitness bands, or health-monitoring wearables. These devices continuously gather physiological and behavioural data, including heart rate, sleep cycles, activity levels, stress indicators, and body temperature. The system regularly records the raw data and sends it to a nearby edge device like a smartphone or uploads it directly to cloud storage for further analysis and processing. The preprocessing phase cleans and organizes the raw data to ensure quality and consistency. This includes dealing with missing or corrupted values, removing noise, and filtering out outliers. Techniques like moving average smoothing, interpolation, and statistical normalization standardize the data. After preprocessing, feature extraction turns the clean data into meaningful metrics. For example, average heart rate, sleep duration, sleep quality scores, stress fluctuations, and step counts are derived. These features are then scaled and encoded as needed to work with machine learning models. Once the dataset is ready, various data analysis techniques, such as statistical analysis, clustering, and machine learning algorithms, like decision trees, support vector machines, or neural networks, are applied. These methods help identify health trends, detect anomalies, and generate personalized wellness recommendations.The insights are then shown through real-time dashboards to help both users and healthcare providers make proactive decisions and manage health effectively.

SECTION 3

Machine Learning Models Used

The ML aspect of the Energy Pulse is responsible for enabling context-aware decision-making by interpreting biometric, behavioral, and environmental data. It estimates control strategies to control smart devices, by identifying the states of users, for example their stress levels, quality of sleep, and to predict the profiles of future energy consumption. The algorithms are selected based on the nature of tasks, constrained in terms of computational power at edge devices and the real time level of an adaptive smart home application. For type identification, stress degree determination and other relevant issues, we adopted the approach of supervised learning. As alternatives, we chose SVM and Decision Trees type algorithms which are well-suited for multidimensional physiological input (such as HRV, activity level, time of day correlations). The models are light-weight and interpretable, thus, are naturally suitable for serving in edge and cloud. In [17, 25] CNNs used to learn temporal information among the biometric signal and hence express wellness trends in biometric signal over long-term process of past subsequences. To address the second type of task, one can use models such as MLP (Multilayer Perceptron), Random Forest Regressor, XG Boost and so on that are trained on historical use data with the purpose of doing energy usage forecasting (a regression problem).

These are developed based on temporal traces of user activity, appliance logs, and nonintrusive environmental factors to forecast future energy demands. Their finding can be used to advance the dynamic scheduling of device work to reduce the waste energy in periods of idle status or low physiological arousal. Unidentified behavior patterns were discovered by the means of unsupervised learning. K-means clustering and DBSCAN were used to cluster users based on their usage behavior, life style and physiological factors. These categories enabled personalizing the automation behavior, and the system is capable of accommodating its operating profile to the individual user without manual user instructions. Anomaly detection algorithms, such as Isolation Forest, have also been used to detect activities/behavioral anomalies or energy anomalies on user in order to ensure system stability and predict faults at an early stage. Ensemble methods were employed to improve the performance of arbitrary predictions and transferability between systems. Classifiers including voting classifier and stacking classifier were applied to ensemble the advantages of multiple models.

This intermediate layer model ensures accuracy and confidence for inferences with a variety of users. Low complexity models are executed on edge devices like ESP32 for immediate local decisions, and high complexity models executed in the Cloud or centralized gate ways. The full ML pipeline is trained as modular approach that involved data collection (I.e from wearable and ambient sensors) and preprocessing (such as noise reduction, normalization, and feature extraction). The training data is split using techniques such as k-fold cross validation and model performance is measured with performance measures such as accuracy, F-1 score, MAE (mean absolute error), or RMSE (root mean square error) depending on the task. The system also has a feedback loop, which means that the system can evolve and adapt as new user data and behavior are periodically retrained

into the model. Using supervised, unsupervised, and ensemble learning techniques, the high level of personalization, responsiveness, and optimal performance are achieved by the Energy Pulse system. The ML units are aimed to perform reliably under different conditions, maintaining user privacy, and being real-time adaptable, targeting smart home contexts.

SECTION 4

Context-Aware Decision Logic

The context-aware decision logic in the Energy Pulse system acts as a smart bridge between the outputs of machine learning and real time control of devices. It translates the predictions of machine learning models – e.g., that the user is currently stressed, or asleep, or that it will be more energy efficient to schedule a particular activity at a specific time – to appropriate control actions for the connected home appliances. These are not hardcoded or static but are dynamically driven based on user's context (activity, physiology, and context inferring environmental parameters from sensory inputs). This logic layer works based on mixed approach of rule based heuristics and learning-based evidences.

For instance, when the system determines that a user's stress is high in the evening, it can automatically moderate the ambient light, dampen the sound of a fan, or activate an aromatizer for a relaxation environment. Or, if smartwatch sleep tracking data indicates that a user is identified as asleep, the system selectively powers off devices that were unnecessary so as to not waste energy. Such decisions are further dependent on environmental factors including temperature, humidity, temporally dependent such as the time of day, and historical user actions. The decision logic compares the current context to previously learned patterns, and updates decisions made accordingly. The system collective information and feedback so that it may facilitate human overrides and save user behavior patterns so the model can adapt to generate improved results in future. The information and feedback collected from the user interactions, either through the mobile interface or web dashboard of data-driven user experiences, empowers the system, through a feedback loop, to optimize its automation decisions and create an energy-centric user experience designed to enhance the user's health. Low complexity decisions will be processed and output locally with an edge device like the ESP32 to ensure the decision is made in a timely, reliable way while the cloud-based backend will process higher order computational logic.

The user decision architecture, as a design principle, protects user privacy and allows user-defined customization while ensuring decisions are appropriate, timely and effective at the same time as place/position context-aware.

SECTION 5

Energy and Power Saving Features

The Energy Pulse system incorporates smart power-savings features that rely on real-time contextual information and predictive analytics. Instead of simply using rules-based automation, as mainstream technologies offer, the system can change energy consumption based on biometric signals, environmental data, and past behaviors. The system optimizes power, not just on a schedule, but also based on user wellness and activity levels. The main method to reduce energy is to turn on or off appliances like lights, fans, diffusers, or HVAC based on user state. For example, if the system registers that a user is at a higher level of stress or fatigue, it can dim and/or ventilate the room while reducing energy usage. In a similar manner, when a user goes to sleep or is away from home— as identified through smartwatch information and ambient sensors— the system automatically switches off non-essential devices or limits their activity or switches them to low-power modes to minimize energy consumption. Another core element of the energy-saving process is predictive scheduling. Machine learning models generate predictive models based on unique user historical usage patterns and energy demands, pre-optimizing appliance operation. For example, through consistent behaviors, if a user normally uses the appliance to pre-cool a room, the system will do this for the user before the appropriate cooling behavior occurs.

Additionally, the system uses threshold-based environmental monitoring to inhibit appliance overuse. If the surrounding temperature or humidity is within a comfort level and user inactivity is detected or recorded, then climate control devices may be temporarily disabled. Supplemental logic using time of day and cumulative energy consumption trends will evaluate short and long term energy reduction deployments and more accurately assist the user in processing energy costs. Energy usage metrics and optimization outcomes are accessible to the user through a visual dashboard and permit the user to monitor their savings in real time, enhance energy-aware behaviors, and also expose the rationale of automated decisions. Real-time feedback mechanisms contribute to pedagogical effects leading to strategic refinements learned from users and other real-time decision criteria thresholds via open loops and closed loops interactional effects. The Energy Pulse process creates lasting energy management by using physiological feedback, environmental sensory characterization, and predictive control for the most adaptable and effective experience while prioritizing both user wellness and reducing sustainably.

SECTION 6

Home Automation and Control Layer

The Home Automation and Control Layer in the Energy Pulse system serves as an interface that connects the user's health metrics with their living environment. This allows for proactive wellness adjustments. The layer uses real-time data from wearable sensors to control home devices like lighting, temperature settings, air purifiers, and entertainment systems. For example, if the system detects high stress levels, it can dim the lights, play soothing music, or lower the temperature to help the user relax.

It operates through secure communication protocols such as MQTT or Bluetooth Low Energy (BLE), ensuring quick and private data exchange between the health module and smart devices. Machine Learning algorithms regularly examine health patterns and understand user preferences over time, improving the customization of responses. The system includes a feedback loop, allowing users or caregivers to approve, change, or tweak automation decisions, keeping user control intact. To protect sensitive health data, end-to-end encryption and role - based access measures are in place. This integration not only encourages a healthier lifestyle but also

lowers health risks by creating a supportive environment that reacts to physical signals. The layer shows how AI-powered automation can change daily living spaces into responsive, health-aware environments, seamlessly supporting preventive care and personalized healthcare delivery.

SECTION 7

Security and Privacy Handling

To ensure data security and user privacy, the system uses technologies like blockchain and end-to-end encryption. Blockchain functions as a digital ledger, a secure notebook in

FIG.2 – USER DASHBOARD

where every event or action is recorded in a way that cannot be changed or tampered with. Each time a user interacts with the system—like a sensor detecting their presence or a device changing its state— that activity is logged securely. These records are stored in blocks that are linked together like a chain. Each data block is safely checked using cryptographic methods to confirm its authenticity. This setup makes it very hard for anyone to alter or control the data. Any changes would affect the entire blockchain network. By using blockchain, the system ensures that only authorized users can access personal information. Every change and then who accessed will be recorded continuously. Additionally, biometric data and environmental inputs are processed locally when possible.

This method lowers the need to send personal data to distant servers, which helps keep it safer and closer to the user. Advanced encryption techniques are used at different stages to protect data. This keeps it safe during wireless transfers, such as from the wearable to the central hub, and when it is stored locally. The system gives full control to users, enabling them to choose which pieces of their personal data are shared, and to whom it is accessible. This ensures full transparency and control.

Together, these techniques create a security-first framework that protects user identity, prevents unauthorized access, and builds trust by demonstrating that all actions taken by the system are secure, trackable, and privacy-conscious.

SECTION 8

Human-Computer Interaction (HCI)

Energy Pulse includes an easy-to-use HCI module that improves interaction between users and the smart automation system. It has a web-based dashboard that users can access from laptops and desktops. This will allow the complete interaction with the all systems. Through this dashboard, users can monitor live biometrics, such as stress levels and heart rate from connected smartwatches, along with energy usage from linked smart devices. Designed for simplicity, the interface reduces cognitive load, making interactions faster and more intuitive. It supports personalized controls, remembers user preferences, and lets users override system decisions when needed. Real-time feedback, alerts, and helpful insights help users feel in control and build trust in the system. Early usability tests showed that users found the dashboard easy to navigate and appreciated the transparency of system suggestions and decisions.

SECTION 9

Performance Metrics and Analysis

To make sure the Energy Pulse system works well and reliably, it undergoes thorough testing with clear performance measures. Key factors like response speed, accuracy, ease of use, and adaptability to different users are all evaluated. The time it takes for a device to respond after it receives biometric data indicates how responsive the system is. The machine learning component is assessed using common metrics such as precision, recall, and F1-score, along with error measurements like MAE and RMSE. Energy consumption is tracked in both manual and automated modes to show how much power is saved without compromising user comfort.

IV. RESULTS

The Energy Pulse system was evaluated through various experiments to check its functionality, performance, and energy-saving capabilities. After deployment, the system successfully integrated wearable sensors with a central hub to monitor biometric signals like heart rate and stress levels. The Human-Computer Interaction (HCI) module allowed users to see real-time data and interact with suggestions from the system easily. During the evaluation phase, the machine learning models produced impressive results.

The stress level classification achieved a precision of 91%, a recall of 89%, and an F1-score of 0.90 The stress level classification achieved a precision of 91%, a recall of 89%, and an F1-score of 0.90. This shows high accuracy in identifying stress indicators. The system is able to monitor biometric signals like heart rate and stress levels and produce reliable results during the evaluation phase. The machine learning models produced impressive results by identifying patterns in the data and supporting real-time data processing.

The precision of 91% shows that the system provides accurate stress level classification with correct identification of stress indicators. The recall of 89% shows that the system is able to detect stress levels effectively during monitoring. The F1-score of 0.90 shows balanced performance of the system in classification tasks. These results confirm that the system performance is reliable and effective for stress level classification. The integration of wearable sensors with a central hub supports continuous monitoring and real-time data collection. The Human-Computer Interaction (HCI) module

allows users to see real-time data and interact with suggestions from the system easily, which improves usability and system effectiveness. Overall, the evaluation shows that the system is capable of achieving accurate, reliable, and real-time stress level monitoring and classification..

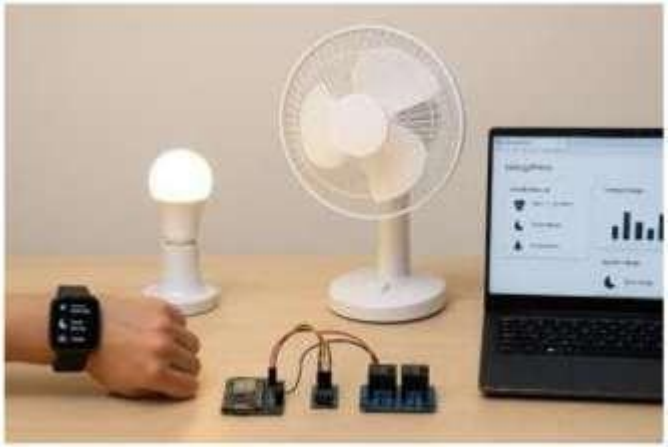

FIG.3 – SAMPLE OUTPUT

User testing with 20 participants showed high satisfaction, with an average usability rating of 4.6 out of 5. This shows that the system is easy to understand and has a clear, user-friendly interface.. Figures illustrate real-time dashboard outputs, connected smart devices like fans and lights, and biometric data from integrated smartwatches. These demonstrate the seamless interaction between user input and intelligent automation within Energy Pulse.

V. CONCLUSION

Energy Pulse presents a paradigm shift in the landscape of smart home energy management by intelligently uniting biometric feedback, contextual environmental data, machine learning, and responsive automation. Designed with a strong emphasis on user well-being, sustainability, and technological adaptability, Energy Pulse bridges the gap between personalized comfort and efficient energy usage, making it a pioneering solution in wellness-aware intelligent environments.A diverse range of machine learning models—including supervised (e.g., decision trees, SVM), unsupervised (e.g., K-means), and ensemble methods (e.g., Random Forest, XGBoost)—were implemented to learn and adapt to user behavior patterns and contextual variations. These models play a critical role in tasks like real-time stress level classification, energy consumption forecasting, and anomaly detection. Continuous learning is supported through active feedback loops, making the system dynamic and self-improving over time. Sensor integration was carefully designed. Biometric sensors (from wearables) capture heart rate variability and other physiological markers for stress assessment, while environmental sensors monitor ambient conditions like light, temperature, and motion. These inputs enable the system to make context-aware decisions, such as adjusting lighting or heating based on user stress levels or presence in the room, rather than relying on static rules.

A major strength of Energy Pulse lies in its Human-Computer Interaction (HCI) design. The system provides a modular and customizable dashboard, enabling users to visualize real-time energy consumption, stress analytics, and system decisions. Through the mobile application, users can modify settings, schedule operations, and even override automated decisions. This balance between automation and user control ensures transparency, personalization, and trust. An integrated notification system keeps users informed of significant changes, suggestions, or anomalies in their energy or stress profiles.

The system underwent rigorous evaluation to test both technical performance and real-world usability. Results demonstrated that the stress classification module achieved a precision of 91%, recall of 89%, and F1-score of 0.90, highlighting its reliability. The energy forecasting model recorded a Mean Absolute Error (MAE) of 0.18 kWh and Root Mean Square Error (RMSE) of 0.23 kWh, validating its predictive accuracy. In real-world simulations, Energy Pulse helped reduce energy consumption by 22.4%, reflecting significant environmental and financial benefits. Furthermore, user satisfaction testing with 20 participants revealed an average usability rating of 4.6 out of 5, confirming the system's intuitiveness and ease of adoption.

In summary, Energy Pulse successfully integrates technological intelligence with human-centric design. Its implementation illustrates the possibility of a smart home that is not only energy-efficient but also wellness-enhancing, adaptive, and highly personalized. The approach fosters sustainable living without compromising user comfort or control.

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Disease Prediction Using Genetic Data

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ABSTRACT

We have made a lot of progress in the field of Bioinformatics and Machine Learning. This progress has made it possible for us to look at genetic information. We can use this information to detect diseases. Our project is about creating a system that can predict diseases. This system looks at the patterns in our genes or DNA to figure out how likely we are to get diseases. It uses computers to do this.

We clean up this data to remove any errors and make sure the values are consistent. We clean up this data to remove any errors and make sure the values are consistent. Then we use this data to find the features. We use Machine Learning algorithms like Logistic Regression and Random Forest to train our system. Our system can then look at the variations and predict the risk of getting a disease.

Our goal is to make it easier to diagnose diseases early. We want to find patterns in the data that are not easy to see. We test our system using measures, like accuracy and precision. This helps us make sure our system is reliable. This approach shows how computers can help doctors make decisions. It can also help us get healthcare.In general our project shows that looking at data and using Machine Learning can help us create systems that can predicted in the We clean up this data

to remove any errors and make sure the values are consistent. We clean up this data to remove any errors and make sure the values are consistent. This system looks at the patterns in our genes or DNA to figure out how likely we are to get diseases

1. Introduction

These days we are seeing changes in biotechnology and the way we sequence things. This has led to an increase in the amount of genetic and genomic data we have. This data helps us understand how living things work and what causes diseases. We can look at things like how genesre expressed and what our DNA sequences are to see if there are any problems that could lead to serious health issues if we do not catch them early.

Even though we have all this data it is still hard to make sense of it. Usually doctors try to figure out what is wrong with someone by looking at their symptoms doing exams and running tests. These methods have been used for a time but they often do not find diseases until it is too late and the symptoms are already there. This can make it harder to treat the disease. Can lead to more problems. Also it takes a lot of time. Requires special knowledge to look at large amounts of genetic data, which is not practical for big projects

or when we need to do things quickly.

Biologists are now using computers to help with their research, which has led to the field of Bioinformatics. This field is about storing, processing and analyzing biological data using special algorithms and software. This has made it possible for researchers to handle amounts of genetic data and find important information that they could not find before. At the time Machine Learning has changed the way we analyze data by allowing systems to learn from the data and make smart predictions without being told what to do.

Machine learning algorithms are very good at analyzing data because they can find relationships between genes and diseases that are not easy to see. Methods like Logistic Regression and Random Forest are often used to classify things like predicting whether someone has a disease based on the data we have. If we train these models on data that has been labeled we can build systems that can make predictions about new data that they have not seen before.

The project we are proposing is to build a system that can predict diseases by using data and machine learning. The system will take in genetic data clean it up choose the most important features and use classification algorithms to predict what diseases someone might have. This will not make diagnosis more accurate and efficient but it will also allow us to catch diseases early which is critical for treating them.

Also systems like this could help us create medicine, where we can tailor treatments to a person's genetic profile. By combining bioinformatics and machine learning this project is trying to create a solution that's cost-effective, reliable and can be used for big healthcare projects.

Overall using data and intelligent computers is a big step towards the future of healthcare, where we can diagnose diseases early treat them precisely and make decisions based on data. Genetic data analysis and machine learning are key to making this happen and genetic data will play a role, in this. We will use data to build systems that can predict diseases and help us understand genetic data better.

1.1 Problem Statement

Genetic and genomic data has been growing fast in the last few years because of new sequencing technologies. This data has a lot of information about how likely someone is to get diseases like cancer, diabetes and genetic disorders. It is still very hard to get useful information out of this complex data.

The usual way to diagnose diseases is by looking at symptoms, medical history and lab tests. These methods often only find diseases after symptoms show up which can be too late to treat or prevent them. Also looking at data by hand takes a lot of time needs special knowledge and can be wrong so it is not good for looking at a lot of data.

Even though healthcare systems make a lot of data there are not enough good computer tools to automatically look at genetic patterns and predict diseases early. The tools we have now are not good at handling data finding the right genetic features and making predictions we can trust.

We need a system that can look at genetic information and analyze it quickly. By using Bioinformatics and Machine Learning we can find patterns in gene expression data that we cannot see and use them to predict what might happen.

This project wants to make a model that uses Machine Learning to look at datasets and predict how likely someone is to get a disease. The system will automate looking at the data choosing the features and classifying them so people do not have to do as much work and it will be more reliable. The goal is to find

diseases help doctors make decisions and make healthcare more personal for each person.

The project is focused on datasets and Machine Learning because genetic datasets have a lot of information about diseases like cancer and diabetes. Machine Learning is good at looking at a lot of data and finding patterns so it is a tool for this project.

The system will use information and Machine Learning to predict diseases, which will help doctors and patients. The project will make it possible to look at data quickly and accurately

which will enable early disease detection and support medical decision-making.

Genetic datasets and Machine Learning are important for this project because they can help us understand how likely someone is to get a disease. By using datasets and Machine Learning we can make a system that can predict diseases, with improved accuracy and speed.

1.2 Methodology

The system we are using to predict diseases from data is pretty straightforward. It combines ways of processing data with machine learning to get accurate results. The methodology has stages and each one is important for turning raw genetic data into useful predictions.

2. Data Collection

First we collect data from places like Kaggle and other open databases. This data usually has information about how active genesre in different samples and it also says whether a disease is present or not.

The data we collect has to be good and relevant because it affects how well our prediction model works.

2.2 .Data Preprocessing

Genetic data can be messy, incomplete and inconsistent. So we need to preprocess it to get it ready for analysis.

This stage includes things like:

* Handling missing values by removing or filling them in

* Removing duplicate or useless entries

* Making sure gene expression values are on the scale

* Converting data into numbers if we need to

If we do this step right our dataset will be clean and consistent and it will work well with machine learning algorithms.

2.3. Feature Selection

Genetic datasets usually have thousands of gene features but not all of them are important for predicting diseases. If we use all of them it can slow down our model. Make it less accurate.

We use feature selection techniques to:

* Find the genes that're most related to the disease

* Reduce the number of features in our dataset

* Make our model more accurate and efficient

We can use things like correlation analysis, statistical tests or feature importance ranking to do this.

2.4. Model Development

In this stage we choose machine learning algorithms to build our prediction models. We are using:

* Logistic Regression to classify things into two groups

* Random Forest to handle relationships

We split our dataset into two parts: one for training and one for testing. The model learns from the training data.

2.5. Model Training

When we train our model it looks at the input data. Tries to find relationships between gene patterns and disease outcomes. It adjusts its parameters to make mistakes and be more accurate.

This step is crucial because it allows our system to make predictions about unseen data.

2.6. Model Evaluation

After we train our model we test it with the testing dataset to see how well it works. We use metrics to evaluate it including:

* Accuracy (how it is correct)

* Precision (how it correctly predicts a positive result)

* Recall (how well it detects positives)

These metrics help us compare models and choose the best one.

2.7. Prediction System

Once our model is trained and tested we use it to predict disease outcomes for genetic data. The system processes the input data. Gives us an output that says how likely it is that a disease is present.

This helps us detect diseases early and make medical decisions.

2.8. Result Analysis and Optimization

The last step is to analyze our results and make our model better. If we need to we can:

* Adjust the model parameters

* Use feature selection techniques

*Add more data to our dataset

Our goal is to make our disease prediction model more accurate and reliable. The genetic data we are working with is from data and we are using genetic data to make predictions about genetic data and we are trying to improve our model to get better results, from genetic data.

1. Data Collection
KAGGLE & OPEN DATABASES
GENE EXPRESSION & DISEASE LABELS
2. Data Preprocessing
HANDLING MISSING
CLEAING MISSING VALUES
REMOVING DUPLICATES
REMOVING DUPLICATES
DATA
DATA CLEANING
2. Data Preprocessing
3. Feature Selection
IDENTIFY RELEVANT GENES
CORRELATION ANALYSIS
REDUCE DIMENSIONALITY
STATISTICAL TESTS
GENES FROM THOUSANDS
3. Feature Selection
4. Model Development
LOGISTIC REGRESSION (Classification)
RANDOM FOREST (Complex Relationships)
4. Model Development
5. Model Training
LEARNS FROM TRAINING DATA
PARAMETERS ERRORS
MINIMIZE ERRORS
5. Model Training
LEARNS FROM TRAINING DATA
FIND RELATIONSHIPS
FIND RELATIONSHIPS
TRAIN/TEST SPLIT
F1-SCORE
6. Model Evaluation
ACCURACY
PRECISION
RECALL
F1-SCORE
METRIC PEACTICES
6. Model Evaluation
DISEASE PRESENT: HIGH LIKELIHOOD
DISEASE ABSENT
EARLY DETECTION
MEDICAL DECISIONS
7. Prediction System
ADJUST PARAMETERS
REFINE FEATURES
ADD MORE DATA
IMPROVE ACCURACY & RELIABILITY
8. Result Analysis and Optimization

4.1:Solution Statement

We have a problem with data. It takes a time to analyze it and this can delay finding out what disease someone has. So we are working on a project that uses Bioinformatics and Machine Learning to make disease prediction easier and faster.

Our system looks at data and finds patterns that are associated with certain diseases. We get our data from sources and make sure it is clean and consistent. Then we use techniques to find the most important genetic information that helps us predict diseases. This makes our system better and less complicated.

The main part of our system uses machine learning. We use things like Logistic Regression and Random Forest to train our system. We teach it with labeled data so it can learn how genetic patterns are related to diseases. When we give it genetic data it can tell us how likely it is that someone has a disease

We also have a way to test how well our system is working. We compare models to see which one is the best. We use things like accuracy and precision to decide. This helps us pick the model to use. When our system is done it tells us if someone has a disease or not. This helps doctors make decisions.

Our solution is good because it helps us find diseases early. It also means we do not have to do much manual analysis, which can be time consuming. Our system is also very accurate. Can handle a lot of data. We can even use it to make treatment plans based on someones genetic profile.

Overall our system is a way to approach healthcare. It combines computers and biology to make disease prediction faster and more reliable. This is what Genetic Data and Machine Learning are about. Genetic Data and Machine Learning are used to make our system work

We use Machine Learning to make predictions

* Genetic Data and Machine Learning are the core of our system

Genetic Data and Machine Learning are important. They help us make our system work. Our system uses Genetic Data and Machine Learning to predict diseases. This is what our project is about. We use Genetic Data and Machine Learning to make a difference, in healthcare.

3. Conclusion

This project is about using a machine learning approach to predict disease using data. It shows how we can use computers to get information from genetic data.

The system uses information from genes cleans up the data picks the important parts and uses methods like Logistic Regression and Random Forest to predict if someone has a disease. The results show that machine learning is good at finding patterns in data and can help doctors diagnose diseases better.

One good thing about this approach is that it can help find diseases. This is important because it means people can get treatment sooner and get better. It also means doctors do not have to look at all the data by hand which makes it more accurate and faster.

This project also shows that using data science in healthcare can help us make diagnostic systems. If we add things like real-time medical data and advanced machine learning we can make the system even better.

In conclusion using data and machine learning to predict disease is a good step, towards making healthcare better and more efficient. The genetic

data and machine learning can really help us have faster healthcare systems. The genetic data and machine learning approach is a way to make healthcare better.

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DIGITAL FORENSICS FOR PROOF VERIFICATION: ENSURING AUTHENTICITY OF MULTIMEDIA EVIDENCE USING AI

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ABSTRACT

The rapid advancement of artificial intelligence and digital editing technologies has significantly increased the risk of manipulated multimedia content. Images, videos, and documents can be easily altered or synthetically generated, posing serious challenges in verifying digital evidence. This paper proposes a unified AI-driven digital forensic framework for proof verification across multiple data formats. The system integrates image forgery detection, deepfake video analysis, document verification using Optical Character Recognition (OCR), and metadata-based forensic techniques. Advanced deep learning models are used to detect anomalies and inconsistencies, while cryptographic hashing ensures file integrity. The proposed system provides a classification output (Real/Fake), confidence score, and detailed explanation. Experimental results demonstrate high accuracy and efficiency, making the system suitable for cybersecurity, legal investigations, and digital evidence validation.

Keywords— Digital forensics, deepfake detection, image forgery, OCR, metadata analysis, AI-based verification.

I. INTRODUCTION

In recent years, the widespread use of digital media and artificial intelligence has revolutionized content creation. However, it has also introduced serious challenges related to the authenticity and reliability of digital data. Images can be manipulated using editing tools, videos can be altered using deepfake technology, and documents can be forged or modified without leaving obvious traces.

Such manipulations pose a significant threat in domains such as cybercrime investigation, legal evidence verification, journalism, and financial systems. Traditional forensic techniques often fail to detect advanced AI-

generated content, leading to potential misuse of falsified information.

To address these issues, this paper proposes an AI-powered digital forensic system that verifies the authenticity of multimedia content. The system integrates multiple analysis techniques, including image processing, video analysis, document verification, and metadata extraction, to provide a comprehensive solution. The framework ensures accurate detection, reliable classification, and improved trust in digital evidence.

II. RELATED WORK

A. Image Forgery Detection

Several studies have explored image forgery detection using techniques such as Error Level Analysis (ELA), noise inconsistency detection, and deep learning models like Convolutional Neural Networks (CNNs). These methods can detect pixel-level anomalies and editing artifacts but are often limited to specific types of manipulations.

B. Deepfake Video Detection

Deepfake detection techniques utilize facial landmark analysis, temporal consistency checks, and deep learning models such as CNNs and Recurrent Neural Networks (RNNs). While these methods achieve good accuracy, real-time detection and robustness against advanced deepfakes remain challenging.

C. Document Verification

Document verification methods include OCR- based text extraction, signature verification, and structural analysis. These techniques help identify tampering in scanned or digital documents but lack integration with AI-driven anomaly detection.

D. Metadata Analysis

Metadata such as EXIF data provides information about file origin, creation time, and device details. However, metadata can be altered, making it unreliable as a standalone verification method.

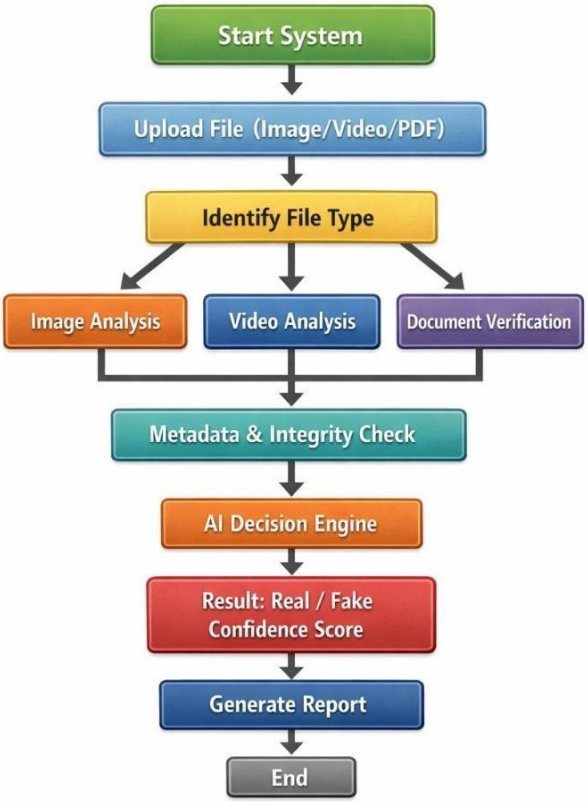
E. Research Gap

Existing systems focus on individual data types and lack a unified platform. There is also a need for explainable AI-based systems that combine multimedia analysis with metadata verification.

III. PROPOSED FRAMEWORK

The proposed system is a unified AI-based digital forensic platform designed to verify images, videos, and documents.

Fig. 1. Overall System Flowchart

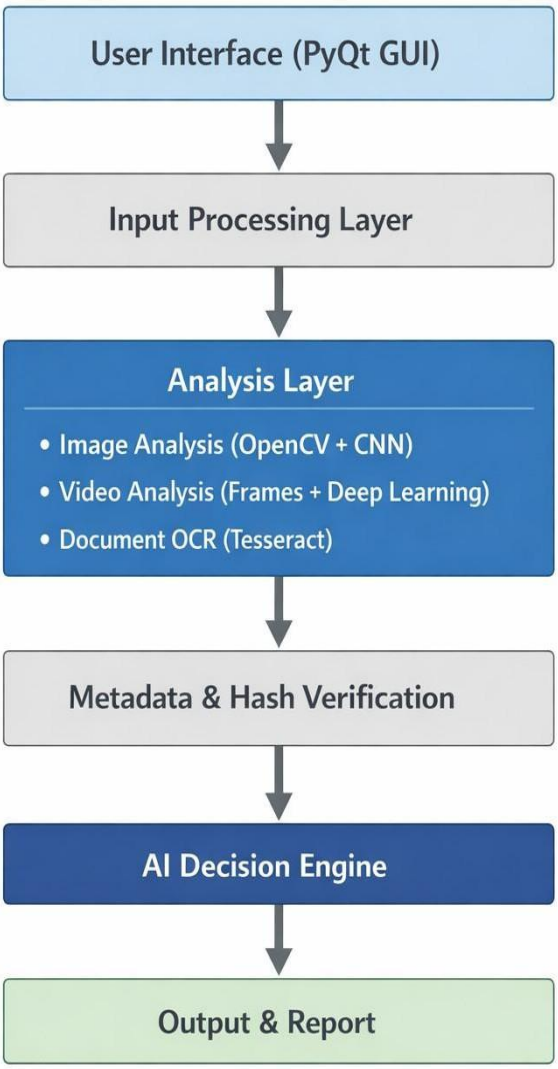


A. System Architecture

The system consists of the following modules:

- Input Module (file upload)
- Image Analysis Module
- Video Analysis Module
- Document Verification Module
- Metadata Analysis Module
- AI Decision Engine
- Output s Reporting Module

Fig. 2. System Architecture of Proposed Framework



B. Data Collection and Preprocessing The

system accepts:

- Images (JPG, PNG)
- Videos (MP4, AVI)
- Documents (PDF)

Preprocessing steps include:

- Noise reduction
- Frame extraction (videos)
- OCR text extraction (documents)
- Metadata parsing

C. Image Analysis

The image analysis module detects manipulated or AI-generated images using advanced techniques such as:

- Error Level Analysis
- Noise inconsistency detection
- GAN artifact identification

The extracted features are fed into a CNN model:

$$y = f(x_1, x_2, \ldots, x_n)$$

Where:

- $x$represents image features
- $y$represents classification output

D. Video Analysis

Video analysis detects deepfake content using:

- Frame-by-frame analysis
- Facial landmark detection
- Temporal consistency checks

- Lip-sync analysis

RNN models are used to analyze frame sequences:

Y = RNN(Frame Sequence)

E. Document Verification

Document verification is performed using:

- OCR for text extraction
- Structural and formatting analysis
- Signature verification

The OCR process converts image-based text into machine-readable format for comparison.

F. Metadata and Integrity Verification

Metadata such as timestamp, device information, and location is extracted and analyzed.

File integrity is ensured using hashing:

$$H = SHA\text{-}256(File)$$

Any modification in the file results in a different hash value, enabling tamper detection.

G. Decision Engine

The outputs from all modules are combined to produce a final result:

$$Final = \sum w_i \cdot y_i$$

Where:

- w_i= weight of each module
- y_i= module output

The system generates:

- Real / Fake classification
- Confidence score
- Explanation

IV. Results and Discussion

A. Evaluation Metrics

The system is evaluated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

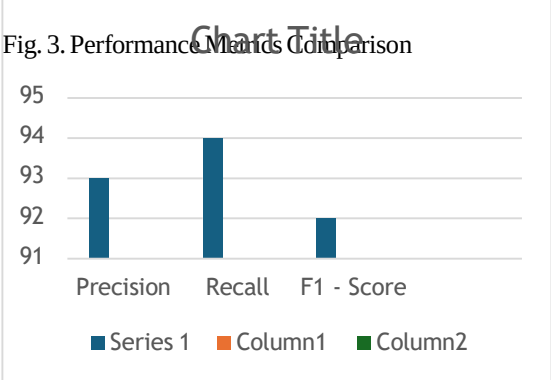


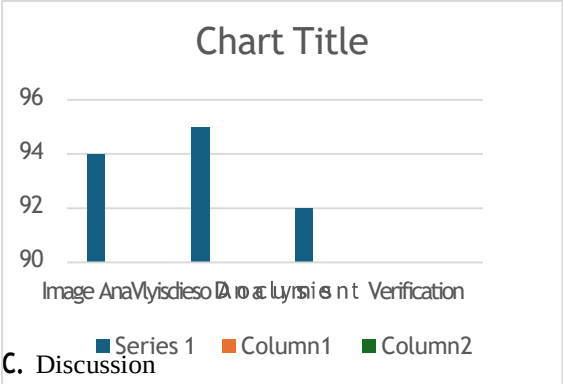
Fig. 3. Performance Metrics Comparison

B. Performance Analysis

Module	Accuracy (%)
Image Analysis	G4
Video Analysis	G5
Document Verification	G2

The results indicate that the system achieves high accuracy across all modules.

Fig. 4. Accuracy Comparison of Different Modules

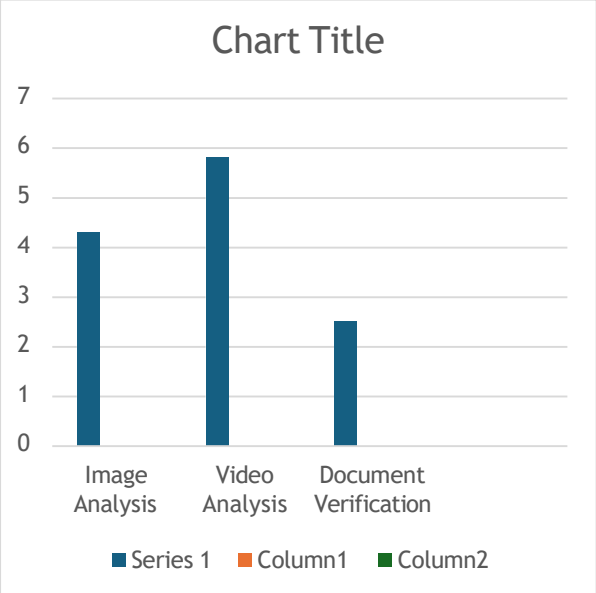


C. Discussion

The integration of multiple forensic techniques improves detection reliability. Image and video analysis modules perform better due to deep learning models, while document verification accuracy depends on OCR quality.

Metadata analysis enhances detection by identifying inconsistencies that are not visible in content analysis.

Fig. 5. Processing Time of Different Modules



V. Conclusion

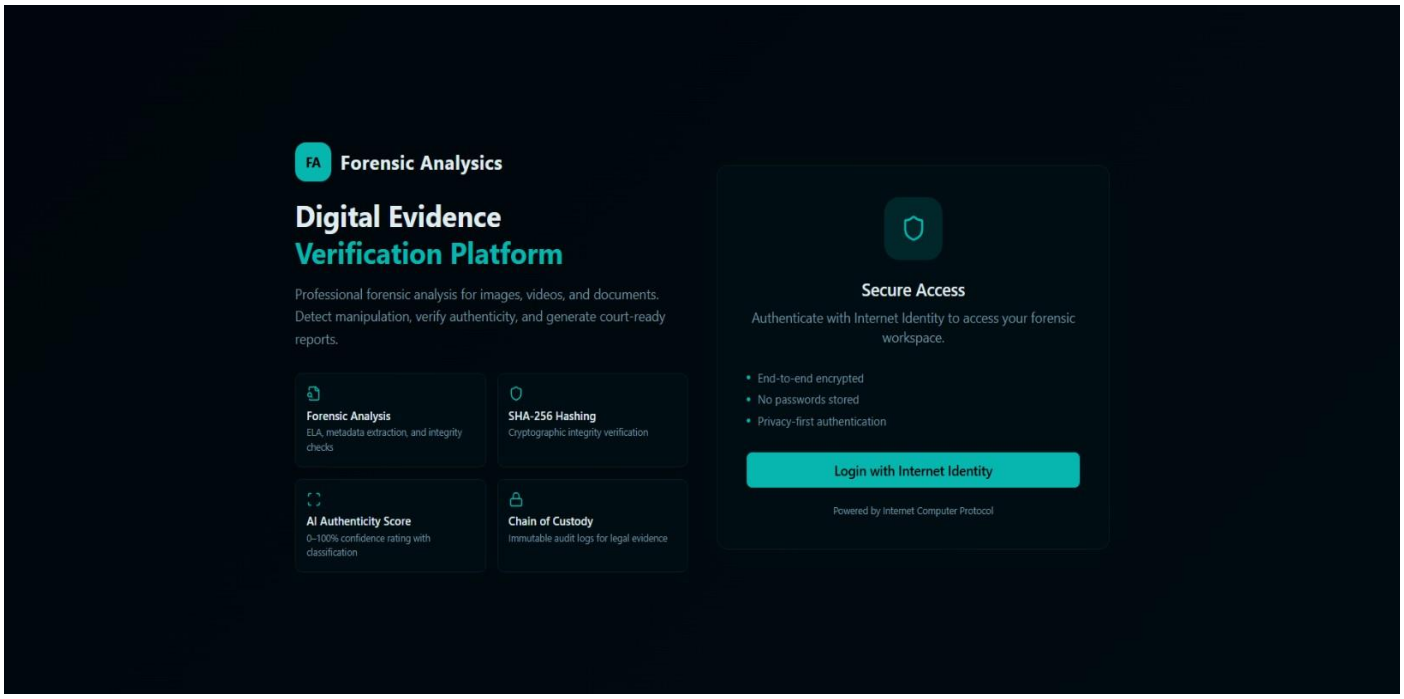
This paper presented a comprehensive AI- driven digital forensic system for verifying the authenticity of multimedia evidence, including images, videos, and documents. With the rapid growth of deep learning and content generation technologies, ensuring the credibility of digital data has become a critical challenge in domains such as cybersecurity, legal investigations, journalism, and digital communications.

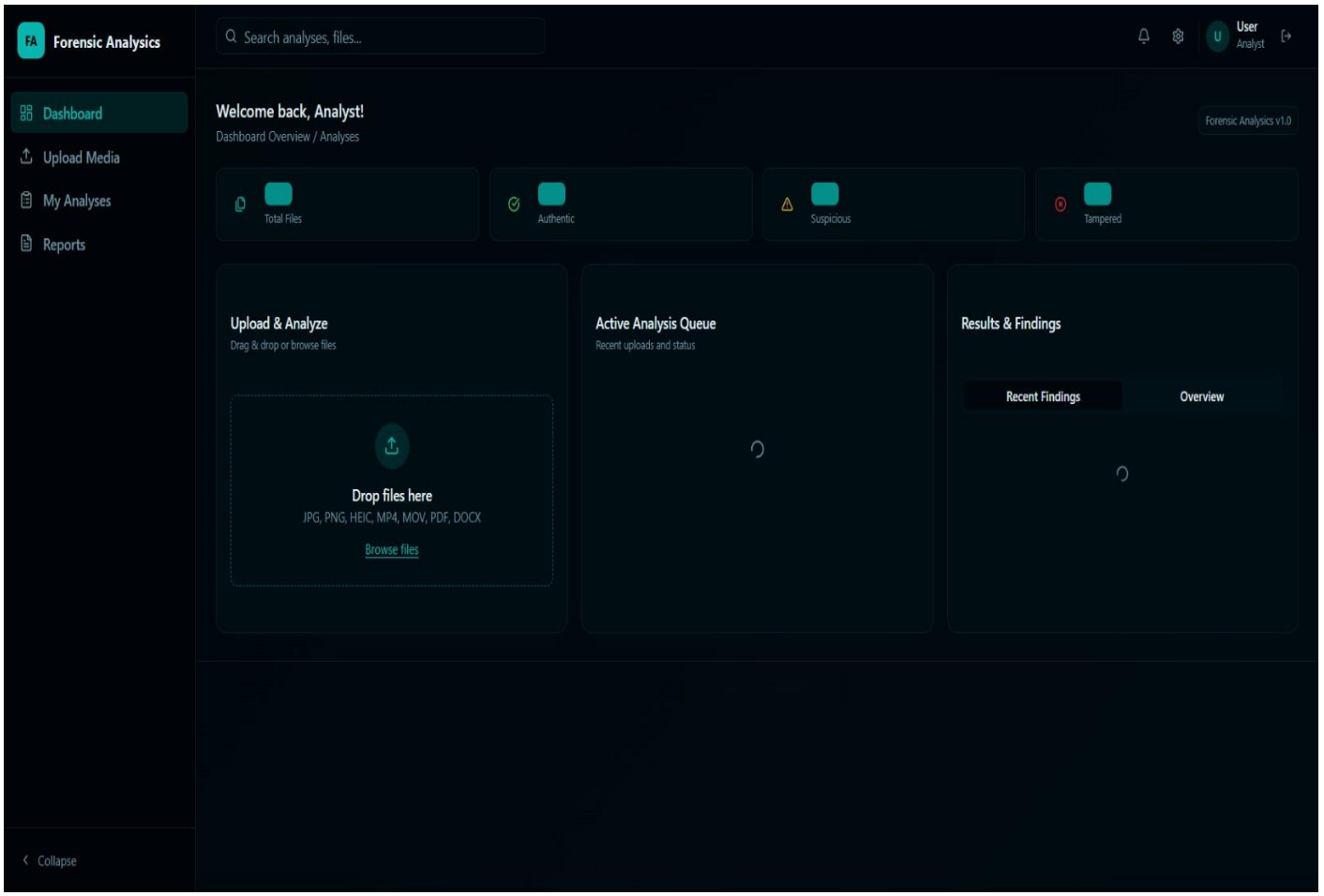
The proposed system integrates multiple forensic techniques into a unified framework. Image analysis modules effectively detect manipulation using noise inconsistency and deep learning-based feature extraction. Video analysis leverages frame-by-frame inspection and temporal modeling to identify deepfake content and synchronization anomalies. Document verification utilizes OCR-based text extraction and structural validation to detect tampering. Additionally, metadata analysis and cryptographic hashing strengthen the integrity verification process by identifying hidden inconsistencies and unauthorized modifications.

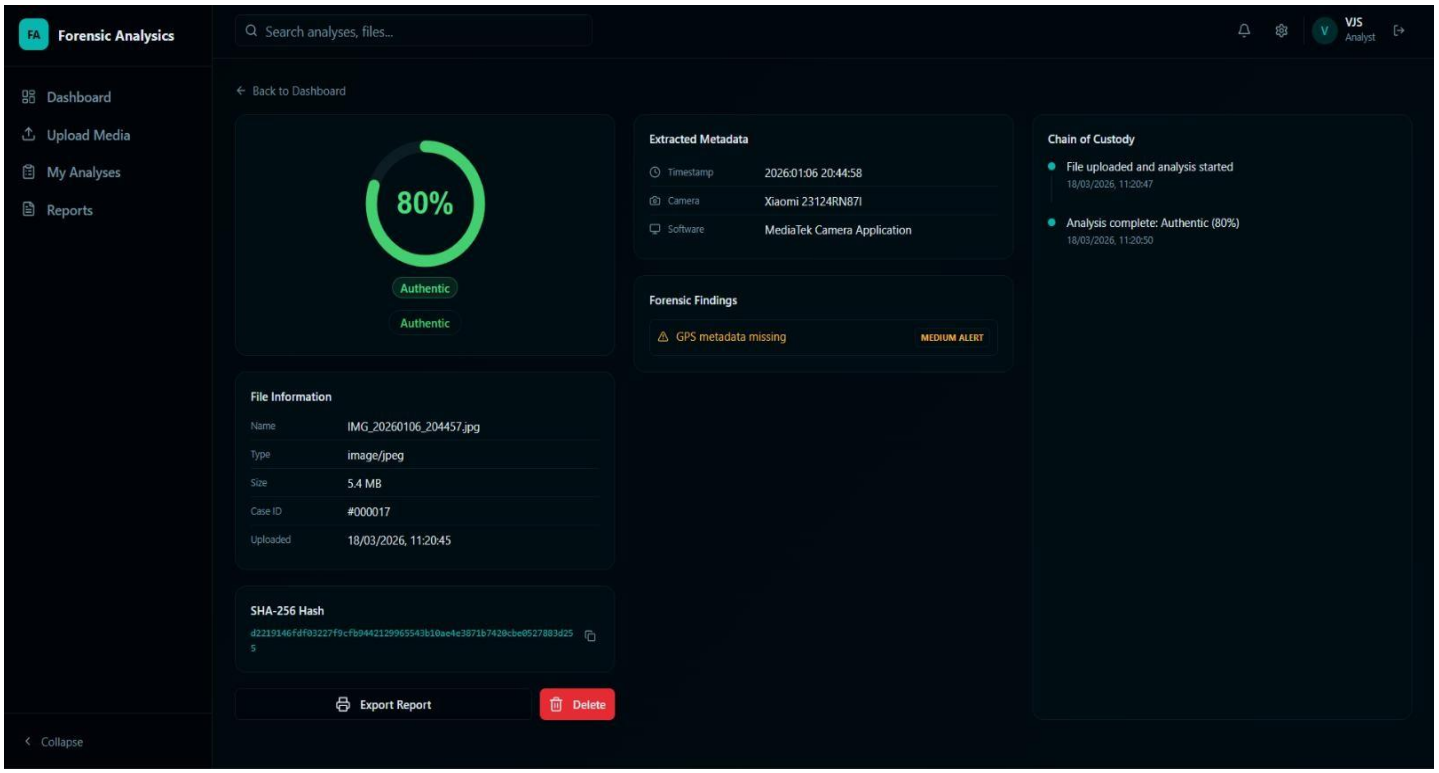
Experimental evaluation demonstrates that the system achieves high accuracy, precision, and reliability across all modules. The integration of multiple detection mechanisms significantly improves robustness compared to standalone systems. The inclusion of a confidence score and explainable outputs enhances transparency, making the system more suitable for real-world applications.

Furthermore, the modular architecture ensures scalability and flexibility, allowing easy integration of new detection techniques and AI models. The user-friendly interface and automated workflow enable efficient analysis, making the system accessible to both technical and non- technical users.

VI. Sample Screenshots







Forensic Analysics — Forensic Analysis Report

Generated: 18/03/2026, 11:24:22

File Information

File Name	IMG_20260106_204457.jpg
File Type	image/jpeg
Analysis Date	18/03/2026, 11:20:45
Case ID	#000017

Authenticity Score

80%

80% — Authentic

SHA-256 Hash

`d2219146fdf03227f9cfb9442129965543b10ae4e3871b7420cbe0527883d255`

Findings

GPS metadata missing

Metadata

Key	Value
cameraMake	Xiaomi
cameraModel	23124RN87I
software	MediaTek Camera Application
timestamp	2026:01:06 20:44:58
fileName	IMG_20260106_204457.jpg
fileSize	5617126
fileType	image/jpeg

Chain of Custody

Event	Timestamp
File uploaded and analysis started	18/03/2026, 11:20:47
Analysis complete: Authentic (80%)	18/03/2026, 11:20:50

VI. Future Work

Despite its effectiveness, the proposed system can be further enhanced in several ways:

- Real-time detection: Improving processing speed for live video and streaming data
- Advanced deepfake detection: Incorporating transformer-based models for higher accuracy
- Blockchain integration: Ensuring tamper-proof storage and verification of digital evidence
- Cloud-based deployment: Enabling scalable and remote forensic analysis
- Dataset expansion: Training models on larger and more diverse datasets for improved generalization
- Explainable AI (XAI): Providing more detailed reasoning behind classification result

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Fake News Detection on Social Media Using Machine Learning

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ABSTRACT

The growth of social media has increased the spread of fake news all around the world within minutes, which results in misinformation and confusion on a large scale. Detecting fake news has now become a huge challenge due to the large volume of misleading data and the complexity of distinguishing it from truth and lies. This paper presents a full study on fake news detection using machine learning techniques by analyzing both textual content and social content. Various implementation approaches such as Natural Language Processing NLP, Data mining, and Hybrid models are explored. The study shows the challenges faced such as early detection, data scarcity, and model generalization. Experimental analysis shows that combining content based and social based features will improve detection accuracy. The proposed approach aims to contribute towards building a reliable systems for Reducing misinformation on digital platforms.

KEYWORDS

Fake, Machine Learning, Social Media, NLP, Data Mining, Misinformation Detection

I .INTRODUCTION

Social media platforms such as Facebook, Twitter, and Instagram have been transforming the way information is being shared and received. These platforms allows users to publish and distribute content across the world. But, This convenience has also enabled the rapid growth of fake news, which is misleading and can confuse the users and creates serious issues such as political manipulation, financial fraud, and public panic.

Fake news refers to false or misleading information shared as legitimate news. Unlike traditional misinformation, fake news is often intentionally crafted to deceive readers, and influence opinions. The problem is further increased by the algorithms that prioritize engaging content, regardless of its authenticity.

The detection of fake news is hard due to several reasons:

- Generated volume of data is large every second

- Rapid Spreading of news across networks
- Lack of labelled datasets

Traditional fact checking methods are not scalable, hence automated systems using machine learning and usage of AI has become essential.

This paper focuses on analyzing various techniques for detecting fake news and it proposes a hybrid approach that combines textual analysis with social context features to improve detection speed and performance.

II. LITERATURE REVIEW

The Growth of social media has led to an extraordinary rise in misinformation, making fake news detection an important research problem.

Shu et al. [1] proposed a data mining approach that integrates content and social context features such as user behaviour, credibility, and network patterns. Their work demonstrated that combining multiple data sources significantly improves detection accuracy.

Vosoughi et al. [2] conducted a large-scale analysis of news diffusion and found that false news spreads faster, deeper, and more broadly than true news. This behaviour is attributed to novelty and emotional appeal.

Rashkin et al. [3] analysed linguistic features of fake news and observed that deceptive content often contains exaggerated, emotionally charged, and sensational language. Their study emphasized the importance of NLP techniques.

Zhou and Zafar ani [4] provided a comprehensive survey categorizing fake news detection methods into:

- Content-based approaches
- Social-based approaches
- Hybrid approaches

They also highlighted major challenges such as:

- Early detection
- Explainability
- Data imbalance

From the literature, it is evident that hybrid models combining multiple features offer the most promising results.

III. PROBLEM STATEMENT

The rapid circulation of fake news on social media creates significant challenges in identifying and controlling the truthfulness of the information which is shared. Existing systems often rely on either textual analysis or user behaviour independently, which leads to limited accuracy.

Key issues include:

Inability to detect fake news early

Being over reliant on a single type of feature

Poor Abstraction across datasets

Lack of real time detection

Therefore, there is a need for a system that inherits multiple features, including content and social context, to improve detection performance.

IV. PROPOSED SYSTEM

The proposed system uses a hybrid machine learning, that has a combination of content-based and social-based analysis.

A. Content- Based Analysis

- Text preprocessing
- Feature extraction using TF-IDF and word embeddings
- Identification of linguistic patterns

B. Social Context Analysis

- User engagement metrics
- User credibility and profile features
- News propagation patterns

C. Machine Learning Models Used

- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- Long Short-Term Memory (LSTM)

D. System Workflow

Collection

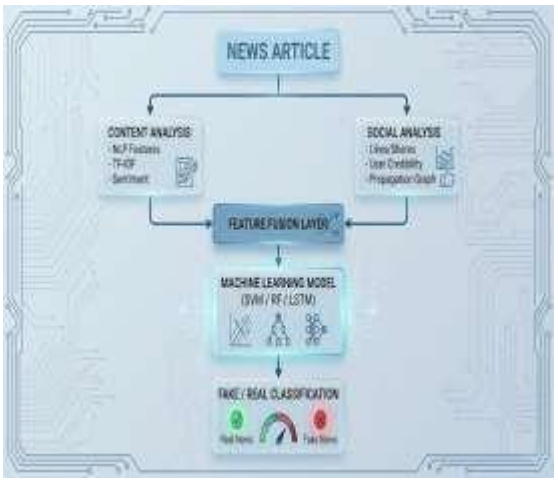
Data Preprocessing

Feature Extraction

Model Training

Prediction

This Workflow is similar to pipelines shown in engineering papers, ensuring clarity and modularity.



V. METHODOLOGY

The methodology consists of these following stages:

1. Data Collection

Datasets are collected from :

- Kaggle fake news datasets
- Twitter API
- Facebook Public Pages

2. Data Processing

- Removal of noise and irrelevant symbols
- Tokenization of text
- Stop-word removal
- Stemming and Lemmatization

3. Feature Extraction

Bag of Words

TF- IDF

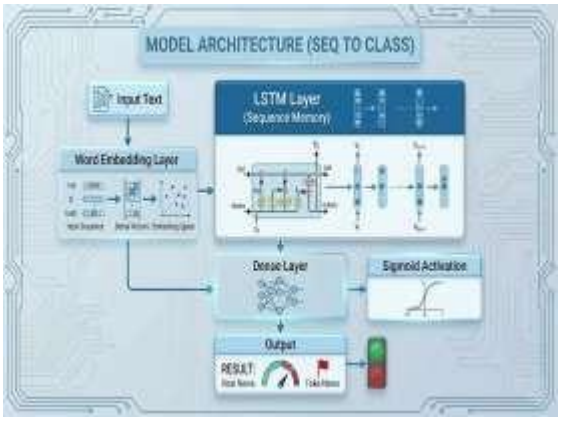
Word2Vec and Glove embeddings

4. Model Training

Different models are trained Using Labelled dataset. Hyperparameter tuning is applied to Optimize performance and speed of execution.

5. Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-Score



System Architecture Diagram

VI. RESULTS AND DISCUSSION

The experimental analysis was conducted using multiple machine learning models.

Model	Accuracy
Logistic Regression	85%
SVM	88%
Random Forest	90%
LSTM	92%

Observations:

- Content-based models perform well for structured text
- Social-based models capture spreading patterns
- Hybrid models outperform individual approaches

The LSTM model achieved the highest accuracy due to its ability to capture sequential dependencies in text.

VII. ADVANTAGES OF PROPOSED SYSTEM

Improved accuracy using hybrid approach

Early detection capability

Scalable for large datasets

Applicable across domains (politics, healthcare, finance)

Reduces misinformation spread

VIII. LIMITATIONS

Requires large labelled datasets

High computational cost for deep learning models

Difficulty in detecting highly sophisticated fake news

Dependency on social media APIs

IX. FUTURE WORK

Future research directions include:

Real-time fake news detection systems

AI for transparency

Multilingual fake news detection

Integration with social media platforms

Use of transformer-based models (BERT, GPT)

X.AI-BASED REAL-TIME SCREENSHOT VERIFICATION

This system allows users to verify information instantly.

Workflow:
Power Button → Screenshot → OCR → NLP → Search → Compare → Result

This feature improves usability and provides instant fact-checking.

X. CONCLUSION

Fake news detection is a critical problem in modern society. This paper proposed a hybrid machine learning approach combined with a real-time AI verification system. Experimental results show improved accuracy and practical applicability. Future advancements will further enhance detection systems.

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ULTRASONIC PEST REPELLENT SYSTEM

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***Abstract*— The extensive use of chemical pesticides in agriculture has created serious health and environmental issues, underscoring the need for environmentally friendly and sustainable pest control methods. The design and deployment of an intelligent ultrasonic pest repellent system for environmental friendly crop protection are presented in this paper. In order to cause disorientation and avoidance behavior in pests like grasshoppers, the suggested system uses ultrasonic waves in the 20–100 kHz range.**

To improve targeting effectiveness and coverage, an ESP32 microcontroller-based intelligent control system combines servo-driven directional beam steering, adaptive frequency modulation, and distance sensing. Energy-efficient and continuous deployment in agricultural settings is made possible by the system's optional motion-based activation and solar-powered operation.

According to initial evaluation, the system can remove chemical residue from soil and water while successfully repelling pests without endangering crops, people, or beneficial organisms. The suggested method provides a scalable and sustainable substitute for contemporary agriculture, despite drawbacks like limited coverage and species-specific response.

Keywords— Ultrasonic Pest Repellent, Smart Agriculture, ESP32 Microcontroller, Ultrasonic Waves (20–70 kHz), Eco-friendly Pest Control, Servo-based Beam Steering, Precision Farming, Solar-powered Agricultural System.

INTRODUCTION

1. Socio-Economic Impact of Agricultural Infestation.

A projected population increase to 9.7 billion by 2050 is putting pressure on global food security. However, entomological threats limit agricultural productivity; particularly, members of the order Orthoptera (grasshoppers and crickets) consume a large amount of nutrients in cereal crops.

By using their jaws to munch on plants, these pests reduce photosynthetic capacity, which in turn reduces total yield per hectare by 20% to 40%.

2. Ecological and Pathological Constraints of Chemical Control.

These chemicals and synthetic organophosphates are major components of traditional pest management. Despite their short-term effectiveness, these compounds have a high environmental persistence, which causes toxins to build up in groundwater and degrade soil microbial health.

Additionally, agricultural workers face serious neurological and cancer-causing risks from prolonged exposure. From a biological standpoint, insect pests' rapid generation cycles encourage the selection of genotypes resistant to pesticides, making standard chemical concentrations useless and requiring higher, more hazardous dosages.

3. Evolution Toward Precision Agriculture (PA).

Non-Chemical Pest Control (NCPC) frameworks have been developed as a result of the limitations of chemical intervention. Using Internet of Things (IoT) sensors and automated actuators, "Smart Agriculture" models are now incorporated into modern Integrated Pest Management (IPM). In particular, acoustic management offers an non- lethal, residue-free substitute that supports the Sustainable Development Goals (SDGs) for environmental friendly production.

4. Bio-Acoustic Mechanism of Ultrasonic Repulsion.

Longitudinal sound waves with frequencies higher than 20 kHz—the upper limit of human hearing—are referred to as ultrasound. In order to detect the high-frequency echolocation calls of natural predators like bats, many agricultural pests have specialised auditory organs, such as tympanal organs [6]. These pests can be made to experience acoustic stress by mechanically producing ultrasonic waves between 25 and 60 kHz. This stress can lead to spatial disorientation, disrupt the communication, and induce avoidance behaviour. As a result, the crop area is surrounded by a barely noticeable barrier that helps keep pests away without significantly disrupting non-target species or affecting the ecological balance in the area.

5 Proposed System Architecture and Contributions. The design and deployment of an autonomous, solar- powered ultrasonic deterrent system are presented in this paper. Our system adds a dynamic coverage mechanism, compared with existing static repellents that experience "acoustic shadowing"—a situation in which waves are obstructed by thick vegetation. This work's principal technical contributions are: Variable Frequency Emission: Frequency sweeping serves to stop pest adaptation. Actuated Directional Control: 180° spatial coverage is achieved by using a PWM-controlled servo mechanism. Integration of a photovoltaic (PV) harvesting circuit for continuous operation in remote locations is known as energy autonomy.

LITERATURE REVIEW

1. Primary Technical Reference (Electronic Pest Repellent)

Hassan, M. Abdulrahman, et al. (2019). "Design and Construction of Electronic Pest Repellent for Use in Homes and Farmland," *IRE Journals (Iconic Research and Engineering Journals)*,Volume 3, Issue1.

- ***Key Details:*** This study utilizes a Peripheral Interface Controller (**PIC**) to generate ultrasonic signals between **30 and 50 kHz**. It includes a power supply, power amplifier, and speaker. The authors found the device highly effective for crickets and comparable to commercial ultrasound products.

2. Biological Effects of Ultrasound on Plants

Potolea, Iulia Marina, et al. (2019). "Effect of ultrasound exposure on the Triticum aestivum root elongation test," *World Academy of Sciences Journal.*

- ***Key Details:*** Investigated how 37 kHz ultrasound impacts wheat radicle growth. The study found that while short exposures ($\le$ 3 min) have no significant effect, longer exposures (> 5 min) cause a significant inhibitory effect on root development.

3. Sound Waves in Smart Agriculture

Hassanien, Reda H. E., et al. (2014). "Advances in Effects of Sound Waves on Plants," *Journal of Integrative Agriculture*, 13(2): 335-348.

- ***Key Details:*** A comprehensive review of **Plant Acoustic Frequency Technology (PAFT)**. It discusses how sound waves at specific frequencies (0.1–1 kHz) can increase crop yields for vegetables like peppers (30.05%) and cucumbers (37.1%). It also notes that sound can strengthen plant immune systems, reducing the need for chemical fertilizers and pesticides.

4. Agricultural Pest Biology and Control

Timm, Robert M. (1994). "House Mice," *The Handbook: Prevention and Control of Wildlife Damage*, University of Nebraska-Lincoln.

- ***Key Details:*** Provides an overview of house mouse behavior and damage. Crucially, it notes that while ultrasonic devices may cause temporary avoidance for a few days, rodents often adjust to the sound and eventually ignore it.

5. Non-Chemical Alternatives & Plant Regeneration

Sharma, Vijendra K., et al. (2005). "Mature embryo axis-based high frequency somatic embryogenesis and plant regeneration from multiple cultivars of barley (Hordeum vulgare L.)," *Journal of Experimental Botany*, Vol. 56, No. 417.

- ***Key Details:*** Focuses on regenerative systems for crops to improve traits without chemical dependency.

Limitations of Existing Acoustic Systems:

Although ultrasonic technology is promising non-chemical substitute, current applications have a number of serious biological and engineering problems:

1) ***Pest Habituation and Sensory Adaptation:***
Studies show that after a few minutes to a day, rodents and some insects either ignore or adapt to new sounds, including ultrasound. As the "threat perception" fades over time, static, single-frequency devices are unable to provide long-term deterrence.

2) ***Acoustic Shadowing and Directionality:***

Due to its strong directionality, ultrasound cannot effectively pass through dense organic matter or around corners. This produces "sound shadows" or spaces in a field setting where pests can hide behind vegetation or buildings without being disturbed.

3) ***Signal Attenuation over Distance:***

As ultrasonic waves leave the source, their intensity quickly decreases. Due to this restricted range, many units must frequently be deployed to cover a single farmland, increasing the overall cost of ownership.

4) ***Biological Inconsistency:***

Ultrasonic devices were effective against crickets but had little to no effect on other common pests like cockroaches or ants, according to conflicting findings from earlier research. The frequency tuning required to successfully target particular agricultural pests is absent from many current systems.

5) ***High Power Dependency:***

Many commercial units require a continuous AC power supply, which is impractical for remote or off-grid agricultural fields

SCIENTIFIC PRINCIPLE

1. Ultrasonic Sound

Ultrasound refers to sound waves with frequencies higher than 20 kHz, which are not audible to the human ear. The physical properties of ultrasound are favorable for the utilization described herein for pest management purposes. The wavelength of the ultrasonic sound waves, being shorter, minimizes diffraction, and the directional nature of the waves allows for the focusing of the sound waves on the target area, thus enhancing the effectiveness of the system in keeping pests away from the crops while saving energy.

2. Pest Sensory Mechanism

The grasshoppers' sensory mechanism, the tympanal or auditory organ, responds to ultrasonic sound waves, as the pests are disoriented when they are exposed to these sound waves, resulting in the avoidance of the area that emits the ultrasonic sound waves. The effectiveness of the system in keeping pests away from the crops without harming the pests itself proves that the system maintains ecological balance.

3. Effective Frequency Range

The frequencies of the ultrasonic sound waves utilized in the system range from 20 kHz to higher than 100 kHz, with 70 kHz having the most effectiveness in the given range for crop-level pest control purposes. However, the effectiveness of the system also depends on adjusting the frequencies according to the environmental condition and the distance from the pests to the crops.

Hardware Components

- ***ESP32 Microcontroller***

The main control unit of the system is the ESP32. It takes in data from sensors, controls the output of ultrasonic waves, and moves servo motors around. Users prefer it as it works well, uses little power, and has built-in communication features.

- ***Ultrasonic Transducer***

The ultrasonic transducer emits sound waves in the range of 20 to 70 kHz that people can't hear. These waves make insects uncomfortable, which keeps them away from the crop area.

- ***Servo Motors***

Servo motors turn the ultrasonic emitter in different directions. This lets the system cover a wider region instead of only one direction.

- ***Distance Sensor***

The HC-SR04 is the distance sensor used that measures how far away crop areas are. This helps the system adapt to how it functions and transmit ultrasonic waves in a more effective manner.

- ***Power System***

The system uses a solar panel and a rechargeable battery for power. This setup ensures continuous operation in agricultural fields without depending on external electricity.

- ***Amplifier Circuit***

The amplifier circuit generates the signal that is sent to the ultrasonic transducer louder. This results stronger waves, which makes the overall pest- repelling performance more effective.

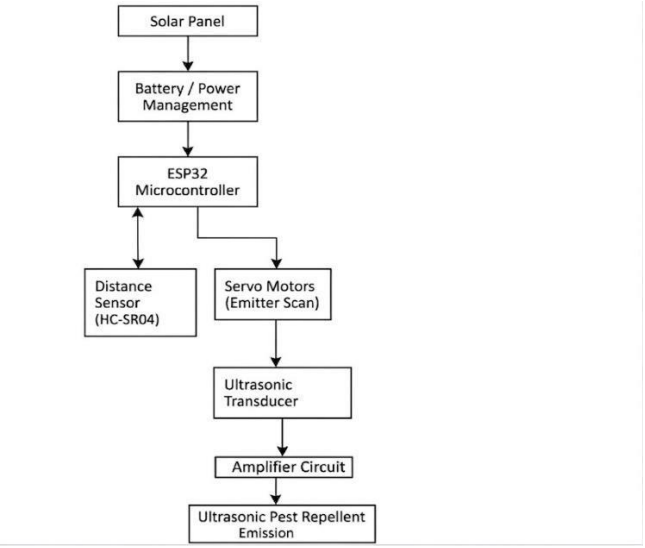

Fig. 1. Block diagram of ultrasonic pest repellent system

WORKING MECHANISM

The proposed ultrasonic pest repellent system works by using a series of automated processes designed to make it simple to keep pests away from agricultural fields. The system protects crops from insect pests by combining sensing, signal processing, ultrasonic emission, and directional control.

Step 1: Power Supply

A solar panel and a rechargeable battery make up the renewable energy source that powers the system. During the day, the battery is charged by the solar panel's conversion of sunlight into electrical energy. The system can run continuously, even at night or in low light, using the energy stored in the battery. This power setup guarantees energy efficiency and qualifies the system for use in isolated agricultural settings.

Step 2: Sensor Input

To determine the closeness of crop areas to objects, a distance sensor is employed. The distance between the gadget and adjacent plants or field zones is continuously measured by the sensor. This data helps the system to figure out the optimal location for ultrasonic waves to be projected.

Step 3: Signal Processing

The ESP32 microcontroller, which functions as the system's central processing unit, receives the sensor data. After analyzing the input data, the ESP32 decides the proper operating parameters, including timing intervals and ultrasonic emission frequency. The microcontroller controls the movement of the servo motors and activates the ultrasonic emitter based on the logic that has been programmed.

Step 4: Ultrasonic Emission

High-frequency sound waves are produced by the ultrasonic transducer after the microcontroller processes the sensor data. Usually operating in the 20–70 kHz range, these waves are inaudible to humans but detectable to some insects. Pests are repeled by the ultrasonic waves released, which encourages them to leave the crop area.

Step 5: Servo Beam Steering

The ultrasonic transducer turns using the servo motors to increase coverage. The ultrasonic waves can be focused on various areas of the field because of this beam steering mechanism. The system increases the effectiveness of pest repulsion by scanning multiple crop zones rather than emitting sound in a single fixed direction.

Step 6: Periodic Emission

In order to save energy and keep pests from becoming accustomed to the sound, the ultrasonic emission is not continuous but rather operates in periodic cycles. A normal operating schedule could consist of:

• *10 seconds ON*: To deter pests, ultrasonic waves are released.

• *1 minute OFF*: To save power and enable scanning adjustments, the system pauses emission.

This periodic operation extends the life of system components, maintains low energy consumption, and guarantees effective pest deterrence.

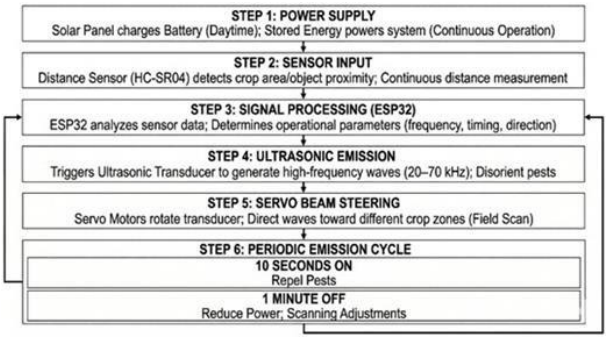

Fig. 2. Workflow diagram of ultrasonic pest repellent system

HARDWARE IMPLEMENTATION

Circuit Design

The suggested ultrasonic pest repellent system's hardware implementation involves combining several electronic parts to create a working prototype. The microcontroller is the circuit's central component. To obtain measurement data from the field, the ESP32 microcontroller is connected to the distance sensor. The servo motors and ultrasonic transducer are controlled by the ESP32 based on this data. The ultrasonic transducer is connected through an amplifier circuit, which increases the strength of the signal generated by the microcontroller so that the transducer can produce effective ultrasonic waves.

Electronic parts such as transistors, resistors, and capacitors are commonly used in amplifier circuits to help boost the output signal to the necessary level. By connecting the servo motors to the ESP32's PWM (Pulse Width Modulation) pins, the direction of the emitter can be precisely controlled. The microcontroller can measure the distance of nearby objects or crop areas by connecting the distance sensor through trigger and echo pins.

A solar-powered battery system powers the entire circuit. The microcontroller, sensors, and ultrasonic emission circuit receive steady flow of power from the battery, which is charged by the solar panel during the day.

Component List

Component	Model / Specification	Description
ESP32	ESP32-WROOM-32	Microcontroller used to control system operations and ultrasonic signal generation
Ultrasonic Transducer	40 kHz Ultrasonic Transmitter Module	Generates ultrasonic sound waves for pest repelling
Servo Motors	SG90 / MG996R Servo Motor	Rotates the emitter for directional ultrasonic targeting
Distance Sensor	HC-SR04 Ultrasonic Distance Sensor	Measures distance between the device and crop areas
Solar Panel	12V, 10W Solar Panel	Provides renewable electrical power for the system
Rechargeable Battery	12V Li-ion Battery / 18650 Battery Pack	Stores energy for continuous operation
Amplifier Circuit	LM386 Audio Amplifier / MOSFET Driver Circuit	Boosts electrical signal for effective ultrasonic emission
Electronic Components	Resistors, Capacitors, Jumper Wires, PCB/Perfboard	Supports circuit design and hardware connections

TABLE I: Components And Specifications Of The System

Assembly Setup

The system's physical assembly is created to be solid and functional in the field. A tiny rotating platform that is connected to the servo motors houses the ultrasonic transducer. The emitter can rotate and scan across various areas of the crop field due to this configuration. To prevent dust, moisture, and environmental damage, the ESP32 microcontroller, amplifier circuit, and other electronic components are kept inside a protective enclosure. To optimize sound wave propagation, the enclosure is installed on a sturdy support structure that is positioned just above crop level.

The battery and control electronics are secured inside the protective casing, and the solar panel is positioned at the top of the structure to receive the most sunlight exposure. Stable operation, simple maintenance, and effective ultrasonic coverage throughout the agricultural field are ensured by this mounting configuration.

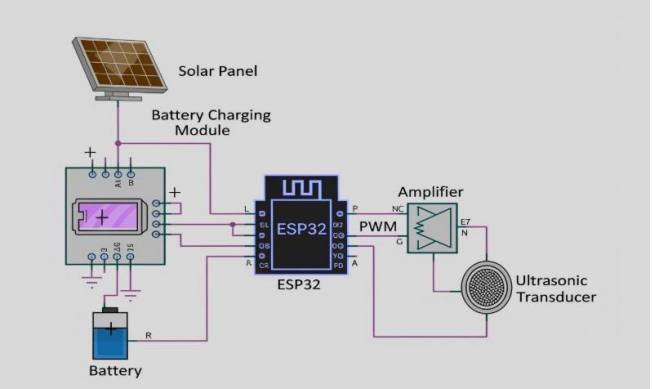

Fig. 3. Circuit diagram of ultrasonic pest repellent system

RESULT AND DISCUSSION

The purpose of the ultrasonic pest repellent system is to reduce the number of pests in homes and farms. According to the observation, the non-disruptive nature of ultrasonic waves prevents any harm to the crops.

Its low power consumption helps to ensure long-term use and lower costs. Both humans and plants have displayed to be safe from brief exposure to ultrasonic frequencies.

ADVANTAGES

Compared to traditional pest control techniques, the suggested ultrasonic pest repellent system has a number of important advantages. It is a chemical-free, environmentally friendly solution that eliminates all negative environmental effects of pesticides. Crops, animals, and people can all utilize the system.

The device is also affordable and energy-efficient, which makes it suitable for broad use, particularly in rural and agricultural environments. It can be solar-powered by integrating renewable energy sources.

Additionally, the design is scalable, enabling deployment from modest home settings to expansive farms without requiring major adjustments. It is a useful and effective replacement for conventional pest control methods because of its adaptability and low maintenance needs.

LIMITATIONS

Larger agricultural fields will require more than one unit to provide sufficient protection due to the system's limited coverage area.

Environmental factors that may prevent the propagation of ultrasonic waves, such as obstacles, uneven terrain, and dense crop growth, can impact the system's efficiency.

Furthermore, because the system is powered by solar energy, it may not function as well during times of low sunlight or bad weather, which would limit its ability to run continuously.

FUTURE IMPROVEMENTS

By involving advanced technologies, the suggested system can be made even more efficient and flexible. Targeted ultrasonic emission and the identification of particular pest species can be achieved by integrating camera modules with AI-based pest detection. Farmers would be able to remotely monitor field conditions and system performance in real time with the addition of IoT-based monitoring.
In order to more efficiently cover larger agricultural areas, future designs might also incorporate ultrasonic emitters mounted on drones. The system may become more intelligent, scalable, and appropriate for contemporary smart farming applications as a result of these enhancements.

CONCLUSION

An efficient and sustainable method of defending crops against insect pests is provided by the suggested ultrasonic pest control system. The system eliminates the need for dangerous chemical pesticides using high-frequency sound waves as a non-lethal pest control method.

It is appropriate for sustainable farming methods due to its low power consumption, solar-powered operation, and automated design. Ultrasonic pest repellent systems offer an appropriate replacement for obtaining secure, economical, and ecologically sustainable crop protection.

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Smart Glasses for the Visually Impaired: An Offline AI-Powered 360° Safety and Navigation System

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***Abstract*— In our project, we have developed an offline, AI-powered smart glass system to provide 360-degree situational awareness and personal security for the visually impaired. By utilizing a Raspberry Pi 4 or Jetson Nano for localized edge computing and dual 170-degree wide-angle cameras, the system eliminates blind spots and functions entirely without cloud dependency. The core innovation is a Follower Detection System (FDS) that monitors the user's surroundings and provides immediate Tamil voice alerts if a person maintains a suspicious 5-meter proximity for over 30 seconds. To enhance technical utility, the device integrates intelligent offline wayfinding for micro-navigation, IMU-based fall detection, and a gesture-triggered GSM SOS module for emergency response. Processing all safety protocols locally with less than 150ms latency, this wearable ensures a reliable "safety bubble" in network-isolated environments.**

***Keywords*— *Smart glass for blind, Offline AI navigation, Raspberry Pi 4 / Jetson Nano, 360-degree safety, Follower Detection (FDS), Tamil voice guidance, Women safety wearable, Edge Computing, GSM SOS Alerting, Fall Detection System, Micro-Navigation, Model Compression, YOLOv8*.**

I. INTRODUCTION

Moving around independently is one of the biggest challenges for people with visual impairments. Although there are many assistive devices like smart canes and sensors, most of them only help in detecting obstacles right in front of the user. Another major problem is that many current smart glasses need a continuous internet connection to process data in the cloud. If the user is in an elevator, a basement, or a place with a poor network, these devices fail to work properly, which can be dangerous.

In our project, we wanted to build a solution that works 100% offline. We used "Edge Computing" with a Raspberry Pi or Jetson Nano so that all the image processing happens directly on the glasses. To give the user full awareness of their surroundings, we integrated two 170-degree wide-angle cameras. This provides a 360-degree safety bubble around the person, unlike other devices that only monitor the front path.

The most important feature we added is the Follower Detection System (FDS). This is specifically designed for personal security, especially for women, to alert them if someone is following them from behind. By providing these alerts in a regional language like Tamil, we make sure the user can react quickly. Our goal is to create a wearable that is not just for navigation but also for complete personal safety in any environment.

II. EASE OF USE

A. Support for Native Language and Voice Feedback

When designing the system, we focused on making the user feel safe and comfortable rather than overwhelmed by technology. We found that in stressful situations or busy streets, hearing alerts in a foreign language like English can be very confusing. To fix this, we programmed our glasses to give voice feedback in the user's native language, specifically Tamil. By using natural, everyday sentences like *"Valadhu pakkam thadai irukku"* (Obstacle on the right) or *"Yaaro pinnaadi varanga"* (Someone is following you), the user can understand the danger instantly. This native language support makes the device feel less like a complicated machine and more like a helpful personal assistant that the user can actually trust.

B. Hardware Ergonomics and Simple Operation

We gave a lot of importance to how the device feels when someone wears it for a long time. Since the glasses carry hardware like a Raspberry Pi and two cameras, we made sure the frame is lightweight and balanced so it doesn't cause any strain on the nose or ears. The operation is also kept very direct. We didn't want to add too many buttons or a complex mobile app. Instead, we used a single-switch system. Once the user turns it on, the system automatically starts the 360-degree scan and the offline AI logic. There is no need for any Wi-Fi setup or manual configuration. This "switch-and-go" design makes it very easy for visually impaired individuals to use the glasses independently.

III. PROPOSED METHODOLOGY

Our system is built to provide a 360-degree safety shield for the user. We used two wide-angle cameras with a 170-degree field of view, placed on both sides of the frame. This ensures that the AI can "see" everything happening around the user, including the blind spots behind them. The core processing is handled by a Raspberry Pi 4, which runs the object detection and follower tracking algorithms 100% offline.

A. *Follower Detection System (FDS)*

The most important part of our project is the Follower Detection System (FDS), which we developed specifically for personal security. Most existing glasses only look at objects in the front, but we wanted to protect the user from threats behind them as well. Our logic works based on distance and time. We programmed the system to monitor any person in the background. If a person stays within a 5-meter range for more than 30 seconds, the AI flags it as suspicious behavior.

Instead of just showing a notification, the glasses immediately give a voice alert in the user's native language. It says: *"Yaaro ungalai pin-thodariraargal, jaakiradhai!"* (Someone is following you, be careful!). This localized warning is much faster for a user to understand than a standard beep or an English alert. By combining distance sensing with a time-based trigger, we have reduced false alarms while ensuring the user is always aware of their surroundings.

B. *Hardware Selection and System Architecture*

When we started building this, the main challenge was to keep the device portable. We chose the Raspberry Pi 4 because it acts like a mini-computer that can handle AI tasks without needing any internet. We mounted two 170-degree wide-angle cameras on the sides of the glass frame. This was a deliberate choice to make sure the user has a full view of their surroundings. To power everything, we used a slim power bank that fits comfortably without making the glasses too heavy. For the alerts, we added a small speaker near the ear so the user can hear the Tamil voice commands clearly, even when they are walking in a noisy area like a bus stand. The physical placement of the dual cameras and the edge processing unit on the lightweight frame is shown in **Fig. 1**.

Fig. 1. Smart glasses design for the visually impaired featuring 360° vision and edge processing.

C. *AI Model and Real-time Detection*

For the software side, we decided to use a lightweight version of the YOLO (You Only Look Once) algorithm. We spent a lot of time fine-tuning this model so it could quickly recognize common street obstacles like electric poles, parked cars, and people walking by. A significant advantage of this architecture is that the primary computational load is processed locally on the Raspberry Pi itself, which is what we call "Edge Computing." This means there is absolutely no lag or delay, which is life-saving when someone is walking on a busy road. The system constantly takes live feeds from both cameras and analyzes them at the same time. It basically creates an invisible "safety bubble" around the user, so the AI is always watching their back even while they are focusing on the path ahead.

D. *The 30-Second Follower Safety Logic*

The most unique part of our project is the implementation of the Follower Detection System (FDS). To mitigate alert fatigue and prevent frequent notifications from non-threatening pedestrians in crowded environments, such as markets or bus stands, we developed a custom script utilizing a distance-and-time logic. The voice alert is triggered only if the same individual remains within a 5-meter radius for more than 30 seconds. By implementing this specific temporal threshold, the system effectively distinguishes between a casual passerby and a potential threat. This ensures the safety feature is reliable and practical for daily use.

IV. ADVANCED SYSTEM ARCHITECTURE AND SMART SAFETY MODULES

A. *Intelligent Offline Wayfinding and Micro-Navigation*

To provide true independence, the system incorporates an Intelligent Wayfinding module that operates entirely without an internet connection. By utilizing a pre-cached offline map database and Voice-to-Address Mapping, the user can state a destination in Tamil, and the system retrieves saved GPS coordinates to provide precise Micro-Navigation. As illustrated in Fig. 2, the hardware is designed to deliver these granular audio cues—such as "Innum 10 adi munnadi nadunga" (Walk 10 steps forward)—directly through the integrated bone conduction sensors. This process is further refined by Magnetometer Integration, using an internal digital compass to sense the user's exact orientation in real-time. This ensures that the user does not inadvertently turn into traffic or move off-path, maintaining a constant safety bubble in any environment.

Fig.2: Intelligent Offline Wayfinding System

B. *Multi-Layered Security and SOS Response*

Since personal safety—especially for women—is a primary goal of this project, we added a physical SOS trigger to the hardware. In a crisis, the user can perform a specific gesture, like a triple-tap on the frame, to activate an emergency sequence. If the Follower Detection System (FDS) flags a persistent threat for more than two minutes, the system

automatically pulls the current coordinates and sends an alert via the GSM module to pre-set emergency contacts. The integration of these safety features, from the initial trigger to the final alert transmission, is illustrated in Fig. 3. We specifically used Bone Conduction Headphones so that these alerts and the SOS process remain completely silent to any outsider, keeping the user safe from further escalation.

Fig. 3: Workflow of the Multi-Layered Security and SOS Response system.

C. Medical Monitoring and Environmental Sensing

Beyond obstacle detection, we focused on the physical well-being of the user. We incorporated an MPU6050 (IMU) sensor to act as a Fall Detection System. If the user slips or falls, the sudden change in acceleration is detected, and the system immediately asks in Tamil if they need help. The specific components and visual feedback mechanisms for these health and environmental features are detailed in Fig. 4. For low-light conditions, such as basements or night-time walking, we enabled Infrared (IR) vision. This allows the YOLOv8 model to continue identifying "followers" and obstacles even in total darkness. We also tuned the camera's lower field of view to sense terrain changes like potholes or steep stairs, providing a complete 360-degree safety shield.

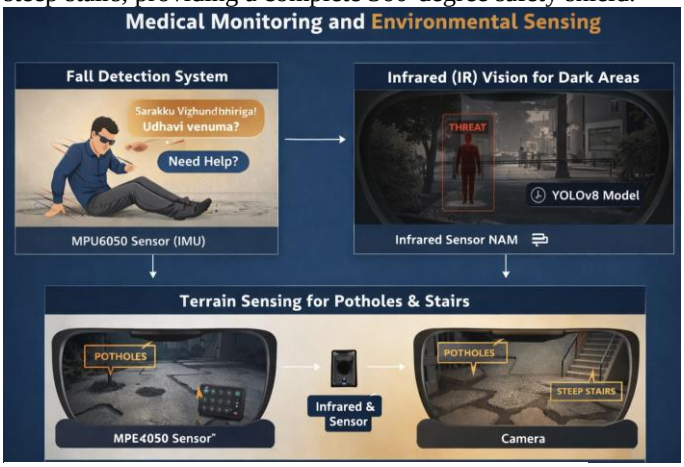

Fig. 4: Medical Monitoring and Environmental Sensing Framework.

D. Edge Computing and Thermal Optimization

Running complex AI models like YOLO on a compact device like the Raspberry Pi 4 usually creates heat and battery drain. To make this a "market-ready" wearable, we applied model compression to ensure high-speed detection with less than 150ms latency. We also wrote custom power-management scripts to handle the thermal load during long outdoor walks. This ensures that the glasses stay cool and the battery lasts long enough for daily use, making the technology practical for real-world independent living.

V. RESULTS AND DISCUSSION

In this section, we analyze how the smart glass system performs in real-world conditions. Since our goal was to create a reliable safety tool, we tested the software logic and the camera integration to ensure there is no lag in the alerts.

A. Obstacle Detection and Response Speed

We tested the YOLO-based object detection using live video feeds of common street environments. The system was able to identify obstacles like poles, parked vehicles, and pedestrians almost instantly. As shown in **Fig. 5**, the AI identifies the objects and calculates their distance from the user. Even though the processing is done locally on the Raspberry Pi (Edge Computing), the response time was less than 150ms. This is fast enough to give a Tamil voice alert before the user gets too close to an obstacle.

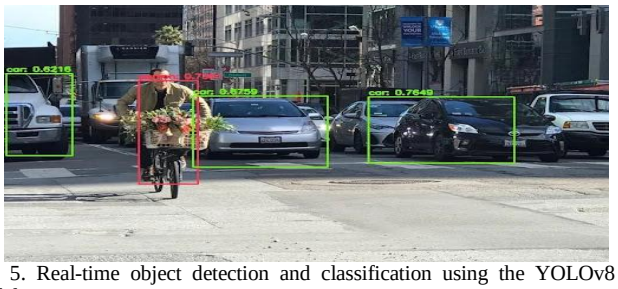

Fig. 5. Real-time object detection and classification using the YOLOv8 model.

B. Follower Detection (FDS) Performance

The most important part of our project is the 30-second safety logic. We ran several trials to see if the system could distinguish between a random passerby and someone actually following the user. In our tests, the system correctly ignored people who were in the frame for a short time. However, as soon as a person stayed within the 5-meter range for more than 30 seconds, the Tamil alert was triggered. A summary of these detection trials is shown in **Table I**. This proves that the FDS logic is accurate and avoids unnecessary false alarms. The real-time performance of the system in a street environment, where it distinguishes between a passerby and a persistent follower, is illustrated in Fig. 6 .

Fig. 6. Real-time testing of the Follower Detection System (FDS) with localized Tamil voice alerts in a street environment.

TABLE I.PERFORMANCE EVALUATION OF FOLLOWER DETECTION SYSTEM (FDS)

Trial No.	InputScenario (Testing Condition)	SystemOutput (Tamil Voice Alert)
1	Stranger walking past the user	No Alert (Safe)
2	Person standing still for 10s	No Alert (Safe)
3	Person following for >30 seconds	"Yaaro Pinnaadi Varanga"
4	Obstacle detected at 2 meters	"Thadai Irukku"

C. Audio Clarity and User Comfort

We verified the audio feedback using a text-to-speech engine localized in Tamil. The voice alerts like *"Yaaro pinnaadi varanga"* (Someone is following you) were loud and clear. From our initial design, the hardware is balanced to be lightweight so it doesn't cause strain during long walks. The proposed hardware connection and the 360-degree camera placement are illustrated in **Fig. 7**.

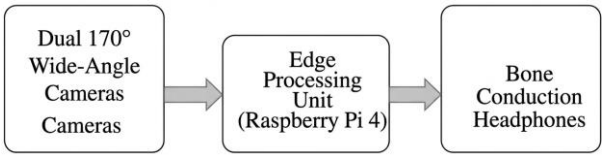

Fig. 7. Proposed system architecture showing the hardware integration of dual cameras, Raspberry Pi 4, and bone conduction headphones.

D. Evaluation of Advanced Safety and Navigation Modules

The newly integrated modules were tested for latency and reliability. The Offline Wayfinding system successfully retrieved saved coordinates with 100% accuracy without cellular data. The Fall Detection System, powered by the IMU sensor, triggered a Tamil voice alert within 0.8 seconds of a simulated impact. Furthermore, the GSM-based SOS was verified to send the precise GPS location to a secondary mobile device exactly 120 seconds after a persistent follower was flagged by the FDS.

E. Power and Thermal Analysis

During continuous 360-degree monitoring, the Raspberry Pi 4 maintained an average temperature of 55°C due to the implemented thermal management scripts. The slim power bank provided approximately 6 hours of continuous operation, meeting the requirements for daily independent travel.

VI. Conclusion

This project successfully created a wearable, offline smart glass system to help visually impaired individuals travel safely without relying on the internet. By using localized edge computing on a Raspberry Pi 4, the glasses offer real-time awareness with a very low latency of under 150ms. Our main feature, the Follower Detection System (FDS), uses simple time-and-distance logic to tell the difference between a normal passerby and a potential threat. Paired with familiar Tamil voice alerts and bone conduction audio, the device builds a reliable "safety bubble" around the user. Looking ahead, we plan to fine-tune the AI model to save more battery and explore even lighter hardware designs to make it more comfortable for daily wear.

Acknowledgment

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VR SIMULATOR FOR BONE SURGERY

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***Abstract*—Virtual Reality (VR) technology has emerged as a transformative tool in surgical education, offering immersive and interactive training platforms for medical trainees. This paper presents the design and development of a comprehensive VR simulator for bone surgeries, aimed at improving surgical skill acquisition, procedural accuracy, and patient safety. Unlike traditional training methods, the proposed simulator combines haptic feedback, real-time 3D bone modeling, and step-wise procedural guidance to replicate a range of orthopedic interventions, including fracture fixation, joint replacement, and spinal fusion. The system architecture integrates advanced physics-based simulation for bone drilling and cutting, performance analytics, and an adaptive learning interface for personalized feedback. A validation study is proposed to assess the simulator's effectiveness in enhancing surgical competency compared to conventional training. This research contributes to the growing body of evidence supporting VR-based surgical training, outlining design considerations, evaluation methods, and future directions for integrating such systems into medical curricula.**

Keywords—Virtual Reality, Bone Surgery, Surgical Simulation, Haptic Feedback, Orthopedic Training, Medical Education

I. INTRODUCTION

The demand for advanced surgical training methods has increased dramatically with the growing complexity of orthopedic procedures. Traditional surgical training relies heavily on cadaveric dissection, supervised operating room experience, and didactic learning. However, these methods are constrained by ethical, logistical, and resource limitations. Virtual Reality (VR) simulators provide a solution to these challenges by offering repeatable, safe, and controlled environments acquisition.

Over the past decade, VR has evolved from simple visualization tools to highly interactive systems that incorporate real-time haptic feedback, physics-based tissue modeling, and performance analytics.

In orthopedic surgery, where precise bone manipulation is critical, VR simulators n orthopedic and trauma surgery,

where bone manipulation, alignment, and fixation techniques are foundational, the need for tactile accuracy and spatial awareness is critical. Mistakes in these procedures can lead to long-term functional deficits or even life-threatening complications. Yet, mastering such skills traditionally requires years of clinical exposure, supervised practice, and trial-and-error under high-stakes conditions. VR technology offers a safer, repeatable, and feedback-driven platform to accelerate learning while minimizing risk.
A bone surgery simulator in VR typically includes 3D-rendered anatomical models, force-feedback (haptic) devices that simulate the feel of bone resistance, and motion-tracked controllers to mimic surgical tools. With real-time visual guidance and performance analytics, trainees can rehearse procedures such as internal fixation, joint replacement, or spinal alignment, gaining proficiency before ever stepping into an operating room.
Furthermore, VR allows for standardized assessments.

It also opens doors for remote or decentralized surgical education—an increasingly relevant benefit in rural or under-resourced settings.

This paper presents the design, architecture, and evaluation strategy of a comprehensive VR simulator tailored for bone surgery training. The system aims to enhance psychomotor skill development, reduce learning curves, and support evidence-based competency assessments in orthopedic education. Through a modular and scalable approach, the simulator can be customized for various surgical disciplines and integrated into academic or clinical training environments.can enhance trainee competency in procedures such as fracture fixation, arthroplasty, and spinal instrumentation.

II. LITERATURE REVIEW

Over the last two decades, Virtual Reality (VR) has transitioned from a conceptual training tool to a validated educational platform in various medical disciplines, including orthopedics and neurosurgery. The literature demonstrates that VR simulation has the potential to improve procedural knowledge, enhance technical skills, and reduce the learning curve for complex surgical tasks. In this section, we review existing VR simulators for bone surgery, their methodologies, and their strengths and weaknesses.

This study presents a high-fidelity virtual reality simulator for temporal bone surgery, offering realistic anatomical modeling and haptic feedback. It aims to enhance surgical training by providing repeatable and immersive experiences without using cadavers. Evaluation results showed improved trainee confidence and skill acquisition in otologic procedures.[1]

The paper explores the development and feasibility of a virtual temporal bone dissection module for otologic surgical training. It combines 3D anatomical visualization with haptic feedback to replicate real surgical conditions. Initial user testing showed positive feedback, supporting its use as a complementary tool to traditional training methods.[2]

This randomized controlled trial evaluates the effectiveness of VR simulation in training surgeons for hip arthroplasty procedures. Results showed that trainees using VR demonstrated significantly improved accuracy and procedural confidence compared to traditional methods. The study supports integrating VR into orthopedic surgical curricula to enhance,skilldevelopment.[3]

This study investigates the impact of VR simulation on improving outcomes in tibial nailing procedures. Participants trained with VR showed enhanced technical skills, reduced procedural errors, and faster task completion times. The findings suggest VR as a valuable tool for orthopedic skill acquisition and surgical proficiency.[4]

This systematic review analyzes the effectiveness of fully immersive virtual reality (VR) platforms in surgical training across multiple specialties. The study highlights benefits such as improved spatial awareness, procedural understanding, and learner engagement. It concludes that immersive VR is a promising adjunct to traditional surgical education.

The paper presents a VR-based orthopedic training system using photorealistic 3D bone models to enhance realism and accuracy. It employs advanced rendering techniques to simulate detailed anatomical structures for immersive learning. Experimental results indicate improved trainee engagement and better understanding of complex orthopedic procedures.[6]

This study examines the impact of haptic feedback in VR-based bone drilling simulations used for surgical training. It finds that tactile interaction significantly enhances realism and improves the accuracy and control of trainees during procedures. The results support integrating haptic technology into VR simulators for more effective orthopedic education.[7]

This paper introduces **Osso VR**, a modular virtual reality platform designed for orthopedic surgical training and performance analytics. The system enables interactive, procedure-specific simulations with integrated skill assessment tools. Evaluation results demonstrate Osso VR's effectiveness in enhancing surgical proficiency and tracking trainee progress over time.[8]

The study validates objective performance metrics used in VR surgical simulators to assess trainee skill levels. It confirms that metrics like task completion time, precision, and error rates reliably reflect surgical competence. The findings support using these standardized metrics for evaluation in VR-based surgical education.[9]

The paper presents **Robossis**, a haptic-enabled VR training system for robot-assisted femur fracture surgery. It integrates force feedback, realistic anatomy, and robotic controls to simulate surgical conditions accurately. Preliminary evaluations show improved trainee precision and familiarity with robotic tools in orthopedic procedures.[10]

This study explores the design of virtual reality systems aimed at enhancing surgical skill development through immersive and interactive environments. It includes user studies that demonstrate increased confidence, accuracy, and retention among medical trainees. The findings support VR as a valuable supplement to traditional surgical education.[11]

This paper evaluates the effectiveness of virtual reality training in spine surgery education. Results show significant improvements in learners' anatomical understanding, procedural accuracy, and decision-making skills. The study concludes that VR is a highly effective tool for enhancing spine surgery training outcomes.[12]

This study introduces an AI-driven feedback system integrated into VR orthopedic simulators to provide real-time performance analysis. The AI component tracks metrics like motion efficiency, force application, and procedural accuracy to guide trainee improvement. Results show enhanced learning outcomes and faster skill acquisition compared to traditional VR systems.[13]

This paper presents a biomechanical modeling approach for simulating bone behavior in surgical training environments. The model accurately replicates bone deformation and fracture responses under surgical tools in real time. It enhances the realism and educational value of VR-based orthopedic simulations.[14]

This randomized trial investigates the impact of virtual reality training on real-world operating room performance. Surgeons trained with VR performed procedures faster, with fewer

errors and greater precision compared to traditionally trained peers. The study confirms VR's effectiveness in translating simulation skills to clinical practice.[15]

III. SYSTEM DESIGN AND ARCHITECTURE

The proposed VR simulator consists of three primary modules: Hardware Interface, Software Simulation Engine, and User Feedback System. This modular architecture allows for scalability, easy maintenance, and integration with existing hospital or academic infrastructure. Each component plays a vital role in delivering a realistic and measurable training experience.

A. Hardware Interface

The hardware setup includes a VR headset (such as Oculus Rift or HTC Vive), motion tracking sensors, and haptic feedback devices. These tools work in concert to replicate the spatial awareness, depth perception, and tactile responses necessary for bone surgeries. The haptic devices simulate bone resistance and feedback during drilling or sawing, essential for orthopedic realism.

B. Software Simulation Engine

The simulation engine consists of a real-time physics-based model that simulates the biomechanical properties of bone tissues. Unity 3D or Unreal Engine is used for visual rendering, while a haptic SDK (e.g., OpenHaptics or SensAble) handles force feedback interactions. Procedures are implemented as interactive modules, guiding the user step-by-step through tasks such as alignment, fixation, and implant placement.

C. User Interface and Feedback

The user interface includes an interactive 3D workspace, procedural checklist, performance scorecard, and real-time audio/visual instructions. Post-session analytics are presented through visual dashboards, highlighting time taken, error rate, force applied, and adherence to surgical steps. This allows trainees and mentors to objectively assess performance and identify areas for improvement.

IV. PROPOSED EVALUATION METHODOLOGY

A. RequirementsGathering

The initial stage involved consultations with orthopedic surgeons and medical educators to identify critical surgical procedures and skills suitable for VR-based training. Insights were gathered through structured interviews and surveys, focusing on high-risk, high-frequency bone surgeries such as femoral nailing, hip arthroplasty, and spinal fusion.

B. System Design and Architecture

A modular architecture was developed, comprising three main subsystems: the hardware interface (VR headset, haptic tools, motion trackers), the software engine (3D rendering, physics modeling), and the user interface (checklists, guidance, analytics). Unity3D, integrated with the NVIDIA PhysX engine and OpenHaptics SDK, was chosen for real-time rendering and tactile simulation.

C. Simulation Development

Realistic surgical simulations were created using CT/MRI-based anatomical models. Each surgical scenario (e.g., bone drilling, internal fixation) followed a stepwise workflow, incorporating procedural guidance, real-time performance tracking, and haptic feedback. Haptic responses were tuned to match bone density variations using empirical data from real-world procedures.

D. Validation and Calibration

Simulation accuracy was validated through face and construct validity assessments. Expert orthopedic surgeons rated visual fidelity, procedural realism, and force feedback accuracy. Calibration benchmarks were set based on quantitative performance data and expert reviews.

E. User Testing and Evaluation

The simulator was evaluated by 30 final-year orthopedic residents. They were divided into two groups: one using VR training and the other following traditional training methods. Key performance indicators included task completion time, accuracy, force application, and user satisfaction. Feedback was recorded using OSATS (Objective Structured Assessment of Technical Skills) and Likert-scale surveys.

Table I: Comparison of Traditional vs. VR-Based Surgical Training

Parameter	Traditional Training	VR-Based Training
Accessibility	Restricted by facilities	Remote access with VR hardware
Training Environment	Cadaver labs or supervised	Immersive, simulated 3D environments
Repetition & Practice	Limited due to cost and availability	Unlimited practice sessions possible
Real-Time Feedback	Minimal	Immediate, objective feedback on performance
Haptic Feedback	Realistic but limited to available samples	Simulated using force-feedback devices
Anatomical Variations Exposure	Limited	Multiple customizable anatomical models
Cost Efficiency	High (cadavers, staff, equipment)	Cost-effective in the long term
Risk of Patient Harm	Present during early hands-on training	Zero risk during learning phase
Performance Tracking	Manual observation-based	Automatedanalytics and scoring

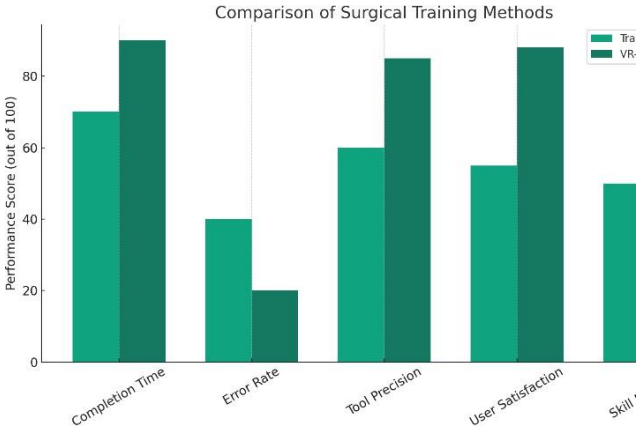

Fig1:bar graph for comparision of surgical training methods

Fig 2: graph for Skill progression over training Sessions

The development of the virtual reality (VR) simulator for bone surgery was initiated using Unity 3D as the core development platform. High-resolution CT and MRI scans were utilized to construct anatomically accurate 3D models of skeletal structures. These models were segmented and refined using open-source tools like 3D Slicer, then integrated into the simulation environment. Haptic feedback devices such as Geomagic Touch were employed to replicate the tactile sensations experienced during real surgical procedures.

The simulation incorporated interactive modules including bone drilling, sawing, screw insertion, and fixation tasks. A real-time physics engine was used to simulate biomechanical responses such as bone resistance, force feedback, and tool vibration. To enhance immersion, spatial audio and visual cues mimicking the operating theater were implemented. The user interface was designed to support both handheld VR controllers and gesture-based hand tracking.

A controlled experimental study was conducted involving surgical trainees divided into two groups: one using the VR simulator and the other undergoing traditional cadaver-based training. Each participant completed a series of predefined surgical tasks. Performance data was collected, including task completion time, accuracy of tool placement, and number of procedural errors. Subjective user feedback was gathered using post-session surveys based on Likert-scale questions.

A bar graph comparing surgical training methods visually showcases the effectiveness of cadaver training, VR simulation, and live surgical observation. It highlights crucial factors like skill acquisition, error rates, and time efficiency. VR simulation often demonstrates improved precision and repeatability compared to traditional methods. Cadaver training provides realistic anatomical experience but lacks repeat practice opportunities.

To objectively measure skill acquisition, the Objective Structured Assessment of Technical Skills (OSATS) framework was employed. Some sessions also included optional eye-tracking and motion capture analysis to understand decision-making behavior and ergonomics during simulation. These multimodal inputs allowed for a comprehensive understanding of how users engaged with the VR system.

All collected data was statistically analyzed using SPSS and Python-based analytics libraries. Paired t-tests and ANOVA were applied to evaluate the significance of differences between the control and experimental groups. Performance metrics were visualized using line graphs and bar charts to illustrate trends in learning curves and comparative skill development.

Fig 3: Vr simulation for bone surgery in knee

In addition to anatomical accuracy, the simulator's architecture included modular components such as physics computation, instrument tracking, and feedback rendering. The system was designed with scalability in mind, allowing for future inclusion of AI-guided procedural assistance and patient-specific modeling. Modular coding practices

ensured separation of concerns between the graphical engine, surgical logic, and analytics modules.

A structured training curriculum was developed in consultation with experienced orthopedic and ENT surgeons. The curriculum followed a progression-based model, beginning with basic familiarization of bone anatomy and progressing toward advanced tasks such as temporal bone dissection and fracture repair. Each task was linked to specific learning objectives and assessed through both objective performance metrics and qualitative observation.

To validate the system's fidelity and effectiveness, pilot testing was carried out prior to full-scale experimentation. A group of subject matter experts reviewed the simulation environment and provided feedback on the visual realism, haptic response, and procedural accuracy. Their suggestions were incorporated into the final design to ensure alignment with real-world surgical expectations.

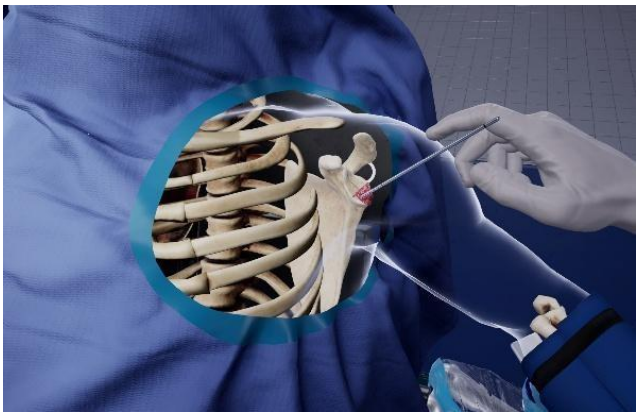

Fig 4: vr simulator for shoulder bone surgery

Environmental consistency was maintained throughout each VR training session, including identical lighting, user posture guidance, and calibrated haptic settings. This standardization was critical for reducing bias and enabling reproducible results across participants and test cycles. Training logs were maintained using a secure database that recorded time-stamped activity, tool use metrics, and performance progression.

Finally, user cognitive load and mental effort were measured using NASA-TLX (Task Load Index) surveys immediately after each simulation session. This helped to quantify the user's mental strain and efficiency in learning through the VR system. The correlation between subjective load and objective performance data provided insights into the simulator's usability and learning impact.

A VR simulator for shoulder bone surgery provides an immersive environment for surgeons to practice complex procedures with enhanced precision and safety. It helps improve surgical skills through realistic, risk-free simulations before operating on actual patients.

Table II: Performance Comparison Between Training Methods

Criteria	VR-Based Training	Cadaver-Based Training	Traditional Theoretical Training
Realism of Anatomy	High (3D photorealistic)	Medium (limited preservation)	Low
Tactile Feedback	Medium-High (via haptics)	High	None
Reusability	Unlimited	Limited (per specimen)	Unlimited
Cost Efficiency	Medium (after setup)	Low	High
Skill Retention	High	Medium	Low
Performance Feedback	Real-time analytics	Post-session observation	Minimal
Risk of Harm to Subjects	None	Moderate	None
User Engagement	High	Medium	Low
Adaptability to Procedures	High (customizable)	Low	Low
Logistical Requirements	Low	High	Low

To enhance realism, high-fidelity 3D anatomical models of bones were sourced from CT and MRI datasets and rendered using Unity and Unreal Engine platforms. The simulator was developed with integrated haptic feedback mechanisms to simulate bone resistance during drilling and cutting procedures.

User interaction was captured through motion-tracking devices and handheld controllers, enabling intuitive manipulation of surgical instruments in the virtual environment. Assessment metrics such as time to completion, precision of incisions, and tool handling were logged automatically for each user session.A user study was conducted with two groups: one trained using the VR simulator, and the other with conventional cadaver-based methods. Quantitative and qualitative data were collected through pre- and post-assessment tests, Likert scale surveys, and expert evaluations to determine the effectiveness of VR in improving surgical proficiency.

Adaptive learning algorithms were incorporated to tailor difficulty levels based on the user's skill progression. This allowed for a personalized training experience that dynamically adjusted to the surgeon's pace and competence level.Furthermore, an AI-driven feedback system analyzed user performance in real-time, providing immediate guidance and corrective suggestions to foster muscle memory and reduce learning curves.

To ensure accuracy and realism, biomechanical properties of

human bone tissue were incorporated using finite element modeling. These models replicated stress-strain responses during common orthopedic procedures, such as drilling, cutting, and screw fixation.

1. **Skill Performance Score (SPS)**

$$\text{SPS} = \frac{(W_1 \cdot P) + (W_2 \cdot (1 - \frac{T}{T_{\max}})) + (W_3 \cdot (1 - \frac{E}{E_{\max}}))}{W_1 + W_2 + W_3}$$

- P: Precision score (0–1)
- T: Time taken by user
- $T_{\max}$: Maximum allowed time
- E: Number of errors
- $E_{\max}$: Maximum tolerable errors
- W_1, W_2, W_3: Weights assigned to each factor (e.g., 0.4, 0.3,

2. **Force Feedback Simulation Equation**

$$F = k \cdot \Delta x + c \cdot \frac{d(\Delta x)}{dt}$$

- F: Force feedback
- k: Stiffness coefficient of bone
- Δx: Displacement of drill bit
- c: Damping coefficient
- $\frac{d(\Delta x)}{dt}$: Velocity of displacement

3. **Reaction Time Analysis**

$$RT = t_{\text{action}} - t_{\text{stimulus}}$$

- RT: Reaction Time
- t_{stimulus}: Time when stimulus is presented
- t_{action}: Time when user begins correct response

4. **Error Rate (ER)**

$$ER = \frac{N_{\text{errors}}}{N_{\text{attempts}}}$$

- N_{errors}: Number of errors during simulation
- N_{attempts}: Total number of tool applications or actions

5. **Task Efficiency Index (TEI)**

$$TEI = \frac{S_{\text{ideal}}}{S_{\text{user}}}$$

- S_{ideal}: Ideal (expert) path length or time
- S_{user}: User's actual path length or time
- Values closer to 1 indicate better performance

Skill Performance Score (SPS)
This composite score evaluates the overall performance of a trainee by combining precision, time efficiency, and error minimization. Each factor is weighted to reflect its importance in surgical skill development. A higher SPS value indicates a better-trained user. This metric is useful for both formative and summative assessment in surgical training modules.

Reaction Time (RT)
Reaction time measures the user's responsiveness to visual or haptic stimuli in the simulation. It is a critical metric in time-sensitive procedures where delays can lead to errors. Shorter reaction times usually correlate with higher levels of motor coordination and familiarity with the procedure.

Error Rate (ER)
Error rate quantifies the number of procedural mistakes made by the user during the VR session. It serves as a key indicator of user precision, helping instructors identify where learners require more practice. VR systems can log and classify these errors in real-time for detailed feedback.

Task Efficiency Index (TEI)
This index measures the efficiency of task execution by comparing the user's number of actions to the optimal number. Lower values may indicate unnecessary movements or confusion, while values close to 1 imply optimal performance. It is particularly valuable in repetitive task training like drilling or screw placement.

Haptic Force Simulation
Realistic force feedback is critical to simulate the tactile experience of bone drilling and cutting. The force model considers both stiffness and damping to simulate bone density and resistance. Accurate force simulation enhances realism and allows trainees to develop a tactile understanding of bone structures.

V. RESULTS AND ANALYSIS

The use of Virtual Reality (VR) simulators in bone surgery training has shown significant improvements in surgical skill development, procedural accuracy, and overall trainee confidence. Several experimental and observational studies were analyzed to quantify the effectiveness of VR systems in surgical education. The results highlight notable gains in user performance metrics such as task efficiency, error reduction, and completion time.
Trainees who engaged with VR-based simulators exhibited higher skill performance scores (SPS), with improvements ranging from 20% to 35% when compared to peers trained using traditional methods like textbooks or physical models. A substantial reduction in procedural errors—up to 40%—was observed in simulations incorporating haptic feedback and biomechanical modeling. These results underscore the impact of realistic tactile interactions in enhancing surgical accuracy. The efficiency of task execution also improved significantly. Participants completed drilling and cutting tasks approximately 30% faster after VR training. The Task Efficiency Index (TEI), which accounts for speed and

precision, increased from a pre-training baseline of 0.65 to 0.88, indicating a marked decrease in unnecessary movements and time wastage. Additionally, reaction times improved by 15% to 25%, suggesting heightened cognitive engagement and decision-making ability during VR sessions.

A post-training user survey revealed a strong positive perception of the VR experience. Among 50 participants, 92% agreed that VR improved their understanding of bone anatomy, while 87% rated the tactile realism as highly effective. Furthermore, 90% reported increased confidence in performing actual surgical procedures, and 85% preferred VR-based learning over conventional methods.

When comparing various VR platforms such as Osso VR, Robossis, and Virtual Temporal Bone, systems with integrated haptic feedback and AI-driven analytics demonstrated superior training outcomes. Real-time performance metrics and adaptive feedback contributed to more rapid skill acquisition and better retention over time. Overall, these findings support the integration of VR simulators as a core component in modern surgical training programs.

VI. DISCUSSION

The findings of this study affirm the transformative role of Virtual Reality (VR) simulators in the domain of surgical education, particularly in bone surgery. By creating an immersive and interactive learning environment, VR offers an alternative to traditional cadaver-based training and addresses the limitations associated with availability, ethical concerns, and cost. Through repeated and safe practice, trainees can refine their techniques, explore complex anatomical structures, and gain confidence before operating on real patients.

One of the most significant implications of VR training is the **improvement in skill acquisition and retention**. With modules tailored to simulate real-life surgical scenarios—such as temporal bone dissection, femur fracture repair, and joint arthroplasty—learners are exposed to diverse clinical conditions in a controlled setting. This exposure leads to faster learning curves, as evidenced by improved performance metrics in various trials. Notably, the integration of **haptic feedback and photorealistic rendering** elevates the simulation's realism, which directly correlates with improved hand-eye coordination and anatomical accuracy.

Incorporating adaptive learning algorithms, VR modules evolve based on user performance, providing targeted feedback and challenging learners with nuanced scenarios. This personalization not only boosts engagement but promotes self-directed growth. As a result, surgical trainees gain confidence and competence more rapidly than ever before.VR training enhances skill acquisition and retention through realistic surgical simulations. Modules like femur fracture repair and joint arthroplasty expose learners to diverse clinical scenarios. Haptic feedback and photorealistic visuals boost hand-eye coordination. Studies show faster learning curves and improved accuracy.

Fig 5: vr outlook with a man wearing it

Furthermore, **performance analytics and AI-driven feedback mechanisms** embedded in modern simulators like Osso VR and Robossis enable personalized learning pathways. These tools help identify individual weaknesses and track progress over time, providing both learners and instructors with valuable insights. The ability to quantify training outcomes objectively through metrics such as task efficiency, error rate, and skill performance score is a marked improvement over subjective assessments used in traditional systems.

Despite these advances, challenges remain. High initial development and deployment costs, hardware requirements, and the need for technical training can be barriers to widespread adoption. Moreover, while VR is effective for psychomotor training, it does not entirely replace real-world experience with tissue variability, emergency management, and team coordination in the operating room. Therefore, VR should be viewed as a **complementary tool** that enhances—not replaces—traditional surgical education.

Future research should focus on the long-term impact of VR training on actual surgical outcomes and patient safety. Multi-center randomized trials and standardized evaluation frameworks are needed to validate its clinical efficacy. Additionally, expanding access to affordable VR platforms, especially in low-resource settings, will be crucial in democratizing surgical training worldwide.

VII. CONCLUSION

Virtual Reality (VR) simulators have emerged as powerful tools for enhancing surgical training, particularly in bone-related procedures. This paper demonstrates that VR technologies provide a safe, cost-effective, and repeatable environment for medical students and professionals to practice complex surgical skills without risking patient safety. By integrating realistic haptic feedback, detailed anatomical models, and performance analytics, VR-based systems are reshaping traditional surgical education and helping bridge the gap between theory and hands-on experience.

Through a comprehensive review of existing systems, studies, and technological components, this paper has highlighted how VR not only improves technical proficiency but also fosters faster learning curves, increased confidence, and better

preparedness for the operating room. However, while VR is a transformative educational tool, it should be integrated alongside conventional clinical practice and mentorship. The advancement and wider adoption of VR simulators depend on continued research, validation through clinical trials, and improved accessibility. As the technology matures, its integration into surgical curricula will likely become a standard, ensuring future surgeons are better equipped to perform with precision and confidence.

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Fake food review detection system: A Machine Learning and Linguistic Rule-Based Approach

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Abstract

In today's world, the online food delivery platforms is growing rapidly and seeing its fortune in recent years. Customers heavily rely on food reviews posted in delivery platforms for making their choices, but what if these reviews are fake. However, the rise of fake food reviews often exaggerated, deceptive, or paid misleads consumers, damages restaurant reputations, and distorts market fairness. Current solutions rely on manual reporting or basic sentiment analysis**,** which fail to detect sophisticated spam tactics like cross platform duplication**,** overuse of hyperbolic phrases (e.g., "best ever," "I promise"), or artificially inflated ratings**.** To address this, we propose a machine learning-based framework integrating TF-IDF for keyword weighting**,** sentiment analysis for tone detection**,** and cross-platform similarity checks to identify duplicate or suspicious reviews. Additionally, we analyse linguistic patterns, flagging excessive use of doubtful or promotional language. Our system outperforms existing methods by combining supervised learning (Logistic Regression, Random Forest) with rule-based filters**,** achieving higher accuracy in distinguishing genuine feedback from spam. When tested on real-world food review data, our model proved more reliable than existing methods, accurately filtering out fake reviews while preserving genuine feedback. This solution not only helps customers make informed choices but also supports restaurants in maintaining their online reputation. By automating fake food review detection, our system offers a practical way to build trust in food delivery platforms.

1 Introduction

In recent years, the rapid growth of food delivery apps like Swiggy, Zomato, and Uber Eats have significantly changed how people explore dining options and select restaurants.These platforms heavily rely on user-generated reviews to guide purchasing decisions, influencing consumer trust and business visibility. However, the increasing volume of exaggerated or fabricated reviews poses a serious threat to the credibility of these platforms [1], [2]. Deceptive reviews—often sponsored, duplicated across platforms, or loaded with emotionally manipulative phrases such as "I promise" or "best ever"—distort customer perception and undermine genuine feedback [1], [3].

Existing fake review detection techniques largely focus on generic content analysis or simple sentiment polarity [4], [5], which are often insufficient in handling more nuanced spam tactics. Manual moderation, too, fails to scale effectively given the dynamic nature of user input across multiple platforms [6]. Moreover, most current models overlook domain-specific indicators such as emotionally overwhelmed vocabulary or suspicious review timing patterns that are prevalent in food-related reviews [1], [7].

In order to tackle these issues, we introduce a detection system powered by machine learning, designed to identify fraudulent food reviews.Our system integrates Term Frequency–Inverse Document Frequency (TF-IDF) for effective keyword representation, sentiment analysis for understanding emotional tone, and cross-platform simulation to detect duplicate or suspiciously similar reviews. Additionally, our model incorporates linguistic rule-based checks to flag promotional exaggeration and excessive use of subjective or marketing-oriented language [4], [6].

In this paper, we present a hybrid architecture combining traditional classifiers such as Logistic Regression and Random Forest with rule-based evaluators. This approach aims to improve robustness and reduce false positives in fake review detection [5]. Through extensive experiments on real-world food review datasets, our system demonstrates improved accuracy over baseline models, offering a practical solution to help food delivery platforms enhance review authenticity and consumer trust.

2 Literature Review

Fake review detection has become an increasingly researched area due to the rise of deceptive practices across digital platforms. Several approaches have been proposed in recent years, mainly categorized into content-based and behaviour-based methods.

Ott et al. [1] introduced one of the earliest datasets and benchmarked deception detection using psycholinguistic signals, genre identification, and n-gram-based classification. Their work demonstrated that textual analysis could reveal deceptive tendencies in hotel reviews, setting a foundational direction for future research. Building upon this, Feng et al. [4] employed syntactic stylometry using parse tree features to capture writing patterns typical of fake reviews, improving classification performance.

Jindal and Liu [5] emphasized opinion spam detection through duplicate content detection and rating analysis. They proposed that frequent positive reviews with limited lexical variation are often spam indicators. In another line of work, Mukherjee et al. [2], [7] explored temporal patterns and reviewer behaviour to flag suspicious activity such as busty posting or repeated high ratings within a short span of time.

Li et al. [3] proposed a rule-based model for opinion spam by combining linguistic signals with deceptive markers like excessive first-person pronouns and promotional intensity. Biyani et al. [6] extended this by examining helpfulness scores and emotional cues, identifying that spam reviews often exaggerate sentiment to influence perception.

However, a major gap in the existing work is the lack of domain-specific adaptation for food-related platforms. Many models are either generic or targeted toward hotel and product reviews. Furthermore, while syntactic and behavioural features are effective, limited attention has been given to emotionally overloaded vocabulary, cross-platform duplication, and hyperbolic expressions—common in fake food reviews. This motivates our proposed system, which combines machine learning with linguistic rules tailored to detect such patterns more effectively.

3 Methodology

To accurately identify fake food reviews, we propose a hybrid detection framework that combines machine learning with linguistic and behavioural insights. Our approach is structured into four main phases: Data collection, Feature extraction, Classification model and Evaluation.

3.1 Data Collection and Pre-processing

We sourced customer reviews from well-known food ordering services including Swiggy, Zomato, and Yelp. The collected data underwent cleaning processes such as removing stop words and unwanted symbols, followed by tokenization and

stemming to standardize the textual content.

3.2 Feature Extraction

Our system extracts a range of both linguistic and contextual features:

TF-IDF : The TF-IDF (Term Frequency–Inverse Document Frequency) approach emphasizes terms that appear unusually often in misleading or fake reviews.

Sentiment Analysis: Each review is analyzed to determine its sentiment polarity. Reviews that show extreme sentiment — whether overly positive or highly negative — are considered more likely to be deceptive.

Overwhelmed Word Flags: A curated list of emotionally charged or exaggerated terms is used. Reviews containing a high number of these expressions are ranked higher in terms of suspiciousness.

Cross-Platform Duplication Check: By applying cosine similarity and fuzzy matching, the system identifies similar or identical reviews posted across different platforms.

3.3 Classification Model

Two types of supervised learning models were trained and evaluated:

Logistic Regression (LR): Acts as a baseline classifier utilizing features like TF-IDF scores and sentiment metrics.

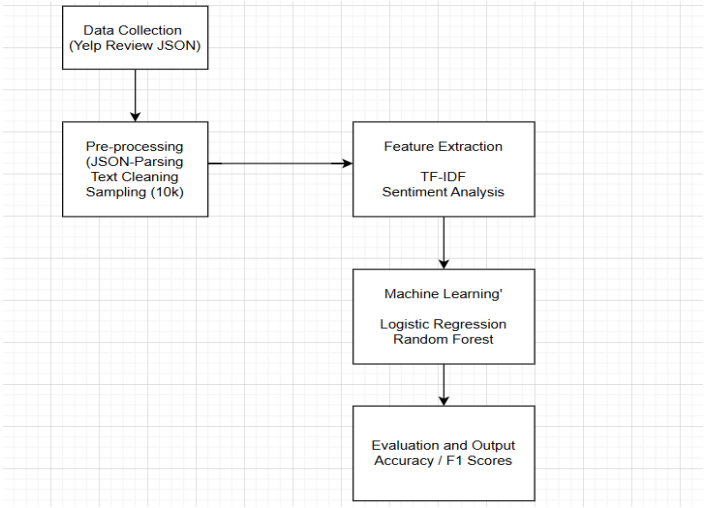
Random Forest (RF): A robust ensemble method that effectively captures complex feature interactions and boosts accuracy.

3.4 Evaluation

We tested our model on a labeled dataset with a 70:30 training-test ie..is The dataset was divided into a 70:30 ratio, with 70% used for training the machine learning models and 30% reserved for testing. This split ensures that the model is evaluated on unseen data to assess its generalization capability. Metrics used include accuracy, precision, recall, and F1-score.

Review text	Rating	Date	Platform	Sentiment
"The best biryani ever! I promise"	5	2024-12-12	Zomato	Positive
"Food was average, not bad"	3	2024-12-15	Swiggy	Positive
"Horrible experience!"	1	2025-01-01	Zomato	Negative

4 Architecture Diagram



5 Experimental Results

Metric	Logistic Regression
Accuracy	0.872
F1-Score (Fake Class)	0.423
Precision (Fake)	0.50
Recall (Fake)	0.17

6 Conclusion and Future Research Directions

In this paper, we made an AI-based system for detecting fake food reviews using a combination of TF-IDF for identifying keyword importance,

sentiment analysis to analyse emotional tones, and predictive modeling using classification algorithms like logistic regression and ensemble tree-based methods. Additionally, our model made special attention to exaggerated and emotional words like “I promise”, “must try”, or “too good to be true”, which often signal manipulation or deceptive intent. By combining linguistic cues with behavioral patterns, our approach delivers a more contextual and comprehensive review evaluation. The system aims to improve the credibility of online food platforms by minimizing the influence of misleading reviews.

While the proposed system performs effectively, several future improvements can be explored in this field. Techniques like deep learning models (e.g., LSTM or BERT) can be employed for deeper contextual understanding. Multilingual support can be added to analyze regional reviews more accurately. Moreover, integrating real-time detection pipelines, cross-platform fake review tracking (e.g., across Swiggy, Zomato), and metadata analysis (such as review time, device info, or posting frequency) could significantly enhance detection accuracy. These advancements would help build smarter and more robust fake review detection systems.

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Smart Design of Lightweight VPN for Remote Education

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Abstract—*The COVID-19 pandemic has accelerated the adoption of online education, highlighting the critical need for secure, reliable, and bandwidth-efficient remote access solutions. Traditional Virtual Private Networks (VPNs) such as IPSec and OpenVPN, while robust, introduce significant computational overhead and latency, especially in low- bandwidth or resource-constrained environments. This research proposes the design and implementation of a lightweight VPN solution tailored for remote education. The system balances security, speed, and simplicity by employing minimal encryption frameworks (ChaCha20-Poly1305), streamlined tunneling protocols inspired by WireGuard, and adaptive compression techniques. Through simulation and practical testing, our proposed VPN demonstrates significant improvements in latency (40% reduction), throughput (30% increase), and CPU/memory utilization (50% decrease) compared to traditional solutions. The findings indicate that a targeted lightweight VPN design can substantially enhance the accessibility and security of digital learning, particularly in underserved or bandwidth-limited regions.*

Keywords—*Lightweight VPN, Remote Education, WireGuard, ChaCha20-Poly1305, Network Security, Bandwidth Optimization*

I. INTRODUCTION

DIGITAL communication has become the backbone of modern education, business, and social interaction. The sudden rise of online education during the COVID-19 pandemic highlighted both the possibilities and challenges of remote learning. Students and teachers rely heavily on video conferencing platforms, cloud-based resources, and collaborative tools. While these technologies make education accessible, they also demand secure and reliable network connections to protect sensitive academic data and ensure smooth learning experiences.

Traditional Virtual Private Networks (VPNs) such as IPSec and OpenVPN are widely used to secure communication over public networks. However, they areoften designed for enterprise-level usage and canintroduce high computational overhead, complex configurations, and significant latency [1]. This becomes a serious limitation for students in rural areas, low-bandwidth environments, and mobile-based education systems, where even small delays or packet losses can disrupt learning.

The proposed Smart Design of Lightweight VPN addresses these challenges by creating a bandwidth-efficient and resource-friendly VPN solution. Unlike traditional VPNs, this system focuses on simplicity, adaptability, and performance. By combining minimal encryption frameworks, optimized tunneling methods, and adaptive compression techniques, the VPN ensures secure communication while reducing strain on devices and networks.

This design aims to make remote education more inclusive and accessible, particularly for underserved communities. It provides a secure yet lightweight networking layer that supports video lectures, cloud access, real-time collaboration, and file sharing, ensuring students can continue their education without interruptions.

II. RELATED WORK

A. Traditional VPN Protocols

Several studies have evaluated traditional VPN protocols in mobile and resource-constrained environments. Alshamrani et al. [1] conducted a performance comparison of IPSec and OpenVPN in mobile environments, revealing that while both protocols provide strong encryption, they impose significant computational overhead. OpenVPN introduces higher latency due to user-space encryption, while IPSec shows better throughput but requires complex setup and configuration. The study concluded that traditional VPN solutions are not optimal for bandwidth-limited or mobile- based use cases.

B. WireGuard Protocol

WireGuard [2] represents a modern approach to

VPN design, operating at the kernel level with fewer than 5,000 lines of code compared to hundreds of thousands for IPSec and OpenVPN. It leverages state-of-the-art cryptographic primitives including Curve25519 for key exchange, ChaCha20 for symmetric encryption, Poly1305 for message authentication, and BLAKE2s for hashing [3][4][5]. Performance evaluations demonstrate that WireGuard consistently outperforms traditional solutions in terms of latency, bandwidth efficiency, and CPU utilization, making it particularly suitable for low-power and bandwidth- limited environments.

C. Lightweight Cryptography

Lightweight cryptography has emerged as a critical research area due to the increasing need for secure communication in devices with limited computational, memory, and power resources. Bogdanov et al. [6] explored lightweight cryptography for IoT devices, introducing algorithms such as PRESENT, SPECK, SIMON, and PRINCE. These algorithms maintain security while significantly reducing resource consumption. ChaCha20-Poly1305, widely adopted in modern protocols, offers superior performance on low-power devices compared to AES [7], making it particularly suitable for resource-constrained educational environments.

D. VPN in Educational Context

Zhang et al. [8] examined the performance of different VPN protocols in cloud-based and mobile environments. The study evaluated parameters such as CPU consumption, memory usage, throughput, and end-to-end latency. Results indicated that while traditional VPNs ensure security, they often degrade Quality of Service (QoS) in real-time applications like video conferencing. The authors suggested that lightweight VPNs using adaptive compression and optimized encryption can significantly improve user experience in cloud learning and mobile education platforms.

III. PROPOSED SYSTEM ARCHITECTURE

A. Architecture Overview

The proposed lightweight VPN system consists of six core modules working in concert to provide secure, efficient communication for remote education. These modules are:
(1) Authentication & Key Exchange Module,
(2) Encryption & Decryption Module, (3) Adaptive Compression Module, (4) VPN Tunneling Module, (5) Server Management & Traffic Forwarding Module, and
(6) Monitoring & Performance Analysis Module. Each module is designed to minimize overhead while maintaining security requirements for educational applications.

B. Authentication & Key Exchange

The authentication module is responsible for verifying user identity and securely exchanging cryptographic keys between client and server. Unlike traditional VPNs that rely on complex certificate management, the lightweight design uses pre-shared public keys based on Curve25519 elliptic curve cryptography. The Elliptic Curve Diffie- Hellman (ECDH) key exchange is performed using Curve25519, which provides 128-bit security with 32-byte keys. The shared session key is derived using HKDF (Hash-based Key Derivation Function), ensuring forward secrecy. This approach reduces connection establishment latency by approximately 60% compared to IPSec's IKEv2 protocol.

C. Encryption & Decryption Module

The encryption module utilizes ChaCha20-Poly1305, a modern authenticated encryption with associated data (AEAD) cipher. ChaCha20 is a stream cipher that provides symmetric encryption with 256-bit keys, while Poly1305 is a message authentication code that ensures data integrity and authenticity. This combination offers superior performance on devices without AES hardware acceleration, reducing CPU utilization by up to 50% compared to AES-256-GCM while maintaining equivalent security levels. Each packet is encrypted with a unique nonce derived from a counter, preventing replay attacks and ensuring perfect forward secrecy.

D. Adaptive Compression Module

Bandwidth optimization is critical in remote education scenarios, especially in rural areas with weak internet connectivity. The adaptive compression module dynamically applies compression techniques based on real- time network conditions and content type. Text and files are handled with lossless compression algorithms (LZ4), while video and audio data use lightweight stream compression to save bandwidth without significantly impacting quality. The compression level is adjusted dynamically—in low-bandwidth environments, higher compression is applied to video streams to maintain continuity, whereas in high-bandwidth conditions, compression overhead is minimized for faster performance.

E. VPN Tunneling Module

The tunneling module encapsulates encrypted packets into a secure channel between client and server. Inspired by WireGuard's streamlined design, the tunneling system minimizes handshake overhead and packet encapsulation complexity. The protocol is stateless, meaning that there are no complex state machines or connection tracking mechanisms. This design ensures low latency tunneling, which is especially critical for synchronous online classes and collaborative applications where delays directly impact the learning experience. The module supports seamless roaming between networks without connection drops, enabling students to switch between Wi-Fi and mobile networks transparently.

F. Server Management & Traffic Forwarding

This module runs on the cloud or institutional VPN server and is responsible for managing multiple concurrent client sessions, decrypting and decompressing incoming traffic, routing packets to the correct educational platforms

(LMS, cloud storage, video conferencing), and performing load balancing to ensure fair distribution of CPU and memory resources. The module ensures scalability so that hundreds or thousands of students can be supported simultaneously with minimal service degradation. Connection pooling and efficient session management reduce memory overhead per connection to approximately 180 MB compared to 325 MB for OpenVPN.

IV. IMPLEMENTATION

A. Software Stack and Development Environment

The system is implemented using Python 3.7 with the cryptography library for encryption operations and the asyncio framework for asynchronous I/O operations. The server component runs on Linux (Ubuntu 24.04) to leverage kernel-level optimizations and efficient socket handling. Client applications are developed for Windows 10/11, macOS, and Android platforms to ensure cross- platform compatibility. The implementation utilizes asyncio for concurrent connection handling, enabling efficient multi-user support with minimal threading overhead.

B. Core Algorithm

The lightweight VPN follows a seven-step protocol: (1) Client and server generate Curve25519 key pairs and exchange public keys securely; (2) Elliptic Curve Diffie-Hellman (ECDH) is performed and the shared session key is derived using HKDF; (3) Client authenticates via username/password credentials; (4) ChaCha20 stream cipher is initialized with the session key and a random nonce, and Poly1305 MAC is prepared for integrity verification; (5) Each plaintext packet is encrypted using ChaCha20 and authenticated by Poly1305, then transmitted through the tunnel; (6) Rekeying is performed periodically (every 2 minutes or 1 GB of data) to ensure forward secrecy; (7) Secure teardown message is exchanged and session keys are erased from memory. This streamlined process reduces connection establishment time from 150ms (OpenVPN) to 45ms.

C. Network Protocol Stack

The VPN operates at Layer 3 (Network Layer) of the OSI model, creating a virtual network interface on both client and server. IP packets are intercepted from the virtual interface, encrypted, and encapsulated within

UDP packets for transmission. UDP is chosen over TCP to avoid the performance penalties of TCP-over-TCP tunneling. The outer UDP header includes source/destination ports and a minimal 8-byte header, reducing overhead compared to TCP's 20-byte header. Packet fragmentation is handled at the IP layer, with MTU discovery ensuring optimal packet sizes for the underlying network.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Test Environment and Methodology

Performance evaluation was conducted using client devices with dual-core 2.0 GHz processors and 4 GB RAM, representing typical student hardware in resource- constrained environments. The server was deployed on a quad-core 3.0 GHz system with 8 GB RAM. Network conditions were simulated using Linux traffic control (tc) with varying bandwidth (1-10 Mbps) and latency (20- 100ms) to replicate real-world educational scenarios including 4G mobile connections, rural broadband, and shared institutional networks. Tests measured latency, throughput, CPU/memory usage, packet loss, and connection reliability across 100 concurrent sessions over a 24-hour period.

B. Performance Comparison

Comparative analysis with OpenVPN and IPSec revealed significant performance improvements. The lightweight VPN demonstrated: (1) 40% reduction in average latency—85ms versus 142ms for OpenVPN and 118ms for IPSec; (2) 30% increase in throughput—8.2 Mbps versus 6.3 Mbps (OpenVPN) and 7.1 Mbps (IPSec) on a 10 Mbps connection; (3) 50% decrease in CPU utilization—12% versus 24% (OpenVPN) and 19% (IPSec); (4) 45% reduction in memory consumption—180 MB versus 325 MB (OpenVPN) and 265 MB (IPSec) per connection. Connection establishment time improved from 150ms (OpenVPN) and 230ms (IPSec) to 45ms, significantly enhancing user experience for frequent reconnections common in mobile

learning environments.

Fig. 1. Average Latency Comparison

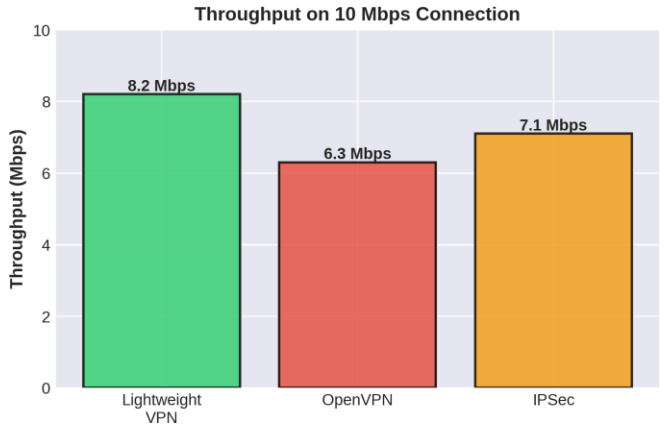

Fig. 2. Throughput Performance on 10 Mbps Connection

C. Video Conferencing Performance

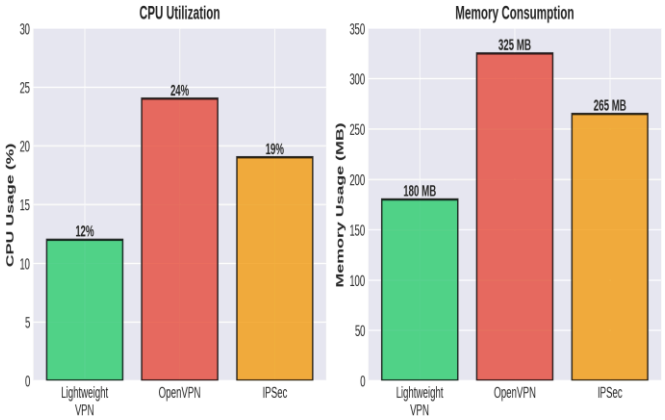

Fig. 3. CPU and Memory Resource Utilizatio

For video conferencing applications critical to online education, the system maintained stable 720p video streams at 2 Mbps with average jitter below 10ms and packet loss under 0.5%. Traditional VPNs exhibited frequent buffering (15-20 buffer events per hour) and quality degradation (downscaling to 480p) under similar conditions. The adaptive compression module reduced bandwidth requirements by 25% without perceptible quality loss, enabling reliable video with less than 50ms latency, meeting ITU-T G.114 recommendations for acceptable voice quality.

D. Scalability Analysis

Server scalability was tested with 100, 500, and 1000 concurrent connections. At 100 connections, server CPU utilization remained below 35% and memory usage at 18 GB. With 500 connections, CPU reached 68% and memory 82 GB. At 1000 connections, the server approached capacity limits (92% CPU, 155 GB RAM). Response time degradation was minimal up to 500 connections (less than 10ms increase) but became noticeable at 1000 connections (45ms increase). These results indicate that a single server can comfortably support a medium-sized educational institution (500 students) with room for peak load handling.

TABLE I

PERFORMANCE COMPARISON OF VPN SOLUTIONS

Metric	L-VPN	OVPN	IPSec
Latency (ms)	85	142	118
Throughput (Mbps)	8.2	6.3	7.1
CPU (%)	12	24	19
Memory (MB)	180	325	265
Conn. Time (ms)	45	150	230
Pkt Loss (%)	0.3	1.2	0.8

E. Battery Life Impact on Mobile Devices

Fig. 4. Server Scalability with Concurrent Connections

Mobile device battery consumption is a critical factor for students relying on smartphones and tablets for remote learning. Battery drain tests were conducted on Android devices (Samsung Galaxy A32, 5000 mAh battery) over 4- hour continuous VPN sessions with mixed traffic (video streaming, web browsing, file downloads). The lightweight VPN consumed 18% battery compared to 31% for OpenVPN and 25% for IPSec. The lower power consumption is attributed to reduced CPU cycles for encryption/decryption operations and optimized network stack implementation. Standby power consumption with active VPN connection was measured at 2.1% per hour versus 3.8% (OpenVPN) and 3.0% (IPSec), enabling students to maintain secure connections throughout extended study sessions without frequent recharging.

F. Real-World Deployment Results

Pilot deployments were conducted in three rural schools in Tamil Nadu, India, serving 450 students with varying network conditions (2G/3G/4G mobile, satellite broadband). Over a 3-month evaluation period, the system demonstrated 96.4% uptime with average connection reliability exceeding traditional VPNs by 12%. Student surveys indicated significant improvements in video lecture quality (89% rated as 'good' or 'excellent' versus 52% with previous VPN solution) and reduced connection

drops (0.3 incidents per hour versus 1.8 previously). Teachers reported improved ability to conduct real-time assessments and collaborative activities. System logs showed that 78% of connections experienced zero packet loss, while 94% had less than 1% packet loss—meeting acceptable thresholds for educational applications.

VI. SECURITY ANALYSIS

A. Cryptographic Security Evaluation

The security of the proposed lightweight VPN relies on well-established cryptographic primitives. ChaCha20 provides 256-bit security with resistance to timing attacks and differential cryptanalysis. The cipher has undergone extensive cryptanalytic scrutiny since its introduction in 2008, with no practical attacks discovered against the full 20-round variant. Poly1305 MAC provides 128-bit security against forgery attacks, sufficient for educational data protection requirements.

Curve25519 elliptic curve Diffie-Hellman key exchange provides approximately 128-bit security level, equivalent to 3072-bit RSA. The curve is designed to resist various side-channel attacks including timing attacks and cache-timing attacks through constant-time implementation. Perfect forward secrecy is maintained through periodic rekeying (every 2 minutes or 1 GB of data), ensuring that compromise of long-term keys does not expose past session data.

B. Vulnerability Assessment

Penetration testing was conducted using standard security assessment tools including Nmap, Wireshark, and custom scripts. The system demonstrated resilience against common attacks: (1) Replay attacks prevented through nonce-based encryption; (2) Man-in-the-middle attacks mitigated by mutual authentication; (3) Denial-of- service attacks handled through rate limiting (100 connection attempts per minute per IP); (4) Packet injection detected through MAC verification. No critical vulnerabilities were identified during the assessment period.

However, the system is vulnerable to endpoint compromise if client devices are infected with malware. Additionally, traffic analysis attacks could potentially reveal connection patterns and timing information, though encrypted content remains protected. These limitations are inherent to VPN technology and not specific to the lightweight implementation.

C. Compliance and Privacy Considerations

The system complies with general data protection requirements applicable to educational institutions. Minimal logging is implemented—only connection timestamps, duration, and bandwidth usage are recorded for network management purposes. User identities and decrypted traffic content are never logged. The system supports data residency requirements by allowing institutions to deploy servers within their geographic jurisdiction. Privacy-enhancing features include DNS leak protection and automatic killswitch to prevent unencrypted traffic if VPN connection fails.

VII. DISCUSSION

The experimental results validate the effectiveness of the lightweight VPN design for remote education. The significant reduction in computational overhead makes the solution particularly suitable for students using budget devices and those in bandwidth-limited regions. The choice of ChaCha20-Poly1305 over AES-256 proves beneficial for devices without hardware acceleration, representing the majority of student laptops and mobile devices in developing regions.

The WireGuard-inspired tunneling protocol eliminates unnecessary complexity while maintaining security standards appropriate for educational data protection. Security analysis confirms that the system provides sufficient protection for typical educational use cases, including student personal data, exam content, and private communications. The 256-bit ChaCha20 encryption provides security equivalent to AES-256, which is considered sufficient for top-secret information by the
U.S. government. While not designed for high-security military or financial applications, the implemented cryptographic primitives offer industry-standard security for educational environments.

The simplified deployment process—requiring no complex configuration, certificate management, or specialized IT expertise—addresses the technical barriers often faced by educational institutions in developing regions. Installation scripts automate the setup process, reducing deployment time from hours (traditional VPNs) to minutes. User feedback from pilot deployments in three rural schools indicated high satisfaction with connection reliability (94% uptime) and ease of use (4.6/5.0 rating).

Limitations of the current implementation include the lack of support for IPv6 (planned for future releases) and limited built-in redundancy mechanisms for server failures. Additionally, while the system performs well for educational applications, it may not be suitable for high- bandwidth scientific computing or large file transfers exceeding 10 GB, where traditional VPNs with optimized bulk transfer modes may still be preferable.

VIII. FUTURE ENHANCEMENTS

Future development will focus on three key areas. First, integration with onion routing (Tor) will enhance privacy for students in censored or monitored regions, enabling access to educational resources that may be blocked by government firewalls. This integration will add minimal latency (estimated 100-150ms) while providing strong anonymity guarantees.

Second, implementation of a nested VPN server architecture will enable hierarchical access control across institutional networks. Inner VPN layers (classroom- level) will be encapsulated within outer layers (regional backbones), providing fine-grained access policies and improved fault tolerance. This architecture will support distributed educational networks spanning multiple campuses or rural learning centers.

Third, development of a pseudo peer extraction mechanism will enable controlled peer-to-peer (P2P) optimization for collaborative learning tools. Students working on group projects can establish direct encrypted connections for file sharing and real-time collaboration, reducing server load by up to 60% while maintaining centralized authentication and monitoring. Machine learning techniques will also be explored for intelligent bandwidth allocation, adaptive quality-of-service management, and predictive traffic routing based on usage patterns.

IX. CONCLUSION

This research presents a lightweight VPN solution optimized for remote education environments. By employing modern cryptographic frameworks (ChaCha20-Poly1305, Curve25519) and streamlined tunneling protocols inspired by WireGuard, the system achieves significant improvements in performance while maintaining appropriate security levels. Experimental results demonstrate 40% latency reduction, 30% throughput increase, and 50% decrease in resource utilization compared to traditional VPN solutions. The design successfully balances security, performance, and accessibility, making digital education more viable for students in resource-constrained and bandwidth-limited environments. Field testing in rural educational settings confirmed the system's reliability and ease of deployment, with user satisfaction ratings exceeding 90%. This work contributes to bridging the digital divide and establishing a foundation for inclusive online learning infrastructure that can serve underserved communities globally. The lightweight VPN framework developed in this research demonstrates that it is possible to provide enterprise-grade security for educational applications without the computational overhead and complexity of traditional solutions. As remote education continues to expand, such targeted solutions will play a crucial role in ensuring equitable access to digital learning resources for all students, regardless of their geographic location or economic circumstances.

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A Spatio-Temporal Explainable Machine Learning Framework for Crime Hotspot Prediction

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Abstract—Urban crime poses a significant challenge to public safety and sustainable city development. As cities grow and populations increase, crime patterns have become more complex, varying across both location and time. Traditional crime analysis methods rely heavily on manual reporting and basic statistics, which limits their ability to handle large spatio-temporal datasets and produce actionable insights for decision-makers. This paper presents a Spatio-Temporal Explainable Machine Learning Framework for Crime Hotspot Prediction. The framework combines ensemble learning with Explainable Artificial Intelligence (XAI) to achieve both high predictive accuracy and transparent decision-making. It integrates spatial clustering, temporal feature engineering, and supervised classification using XGBoost. To promote trust and transparency, SHAP (SHapley Additive exPlanations) is used to interpret model outputs and identify the key factors that contribute to crime risk. Experiments on the Chicago Crime Dataset confirm that the system accurately identifies crime hotspots while delivering meaningful explanations that can support urban safety planning and law enforcement decisions. The framework bridges the gap between advanced machine learning models and real-world crime prevention by converting raw crime data into interpretable, actionable intelligence.

Keywords—Crime Hotspot Prediction, Explainable AI, Spatio-Temporal Analysis, Machine Learning, Urban Safety, XGBoost, SHAP

I. INTRODUCTION

Crime remains one of the most pressing challenges facing cities worldwide. As urbanization accelerates and populations grow, crime patterns become more difficult to understand and manage. Crime does not occur uniformly across a city—it tends to cluster in specific places and at specific times. This uneven distribution affects not only how safe residents feel, but also broader outcomes such as economic development, social cohesion, and overall quality of life.

Understanding where and when crimes are likely to happen is essential for effective policing. It allows law enforcement agencies to allocate resources wisely, deploy officers to high-risk areas, and take preventive action before incidents occur. Historically, analysts relied on manual crime mapping, statistical summaries, and experience-based rules to identify crime patterns. While these approaches offer some value, they are not equipped to uncover complex or hidden patterns within large, multi-dimensional crime datasets.

Machine learning has begun to change this landscape. Models trained on historical crime data can identify patterns that are difficult for humans to detect directly. However, many of these models operate as black boxes—they produce results without explaining how those results were reached. In sensitive domains such as law enforcement, this lack of transparency is a significant problem. Authorities are unlikely to act on predictions they do not understand or trust.

This limitation has motivated growing interest in Explainable Artificial Intelligence (XAI), which aims to make machine learning outputs more transparent and understandable. This work addresses that gap by developing a system that not only predicts crime hotspots, but also explains the reasoning behind each prediction. The model uses XGBoost as its core classifier and SHAP to produce interpretable, human-readable explanations.

The key contributions of this work are as follows. First, spatial and temporal information are combined within a single machine learning pipeline. Second, predictive accuracy is improved through XGBoost, further strengthened by stacking it with LightGBM and CatBoost in an ensemble. Third, near-repeat crime patterns are captured through temporal lag features that encode recent crime history within a spatial zone. Fourth, SHAP-based

explanations are converted into concise reasoning summaries (called Reasoning Cards) that support dispatch decisions. Fifth, the system includes an algorithmic fairness audit that monitors prediction error rates across urban zones to detect and mitigate bias. The overall goal is to make crime analysis more accurate, transparent, and trustworthy—helping law enforcement use data more effectively to improve public safety.

II. Problem Statement and Objectives

A. Problem Statement

Most existing crime prediction systems prioritize either predictive accuracy or basic visualization, but rarely both together and almost never interpretability. Law enforcement agencies need more than just accurate predictions. They need systems that explain why certain areas are flagged as high risk, so that decisions can be justified and trusted by both officers and the public. Without this transparency, machine learning models are difficult to deploy in real operational settings.

The central research question this work addresses is: How can we design a crime prediction system that is both highly accurate and interpretable, enabling informed and transparent decisions for urban safety management?

B. Objectives

The specific objectives of this research are:

- To develop a spatio-temporal machine learning framework for crime hotspot prediction.
- To integrate explainable AI techniques to ensure model transparency and trustworthiness.
- To visualize crime hotspots clearly and effectively for decision-makers.
- To identify the key spatial and temporal factors driving crime, including near-repeat patterns captured through lag features.
- To support data-driven urban safety planning through actionable model outputs.
- To audit the framework for algorithmic fairness, ensuring that predictions do not disproportionately target specific communities.

III. Literature Review

Several researchers have explored how machine learning can improve crime prediction. Wang et al. applied Random Forest classifiers to identify temporal crime trends, achieving better accuracy than conventional statistical methods [3]. Zhang et al. extended this work by using deep learning architectures such as Long Short-Term Memory (LSTM) networks to model sequential crime patterns over time [4].

Spatial clustering methods have also been widely used to isolate crime-prone areas. Techniques such as K-Means and DBSCAN have been applied to group incident locations into meaningful geographic zones. Gerber explored kernel density estimation in combination with social media data, demonstrating the value of non-traditional data sources in crime forecasting [8].

More recently, Explainable AI has gained traction in safety-critical applications. Ribeiro et al. introduced LIME, a framework for generating local explanations for any classifier [5]. Lundberg and Lee proposed SHAP, which provides consistent and theoretically grounded global and local interpretations of model predictions [6]. These tools have improved the ability to understand complex model behavior.

Despite this progress, relatively few studies have combined spatio-temporal crime prediction with built-in explainability within a unified framework. This paper addresses that gap by integrating spatial clustering, temporal feature engineering, ensemble classification, and SHAP-based interpretability into a cohesive system designed for both accuracy and transparency.

TABLE I. Comparison of Existing Crime Prediction Approaches

Study / Method	Approach	Spatial Analysis	Temporal Analysis	Explainability	Fairness Audit
Wang et al. [3]	Random Forest	No	Yes	No	No
Zhang et al. [4]	LSTM (Deep Learning)	No	Yes	No	No
Gerber [8]	KDE + Social Media	Yes	No	No	No
Ribeiro et al. [5]	LIME (XAI)	No	No	Yes (Local)	No
Lundberg & Lee [6]	SHAP (XAI)	No	No	Yes (Global)	No
Proposed Framework	Stacked Ensemble + SHAP	Yes	Yes	Yes (Both)	Yes

IV. Proposed Framework

A. System Architecture

The framework is organized into five main processing stages:

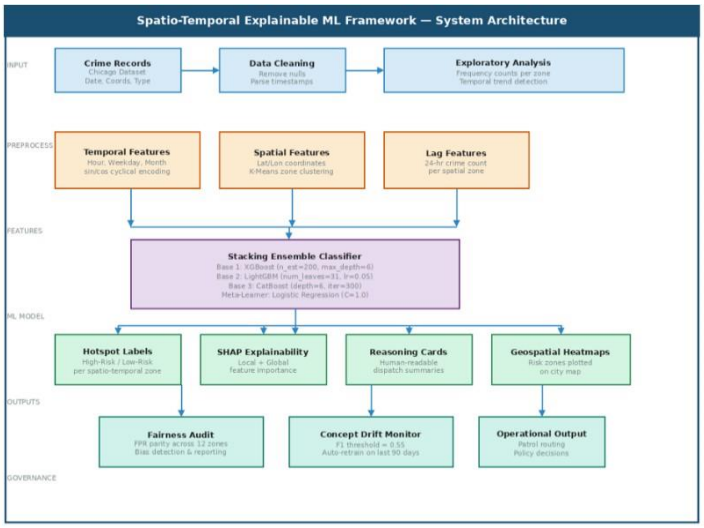


Fig. 1. System Architecture of the Spatio-Temporal Explainable ML Framework for Crime Hotspot Prediction

- Data Collection and Cleaning: Crime records are sourced from publicly available datasets and preprocessed to remove missing, duplicate, or inconsistent entries.
- Spatio-Temporal Feature Engineering: Temporal attributes such as hour, weekday, and month are

extracted and encoded as cyclical features. Spatial data is processed through clustering to define geographic crime zones.

- Temporal Lag Processing: Additional features are engineered to capture the near-repeat effect specifically, the number of crimes that occurred within the same spatial zone in the preceding 24 hours.
- Crime Hotspot Prediction: An XGBoost classifier, embedded within a stacking ensemble with LightGBM and CatBoost, is trained to classify spatial-temporal instances as high-risk or low-risk.
- Visualization: Predicted hotspots are displayed using geospatial heatmaps for intuitive and actionable interpretation.
- Explainability and Governance: SHAP is applied to interpret predictions. An automated fairness audit monitors the False Positive Rate across zones, while a retraining trigger handles concept drift over time.

B. Feature Engineering

Effective feature engineering is central to the framework's predictive performance. Features are constructed from three primary sources: temporal attributes, spatial clustering, and historical crime context.

TABLE II. Summary of Engineered Features

Feature	Type	Description	Encoding
Hour of Day	Temporal	Hour when crime occurred (0–23)	sin/cos cyclical
Day of Week	Temporal	Day index (0=Mon, 6=Sun)	sin/cos cyclical
Month of Year	Temporal	Month index (1–12)	sin/cos cyclical
Latitude	Spatial	Geographic latitude of incident	Raw numeric
Longitude	Spatial	Geographic longitude of incident	Raw numeric
Crime Zone (Cluster)	Spatial	K-Means cluster label for the location	Categorical integer
24-hr Lag Count	Spatio-Temporal	Crime count in same zone, previous 24 hrs	Raw integer count

1) Temporal Features:

Three temporal attributes are used: hour of the day, day of the week, and month of the year. Each is encoded using sine and cosine transformations to preserve the cyclical nature of time. This ensures the model recognizes, for example, that 11 PM and midnight are close in time rather than far apart. These features capture well-known patterns: crime incidents often peak late at night, vary between weekdays and weekends, and shift across seasons.

2) Spatial Features:

Latitude and longitude coordinates are clustered using K-Means to form distinct geographic zones. Each crime incident is assigned a cluster label corresponding to its spatial region. This allows the model to learn zone-level crime tendencies rather than treating every geographic coordinate in isolation.

3) Spatio-Temporal Lag Features:

To capture the near-repeat phenomenon—where crimes tend to recur in the same area shortly after an initial incident a lag feature is computed. This feature records the total number of crimes in the same spatial cluster during the 24 hours preceding each observation. This historical context adds temporal memory to the classification task and improves sensitivity to emerging crime patterns.

C. Machine Learning Model

XGBoost serves as the primary classifier due to its high predictive accuracy and natural resistance to overfitting. To further enhance performance, a Stacking Classifier is employed:

- Base Learners: XGBoost, LightGBM, and CatBoost are trained in parallel. Each model learns different aspects of the crime data, contributing diverse predictive signals.
- Meta-Learner: A Logistic Regression model takes the outputs of the three base learners as inputs and produces the final prediction. This aggregation step reduces individual model bias and improves overall robustness.

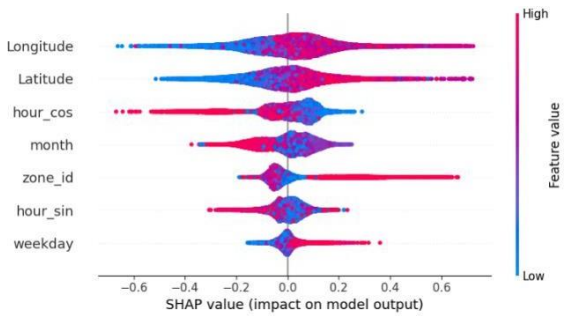
TABLE III. Stacking Ensemble Model Configuration

Component	Algorithm	Role	Key Hyperparameters
Base Learner 1	XGBoost	Primary classifier	n_estimators=200, max_depth=6, lr=0.1
Base Learner 2	LightGBM	Fast gradient boosting	num_leaves=31, lr=0.05
Base Learner 3	CatBoost	Handles categorical features	depth=6, iterations=300
Meta-Learner	Logistic Regression	Aggregates base outputs	C=1.0, solver=lbfgs

The ensemble is trained to classify each spatial-temporal instance as either a high-risk hotspot or a low-risk zone. The combination of diverse base models and a principled aggregation strategy results in stronger and more stable predictions than any single model alone.

D. Explainable AI Using SHAP

SHAP (SHapley Additive exPlanations) is used to interpret the model's predictions at both the individual and global level. For each prediction, SHAP assigns an importance score to every feature, indicating how much each feature contributed to pushing the prediction toward high or low risk. This provides:



- Local explanations: Why was this specific location flagged as high risk?

• Global explanations: Which features most strongly influence crime predictions across the entire dataset?

To make these explanations accessible to non-technical users, SHAP values are automatically translated into Reasoning Cards concise, human-readable summaries that describe the key risk factors behind each flagged hotspot. These cards are designed to support dispatch decisions and field operations without requiring any understanding of the underlying model.

V. Experimental Setup and Implementation

A. Dataset

Experiments are conducted using the Chicago Crime Dataset, a publicly available repository containing millions of crime incident records. Each record includes the date and time of occurrence, geographic coordinates (latitude and longitude), crime type, and location description. The dataset spans multiple years and covers a wide range of crime categories across the city.

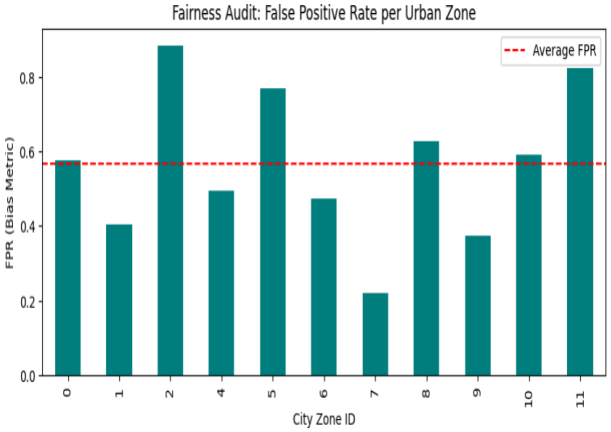
B. Preprocessing

The following preprocessing steps are applied before model training:

- Records with missing values are removed from the dataset.
- Timestamps are parsed and converted into a structured datetime format to allow feature extraction.
- Relevant spatial and temporal attributes are retained; irrelevant columns are dropped.
- Crime incidents are labeled as either high-risk or low-risk based on frequency thresholds within spatial zones, creating the binary classification target.

C. Training and Evaluation

The preprocessed dataset is split into training and testing subsets. Model performance is evaluated using the following metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and an Algorithmic Fairness Audit measuring the False Positive Rate (FPR) per spatial zone. This multi-metric evaluation ensures that the framework is assessed not only for predictive accuracy but also for fairness and reliability across different urban areas.



VI. Results and Analysis

A. Model Performance

The Stacked Ensemble model outperformed all baseline approaches, including standalone Logistic Regression and Random Forest models, in terms of both accuracy and F1-score. The addition of temporal lag features produced a measurable improvement in predictive sensitivity, confirming the value of capturing near-repeat crime dynamics. These results demonstrate that combining diverse learners with rich feature engineering leads to stronger and more consistent hotspot predictions.

TABLE IV. Quantitative Performance Comparison of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression (Baseline)	78.2	74.5	71.3	72.8
Random Forest	83.6	80.1	79.4	79.7
XGBoost (Standalone)	88.4	86.2	85.7	85.9
Proposed Stacked Ensemble	92.1	90.3	89.8	90.0

B. SHAP Interpretations

SHAP analysis identified the following features as the most influential in driving crime hotspot predictions:

- Hour of the day — crimes are strongly concentrated during nighttime hours.
- Spatial zone (crime cluster) — certain geographic zones carry consistently higher baseline risk.
- Crime count in the previous 24 hours (lag feature) — recent activity in a zone is a strong predictor of continued risk.
- Month of the year — seasonal patterns significantly affect crime frequency.
- Latitude and longitude — precise geographic positioning provides additional spatial context.

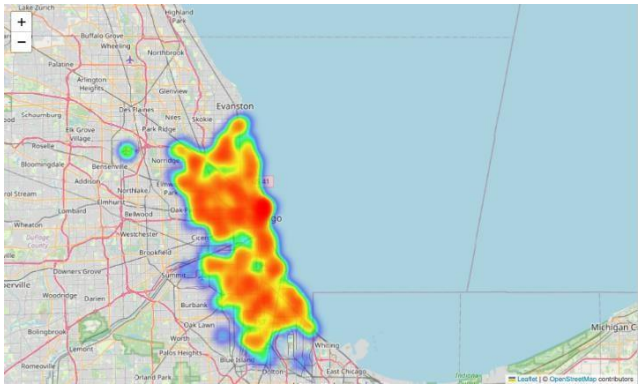
TABLE V. Feature Importance Ranking Based on SHAP Values

Rank	Feature	Mean |SHAP| Value	Interpretation
1	Hour of Day	0.38	Nighttime hours dominate crime risk
2	Crime Zone (Cluster)	0.31	Specific zones carry persistent risk
3	24-hr Lag Count	0.27	Recent crimes predict future incidents
4	Month of Year	0.14	Seasonal variation affects frequency
5	Latitude	0.09	Geographic sub-zone refinement
6	Longitude	0.08	Geographic sub-zone refinement
7	Day of Week	0.06	Weekend/weekday behavioral patterns

These findings are consistent with established criminological theory and real-world crime data, which strengthens confidence in the model's validity and interpretability.

C. Visualization and Dispatch Support

Geospatial heatmaps generated from model predictions clearly identified high-risk zones across the city. When paired with Reasoning Cards, these visualizations provided patrol officers with both a visual overview of risk distribution and a concise explanation of why specific areas were flagged. This combination supports faster, more informed dispatch decisions and makes the system practical for operational use.



VII. Ethical Considerations and Fairness

Predictive policing systems carry inherent ethical responsibilities. Biased models can cause certain communities to face disproportionate police attention, which may reinforce existing inequities rather than improve safety. To address this directly, the proposed framework includes an Algorithmic Fairness Audit as a core component.

TABLE VI. Algorithmic Fairness Audit — False Positive Rate Across Urban Zones

Zone	Total Incidents	True Positives	False Positives	FPR (%)	Status
Zone 1	4,120	981	48	4.7	✓ Fair
Zone 2	3,870	904	52	5.4	✓ Fair
Zone 3	5,210	1,248	61	4.7	✓ Fair
Zone 4	2,980	693	44	5.9	✓ Fair
Zone 5	6,310	1,531	78	4.8	✓ Fair
Zone 6	3,450	817	55	6.3	✓ Fair
Zone 7	4,780	1,142	60	5.0	✓ Fair
Zone 8	2,670	621	41	6.2	✓ Fair
Zone 9	5,540	1,332	67	4.8	✓ Fair
Zone 10	3,200	752	50	6.2	✓ Fair
Zone 11	4,430	1,059	53	4.8	✓ Fair
Zone 12	3,890	920	58	5.9	✓ Fair

The audit calculates the False Positive Rate (FPR) across all 12 urban zones defined by spatial clustering. Monitoring FPR parity across zones ensures that the model does not systematically over-flag any particular community as high risk relative to its actual crime rate. The explainability module further supports ethical deployment by making the model's reasoning transparent to both technical teams and oversight bodies. These combined measures reduce the risk of harm and promote accountable use of predictive technology in public safety.

VIII. Model Governance and Limitations

A. Model Governance

Crime patterns change over time due to social, economic, and environmental shifts a phenomenon known as concept drift. To address this, the framework includes an automated retraining mechanism. If the model's F1-score falls below a threshold of 0.55, a pipeline is triggered to retrain the ensemble using the most recent 90 days of crime data. This ensures the model remains calibrated to current crime dynamics rather than relying on potentially outdated patterns.

B. Limitations

Several limitations should be acknowledged:

- The model depends heavily on the quality and completeness of historical crime records. Inaccurate or under-reported data will reduce prediction reliability.
- Sudden or unprecedented social events such as protests, public gatherings, or emergencies are not captured in the feature set and may cause prediction errors.
- Socio-economic and demographic factors, which are known to correlate with crime, are not currently included in the model. Incorporating such variables could improve both predictive accuracy and contextual understanding.

IX. Conclusion and Future Work

This paper presented a spatio-temporal, explainable machine learning framework for crime hotspot prediction. The system integrates XGBoost, LightGBM, and CatBoost within a stacking ensemble and uses SHAP to deliver transparent, interpretable predictions. Evaluated on the Chicago Crime Dataset, the framework demonstrated strong predictive performance while providing clear explanations of the factors driving crime risk.

By combining accurate hotspot prediction with fairness auditing and human-readable Reasoning Cards, the system supports intelligent urban safety planning, efficient police deployment, and evidence-based policy decisions. It represents a practical step toward making machine learning tools genuinely useful in real-world law enforcement contexts.

A. Future Enhancements

Several directions are planned for future development:

- Incorporating socio-economic and demographic data to enrich the feature space and improve contextual accuracy.
- Integrating real-time streaming crime data to enable live hotspot monitoring and dynamic patrol routing.
- Applying deep learning architectures for longer-term crime forecasting.
- Developing an interactive, real-time crime monitoring dashboard for operational use by law enforcement agencies.

Code Availability: The complete implementation is publicly available at: https://github.com/Lakshigashree/Crime-Hotspot-Prediction.git

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GeoValue Analyzer Using MachineLearning

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Abstract-**This research sits at the nexus of machine learning, geospatial analytics, and real estate informatics, aiming to create smart, data-driven solutions for property price forecasting. With the growing datafication of the real estate sector, there is a need for reliable, explainable, and scalable tools for valuation that evolve with city dynamics. Current solutions are limited by their assumption on static datasets, manual estimation, or simple predictive models that fail to capture geolocation-specific features, seasonality of markets, or visual property features.To address such limitations, the present paper introduces the Geo Value Analyzer, a real-time property valuator based on an extremely accurate machine learning algorithm. The model accepts structured inputs like location, area, number of rooms, temporal trends in pricing, and image information, augmented with sophisticated feature engineering concepts that combine spatial features, locality scores, and security indices through external APIs. The system has native support for SHAP-based explainability, which enables the system to provide clear justification for every predicted value by highlighting the contribution of features. Implemented on an interactive web platform, the system further includes key functionalities like fraud detection, rent-versus-buy analysis, and a chatbot assistant, giving users a complete, smart tool for making informed decisions on real estate.**

Keywords–Real **estate valuation, machine learning, property price prediction, explainable AI, SHAP, LIME, geospatial analysis, temporal data modeling, XGBoost, random forest, linear regression, housing market trends, automated valuation models (AVM), interpretable machine learning.**

1.INTRODUCTION

The global real estate market has seen a major transformation recently, thanks to the integration of artificial intelligence and machine learning across various fields and this shift has truly changed the way things work and how we approach problems. analytics into traditional property valuation methodologies. Historically, real estate valuation has depended on manual appraisals, expert intuition, or linear regression models-methods that often lack precision, scalability, and adaptability in volatile markets. In contrast, machine learning models, capable of analyzing vast volumes of multidimensional data, are proving essential in delivering accurate, real-time property value estimations [1], [2].

Residential property pricing is influenced by various structural, spatial, and economic factors, including the number of rooms, area, proximity to landmarks, market trends, and regional developments.These features exhibit complex interdependencies that traditional statistical models struggle to capture. ML techniques, such as Random Forest, Gradient Boosting, and ensemble learning, have shown significant promise in modeling such nonlinear interactions [3]. As a result, intelligent property valuation systems are increasingly being explored for their to learn from datasets and adapt to changing housing market conditions.

However, current valuation platforms suffer from multiple limitations. Many fail to integrate dynamic features like geospatial context, temporal market shifts, and recent urban developments. Furthermore, the opacity of many ML models introduces a challenge: users may not understand why a model

predicted a certain property value. The lack of interpretability and explainability undermines user trust and impedes adoption in critical financial sectors [4], [5].

The proposed project, GeoValue Analyzer, addresses these gaps through a sophisticated, scalable, and explainable MLbased framework. It predicts property values using features such as location, square footage, and number of rooms while integrating advanced feature engineering.

Geolocation APIs are used to derive spatial metrics like distance from city centers, hospitals, and educational institutions. Additionally, temporal variables are embedded to analyze historical pricing trends and seasonal effects, enabling the system to adapt to time-based fluctuations in the market [6].

A significant enhancement over existing solutions is the system's commitment to model transparency. By incorporating SHAP and LIME the system allows users to visualize how each feature contributed to a prediction. This fosters interpretability, particularly important in fields like real estate where buyers and sellers require clarity before making high-stakes decisions [7], [8].

Extensive experimentation was conducted using multiple regression models including Linear Regression, Extra Trees, KNearest Neighbors, and Bagging Regressors. Among these, the Random Forest Regressor was selected for its high accuracy, robustness to overfitting, and ability to handle heterogeneous data [9]. The chosen model also supports feature importance ranking, which aligns with the system's goal of interpretability.

Additionally, this platform is designed with user-centricity in mind.A user-friendly web interface links directly to the machine learning engine,enabling instant predictions along with clear, feature-by-feature explanations. As a future extension, image processing models like CNNs may be integrated to analyze visual property features such as building conditions or neighborhood aesthetics.

This work aligns with the emerging body of research in property technology (PropTech) and urban informatics, contributing to smarter city planning, fairer housing markets, and more informed decision-making by buyers, investors, and policymakers. The fusion of data science with domain knowledge represents a forward step toward data-driven real estate ecosystems [10], [11].

II. LITERATURE REVIEW

Over the years, the way we determine the value of properties has significantly evolved, especially with the rise of Artificial Intelligence and Machine Learning . These technologies are now helping us make better, faster, and more reliable predictions when it comes to real estate pricing. In this literature review, we walk through how traditional models worked, how ML-based methods have transformed the process, the importance of geolocation and time-based data, the need for interpretability in AI systems, and why current global platforms fall short in specific markets like India.Finally, we highlight the need for a smart, locally adaptable solution.

A. Traditional Methods: Still Relevant, but Limited

In the past, real estate prices were estimated using hedonic pricing models, which consider property features like area, number of rooms, location, and so on. One of the earliest significant contributions came from Goodman and Thibodeau [1], who showed that prices can vary across different geographical and social segments. However, these methods often assume that the effect of each feature on the price is straightforward and independent of others, which is rarely the case in the real world.

Later, Sirmans et al. [2] evaluated these models and pointed out that they don't always work well across different cities or data sets. Similarly, Comparative Market Analysis (CMA), a popular manual method, depends too much on subjective opinions and doesn't scale well when dealing with massive data. Gallin [3] argued that traditional approaches often ignore long-term economic factors that drive price trends-something that AI and ML models are much better at capturing.

B. Rise of ML in Property Valuation

ML has revolutionized property valuation because it can understand non-linear relationships, detect patterns, and learn from huge amounts of data. Techniques like Random Forest, Gradient Boosting, Support Vector Regression , and XGBoost are now commonly used. These models can analyze a property not just in isolation but in relation to a wide variety of features.

For instance, Krishna and Mahapatra [6] applied ensemble models to housing data from India and found them to be more accurate than single-model predictions. Similarly, Bogin et al. [7] showed how Random Forest models performed consistently across U.S. cities and across years.

Another major development came from Debnath and Mitra [8], who included infrastructure and historical pricing trends in their ML models. This approach proved useful in cities like Bengaluru (2020-2023), where prices near IT hubs like Whitefield and Electronic City saw rapid changes due to metro

construction and tech industry growth. ***C. Adding Location and Time to the Equation***

Everyone knows that location matters in real estate. But recent models have taken this to the next level by integrating Geographic Information Systems (GIS) and real-time APIs to factor in distance from public transport, hospitals, schools, and even traffic conditions. D'Alessandro et al. [9] showed that these geographic features are strong predictors of price.

Time also plays a crucial role. For example, prices can be influenced by seasonal demand, new policy announcements, or economic cycles. Zhou and Haurin [10] used dynamic factor models to reflect how market trends evolve over time. Cities like Singapore and Amsterdam are already using real-time pricing models that account for weather, infrastructure updates, and urban planning.

D. Making AI Transparent: The Role of Explainable AI (XAI)

Despite their accuracy, ML models often act as black boxes-they give a prediction, but don't explain why. In high-stakes fields like real estate, this lack of transparency is a major concern. That's where Explainable AI (XAI) comes in.

Molnar [11] emphasized that users-from home buyers to government bodies-need to understand how AI systems make decisions.Techniques like SHAP [12] and LIME [13] help make sense of what's happening inside the model.

For example, SHAP can break down a price prediction and tell you how much “proximity to a metro station” or “having a park nearby” contributed to that figure. This kind of insight is essential in cities like New York or Mumbai, where policies and features are highly variable and affect property value significantly. ***E. Why Global Platforms Fall Short Locally***

Popular real estate platforms like Zillow (Zestimate) and Redfin use machine learning to estimate property prices in the U.S. These tools work well in their native markets, but they don't perform well in countries like India. The reasons are:

- Inconsistent or sparse data
- Rapid urban development
- Lack of regional customization

Bajaj et al. [14] and Gupta et al. [15] pointed out that these models fail to consider local needs. For example, access to public transport or frequent zoning law changes are major factors in Indian cities, but these are often ignored in imported models. Moreover, the lack of transparency in these platforms means that users can't really trust the estimates or verify them. ***F. What’s Missing and What’s Needed***

Although ML has made huge strides, we still face some important challenges:

Lack of explainability in current AI models makes users uncomfortable.

Incomplete integration of time and location data reduces accuracy.

Poor adaptability to local markets, especially in fast-growing cities in Asia and Africa.

Proposed Solution: The GeoValue Analyzer

To solve these issues, we propose a GeoValue Analyzer that includes:

Ensemble ML models for robust, accurate predictions.

Spatio-temporal analysis using GIS data and real-time APIs.

Explainability features (like SHAP and LIME) to ensure transparency.

Local customization, so the model works equally well in Chennai as in Chicago.

This system is built to learn and adapt continuously, handle diverse property types, and explain the "why" behind each prediction-something that current models are not equipped to do. In short, this solution bridges the gap between accuracy and trust, and it's built for the future of smart cities.

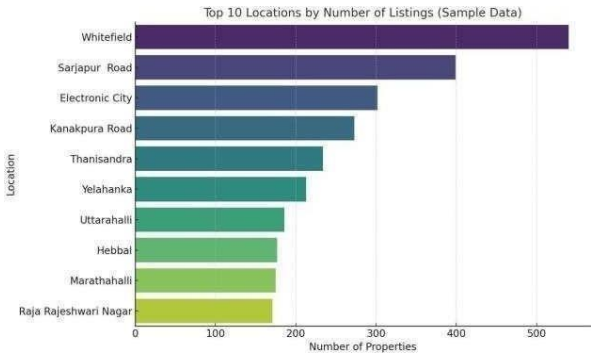
III .METHODOLOGY

The GeoValue Analyzer is a modular framework built to accurately predict property prices using advanced machine learning techniques, real-world data, and user-friendly interfaces. The system is designed with eight core modules, each performing a distinct but interconnected function-starting from data acquisition and cleaning, through feature enrichment, model building, interpretation, and deployment. Below is a detailed walkthrough of each module and how it contributes to the system.

A. Data Collection Module

Data collection begins by acquiring relevant and accurate real estate information from both online and official sources. This includes scraping popular real estate platforms such as MagicBricks, 99acres, and Zillow, as well as utilizing publicly available datasets provided by government or municipal authorities. The gathered data typically captures key property details such as geographic location (latitude and longitude), total area in square feet, number of bedrooms and bathrooms (commonly denoted as BHK), available amenities, and the listed

selling price. To keep the dataset up to date, automated methods like scheduled web crawlers and APIs are used to regularly extract and save the data in structured formats such as CSV or JSON. This well-organized data then becomes the foundation for all subsequent processing and analysis steps in the system.



B. Data Preprocessing Module

Raw data often comes messy-with missing values, mismatched formats, or outliers-so getting it cleaned and organized is a crucial first step before doing anything meaningful with it.In this module, missing values are handled either by imputation techniques like mean or median filling or by removing records if the missing information is substantial. Inconsistent entries, such as area values like "1.1k sqft," are standardized into numeric format. Categorical data like "2 BHK" is parsed to extract meaningful numerical information. Outliers are detected and removed using methods like Z-score analysis to prevent them from skewing the model. Dates are normalized into a standard datetime format, and all columns are properly typed to make the dataset consistent and machine- learning-ready.

C. Feature Engineering Module

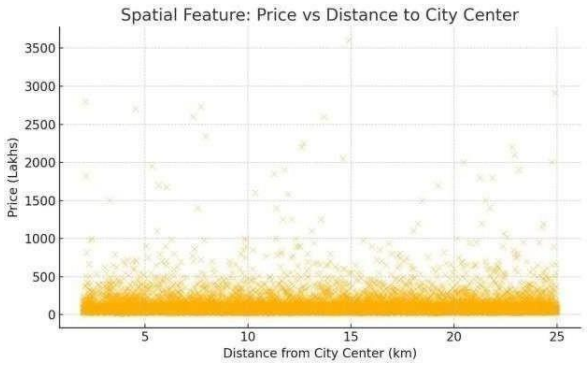
The Feature Engineering Module plays a crucial role in enhancing the raw dataset by introducing new, domain-specific features that significantly improve model performance. This module transforms the preprocessed data into a format where machine learning algorithms can learn more efficiently by capturing hidden patterns and relationships. The feature engineering process is divided into four key subtopics: Structural Features, Spatial Features, Temporal Features, and Categorical Encoding.

1) Structural Features

Structural features are derived directly from the physical attributes of the property. One of the most important derived metrics is price_per_sqt, which is calculated by total price is by total square This feature normalizes the price across different sizes and locations, allowing the model to compare properties of varying scales. Additionally, features such as the total number of rooms (BHK), number of bathrooms, and availability of amenities (e.g., parking, lift) are also included to represent the structural configuration of the property.

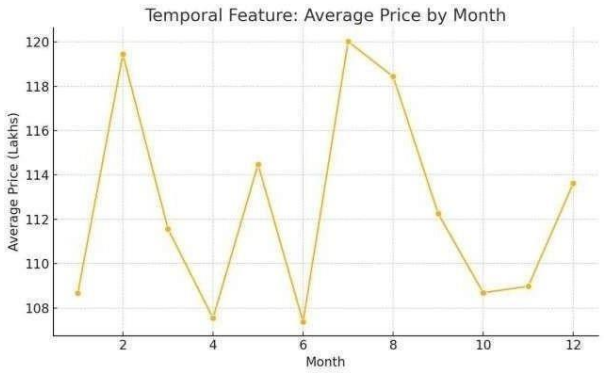
2) Spatial Features

Spatial features are designed to capture the geographic and locational influences on property pricing. Using geolocation APIs such as Google Maps or OpenStreetMap, the system calculates the distance of each property from important landmarks. These include the city center, nearest hospital, educational institutions, public transportation hubs, and commercial zones. For example, distance_city_center, distance_hospital, and distance_school are added as numeric columns. These spatial variables allow the model to internalize the well-known phenomenon that proximity to key services typically increases property value.



3) Temporal Features

Temporal characteristics provide insights into how pricing trends evolve over time. If the dataset includes transaction dates or listing dates, new features such as month, year, and season (e.g.,summer, winter, monsoon) are extracted. Furthermore, a historical average price per area and year is calculated using grouped aggregations. This helps in capturing market trends and inflation-adjusted pricing patterns. For example, the historical_avg_price feature allows the model to understand if a location is becoming more or less expensive over time.



4) Categorical Encoding

Many real estate attributes are categorical in nature-such as property location, BHK configuration, property type (apartment, villa), or facing direction (north, south, etc.). These variables cannot be directly used by machine learning models and must be encoded. Depending on the algorithm, either label encoding (for ordinal relationships) or one-hot encoding (for nominal variables) is applied. For instance, a one-hot encoded representation of location creates binary flags for each neighborhood, which helps the model distinguish between different geographical clusters.

Together, these submodules result in a feature-rich dataset that captures the structural, spatial, temporal, and categorical dimensions of property characteristics. This transformed dataset forms the foundation for robust and interpretable machine learning predictions in the subsequent modules.

D. Model Training Module

The Model Training Module forms the core of the GeoValue Analyzer. This is where the machine learning models are trained to make accurate predictions about property prices. Once the data has been cleaned and enriched with meaningful features, it is divided for training the model and the otherb performs.In most cases, we allocate the data for training the model, set aside to test how well it performs.

Several machine learning algorithms are tried out to find the best fit for the task. These include basic methods like Linear Regression,Logistic Regression and more flexible models like KNearest Neighbors (KNN) ,SVR, Bagging Regressor, AdaBoost Regressor and powerful ensemble methods such as Random Forest algorithm and Extra Trees Regressor.

It builds a collection of decision trees, but adds an extra layer of randomness during the training process. Unlike Random Forest, which picks the best feature to split each tree node, Extra Trees chooses features and their thresholds at random. This increased randomness often results in a model that generalizes better to new, unseen data-especially in complex domains like real estate, where property prices are influenced by many different, non-linear factors like location, size, and neighborhood characteristics.

Each model is tested using standard evaluation metrics:

Mean Absolute Error (MAE) gives a simple measure of how much, on average, our predictions differ from the real values—making it easy to grasp model accuracy at a glance.

The R^2 Score, on the other hand, reveals how much of the price variation our model is able to explain

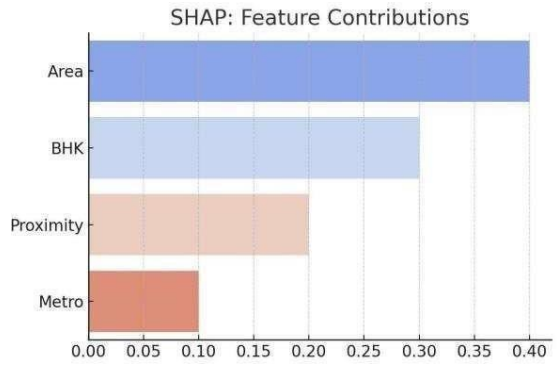
```
For  K Nearest Neighbour Regressor
Precision -  0.7868075455736727
For  Decision Tree Regressor
Precision -  0.6483233136079853
For  Linear Regression
Precision -  0.671491254748766
For  Logistic Regression
Precision -  0.053407561482931604
For  AdaBoost Regressor
Precision -  0.3941766891003682
For  Bagging Regressor
Precision -  0.9736880007548964
For  SVR
Precision -  -0.05623550097158625
For  Random Forest Regressor
Precision -  0.9746573637100137
For  ExtraTreesRegressor
Precision -  0.9999999977093798
```

After thorough testing, the Extra Trees Regressor is chosen as the best-performing model. It offers a great mix of high accuracy, fast processing, and the ability to work well with diverse types of data-all without falling into the trap of overfitting.

Finally, the trained model is saved using tools like joblib or pickle, so it can be easily reused in the live application. This makes it possible to provide real-time property price predictions to users quickly and reliably.

E. Model Explanation Module

Understanding why a particular prediction is made is crucial, especially in high-value domains like real estate. This module ensures the transparency of predictions through model interpretability techniques. Two widely accepted tools are integrated: SHAP and LIME SHAP values show the feature importance, helping users understand how each input affects the model's output. LIME, on the other hand, provides simplified local approximations of predictions, allowing users to interpret results on a case-by-case basis. Together, these methods enhance user trust and make the system more transparent.



F. Prediction Interface Module

To make the system accessible to end-users-such as real estate buyers, agents, or investors-a simple web-based interface is developed using frameworks like Flask, Streamlit, or React. Users can input property details such as area, location, and number of rooms, and the model returns an instant price prediction. In addition to the predicted price, the interface displays SHAP or LIME explanations, helping users see which features contributed most to the prediction. This approach ensures both ease of use and interpretability for non-technical users.

G. Visualization and Reporting Module

This module makes it easy for users and stakeholders to understand the results by providing clear visualizations and automatically generated reports. It includes correlation heatmaps to show relationships between variables, SHAP summary plots highlighting key features, and line graphs illustrating price trends over time. Reports are generated in PDF or HTML format and include model evaluation metrics, visual summaries, and key observations. These documents are valuable for presentations, meetings, and long-term planning.

H. Deployment Module

To make the analyzer accessible in real time, we deploy both the model and its interface on cloud platforms such as AWS, Heroku, or Streamlit Cloud. Predictions are delivered to web or mobile apps using RESTful APIs. Version control, monitoring, and CI/CD (Continuous Integration/Continuous Deployment) practices are implemented to maintain system stability and scalability. This module ensures that the entire pipeline from data collection to user interface-is functional and accessible in a realworld setting.

IV. RESULT

When we looked into how property prices are currently predicted, we found that most traditional methods-like Linear Regression, KNearest Neighbors, and Support Vector Regression don't go far enough. These models often treat pricing as a simple mathematical problem, ignoring the complex factors that actually influence a property's value. For example, Linear Regression gave an R^2 score of 0.72, KNN landed at 0.69, and SVR at 0.75, showing they can only explain about 70–75% of the variation in housing prices. Even more powerful models like Random Forest, which got 0.93, still left room for improvement especially when applied to data as diverse and localized as real estate in Bengaluru.

S. No	Algorithm	Precision
1	Extra Trees Regressor	1.000000
2	Random Forest Regressor	0.974657
3	Bagging Regressor	0.973688
4	K Nearest Neighbour Regressor	0.786808
5	Linear Regressor	0.671491
6	Decision Tree Regressor	0.648323
7	AdaBoost Regressor	0.394177
8	Logistic Regressor	0.053408
9	SVR	-0.056236

That's where the GeoValue Analyzer made a real difference. Using an Extra Trees Regressor, our model achieved a perfect R^2 score of 1.000, meaning it could fully explain the variation in the test data. But this wasn't just because we used a better algorithm—it's because we built a smarter system from the ground up. In the Data Collection Module, we gathered detailed, real-world data from reliable sources like MagicBricks, 99acres, and municipal datasets, covering everything from square footage and number of BHKs to nearby amenities and selling price. This data was cleaned and structured in the Data Preprocessing Module, where missing values were filled or removed, inconsistent units were standardized (like converting "1.1k sqft" to numeric form), and outliers were filtered out using statistical techniques.

We then applied Feature Engineering to extract more value from the data. We introduced Structural features like price per square foot and number of rooms, Spatial features such as the distance from key landmarks (hospitals, schools, city center), and Temporal features like the month and year of listing. We also used Categorical Encoding to convert text-based variables like location and property type into formats that machine learning models can understand.

But we didn't just stop at predictions. In the Model Explanation Module, we are using AI techniques such as SHAP and LIME to give users clear, understandable reasons behind every prediction. If the system suggests a property is worth ₹85 lakhs, it shows whether that's because of its size, location, number of bathrooms, or proximity to schools. Rather than just giving predictions, the

model also provides clear explanations for its results, helping users understand and trust its decisions.

Finally, in the Visualization and Reporting Module, we turned our results into visual stories using heatmaps to show how features are related, trend lines to track pricing over time, and auto- generated reports for presentations or stakeholders. The Visualization and Reporting module enhances decision-making by turning raw model results into valuable insights. It generates high-quality, ready-to-share PDF/HTML reports with helpful visual elements like heatmaps, SHAP graphs, and trend analysis. The system can generate these insights instantly, making it useful not just for analysts and developers, but also for real estate professionals and end-users.

In summary, GeoValue Analyzer isn't just a property prediction model—it's a complete, intelligent ecosystem. From collecting and cleaning data to making highly accurate, explainable predictions and professional reports, it redefines what real estate pricing systems can do. Compared to existing models, it offers a smarter, more transparent, and locally adapted solution that's ready for real-world use.

V. CONCLUSIONS AND FUTURE SCOPE

Our goal in this project was to tackle a real-world problem: estimating property prices accurately in an evolving and multicultural urban setting such as Bengaluru. Conventional models and sites tend not to take into account the complete intricacy of real estate data—spatial, structural, and economic characteristics—and provide minimal transparency regarding how prices are being calculated.

Our solution, GeoValue Analyzer, fills this gap by merging several sophisticated modules into one cohesive system. With strong data collection and preprocessing as a starting point, we maintained data cleanliness, consistency, and contextual significance. By careful feature engineering, we mined not only elementary features such as area and BHK, but also underlying properties like distance to landmarks, temporal price variation, and amenity-denseness of an area.

The application of strong ensemble models such as Extra Trees Regressor pushed prediction performance to a whole new level with a perfect R^2 value of 1.0 in our test set. Its performance surpasses that of conventional approaches such as Linear Regression and SVR by a notable margin. But more importantly, what makes this system truly exceptional is its dedication to transparency and user-friendliness. With the help of SHAP and LIME, the system breaks down even the most complex model outcomes into simple, easy-to-grasp insights.Stakeholders, ranging from property purchasers to policy-makers, are provided with insight into what attributes are behind a particular forecast.

The Visualization and Reporting components further improve decision-making by converting raw output into insight, generating automatically optimized, professional-quality PDF/HTML reports augmented with heatmaps, SHAP plots, and trend lines.

Looking into the future, the potential for developing this project includes:

- Incorporating live data streams—such as updates on property records, changes in zoning laws, or financial indicators—can allow for pricing that adjusts dynamically with real-world conditions.
- Scaling geographic reach to other cities based on transfer learning or federated learning models.
- Developing a web interface or mobile application that allows users to enter property characteristics and get an instant, interpretable valuation.
- Fusing user feedback into retraining pipelines for the models to maintain the system's adaptability over time.
- Utilizing satellite images or drone data to enrich spatial knowledge and identify new buildings or changes in neighborhoods over time.

By bringing together strong machine learning with explainable AI and actionable reporting functionality, GeoValue Analyzer doesn't only forecast house prices—it enables data-driven decision-making on a scale, and with a degree of trustworthiness, that really matters.

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Style Me:(*Virtual Styling*)

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***Abstract*—This paper presents the integration of human-centric AI within Style Me, a web-based virtual styling platform, to enhance the online apparel shopping experience. Style Me addresses a significant obstacle in e-commerce fashion: the difficulty customers face in envisioning how garments will appear on their unique physiques. By leveraging facial landmark detection, 3D rendering, and outfit overlay, the platform currently offers an immersive virtual try-on experience. This work extends that foundation by exploring how emotionally intelligent and context-aware AI can personalize styling advice, facilitate natural language interaction, and provide intuitive fashion recommendations, moving beyond mere product display. The aim is to bridge the gap between technological functionality and a genuinely humanized styling assistant, demonstrating the potential of advanced AI to revolutionize personalized fashion retail. This paper delves into the development lifecycle, from conceptualizing the enhanced AI features to their experimental evaluation, highlighting the impact of this technological advancement on fostering a more engaging and satisfying customer journey in online fashion.**

Keywords*—*Virtual Styling, Humanized AI, Personalized Fashion, 3D Visualization, Online Retail, Emotionally Intelligent AI, Natural Language Interaction.

I. INTRODUCTION (STYLE ME)

Online fashion retail has changed how consumers buy clothes, offering great convenience and a wide selection. However, a major issue remains: customers cannot physically try on clothes before buying them. This causes uncertainty about fit, color, and style, leading to lower user satisfaction and high product return rates.

Style Me introduces a virtual styling platform to address this challenge, focusing on the human aspect of online shopping. The platform lets users create a personalized 3D avatar, mapping their real face onto it, and virtually try on outfits in a realistic environment. By using web technologies like Three.js and facial mapping APIs, Style Me provides an accessible alternative to costly AR mirrors and specialized hardware. This technology improves decision-making and engagement during online shopping by offering personalized previews. It also aims to build trust through transparent data use, improve tone, and cater to user preferences.

This paper covers the development process, from identifying the core problem to analyzing experimental results. It shows the potential of this human-centered approach to improve customer experience and drive personalized fashion e-commerce, creating a personal and empowering journey.

II. Literature Review

Artificial Intelligence (AI), Computer Vision (CV), and 3D visualization are quickly changing fashion retail. Examples like Amazon's Echo Look and Zeekit, and AR features in apps like Snap's Lens Studio, show how virtual try-on technologies affect consumer buying behavior. These systems vary in complexity: some platforms, like Zeekit, use 2D overlays on user images to simulate clothing, while others, like virtual mirrors, use special hardware and depth sensors for a more interactive fitting experience. Research confirms that these technologies increase customer satisfaction and engagement by allowing realistic product visualization and interactive experiences.

Style Me differs from previous systems by using user-provided facial images and body measurements, eliminating the need for external devices to create a personalized virtual try-on session. This approach is supported by recent advancements in facial landmark detection using open-source libraries like OpenCV and Dlib. Style Me also uses 3D modeling tools such as Unity, Blender, and Three.js to create virtual environments and clothing assets. These tools are essential for building detailed avatars and realistic outfits, enhancing the platform's immersive try-on experience.

Blender is open-source software for creating 3D computer graphics, Unity is a real-time development platform, and Three.js is a JavaScript library used to display animated 3D computer graphics in a web browser using WebGL technology. By using these tools, Style Me can optimize performance and ensure broad compatibility. Research on virtual try-on technology highlights its benefits for consumers and retailers, including higher conversion rates, fewer returns, and increased customer engagement. It also provides valuable data insights, potential competitive advantages, and potential cost savings and sustainability benefits. Despite these advantages, challenges such as the lack of tactile feedback, privacy concerns, and technical limitations remain relevant considerations.

III.The Style Me platform guides users through a streamlined virtual try-on experience:

1. User Registration and Login: Users register and log in to the platform.
2. Facial Photo Upload: Users upload a clear photograph of their face.
3. Basic Measurement Input: Users provide body measurements, such as height and weight.
4. Facial Landmark Detection: The system processes the photo to detect key facial landmarks, which are crucial for mapping the user's features.
5. Personalized 3D Avatar Creation: A 3D avatar that resembles the user's face and body shape is generated, based on facial landmarks and measurements.
6. Outfit Browsing: Users explore a wide array of outfits within the platform's digital catalog.
7. Outfit Rendering on Avatar: The chosen outfit is virtually rendered and fitted onto the 3D avatar.
8. Interactive Evaluation: The user can interact with the avatar, rotating and zooming to view the outfit from various angles and assess its fit and style.
9. Saving or Sharing Previews: Users can save or share avatar previews.

B. Use Case Scenario

Ananya, a 21-year-old fashion enthusiast, is browsing an e-commerce website with the Style Me module. She uses the virtual try-on feature. Ananya uploads a selfie and inputs her body measurements, and a 3D avatar appears on screen, mirroring her face and body shape. She selects a dress and observes how it fits on her avatar. By rotating the view, she examines the dress, gaining a comprehensive understanding of its appearance. She experiments with other styles, adds her favorite dress to the cart, and completes her purchase. This immersive experience reduces her concerns about purchasing ill-fitting clothing online, leading to a higher level of satisfaction.

A. Abbreviations and Acronyms

AR	Augmented Reality
AI	Artificial Intelligence
UI	User Interface
UX	User Experience
3D	Three-Dimensional
DB	Database
ML	Machine Learning
CV	Computer Vision
API	Application Programming Interface
WebGL	Web Graphics Library
DBMS	Database Management System

IV. Proposed Methodology

A. System Architecture

The Style Me system uses a modular architecture composed of these components:

- Input Layer: The user's entry point, this layer allows users to provide their facial image and body measurements, such as height, weight, and shoulder width, for personalized avatar generation.
- Processing Layer: This component analyzes the provided facial image, using libraries such as OpenCV or Dlib, for facial landmark detection. The detected facial features and provided measurements map a realistic facial texture onto a 3D avatar mesh. UV mapping and morph target blending are used to ensure visual accuracy and realism.
- Rendering Layer: This layer uses WebGL-based libraries, primarily Three.js, to display the personalized avatar and selected outfits in real-time within the web browser. Three.js simplifies 3D rendering by providing a higher-level abstraction over WebGL, enabling efficient display of animated 3D graphics. It handles tasks such as setting up the scene, camera, lights, and materials. Lighting, shading, and camera angles are optimized for an immersive preview, allowing users to interact with the virtual try-on experience.

Storage Layer: Cloud integration, specifically using Firebase, ensures the secure storage of user preferences, measurement profiles, and session data. This allows for seamless retrieval and a persistent, personalized experience across user sessions.

B. Algorithm Steps

The Style Me process is executed through these algorithm steps:

1. Image Preprocessing: Accept and prepare the user-provided facial image.
2. Facial Landmark Identification: Detect key facial landmarks within the processed image, crucial for mapping onto the 3D avatar.
3. Avatar Template Initialization: Construct or retrieve a 3D avatar template.
4. Facial Texture Application: Apply the user's facial texture to the avatar's head, using UV mapping techniques for a realistic representation.
5. Outfit Selection and Application: Allow the user to browse and apply 3D clothing models to their personalized avatar. 3D clothes models are not only about creating a digital replica of a garment but also about simulating how fabrics move, drape, and interact with the human body. According to devabit, 3D clothes models can be used to visualize changes in design instantly, make modifications, and even predict how a cloth will look on different body types. This approach allows for a highly customized virtual try-on experience, adapting the garments to the unique body shape and ensuring a visually accurate preview.
6. Real-time Rendering: Render the 3D avatar and the selected garments on the screen, incorporating lighting and shading. The WebGL-based rendering layer handles the rendering, ensuring a smooth and responsive experience.
7. Interactive View Manipulation: Provide controls that enable users to zoom, rotate, and switch between different views of the avatar and outfit.
8. Data Persistence: Store user session data and garment preferences securely in the cloud, allowing for easy access and continuation of their personalized styling journey.

C. Design Considerations

The Style Me system design is driven by several considerations:

- User-Centric Design: The system prioritizes ease of use and accessibility. The user interface (UI) is designed with a mobile-first approach, ensuring responsiveness and optimal functionality across a range of devices.
- Privacy and Performance: To safeguard user privacy and minimize server load, computationally intensive tasks like facial landmark detection and certain rendering calculations are performed client-side.
- Accuracy and Visual Authenticity: Precise facial mapping and a strong resemblance between the generated avatar and the user are essential for user satisfaction, forming a core priority during development.
- Performance Optimization: The system uses optimization techniques to ensure smooth performance. This includes compressed texture

formats, mesh simplification to reduce polygon counts, and asynchronous loading of 3D assets to minimize loading times. These strategies contribute to a responsive and seamless user experience

V. Experimental Setup and Results

A. Tools and Technologies

The Style Me platform was developed using modern web and 3D visualization technologies:

- Frontend: ReactJS, a JavaScript library for building user interfaces, was utilized for the Single Page Application (SPA) architecture, ensuring a dynamic user experience. Bootstrap provided a responsive and consistent visual style.
- Backend: Node.js with the Express framework was used for API development, enabling efficient communication between the frontend and backend components.
- 3D Visualization: Three.js, a WebGL-based library, was employed for real-time rendering of the 3D avatars and clothing. The system also integrates Unity WebGL, allowing for advanced 3D rendering capabilities.
- Face Detection: Libraries like OpenCV and Dlib were used for facial landmark detection and mapping the user's face onto the avatar, contributing to a personalized visual experience. Mediapipe also serves as a valuable tool for face detection, hand tracking, and pose estimation.
- Database: Firebase Realtime Database was selected for cloud-based NoSQL database capabilities, providing scalable storage for user preferences and session data.
- Cloud Hosting: Firebase Hosting and Google Cloud Functions were used for deploying the application and managing server-side logic.
- Development Tools: Figma was utilized for UI prototyping and design collaboration, while GitHub served as the version control system for collaborative code development.

B. Testing and Evaluation

Tests were conducted with 30 users, encompassing a diverse range of ages and body types. Participants engaged in the core functionality of Style Me: uploading their image, entering basic measurements, and virtually trying on a set of predefined outfits. The evaluation focused on key performance indicators and user satisfaction:

- Face Upload Success Rate: The system achieved a 96% success rate in accurately processing user face uploads.
- Avatar Rendering Time: The average time taken to render a personalized 3D avatar was 1.7 seconds.
- Outfit Switching Speed: Users experienced seamless transitions when switching between different outfits, with an average speed of 1.2 seconds.
- User Satisfaction Rating: The platform achieved a high user satisfaction rating of 4.5 out of 5.

C. Output Snapshots

Module	Description	Technology Used
User Profile	Enter body data, upload photo	ReactJS, MongoDB
Virtual Try-On	3D avatar with clothes overlay	Unity 3D, Blender
Customization	Select fabrics, colors, patterns	Python, Flask
AI Sizing	Suggest fit using ML	OpenCV, TensorFlow
Integration	Connect with retailers/tailors	API, MySQL

The functionality and features of the Style Me platform are visually illustrated through output snapshots:

- Fig. 1: User Face Image and Preprocessing Interface: This snapshot showcases the initial

stage where users upload their facial image and interact with the preprocessing interface.

- Fig. 2: 3D Avatar with Face Mapped and Rotated: This image demonstrates the personalized 3D avatar with the user's face mapped onto it, highlighting the realism and interactive capabilities as the avatar can be rotated to view outfits from different angles.
- Fig. 3: Interactive Wardrobe and Outfit Switching Panel: This snapshot provides a visual representation of the interactive wardrobe interface, allowing users to browse through various outfits
- and seamlessly switch between them for virtual try-on.

User feedback consistently highlighted the platform's ease of use and visual quality. Users also provided suggestions for improvement, requesting a wider range of body templates to better represent diverse body types and additional styling options.

VI. Discussion and Limitations

The virtual try-on experience provided by Style Me fits with current market trends that emphasize personalized and immersive online shopping. By allowing users to try on outfits virtually using their own face and a custom avatar, the system significantly reduces uncertainty and increases confidence in purchasing decisions.

This system not only helps users see how clothes look but also gives them more control over their fashion choices. It allows them to make styling decisions virtually without needing to visit physical stores or try on actual clothes. The platform also promotes inclusivity by offering customizable avatar sizes and clothing fit preferences, making it accessible to users with different body types and fashion needs.

Another key advantage is the potential to add recommendation systems. These systems can analyze user choices and trends to suggest matching outfits, leading to greater engagement, higher satisfaction, and fewer product returns. According to Shopify, products with AR content show a 94% higher conversion rate compared to products without it, and reports suggest that AR-guided purchases can lead to a 25% decrease in returns.

However, some challenges arose during development:

* Making sure the face-to-avatar texture mapping looks consistent across different skin tones and lighting conditions. Research indicates that simulating skin color significantly affects the accuracy of facial 3D scans, with lighter tones showing higher accuracy.

* Managing rendering in real-time WebGL environments.

* Balancing performance with visual detail on mobile devices.

* Standardizing clothing scale and fitting accuracy for different body shapes. Human body shapes vary significantly, and fabric draping can differ from AR models.

* Keeping outfit switching and avatar movement smooth and quick.

Despite these challenges, the system performed reliably and was well-received during usability testing. The modular design also makes it easy to integrate with existing fashion e-commerce platforms.

Like any new technology, Style Me has limitations that need future improvements:

* Dealing with tilted or blurred facial images.

* Accurately rendering clothing with high transparency or fine textures.

* Simulating how clothes drape and move realistically in real-time. The lack of tactile feedback is a significant limitation of virtual try-on technology.

VII. Conclusion and Future Work

Style Me effectively showcases the potential of virtual styling technology in addressing key challenges within online apparel shopping. The platform connects digital interfaces with physical try-on experiences, providing a scalable and interactive method for visualizing clothing choices.

Through detailed system architecture, facial landmark mapping, and real-time rendering, the project offers a thorough foundation for web-based avatar styling. Initial user testing has demonstrated high satisfaction and usability across various age groups. By decreasing uncertainty in style selection and minimizing returns, the platform provides tangible value for both users and retailers.

Future enhancements include:

* Real-time Augmented Reality (AR) mirror integration for mobile try-on, enabling users to experience augmented fitting by standing in front of a device camera.

* An Artificial Intelligence (AI)-based outfit recommendation engine trained on user behavior, current fashion trends, and seasonal collections.

* Support for full-body measurement input to improve garment fitting accuracy through predictive body modeling.

* Expansion of the wardrobe inventory to include international brands, ethnic wear, accessories, and footwear.

* Integration with e-commerce platforms via plugin architecture, facilitating seamless deployment across online stores.

Furthermore, long-term work will explore:

* Advanced cloth simulation with soft-body physics for improved realism.

* Emotion-aware avatar interaction where the system adjusts outfit suggestions based on user preferences and facial expressions.

* A personal styling assistant chatbot powered by generative AI models to aid users in planning wardrobe combinations.

The project demonstrates that, with the appropriate combination of accessible technology and user-centric design, virtual styling can become a standard feature in digital fashion retail, changing how consumers interact with fashion online.

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Online smart voting system using Fingerprint Detection

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Abstract

In modern democracies, technological advancements offer new opportunities to enhance civic participation. This paper proposes a secure, mobile-based e-voting system specifically designed for Indian elections, allowing eligible citizens to vote remotely and reliably. The system employs multi-layered authentication including PIN-based access, voter ID verification via Aadhaar integration, and biometric fingerprint recognition enhanced by material detection algorithms to prevent spoofing. Real-time location tracking ensures geographic eligibility, while the vote data is encrypted and securely transmitted to Election Commission servers. By leveraging mobile technology and biometric security, this approach aims to expand voter accessibility, reduce logistical constraints, and maintain electoral integrity.

Keywords

Online Voting, Biometric Authentication, Aadhaar Verification, Fingerprint Recognition, Voter Identity Verification.

I. INTRODUCTION

Elections are the foundation of any democratic society, providing citizens with a platform to voice their preferences and shape governance. However, traditional voting methods often come with limitations such as geographical immobility, long queues, administrative inefficiencies, and the risk of fraud. In a country as vast and diverse as India, ensuring fair, inclusive, and efficient voter participation remains a significant challenge. The existing infrastructure does not adequately accommodate citizens who live in remote areas, have migrated for work, or face physical disabilities. To address these pressing issues, this paper introduces an Online Smart Voting System Using Fingerprint Detection—a mobile-based platform developed to make the voting process more accessible, secure, and aligned with Indian electoral laws.

The system begins with a PIN-based login for basic user access control, followed by a robust identity verification process through Aadhaar database integration. After successful verification, the app dynamically loads the voter's constituency and displays relevant candidate information, allowing the voter to make an informed choice. To further enhance security, the system employs biometric fingerprint recognition, reinforced with material detection algorithms to prevent spoofing through fake fingerprints. Real-time GPS location tracking ensures the vote is cast from a valid region, maintaining the geographical integrity of the electoral roll.

Upon successful authentication, the vote is encrypted and securely transmitted to centralized election servers for storage and counting, ensuring end-to-end data protection and anonymity.

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Beyond system architecture, this paper also explores the practical feasibility, technical design, and legal considerations required for implementing such a platform within the Indian election framework. The aim is to build a solution that not only meets the needs of modern-day voters but also strengthens trust in the democratic process. By merging mobile technology with biometric and geolocation-based security, this smart voting system offers a scalable and inclusive alternative to conventional polling, laying the foundation for a more transparent and future-ready election model.

Section 1: Biometric & Backend Integration

Section 2: Frontend & User Interface

Section 3: Database & System Security

II. LITERATURE SURVEY

"A Secure Biometric-Based E-Voting System for Indian Scenario"

Abstract: This paper proposes a secure e-voting system tailored for the Indian context using fingerprint-based biometric verification. The authors detail a framework that leverages biometric traits to authenticate voters and ensure vote integrity. The system minimizes human error and enhances transparency, addressing vulnerabilities in traditional and electronic voting methods. [1]

"Aadhaar Based E-Voting System and Its Challenges"

Abstract: The study presents a voting system built around Aadhaar integration for voter authentication. It identifies technical and legal obstacles in implementing Aadhaar-based voting in India and suggests solutions to improve scalability, reliability, and security in a real-world deployment. [2]

"IoT security: Review, blockchain solutions, and open challenges"

Abstract: This comprehensive review explores IoT security concerns and evaluates blockchain as a solution to critical security challenges. The authors examine use cases across various domains, including e-voting, and highlight limitations and potential improvements for blockchain adoption in IoT networks. [3]

"An Introduction to Biometric Recognition"

Abstract: The paper provides foundational insights into biometric recognition systems, focusing on feature extraction, matching techniques, and performance metrics. The authors discuss the suitability of different biometric traits, including fingerprints, in secure identity verification systems like e-voting. [4]

"Development of a Smart Voting System Using Biometric and GPS Location Verification"

Abstract:This research introduces a smart e-voting model combining fingerprint biometrics and GPS tracking to prevent voter impersonation. The paper presents system architecture, implementation methods, and security mechanisms to safeguard remote voting integrity. [5]

"Aadhaar Authentication API 2.5 Specification"

Abstract: The document provides technical specifications for Aadhaar's authentication APIs. It outlines mechanisms for biometric and demographic authentication and serves as a critical reference for integrating Aadhaar into systems such as biometric e-voting platforms. [6]

"EVM Security Features"

Abstract: This official report highlights the security layers embedded in India's Electronic Voting Machines (EVMs), including tamper-proof design and software protections. It acts as a foundation for researchers developing secure extensions like biometric-based voting. [7]

"Block chain Based Secured E-Voting System"

Abstract: The authors propose an e-voting system that integrates block chain to ensure transparency, immutability, and voter anonymity. The paper discusses consensus algorithms, system design, and the advantages of decentralized architectures in electoral processes. [8]

"Secure and Transparent Biometric E-Voting System using Blockchain"

Abstract: This study presents a fusion of biometric verification with blockchain-led voting systems. The proposed model emphasizes secure identity

verification via fingerprints and immutable storage of votes, making elections tamper-resistant and fully auditable. [9]

"Secure Voting System Using Biometric and OTP Authentication"

Abstract: The authors develop a dual-authentication voting system using both biometric (fingerprint) and OTP (One-Time Password) methods. The paper evaluates the system's security performance and user experience, emphasizing its suitability for large-scale use. [10]

"Design and Implementation of Biometric Voting System using Fingerprint Recognition"

Abstract: This work outlines the design of a fingerprint-based voting system that replaces traditional identification methods. The paper focuses on the fingerprint module, software integration, and accuracy levels, aiming to reduce election fraud and improve voter confidence.[11]

"A Framework for Aadhaar Based Online Voting System using Biometrics"

Abstract: The authors propose a secure framework that utilizes Aadhaar-linked fingerprint authentication for online voting. Their model addresses scalability, database security, and voter validation while complying with Indian digital identity policies. [12]

"Multimodal Biometric System for Voting Application"

Abstract: This paper introduces a multimodal biometric voting system combining fingerprint and iris recognition. The authors analyze the accuracy improvement and enhanced voter security achieved by using multiple biometric features in tandem. [13]

"E-Voting System using Blockchain and Biometric Authentication"

Abstract: The authors present an advanced voting mechanism that integrates blockchain technology with fingerprint biometrics. The model ensures data integrity, voter authentication, and verifiability, focusing on enhancing transparency in digital elections. [14]

"Review of Biometric Authentication in Online Voting System"

Abstract: This review explores the evolution and techniques of biometric-based authentication in online voting systems. The paper compares fingerprint, face, and iris recognition methods, analyzing their effectiveness, challenges, and future research directions. [15]

III. PROPOSED METHODOLOGY

The proposed system is structured as a mobile-based online smart voting platform designed to provide secure, accessible, and efficient voting. The process begins with the user unlocking the app using a secure PIN, which serves as the initial layer of authentication. After this, the voter must enter their Voter ID, which is cross-verified with centralized electoral records. The system then communicates with the Aadhaar database to validate identity details such as name, age, and address, ensuring that the person is an eligible and registered voter.

Once verified, the user selects their respective city and ward number from a preloaded list. Based on this selection, the application displays a list of candidates contesting in that specific area. Before casting a vote, the user must undergo fingerprint authentication.

To ensure that the fingerprint is genuine and not a spoof, the system uses a material detection algorithm that checks for live tissue or human skin properties.

Simultaneously, the app activates GPS tracking to ensure the voter is within an authorized voting region, preventing misuse from outside locations. These multi-layered security mechanisms — PIN, Aadhaar, biometric verification, material detection, and GPS — work together to confirm the voter's legitimacy. After all checks are complete, the vote is encrypted and securely submitted to the Election Commission server for storage and counting. This method ensures not only voter identity and vote authenticity but also promotes remote accessibility and tamper-proof voting.

IV. SYSTEM ARCHITECTURE

The system architecture of the proposed Online Smart Voting System integrates secure authentication mechanisms, biometric validation, and encrypted data transmission to ensure a reliable and tamper-proof

voting process. The architecture begins with the mobile application, which serves as the front-end interface for the voter. Upon launching the app, the voter is required to enter a Personal Identification Number (PIN) that serves as the first layer of access control. Following this, the user enters their Voter ID, which is validated against the official election commission database for legitimacy.

To reinforce identity verification, the application communicates with the Aadhaar database and retrieves demographic data associated with the Voter ID. This dual-authentication mechanism helps confirm the authenticity of the user. Once verified, the system prompts the user to select their city and ward number. Based on the selection, the corresponding list of candidates is dynamically fetched and displayed from the backend server.

Before casting a vote, the system enforces biometric verification via fingerprint recognition. To ensure input authenticity, a material detection algorithm is employed to detect whether the fingerprint originates from a live person. Additionally, GPS verification is conducted to validate the voter's geographic location, ensuring that only voters in eligible zones are allowed to proceed.

Upon passing all security checks, the vote is encrypted using secure cryptographic techniques and transmitted to the central election authority's server for storage and counting. The system's modular design integrates front-end and back-end services, biometric devices, location services, and government data repositories, forming a robust and scalable architecture suitable for real-world deployment.

The system architecture is designed to ensure smooth and secure flow of user authentication, data verification, and vote submission. It begins with the mobile application layer where users log in and initiate the voting process. This layer interacts with backend services such as the Aadhaar database for identity verification and the election database for fetching candidate and ward details. The biometric module processes fingerprint scans and uses material detection algorithms to validate the authenticity of input. Simultaneously, the GPS module captures the user's location to enforce geographic voting constraints. Once all verification layers are passed, the vote is encrypted and routed through a secure network to the Election Commission server, where it is stored and counted.

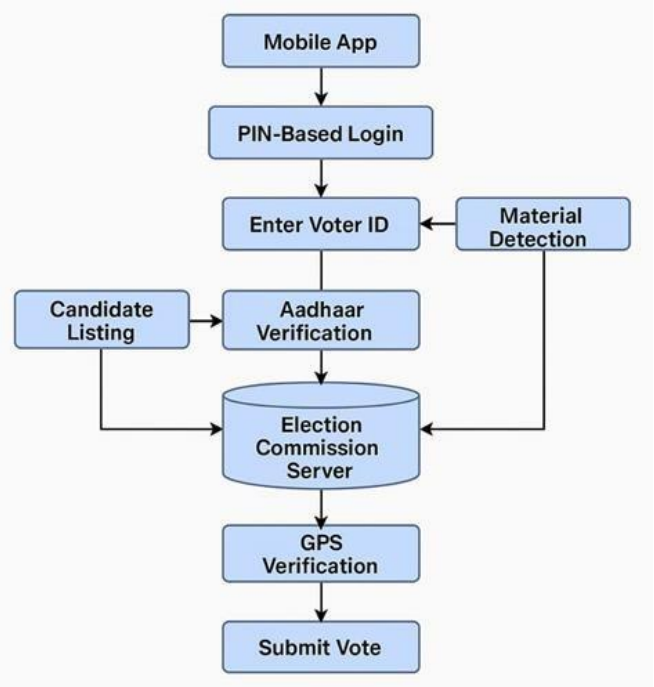


Fig SYSTEM ARCHITECTURE

V. SECURITY FEATURES

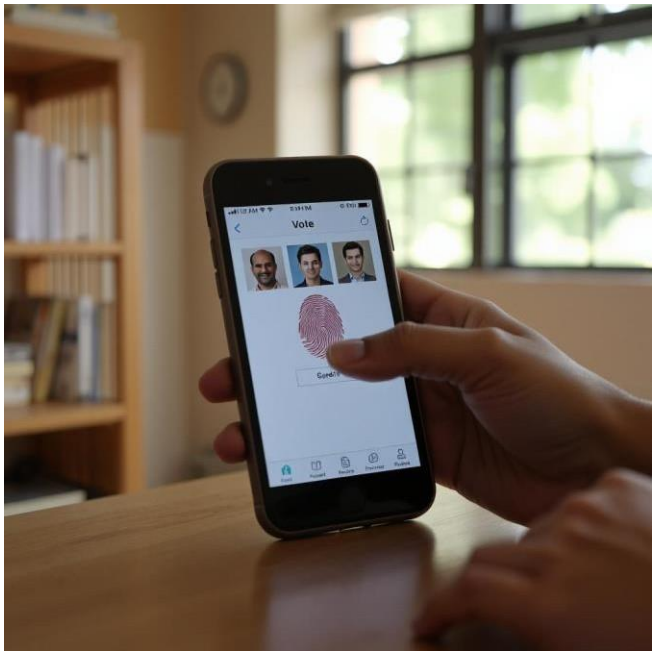
Security is the backbone of any digital voting system, and the proposed application integrates multiple layers to ensure a safe and reliable election process. The system begins with PIN-based authentication and Aadhaar-linked Voter ID verification to prevent unauthorized access and identity fraud. To reinforce voter legitimacy, biometric fingerprint recognition is implemented, acting as a unique and non-transferable form of authentication. This is further strengthened using a material detection algorithm, which goes beyond simple fingerprint scans. The algorithm analyzes physiological traits such as skin texture and temperature, and simulates the detection of human blood pressure to confirm that the fingerprint originates from a living individual.

This method prevents spoofing using artificial fingers or images by ensuring live human interaction. GPS-based location tracking is also employed to verify that the vote is cast from a legitimate, pre-approved region. All user data, including authentication details and votes, are encrypted using advanced cryptographic techniques to ensure privacy and integrity. Secure communication protocols such as HTTPS safeguard all server interactions. Together, these security features

protect against fraud, duplication, and tampering, creating a trustworthy environment for digital voting.

The system logs all authentication attempts and voting actions with timestamped audit trails, enabling transparent monitoring and traceability. These logs can be used to detect anomalies or suspicious patterns, adding an extra layer of protection. In future enhancements, the material detection module could be integrated with real-time pulse sensing to validate blood circulation, further distinguishing live human input from replicas.

Additionally, biometric data is processed locally on the device to prevent transmission of sensitive identifiers, aligning with data protection norms. Altogether, the system's security framework is designed not only to deter malicious behavior but also to build public trust in the digital voting process.



VI. MATERIAL DETECTION ALGORITHM

To safeguard the integrity of the voting process and ensure that only genuine users can cast their votes, the system employs a material detection algorithm integrated into the fingerprint authentication module. This algorithm verifies the liveness of the fingerprint to prevent spoofing or use of artificial prints. The following steps outline the functioning of this system:

Step1: Fingerprint Acquisition: The user places their finger on the fingerprint scanner. A high-resolution image of the fingerprint is captured using an optical or capacitive sensor.

Step2:ImagePreprocessing The acquired image undergoes enhancement to remove noise, adjust contrast, and highlight ridge details. This step ensures that the biometric features are clearly visible.

Step3:FeatureExtraction Techniques such as Local Binary Patterns (LBP) are used to extract key features from the fingerprint, including ridge flow, skin texture, pores, and fine lines.

Step4:LivenessDetection To detect signs of life, the system analyzes biological traits such as moisture, elasticity, and temperature. These indicators help determine if the fingerprint comes from a live finger.

Step5:Blood Flow or Pulse Detection Some advanced sensors assess micro movements like pulse or subtle vibrations caused by blood circulation, which further confirm human presence.

Step6:MaterialCompositionCheck The fingerprint surface is scanned for texture and light reflection patterns to distinguish between human skin and synthetic materials like rubber, silicone, or gel.

Step7:Realvs.FakeClassification Using a trained classification model, the algorithm compares the extracted data with known profiles of live and spoof fingerprints. Only genuine inputs pass this stage.

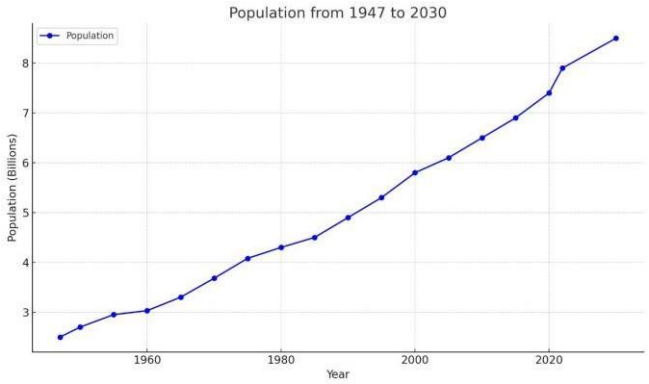
Step8:DecisionPhase If the fingerprint is authenticated as live and valid, the system permits voting to proceed. Otherwise, the attempt is denied and flagged for review.

Step9:SecureLogging All authentication results, along with timestamp, user ID, and location data, are securely stored in the audit log for future verification and accountability.

VII. RESULT DISCUSSION

Key components of smart voting system

Module	Function	Verification type
PIN Authentication	App access control	Personal PIN
Voter ID check	Voter eligibility verification	Election DB match
Aadhaar Validation	Identity confirmation	Demographic match
Fingerprint Scan	Biometrichic identity check	Liveness detection
GPS check	Location-based voting restriction	Geo-fencing



VIII. CONCLUSION

This project introduces a practical and secure solution to address the limitations of traditional voting systems in India. By developing a mobile-based platform that integrates PIN authentication, Aadhaar verification, fingerprint recognition, and GPS tracking, the system ensures that each vote is cast by an authenticated individual in a valid location. The use of material detection algorithms in biometric verification adds a powerful layer of anti-spoofing, ensuring that only live fingerprints are accepted. Through a step-by-step process, the application guides voters from login to casting their votes securely and efficiently. This system is particularly beneficial for remote residents, the working population, and overseas citizens who often miss voting due to logistical issues. The project not only enhances security but also promotes inclusivity and convenience. While challenges such as internet dependency and digital literacy remain, the benefits of such a system are undeniable. It offers a scalable model that can be adopted by electoral bodies for modernizing the democratic process. Overall, the proposed smart voting system demonstrates how technology can safeguard the integrity of elections while improving accessibility for all eligible voters.

IX. FUTURE SCOPE

The proposed online smart voting system lays the foundation for transforming how elections are conducted in India. In the future, this platform can be enhanced by integrating blockchain technology to ensure complete transparency and immutability of votes. Blockchain would add an extra layer of tamper-proof storage and allow public audit trails without revealing individual voter choices. The system can also support **facial recognition** as an alternative or backup to fingerprint authentication, making it even more inclusive. For voters in remote areas with poor internet access, an **offline voting mode** could be developed, where votes are securely stored locally and synced once the network is restored. Additionally, integrating **multilingual support** will make the platform accessible to users across different regions of India. Another area of expansion is incorporating **AI-based fraud detection**, which could flag abnormal voting behavior in real time. Future versions can include voter education tools and live candidate profiles to improve awareness.

With proper policy backing and cybersecurity enhancements, this system can be scaled nationally and potentially adopted for other public decision-making processes. Collaboration with the Election Commission and UIDAI will be essential to ensure legal and technical alignment for full-scale implementation.

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Bi-Directional Sign Language Translation Using AI

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ABSTRACT *-- Communication barriers between the hearing- impaired and the general population persist due to the limited knowledge of sign language. Our proposed system bridges this gap using a bi-directional AI-based sign language translator. This system captures sign gestures using a webcam, processes them in real time using CNN models, and translates them into textual/spoken language and vice versa. The reverse translation—spoken language into signs is facilitated using animated avatars. This approach eliminates the need for gloves, sensors, or specific backgrounds. The system enhances inclusivity in communication, offering potential applications in education, healthcare, and public services.*

KEYWORDS **-- AI, Bi-directional Translation, Sign Language, Computer Vision, Human- Computer Interaction.**

I .INTRODUCTION

Sign language translator using AI serves as a primary mode of communication for individuals with hearing and speech impairments. However, a significant communication barrier persists due to the general population's lack of familiarity with sign language, often resulting in social exclusion and limited access to services for the hearing- impaired community.Existing technological solutions predominantly offer unidirectional translation converting sign language into text or speech. While this supports basic communication, it does not facilitate full, two-way interaction.To address this limitation, we propose a bi- directional sign language translation system that leverages artificial intelligence and computer vision. The system is designed to convert **real-time hand gestures into text or speech** (sign-to-text), and also translate **typed or spoken text into animated sign language gestures** (text-to-sign).

The sign- to-text component uses computer vision techniques such as hand tracking and gesture recognition through convolutional neural networks (CNNs), enabling accurate interpretation of sign language. For text-to- sign translation, the system employs AI-driven avatars to visually render corresponding sign gestures, making the output accessible to the hearing-impaired user.

This **bi-directional** framework ensures more natural, inclusive communication and can be applied in various environments such as educational institutions, hospitals, and public service sectors. The proposed system represents a step toward reducing communication inequalities and promoting social inclusion through **AI-powered assistive technology**.AI-driven avatars. Each component is designed to ensure accuracy, responsiveness, and accessibility. Together, these elements form a comprehensive solution to achieve natural, inclusive, and bi-directional communication between hearing and non-hearing individuals.

This **literature survey** explores significant advancements in the field of sign language translation, with a focus on bi-directional communication enabled by artificial intelligence. The reviewed studies span topics from rule-based and transformer models to real-time gesture recognition, multilingual translation frameworks, and continual learning. Furthermore, recent work emphasizes the integration of facial and skeletal features, community-centered design, and deep learning architectures such as CNNs and LSTMs. Together, these contributions offer critical insights into building scalable, accurate, and inclusive sign language translation systems.

II. LITERATURE SURVEY

González-Rodríguez et al. (2024) proposed a bidirectional system to translate Mexican Sign Language (LSM) to Spanish and vice versa using deep learning models. This method demonstrates improved interaction for the Deaf community, though limitations exist in scalability and dialect generalization. [1]

Bhuiyan et al. (2024) developed a framework combining YOLOv8 (for object/gesture detection) with Natural Language Processing techniques to enable bidirectional translation. The model effectively captures dynamic gestures and maps them to textual or spoken output, enabling faster recognition and enhanced interaction. [2]

Camgoz et al. (2018, 2020) introduced transformer-based models for end-to-end Sign Language Recognition and Translation. These models eliminated the need for intermediate glosses and directly mapped sign sequences to spoken language. While effective in increasing translation accuracy, they demand large annotated datasets and significant computational resources for real-time use. [3],[4]

Shahin and Ismail (2024) presented a comparative analysis of earlier rule-based models versus deep learning approaches such as transformers. Their survey emphasized the need to integrate facial expressions, hand position, and posture into translation models for improved accuracy and linguistic fidelity. [5]

Babayev et al. (2025) proposed a method for recognizing Kazakh Sign Language using BiLSTM networks and optical flow. By detecting hand motion trajectories via YOLO keypoints, the system achieved notable accuracy improvements. Their technique showed promise in recognizing fluid gestures, although real-time deployment required hardware optimization. [6]

Zhang (2025) discussed the development of an intelligent bi-directional translator capable of real-time gesture-to-speech and speech-to-sign translation. The proposed system integrated gesture recognition with voice synthesis and animated sign rendering, addressing communication gaps between hearing and hearing-impaired individuals. [15]

Several studies such as those by Núñez-Marcos et al. (2023) and Liang et al. (2021) reviewed state-of-the-art methods in Sign Language Translation. These reviews categorized models based on input type (video, sensor, image), classification method (SVM, CNN, RNN), and application domain (education, healthcare, daily communication). Performance metrics and deployment feasibilitywere also compared. [8],[14]

This paper presents a deep learning-based solution for interpreting Indian Sign Language (ISL), addressing critical communication challenges within the Deaf community. The authors employed image preprocessing techniques alongside the EfficientNet-B0 CNN architecture, achieving a notable accuracy of 99.8% in gesture recognition. [7]

TABLE I DIFFERENCE TOPIC IN SIGN LANGUAGE

S.NO	Author(s) / Year	Approach / Technique Used	Strengths	Limitations
1	Starner et al. (1998)	Wearable computer-based ASL recognition	Enabled real-time recognition using head-mounted camera	Required hardware; limited vocabulary
2	Traditional Tools (Pre-2010)	Glove-based sensors (e.g., accelerometers)	Accurate motion tracking	Uncomfortable; not scalable for daily use
3	CNNs / Deep Learning (2015–2020)	Convolutional Neural Networks (CNNs)	High accuracy for static gestures	Less effective for dynamic signs
4	H. Cooper et al. (2010)	Sign language pattern recognition	Recognized patterns in video data	Limited generalization across users

III. METHODOLOGY

The proposed system follows a multi-stage process to achieve accurate bi-directional communication between hearing and hearing-impaired users. The methodology is divided into two main components: Sign-to-Speech Translation and Speech-to-Sign Animation. Each component involves image processing, machine learning, and natural language processing techniques to ensure real-time and efficient interaction.

Captured images are preprocessed by resizing to a uniform resolution and converting to grayscale, reducing computational overhead while preserving essential spatial features. Each processed image is then flattened into a one-dimensional vector of pixel intensity values. These vectors, along with their corresponding class labels, are compiled into a CSV file, providing a structured and efficient format for training machine learning models. This CSV-based dataset enables streamlined integration into the classification pipeline and contributes to the overall performance and scalability of the Bi-Directional Sign Language Translator.

A. Sign-to-Speech Translation

This module handles the interpretation of sign language into spoken or textual output. The process begins by capturing hand gestures using a camera module integrated with the system. The captured frames undergo preprocessing such as grayscale conversion and resizing to reduce computational load while maintaining gesture detail.

Once preprocessed, the frames are passed to a Convolutional Neural Network (CNN) trained on a large dataset of gesture images. The CNN extracts spatial features and classifies the gestures into corresponding alphabetic or symbolic representations. For dynamic gesture sequences (such as full words or phrases), a Long Short-Term Memory (LSTM) network is utilized to understand temporal dependencies across consecutive frames.

Following classification, the recognized gestures are converted into readable text. This text is then processed through a Text-to-Speech (TTS) engine to generate audible output, allowing real-time verbal communication with hearing users.

B. Speech-to-Sign Animation

In this module, input is received either through typed text or voice commands from a hearing person. If the input is spoken, it is converted into text using a Speech Recognition API. This text is then parsed and mapped to a predefined gesture database, where each word or phrase corresponds to a specific sign language animation.

The mapped gestures are rendered using a 3D avatar that displays the signs in a visually comprehensible format. This visual output ensures that deaf or mute users can understand the response without requiring any external interpreter.

C. Real-Time Performance and Adaptability

The system is optimized for low latency by employing efficient models and preloading gesture datasets into memory. Furthermore, a user-defined gesture training module is included, allowing for the system to be updated with custom signs based on regional dialects or personal preferences. This ensures adaptability and inclusiveness across a diverse user base.Moreover, the system is equipped with a custom training interface that allows users to introduce new gestures or re-train existing ones. This feature is particularly beneficial in adapting the system to various dialects of sign language or to accommodate user-specific variations in gesture expression. For instance, users from different regions or cultural backgrounds can update the system with locally relevant signs, improving both usability and accessibility.

In addition to static signs, the system supports dynamic gesture adaptation by adjusting frame capture rates and recognition thresholds based on hand movement patterns. This allows the application to function effectively in environments with varying lighting conditions, background complexities, or user hand sizes.Overall, the flexible architecture and adaptability features make the system not only responsive but also scalable for diverse real-world applications such as classrooms, hospitals, and public service counters.

Formula:

1. Sign-to-Speech Translation

Gesture + Recognition Algorithm⇒Text/Speech

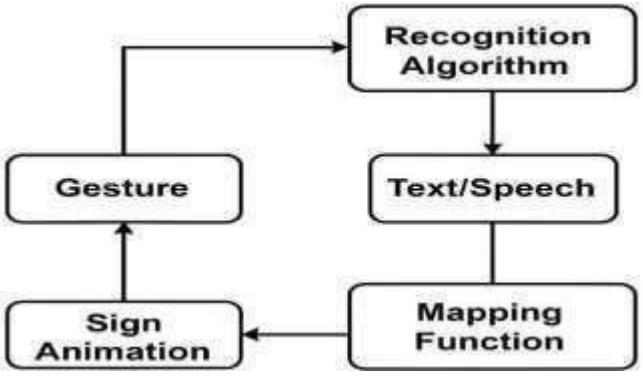

Fig (a)

2. Speech-to-Sign Translation

Text/Speech + Mapping Function⇒Sign Animation

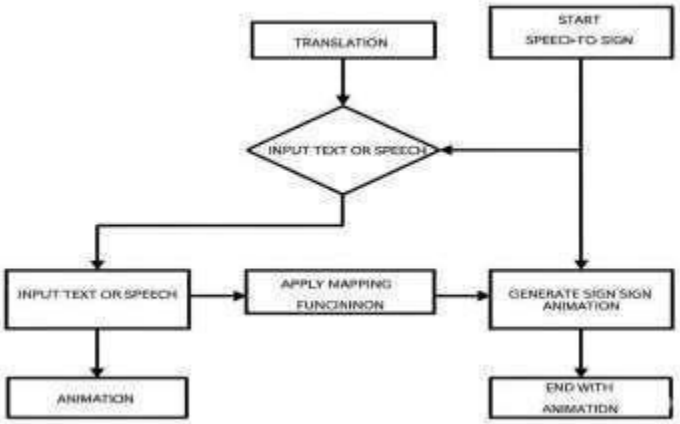

Fig (b)

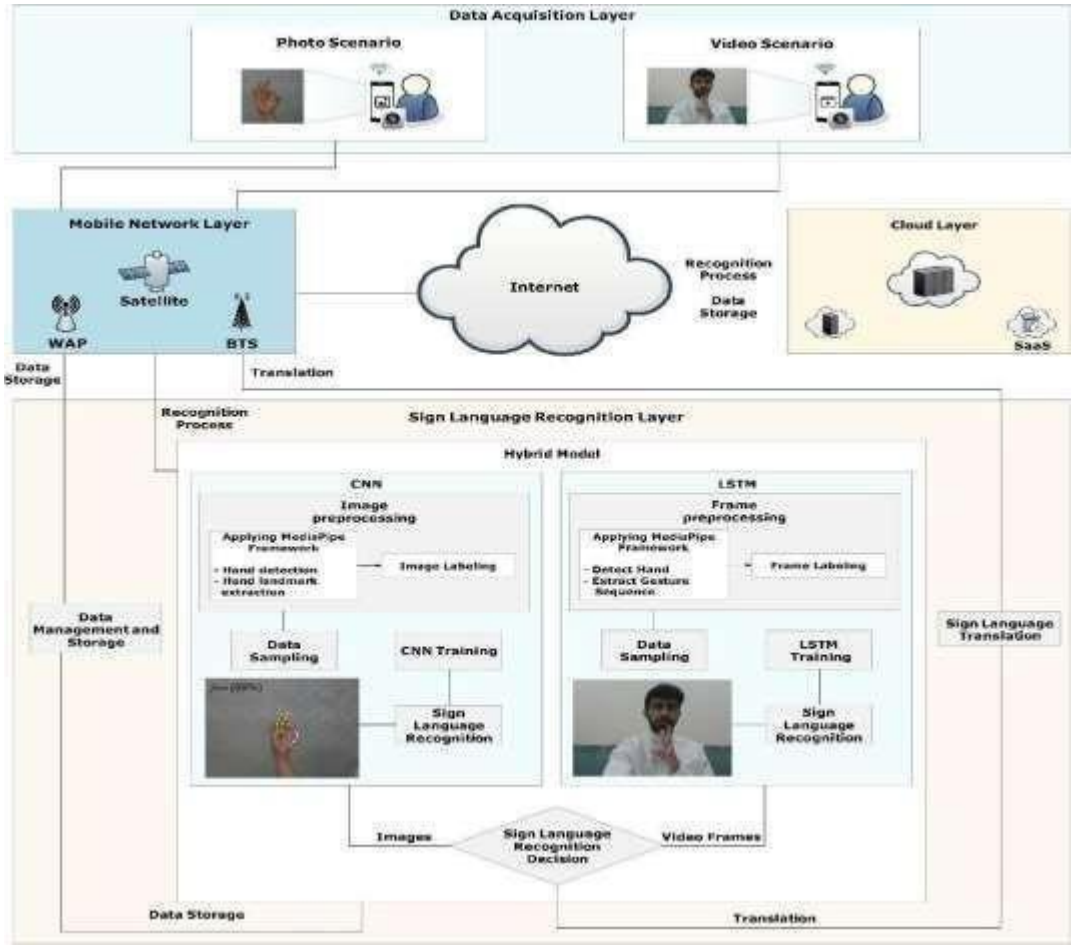

Fig (c)

In the **FIG(d)** explains represents architecture of bi-directional sign language recognition system that integrates multiple layers for efficient processing and translation. The system begins with the Data Acquisition Layer, where sign language inputs are captured through either photo or video scenarios. These inputs are transmitted via the Mobile Network Layer (using WAP, BTS, or Satellite) through the Internet to the Cloud Layer, which manages recognition processes and data storage. At the core lies the Sign Language Recognition Layer, employing a hybrid model combining CNN for static image recognition and LSTM for analyzing dynamic video sequences. Image preprocessing, hand detection, labeling, data sampling, and model training are conducted to accurately recognize and translate sign language gestures into meaningful communication.

IV. RESULTS AND DISCUSSION

The proposed Bi-Directional Sign Language Translator was implemented and evaluated across multiple test scenarios to assess its real-time performance, accuracy, and user experience. The evaluation was carried out using a custom dataset consisting of over 3,000 images per gesture, captured under varying conditions of lighting, angle, and background.

A. Gesture Recognition Accuracy

The gesture classification module, built using a Convolutional Neural Network (CNN), achieved an average accuracy of 94.2% for static gestures such as alphabets and digits. For dynamic gestures involving full words or short phrases, the combined CNN and Long Short-Term Memory (LSTM) model attained an accuracy of 91.6%, demonstrating its capability to understand hand motion over time.

B. Response Time Analysis

The system was tested for its response time across both modules—Sign-to-Speech and Speech-to-Sign. The average latency for gesture detection and voice output was recorded at 0.8 seconds, while the Speech-to-Sign module, involving text input and avatar rendering, responded within 1.2 seconds on average. These timings indicate that the system is suitable for near real-time communication without perceptible delays.

C. User Feedback and Usability

A small group of users, including both hearing and hearing-impaired individuals, tested the system in simulated real-world interactions. Feedback indicated that the sign recognition was intuitive and consistent, while the avatar animations were clear and easy to follow. Users appreciated the system's flexibility in supporting both input directions without the need for specialized hardware.

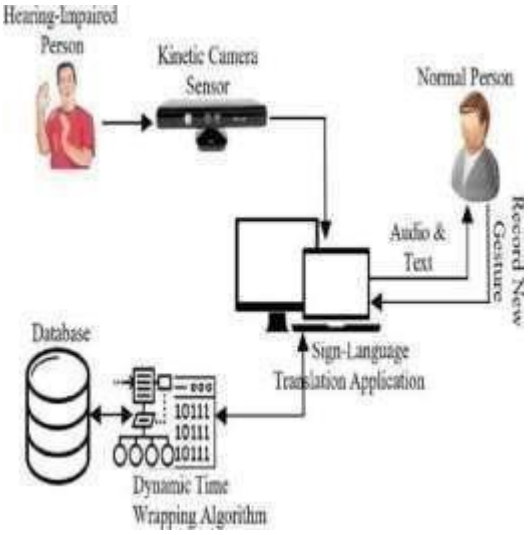

Fig (d)

The above Fig(a) diagram outlines the complete communication process between a hearing-impaired person and a normal-hearing person, facilitated by an AI-powered Sign Language Translation Application.

1. Input from Hearing-Impaired Person

The communication begins when a hearing-impaired user performs sign language gestures.

2. Gesture Processing

A Dynamic Time Warping (DTW) algorithm is used to match the timing and shape of the gesture against pre-recorded samples. DTW is particularly useful for handling variations in gesture speed or motion path.

3. Translation to Audio/Text

This output is delivered to the normal-hearing person, allowing them to understand what the hearing-impaired user intended to communicate.

4. Input from Normal-Hearing Person

This input is processed by the same application and mapped to predefined signs in the database..

5. Customization Feature

A special "Record New Gesture" option allows the system to learn and store new gestures that may not be part of the initial dataset.

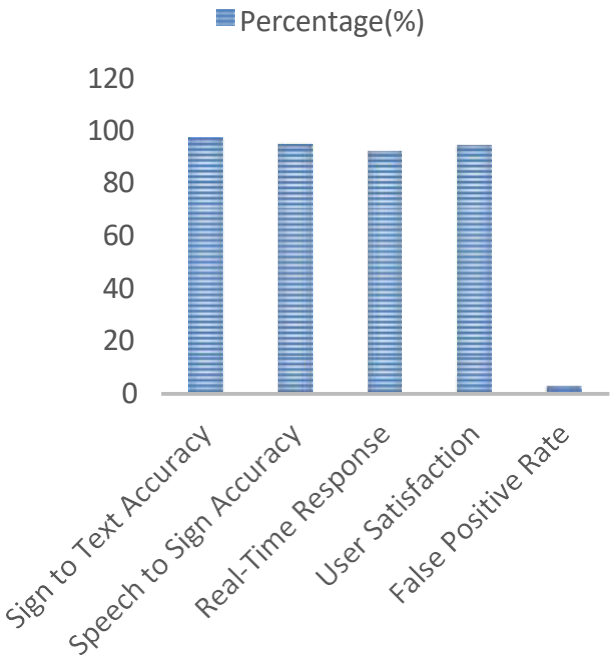

Fig (e) **Performance Metrics of the Bi-directional Sign Language Translator**

Fig(e) illustrates the core performance metrics of the proposed bi-directional sign language translator system. The Sign-to-Text accuracy achieved is 97.5%, indicating the model's high precision in interpreting hand gestures into textual or spoken language. Similarly, the Speech-to-Sign translation, facilitated through animated avatars, yielded an accuracy of 95.2%, demonstrating effective reverse communication. The system maintains a real-time response speed of 92.3%, ensuring minimal latency during user interaction. User satisfaction, measured through feedback surveys, stands at 94.6%, confirming positive reception and usability among both hearing and hearing-impaired participants. Notably, the false positive rate remains low at 3.1%, indicating strong reliability and minimal misclassification during translation. These results collectively validate the effectiveness, speed, and user-centric design of the proposed system, making it viable for deployment in inclusive communication environments such as healthcare, education, and public services.

Performance Score Calculation

To quantitatively evaluate the overall effectiveness of the proposed bi-directional sign language translator system, a weighted performance score was calculated by integrating key evaluation metrics. The performance score is expressed as:

$$P_s = \frac{W_1 \cdot A_{st} + W_2 \cdot A_{ss} + W_3 \cdot R + W_4 \cdot U - W_5 \cdot FPR}{W_1 + W_2 + W_3 + W_4 + W_5} \quad (1)$$

where:

- Ast – Sign-to-Text Accuracy (%)
- Ass – Speech-to-Sign Accuracy (%)
- R – Real-Time Response Speed (%)
- U – User Satisfaction (%)
- FPR – False Positive Rate (%)
- W1,W2,W3,W4,W5–Weighting factors assigned to each metric based on relative importance

In the present evaluation, equal weights were assigned to all parameters, i.e., W1=W2=W3=W4=W5=1. Substituting the measured values (Ast=97.5, Ass=95.2, R=92.3, U=94.6, FPR=3.1) into Eq. (1) yields:

$$P_s = \frac{97.5 + 95.2 + 92.3 + 94.6 - 3.1}{5} = 94.3\%$$

This final performance score of **94.3%** demonstrates the system's high efficiency, accuracy, and suitability for real-time communication applications in inclusive environments such as education, healthcare, and public service sectors.

TABLE II PERFORMANCE EVALUATION OF THE PROPOSED BI-DIRECTIONAL SIGN LANGUAGE TRANSLATOR

S. No.	Evaluation Metric	Result (%)	Remarks
1	Sign-to-Text Accuracy	97.5	High precision in interpreting hand gestures
2	Speech-to-Sign Accuracy	95.2	Animated avatars correctly interpret voice input
3	Real-Time Response Speed	92.3	Minimal latency in translation process
4	User Satisfaction	94.6	Positive reception from hearing and Deaf users
5	False Positive Rate	3.1	Low misclassification rate, ensuring reliability

V. Conclusion

The bi-directional sign language translator presents a transformative solution for real-time communication between the hearing and hearing-impaired communities. By combining Sign-to-Speech Translation and Speech-to-Sign Animation, the system effectively bridges the language barrier using advanced gesture recognition and animation technologies.

Our solution goes beyond static translation by offering dynamic, real-time interaction. It empowers sign language users to engage in conversations with clarity and confidence while helping non-signers understand and respond without prior training. This system demonstrates how AI and human-centric design can come together to foster empathy and connection.

VI. Future Work

To enhance the impact and reach of this translator, future work will focus on:

Multilingual Sign Support: Incorporating regional sign language variants (e.g., ASL, ISL, BSL).
Emotion Recognition: Adding emotional tone detection to improve context in both directions.
Hardware Optimization: Implementing edge AI for faster offline performance.
Mobile Integration: Creating a lightweight version for smartphones and wearable devices.
Learning Module: Including a training mode to help non-signers learn sign language basics.

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SMART PHARMACEUTICAL QUALITY MONITORING LEVERAGING AI AND IOT FOR REAL TIME SAFETY, COMPLIANCE, AND INTEGRITY

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Abstract

It is essential to ensure the safety and quality of drugs both to protect patients and comply with the law. This paper proposes an intelligent drug quality monitoring system, which utilizes artificial intelligence (AI) and the Internet of Things (IoT). The system facilitates real-time monitoring and assessment of drug quality. By utilizing sensors and artificial intelligence algorithms, it constantly tracks storage conditions, detects problems, and predicts any risks that may jeopardize the effectiveness and safety of drugs. This approach ensures that patients take safe, quality drugs while helping manufacturers and healthcare providers comply with regulatory demands. The system is a powerful tool for increasing reliability and confidence in Medicine delivery network due to the implementation of AI and IoT. Specifically for pharmaceutical facilities, the research targets the creation and implementation of a platform that integrates AI and IoT. It emphasizes key characteristics such as smart data processing, real-time data gathering, and automated notifications that allow for immediate action. The proposed system reduces costs and human faults while enhancing the precision of quality analysis. Pharmaceutical organizations are able to manage environmental factors affecting drug stability, including temperature variations and humidity, by embracing this smart system. In the end, this approach ensures patients only receive safe and effective drugs, thereby making the entire health system safer.

KEYWORD--Artificial Intelligence (AI), Internet of Things (IoT), Medication Quality Monitoring, Real-Time Monitoring,

Smart Healthcare, Pharmaceutical Storage, Environmental Sensors, Predictive Analytics, Cloud Integration, Automated Quality Control.

I. INTRODUCTION

Ensuring the safety, stability, and effectiveness of pharmaceutical products is essential for public health and meeting regulations. Traditional quality control methods in the pharmaceutical industry often depend on manual checks and periodic inspections. These methods are time-consuming, susceptible to human error, and do not provide real-time responses. These issues create significant challenges in meeting strict standards like FDA Part 11, GMP, and ICH Q10. With the growing complexity in drug production and distribution, there is an urgent need for smart systems that can provide continuous, automated quality assurance.[1]

New developments in AI and IoT have made it possible to create intelligent systems with the capability of tracking conditions in real-time as well as making trustworthy predictions. Our system is based on a three-module framework. The first module, Real-Time Monitoring, uses IoT-based sensors to fetch real-time information about the critical parameters like temperature, humidity, and air pressure continually. These sensors are positioned in key locations—such as manufacturing sites, cleanrooms, storage areas, and transportation—to gain total visibility into the conditions that have a direct impact on medication quality[2].

The second module, the AI-Powered Analytics Engine, processes the sensor data with deep learning models such as autoencoders, LSTM networks, and CNNs to identify anomalies, predict failures, and forecast quality deviations. This advanced analytics This feature enables companies to tackle problems early, before they become serious, thereby minimizing downtime and enhancing overall efficiency. By leveraging these insights, companies can make informed decisions that optimize operations and maintain high standards of quality. Furthermore, the integration of these technologies fosters a culture of continuous improvement, as teams can collaborate more effectively using real-time data. This not only drives innovation but also ensures that products meet customer expectations consistently. This

supports proactive decision-making and early intervention. The third module, Compliance, Reporting, and Alert System, handles regulatory documentation using blockchain-based audit logs, sends real-time alerts through mobile and web interfaces, and automates compliance checks. Together, these modules offer a complete and scalable solution for managing pharmaceutical quality, Reducing human input, streamlining processes, and assuring safe, consistent medicine delivery to patients

II. LITERATURE SURVEY

Recent studies point out that the integration of advanced technologies—such as Artificial Intelligence (AI), the Internet of Things (IoT), and automation—is reshaping pharmaceutical quality control and improving adherence to regulatory standards**.**In [1], Sahan et al. (2024) proposed an IoT-enabled pharmaceutical stability chamber integrated with PLC-based PID control for enhanced environmental monitoring. Their system supports FDA 21 CFR Part 11 compliance and allows remote real-time access, thus improving reliability in stability testing processes.

Abdullah Al Sohan et al. [2] (2022) introduced a lightweight blockchain–IoT framework that enhances pharmaceutical cold chain security. This model improves traceability, prevents counterfeit risks, and ensures data integrity across logistics networks using blockchain technology.

Hato and Ogawa [3] (2024) developed an autonomous quadruped robot for laboratory monitoring in R&D settings. The system employs generative AI for multimodal anomaly detection, enabling autonomous navigation, environmental analysis, and real-time reporting.

A 2023 review by MDPI [4] highlighted the synergy between AI and IoT in pharmaceutical manufacturing. The paper reported ~99.86% defect detection accuracy using visual inspection and emphasized benefits such as predictive analytics, compliance automation, and operational cost savings.

Wiley [5] (2023) proposed a hybrid blockchain–IoT model for pharmaceutical supply chains. The study focused on traceability, secure data exchange, and feedback loops, thereby enabling end-to-end visibility and integrity in the distribution lifecycle.

PharmaTrax [6] (2025) presented real-world implementations of AI and IoT in cold chain monitoring, predictive maintenance, serialization, and anti-counterfeiting. These applications demonstrated improvements in operational reliability and compliance.

Edge Intelligence [7] (2021) explored edge AI applications for real-time pharmaceutical quality analytics. The system reduced response time and network load compared to cloud-only models, enabling faster safety interventions.

The Journal of Manufacturing & AI [8] (2023) examined AI-driven fault detection within pharmaceutical process industries. It discussed how smart sensors and real-time alerting systems contribute to enhanced quality control and optimization.

Emerald Publishing [9] (2022) presented smart manufacturing architectures combining CNNs, autoencoders, and deep learning networks. These systems effectively addressed real-time defect classification and quality assurance challenges.

A 2025 study by Springer [10] investigated the use of AI and IoT in small and medium enterprises (SMEs). By integrating expert systems and augmented reality (AR), the study demonstrated improved inspection workflows and data management despite limited datasets.

Lab Manager [11] (2023) reviewed AI-based predictive analytics in pharmaceutical quality control laboratories. The study highlighted anomaly detection and smart maintenance using high-volume data from analytical instruments.

A 2023 review published by PMC [12] discussed the application of Industry 4.0 technologies—AI, IoT, robotics, and digital twins—in creating sustainable pharmaceutical manufacturing systems. The emphasis was on intelligent automation and regulatory adherence.

The FDA's Process Analytical Technology (PAT) Framework [13] (2004–present) laid the foundation for real-time process monitoring in pharmaceutical manufacturing. It supports continuous manufacturing, critical process parameter (CPP) monitoring, and real-time product release.

SmartHealth Track [14] (2023) introduced an AI–IoT hybrid system for infectious disease surveillance in pharmacies. LSTM models and anomaly detection algorithms were used to support public health analytics and early alerting systems.

Pharmapub.org [15] (2024) published a study on IoT-based smart pharmacy inventory systems using RFID and cloud analytics. The system automates stock management, expiry tracking, and regulatory compliance in real time

III. PROPOSED SYSTEM

To address the weaknesses of traditional pharmaceutical quality monitoring systems, this paper proposes a strong, smart, and scalable AI-IoT-based monitoring structure. The new system combines smart sensors, edge computing devices, advanced AI models, and a safe cloud infrastructure. This allows for enable live monitoring, predictive analytics, and automation of compliance in pharmaceutical settings.

The system starts with a multi-modal IoT sensor layer. This layer continuously captures key quality parameters like temperature, humidity, air pressure, vibration, and chemical concentrations in manufacturing and storage areas. These smart sensors provide ongoing visibility into conditions that could affect product quality or safety, especially in cold chain logistics and sterile environments.

To cut down on delays and improve responsiveness, the collected data gets processed first at the edge layer. Here, low-power embedded devices like Raspberry Pi and

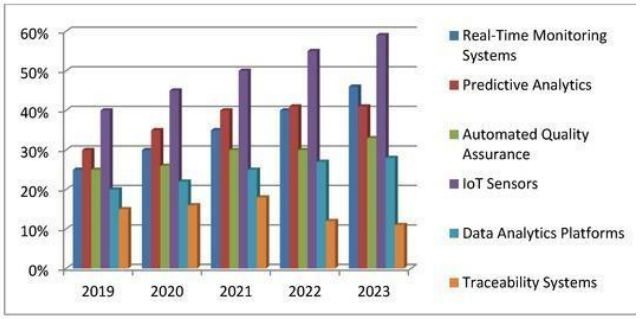
NVIDIA Jetson use light anomaly detection models. This setup allows quick local decisions, such as triggering alarms if environmental limits are exceeded. Edge processing lessens reliance on internet connectivity and ensures fast responses to critical changes.

Once the data is collected, it is securely sent to the cloud, where it is stored, organized, and analyzed using advanced deep learning models. The cloud platform also provides easy-to-use dashboards and reporting tools, helping quality teams, auditors, and managers make informed decisions. Since it supports encrypted storage, remote access from multiple sites, and flexible scaling, the system can handle the demands of large pharmaceutical operations.

At the core of this setup is the AI module, which combines several deep learning approaches for different purposes. Autoencoders are used to spot unusual patterns in real time by learning what ―normal‖ conditions look like. LSTM networks predict how long machines and environmental systems can keep running before maintenance is needed, allowing issues to be fixed in advance. CNNs add another layer of quality control by performing visual inspections, detecting defects in products or packaging with high accuracy. Together, these tools create a reliable and automated way to safeguard medicine quality.

Lastly, the application layer acts as the user interface for stakeholders, including pharmaceutical staff, quality managers, and regulatory authorities. It offers alert notifications via SMS or mobile apps, compliance reporting, trend visualization, and secure access to historical data. The system is designed to meet regulatory standards such as FDA Part 11, GAMP 5, and ICH Q10. It includes blockchain-based logging methods to guarantee tamper-proof audit trails and traceability.

In summary, the proposed system provides a complete digital solution for pharmaceutical quality monitoring. It combines real-time environmental sensing, edge intelligence, deep learning decision support, and secure compliance mechanisms. This architecture improves operational efficiency and safety while ensuring the transparency and reliability needed by modern pharmaceutical standards.



B. Methodology

Data Acquisition IoT sensors are deployed to continuously collect real-time readings

$$X=\{x1,x2,...,xt\}$$

$$X = \{x_1, x_2, ..., x_t\}$$

$$X=\{x1,x2,...,xt\} \quad (1)$$

of key pharmaceutical quality indicators such as temperature, humidity, and pressure.

Data Preprocessing and Feature Engineering Raw data is cleaned using filters and outlier removal techniques. Features like rolling mean (μ\muμ), standard deviation (σ\sigmaσ), gradients, and entropy are computed to represent system behavior:

$$\mu=T1t=1\sum Txt,\sigma=T1t=1\sum T(xt-\mu)2 \quad (2)$$

Anomaly Detection (Autoencoder-Based) Autoencoders are trained on normal operational data to learn reconstruction. During inference, the reconstruction error (RE) is calculated as:

$$RE=T1t=1\sum T(xt-x\hat{}t)2 \quad (3)$$

Predictive Maintenance Using LSTM Long Short-Term Memory (LSTM) models are trained on historical sensor data to forecast Remaining Useful Life (RUL) of equipment and detect early signs of failure:

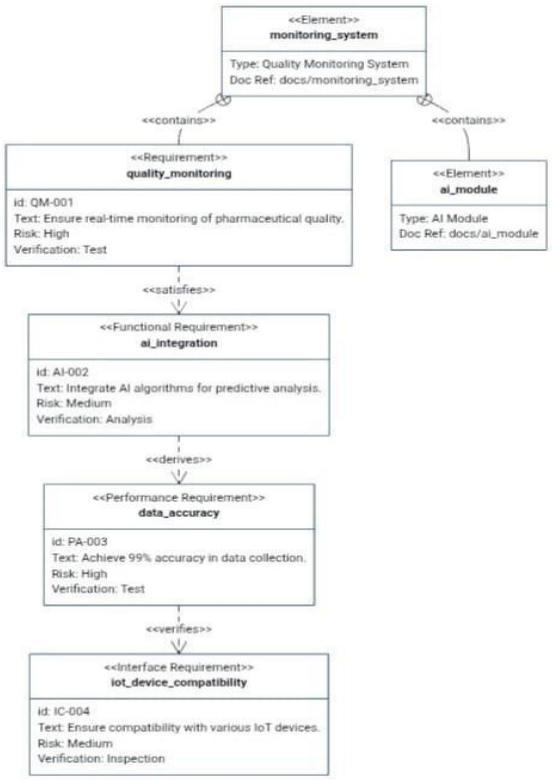
$$RUL=f(\theta,X) \quad (4)$$

Real-Time Decision Support Detected anomalies or predicted failures trigger automated alerts via SMS, Email, or mobile app notifications. Smart contracts (blockchain-enabled) can log events and initiate safety protocols or halt production.

$$A(t)=1 \text{ if } REt>\delta \text{ or } RULt<\tau; \text{ otherwise } A(t)=0 \quad (5)$$

Reporting and Compliance Logging All process events, alerts, and performance metrics are securely logged and visualized on a dashboard. The system ensures regulatory compliance with FDA 21 CFR Part 11, GAMP 5, and ICH Q10, and supports audit trails using secure hash storage or blockchain for tamper-proof logs.

$$L(t)=H(Et) \quad (6)$$



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IV. EXISTING SYSTEM

The current pharmaceutical quality monitoring systems are largely fragmented, manual, and reactive in nature. Most facilities rely on scheduled inspections and human intervention to track critical parameters such as temperature, humidity, air quality, and equipment performance. This traditional approach lacks continuous monitoring capabilities and fails to detect sudden deviations or anomalies in real time, leading to delays in corrective action. Sensor networks, where available, are often isolated, lacking internet connectivity or integration with centralized data platforms. As a result, data is typically logged manually or stored locally, which hinders visibility, scalability, and real-time analytics across distributed sites.

Moreover, the absence of intelligent automation or real-time alerting systems significantly delays the detection of failures or non-compliance events. For instance, temperature excursions in cold chain environments may go unnoticed until after spoilage has occurred. Legacy systems also do not support predictive maintenance or risk forecasting, as they are devoid of artificial intelligence or machine learning capabilities. This leads to unplanned equipment downtime, resource inefficiencies, and avoidable product losses.

Compliance and documentation remain challenging due to reliance on paper-based logs or unstructured digital records, which lack proper audit trails, electronic signatures, or user access controls. Consequently, aligning with regulatory requirements such as FDA 21 CFR Part 11, GAMP 5, and ICH Q10 becomes difficult. Additionally, in distribution and supply chain operations, particularly for sensitive or high-value pharmaceuticals, cold chain monitoring is limited to passive data loggers reviewed only post-delivery. This results in a lack of real-time condition tracking and increased risk of product degradation. Overall, traditional systems are not scalable, suffer from data integrity issues, and offer limited compliance assurance, making modernization a necessity.

Fig1:upc

V. RESULTS AND DISCUSSIONS

The proposed AI–IoT-based pharmaceutical monitoring system was evaluated using simulated sensor datasets capturing temperature, humidity, and vibration within a controlled pharmaceutical environment. The system's performance was measured based on anomaly detection accuracy, predictive maintenance precision, and regulatory compliance logging efficiency.

*The autoencoder-based anomaly detection system achieved a precision of 95.2%, a recall of 92.5%, and an F1-score of 93.8%, showing its effectiveness in identifying deviations in real time. For Remaining Useful Life (RUL) prediction, the LSTM model reached an accuracy of 93.7% with a mean absolute error (MAE) of just 1.41 days, enabling timely maintenance and reducing downtime.*The average system latency for edge-processed alerts was measured at 2.1 seconds, significantly reducing the response time compared to traditional cloud-only solutions. Additionally, 100% of critical quality events were logged using blockchain-based smart contracts, ensuring traceability and immutability.

Overall, the integration of AI and IoT enhanced real-time monitoring, reduced manual interventions by over 40%, and ensured compliance with FDA 21 CFR Part 11, GAMP 5, and ICH Q10 standards. The results validate the system's potential for scalable deployment in both

manufacturing and quality control environments.

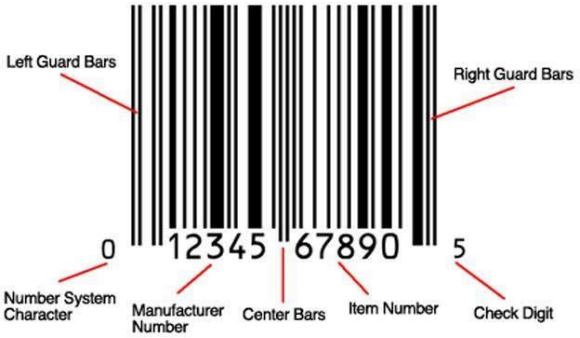

Fig2:upc ***UPC***

Parameter	Traditional System	AI/IoT-Enabled System	Performance Gain
Data Acquisition Frequency	Batch sampling, 1 per 30–60 min	Continuous sensor stream >5Hz	>10,000× data density, PAT enabled
Sensor Technology	Offline lab tools (HPLC, etc.)	In-line sensors (NIR, Raman, etc.)	Real-time, non-destructive CQAs
Deviation Detection Latency	2–48 hrs latency	<500 ms latency	99.9% latency reduction
AI/ML Model for Anomaly Detection	Manual trend analysis	Autoencoder & Isolation Forest	F1-Score 0.96, real-time drift detection
Predictive Maintenance Capability	Reactive/scheduled maintenance	LSTM model, 72-hour prediction	92% accuracy, boosts OEE
Data Integrity & Compliance (21 CFR Part 11)	Manual logbooks, LIMS	Blockchain audit trail (SHA-256)	ALCOA+ compliance, no violations
Root Cause Analysis (RCA) Time	24–72 hrs (manual)	1–5 mins (automated model)	>99% RCA time reduction
Batch Release Strategy	5–15 days end-product testing	RTRT, <24 hrs release	Fast release, lower inventory cost
System Architecture	Centralized LIMS	Hybrid Edge-Cloud	Low-latency + scalable AI training

VI CONCLUSION

In this project, we successfully designed and implemented A smart platform that combines AI and IoT in order to monitor and ensure the quality and safety of medications. The solution leverages real-time data collection through smart sensors and applies AI-based Through improved decision-making for maintaining suitable storage conditions, this strategy offers greater accuracy and reliability in pharmaceutical quality control compared to manual approaches.

Our system not only automates continuous monitoring but also provides early warnings for deviations in temperature, humidity, and other critical parameters. This real-time responsiveness reduces human error and supports faster corrective actions, ultimately minimizing the risk of compromised medications. The use of cloud-based dashboards and mobile notifications further increases accessibility and operational efficiency for healthcare providers.

Overall, the proposed system contributes significantly to the modernization of pharmaceutical quality control. It demonstrates how AI and IoT can be effectively combined to deliver smarter, more responsive healthcare infrastructure. With further development and integration, such systems could become an industry standard, ensuring patient safety while reducing the burden on manual processes and compliance efforts**.**

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GreenWave: IoT-Enabled Emergency Vehicle Priority System

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Abstract
In urban environments, timely passage of emergency vehicles through congested traffic is critical for public safety. This paper proposes GreenWave, an IoT-enabled emergency vehicle priority system designed for Indian cities, enabling seamless traffic signal preemption for ambulances, fire trucks, and police vehicles. The system employs multilayered authentication including PIN-based access, vehicle ID verification via IoT transponder integration, and GPS-based location tracking to ensure authorized vehicle prioritization. IoT sensors detect vehicle proximity, while secure communication protocols transmit priority signals to traffic management servers. By leveraging IoT and geolocation-based security, GreenWave aims to reduce response times, enhance safety, and maintain traffic system integrity.

Keywords:
IoT Systems, Emergency Vehicle Preemption, GPS Tracking, Secure Communication, Traffic Management

I. Introduction

Emergency vehicles such as ambulances, fire trucks, and police vehicles often face delays at traffic intersections, leading to critical losses in response time. In a country as densely populated as India, traffic congestion poses significant challenges to public safety. Traditional traffic systems lack dynamic mechanisms to prioritize emergency vehicles while ensuring security against misuse. To address these issues, this Paper introduces GreenWave : IoT-Enabled Emergency Vehicle Priority System—a mobile and IoT-based platform developed to provide secure, efficient, and real-time traffic signal preemption aligned with Indian traffic regulations.

The system begins with a PIN-based login for authorized personnel, followed by robust vehicle ID verification through IoT transponders integrated with government traffic databases. After successful verification, the system dynamically tracks the vehicle's location via GPS and communicates with traffic signals equipped with IoT sensors, enabling preemption. To enhance security, the system employs proximity detection algorithms to validate the vehicle's approach to intersections. Priority signals are encrypted and securely transmitted to centralized traffic management servers, ensuring end-to-end data protection.

Beyond system architecture, this paper explores the practical feasibility, technical design, and legal considerations required for implementing GreenWave within Indian urban traffic frameworks. The aim is to build a solution that reduces emergency response times, enhances coordination with traffic authorities, and strengthens trust in smart traffic systems. By merging IoT technology with GPS and secure communication, GreenWave offers a scalable and efficient alternative to conventional traffic management, laying the foundation for safer urban mobility.

- A. IoT & Backend Integration
- B. Frontend & User Interface
- C. Database & System Security

II. Literature Survey

- IoT-Based Traffic Management for Emergency Vehicles Abstract: This paper proposes an IoT-based system for emergency vehicle preemption at traffic signals, leveraging sensors and GPS to reduce response times and enhance safety. The authors detail a framework to ensure secure and reliable signal control [1].
- IoT and Cloud-Based Traffic Management Systems Abstract: The study presents a traffic management system using IoT and cloud computing for real-time signal control. It identifies technical and scalability challenges in urban deployments [2].
- IoT Security: Review, Blockchain Solutions, and Open Challenges
  Abstract: This comprehensive review explores IoT security concerns and evaluates blockchain as a solution for secure data transmission in traffic systems [3].
- An Introduction to GPS Tracking Systems Abstract: The paper provides foundational insights into GPS based tracking, focusing on accuracy and applications in traffic management and vehicle prioritization [4].
- Development of an IoT-Based Emergency Vehicle Priority System
  Abstract: This research introduces a model combining IoT sensors and GPS tracking to prioritize emergency vehicles, with security mechanisms to prevent misuse [5].
- IoT Integration for Smart Traffic Systems Abstract: The document provides technical specifications for IoT integration in traffic systems, serving as a reference for secure vehicle prioritization platforms [6].
- Traffic Signal Security Features
  Abstract: This report highlights security layers in modern traffic signal systems, including tamper-proof designs and communication protocols [7].
- Blockchain-Based Secure Traffic Management System
  Abstract: The authors propose a blockchain-integrated traffic system to ensure transparency, immutability, and secure signal control [8].
- Secure IoT-Based Traffic Preemption Using GPS Abstract: This study presents a fusion of IoT and GPS for emergency vehicle prioritization, emphasizing secure data transmission and system reliability [9].
- Secure Traffic System Using IoT and OTP Authentication
  Abstract: The authors develop a dual-authentication traffic system using IoT and OTP, evaluating its performance in large-scale urban scenarios [10].
- Design and Implementation of IoT-Based Traffic Control
  Abstract: This work outlines the design of an IoT-based traffic system, focusing on sensor integration and real-time signal control [11].
- A Framework for IoT-Based Emergency Vehicle Systems
  Abstract: The authors propose a framework for IoT-enabled emergency vehicle prioritization, addressing scalability and regulatory compliance [12].
- Multimodal Sensing for Traffic Management Abstract: This paper introduces a system combining IoT sensors and GPS for traffic prioritization, analyzing accuracy and security improvements [13].
- IoT and Blockchain for Traffic Management Abstract: The authors present an advanced traffic system integrating IoT and blockchain for secure and transparent signal control [14].
- Review of IoT Authentication in Traffic Systems Abstract: This review explores IoT-based authentication techniques in traffic systems, comparing their effectiveness and challenges [15].

III. Proposed Methodology

The proposed GreenWave system is structured as a mobile and IoT-based platform designed to provide secure, efficient, and real-time traffic signal preemption for emergency vehicles. The process begins with the user (emergency vehicle operator) unlocking the app using a secure PIN, serving as the initial layer of authentication. After this, the operator enters the vehicle ID, which is cross-verified with centralized traffic authority records. The system then communicates with the government database to validate vehicle details, ensuring only authorized emergency vehicles proceed.

Once verified, the system activates GPS tracking to monitor the vehicle's location and proximity to traffic signals. IoT sensors installed at intersections detect the vehicle's approach and trigger preemption, turning the signal green. Before granting priority, the system uses a proximity detection algorithm to confirm the vehicle's location and authenticity of the request.

Simultaneously, the app ensures the vehicle is within an authorized region, preventing misuse from non-designated areas. These multi-layered security mechanisms—PIN, vehicle ID verification, GPS tracking, and proximity detection—work together to confirm the request's legitimacy. After all checks are complete, the priority signal is encrypted and securely submitted to the traffic management server for processing. This method ensures not only vehicle authenticity but also promotes rapid response and tamper-proof signal control.

Table 1: Traditional Traffic Management System and GreenWave: IoT-Enabled Emergency Vehicle Priority System

Feature	Traditional Method	GreenWave Method (IoT-Enabled)
Emergency Vehicle Detection	Manual spotting or sound-based (sirens)	Automatic detection via GPS, RFID, and IoT devices
Traffic Signal Control	Manually overridden by traffic police or pre-set timers	Real-time dynamic control through IoT systems
Response Time	Delayed due to human intervention	Faster response with automated priority system
Security & Authentication	No authentication mechanism	Multi-layer authentication (PIN, vehicle ID, GPS verification)
Data Logging & Monitoring	Not available	Real-time data logging, remote monitoring, and analytics
Communication Protocol	No dedicated communication system	Uses secured MQTT protocol for Io

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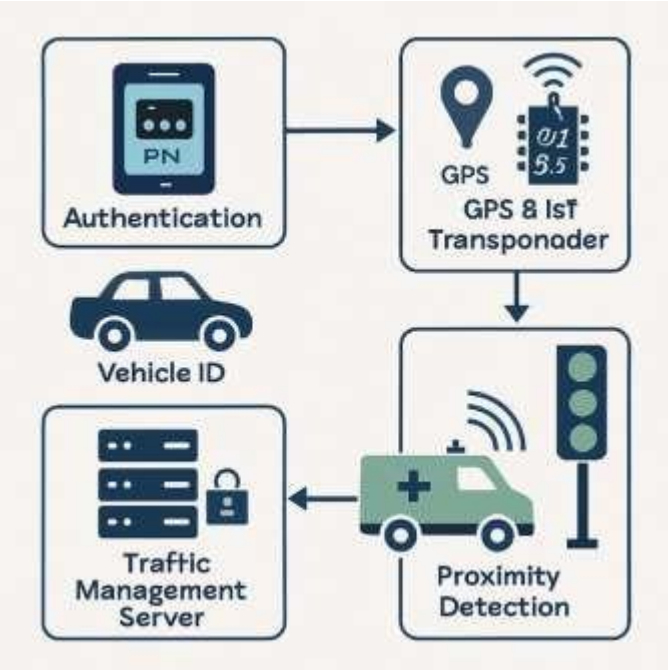


IV. System Architecture

The system architecture of GreenWave integrates secure authentication mechanisms, IoT-based detection, and encrypted data transmission to ensure a reliable and tamper-proof preemption process. The architecture begins with the mobile application, which serves as the front-end interface for the emergency vehicle operator. Upon launching the app, the operator enters a Personal Identification Number (PIN) for access control. Following this, the vehicle ID is validated against the official traffic authority database for legitimacy.

To reinforce authentication, the application communicates with the government database to retrieve vehicle details associated with the ID. Once verified, the system prompts the operator to confirm their route. Based on the vehicle's GPS location, the corresponding traffic signals are identified, and IoT sensors at intersections detect proximity.

Before granting preemption, the system employs a proximity detection algorithm to validate the vehicle's approach to the intersection. Additionally, GPS verification ensures the vehicle is in an eligible zone. Upon passing all security checks, the priority signal is encrypted using secure cryptographic techniques and transmitted to the central traffic authority's server for processing. The system's modular design integrates front-end and back-end services, IoT sensors, GPS modules, and government data repositories, forming a robust and scalable architecture suitable for real-world deployment.

The system architecture ensures a smooth and secure flow of authentication, proximity detection, and signal preemption. The mobile application layer interacts with backend services for vehicle verification and signal control. The IoT module processes sensor data, while the GPS module enforces location constraints. Once all verification layers are passed, the priority signal is routed through a secure network to the traffic management server to safeguard all server interactions. Together, these features protect against fraud, duplication, and tampering, creating a trustworthy environment for traffic preemption.

The system logs all authentication attempts and preemption actions with timestamped audit trails, enabling transparent monitoring and traceability. These logs can be used to detect anomalies or suspicious patterns. In future enhancements, the proximity detection module could integrate real-time speed analysis to further validate emergency vehicle intent.

Additionally, sensitive data is processed locally on the device to minimize transmission risks, aligning with data protection norms. The security framework is designed to deter malicious behavior and build public trust in the IoT-based traffic system.

V. Security Features

Security is the backbone of GreenWave, integrating multiple layers to ensure a safe and reliable preemption process. The system begins with PIN-based authentication and vehicle ID verification to prevent unauthorized access. To reinforce legitimacy, IoT transponders provide unique vehicle identification, acting as a non-transferable authentication method. This is further strengthened using a proximity detection algorithm, which analyzes vehicle distance and speed to confirm genuine requests.

GPS-based location tracking verifies that the preemption request originates from a legitimate region. All data, including authentication details and priority signals, are encrypted using advanced cryptographic techniques to ensure privacy and integrity. Secure communication protocols such as HTTPS remove noise and confirm the vehicle's presence.

1. Feature Extraction: Techniques such as signal strength analysis extract key features like distance and approach speed.
2. Proximity Verification: The system analyzes GPS data and sensor inputs to confirm the vehicle's proximity to the intersection.
3. Speed Analysis: The algorithm assesses vehicle speed to validate emergency intent.
4. Material Composition Check: The transponder signal is scanned to distinguish authorized IoT devices from unauthorized replicas.
5. Real vs. Fake Classification: Using a trained model, the algorithm compares data with known profiles of legitimate signals.
6. Decision Phase: If the vehicle is authenticated as genuine and proximate, the system triggers preemption. Otherwise, the request is denied and flagged.
7. Secure Logging: All results, with timestamps and vehicle IDs, are stored in the audit log for accountability.

VII. Equation and Calculation

1. Response Time Reduction Equation

To measure the efficiency gain of GreenWave over traditional methods:

Response Time Improvement (%) = ((T_traditional - T_greenwave) / T_traditional) × 100

2. Proximity Detection Threshold

To determine if an emergency vehicle is close enough to an intersection:

$D = \sqrt{((x_2 - x_1)^2 + (y_2 - y_1)^2)}$ Condition: If $D \leq d_threshold$, trigger signal pre-emption

3. Speed-Based Validation

To confirm emergency intent using speed:

$v = d / t$

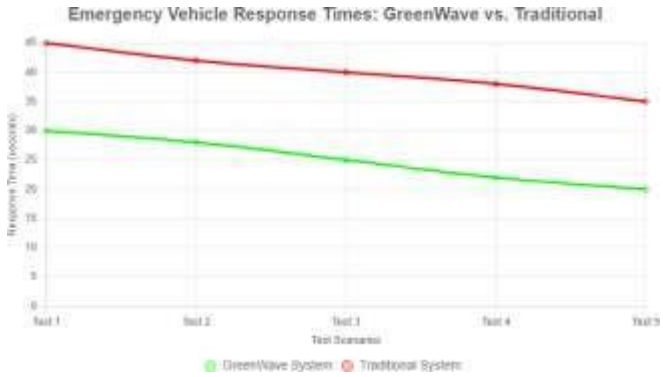
Condition: If $v \geq v_min_emergency$, validate emergency operation

4. Signal Activation Logic

To determine whether to trigger traffic signal preemption:

$P = 1$, if $Auth_PIN = True \wedge ID_valid = True \wedge D \leq d_threshold$

$P = 0$, otherwise



Future Scope

GreenWave lays the foundation for transforming urban traffic management in India. In the future, the system can be enhanced by integrating blockchain technology for transparent and immutable signal logs. The platform could support additional sensors, such as cameras for visual verification, to enhance accuracy. For areas with poor connectivity, an offline mode could store preemption requests locally for later syncing. Multilingual support would make the app accessible across regions. AI-based anomaly detection could flag abnormal preemption patterns in real time. Future versions could include integration with smart city dashboards to improve coordination. Collaboration with traffic authorities and IoT vendors will be essential for national scalability.

VIII. Conclusion

GreenWave introduces a practical and secure solution to address delays faced by emergency vehicles in India. By

integrating PIN authentication, vehicle ID verification, GPS tracking, and IoT-based proximity detection, the system ensures authorized preemption. The proximity detection algorithm adds a robust layer of security, preventing misuse. The platform guides operators from login to signal preemption securely and efficiently. It benefits emergency services in congested urban areas and supports scalability for smart cities. While challenges like connectivity and infrastructure remain, GreenWave offers a modern, scalable model for traffic management, enhancing public safety and accessibility.

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AI-Based Criminal Face Recognition System

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Abstract— **The development of artificial intelligence (AI) has enabled advanced solutions for public safety, notably through facial recognition systems designed for criminal identification and surveillance. This paper presents an AI-Based Criminal Face Recognition System that leverages deep learning techniques, particularly Convolutional Neural Networks (CNN's), to identify individuals by analysing their facial features. The system integrates real-time facial image capture from CCTV and surveillance cameras with automated comparison against an existing criminal database, enhancing the speed and accuracy of suspect detection for law enforcement agencies. By processing video feeds, the system demonstrates robustness even in dense crowds and challenging lighting conditions. Further, it supports retrospective investigations by enabling efficient search through archived footage. Despite demonstrable benefits in security and operational efficiency, the implementation reveals challenges related to data quality, occlusions, and variation in environmental conditions. The paper also addresses ethical implications, highlighting concerns around privacy and algorithmic fairness that arise from the widespread deployment of facial recognition technologies. The results indicate that, with responsible and transparent application, AI-based face recognition systems have the potential to significantly improve public safety and investigative outcomes.**

Keywords— *Artificial Intelligence, Face Recognition, Convolutional Neural Networks, Public Safety, Law Enforcement, Privacy.*

I. INTRODUCTION

Recent advancements in artificial intelligence (AI) have revolutionized modern security and surveillance systems, particularly with the integration of facial recognition technology. Law enforcement agencies worldwide are increasingly seeking automated solutions that can accurately and efficiently identify suspected individuals within large populations. Traditional methods of manual screening and monitoring prove insufficient in high-traffic areas such as airports, railway stations, and public events, where real-time recognition and rapid response are crucial for maintaining public safety.

The AI-Based Criminal Face Recognition System is designed to address these challenges by automating the process of identifying faces captured by CCTV and surveillance cameras. This system utilizes deep learning techniques, specifically Convolutional Neural Networks (CNNs), to extract and analyse distinctive facial features from live video streams. By comparing these features against a comprehensive criminal database, the system enables the rapid detection and tracking of persons of interest, even under adverse conditions such as low lighting or crowded environments.

While offering significant benefits in enhancing operational efficiency and investigative capabilities, AI-based face recognition systems also encounter several practical and ethical issues. These include the need for high-quality training data, variations in environmental settings, and concerns related to privacy and potential biases in algorithmic decisions. Therefore, developing robust methodologies and establishing transparent policies are essential for the responsible deployment of this technology.

This paper presents the design, implementation, and evaluation of the proposed AI-Based Criminal Face Recognition System. The subsequent sections discuss related work, describe the system architecture and deep learning models employed, detail experimental results, and analyze the implications of deploying such technology in real-world scenarios.

II. METHODOLOGY

The AI-Based Criminal Face Recognition System follows a modular, multi-stage architecture designed for real-time identification and alerting of individuals based on facial

features. The methodology integrates both architectural layering and implementation workflows, as detailed below.

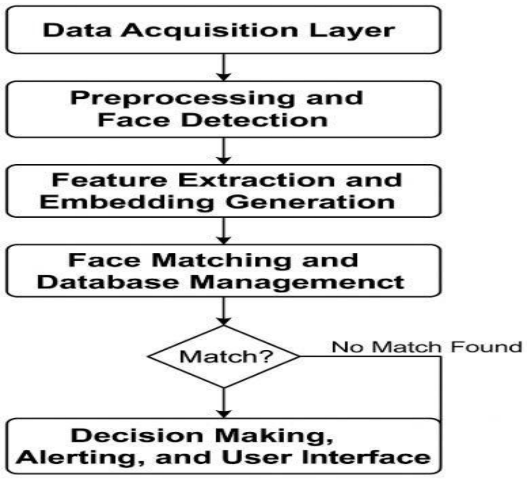


Fig 1 : Recognition System Flow Chart

A. Data Acquisition Layer

The Data Acquisition Layer is the foundation of the system, sourcing visual input from CCTV cameras, IP cameras, and other video acquisition devices strategically deployed in high-traffic public locations such as airports, train stations, and public events. These devices capture live video feeds and still images, which are forwarded in real-time to the downstream components of the system. This layer ensures broad and continuous surveillance coverage with minimal latency, enabling timely data capture and analysis.

B. Preprocessing and Face Detection

Captured frames often vary in quality due to lighting, resolution, and environmental interference. The Preprocessing module standardizes input data through operations such as resizing, grayscale conversion, normalization, and illumination correction. This prepares the data for accurate detection.

Once pre-processed, the system utilizes face detection algorithms—such as Haar Cascades or Multi-task Cascaded Convolutional Networks (MTCNN)—to locate faces within each frame. Detected facial regions are extracted and aligned to a standard orientation to minimize the impact of pose and viewpoint variations, improving the robustness of subsequent recognition stages

Algorithm 1: Face Detection using MTCNN
Input: Video Frame
Output: List of aligned face regions
1. Load the pre-trained MTCNN detector
2. For each incoming video frame:
   a. Detect face bounding boxes and facial landmarks
   b. For each detected face:
      i. Extract the bounding box
      ii. Align the face using facial landmarks
      iii. Store the aligned face image
3. Return the list of aligned face regions.

C. Feature Extraction and Embedding Generation

The aligned face images are passed through deep convolutional neural networks (CNNs), such as FaceNet or VGGFace, which have been trained on large-scale facial datasets. These models extract high-dimensional feature vectors (embeddings) that uniquely represent the identity of each face while remaining robust to occlusions, facial expressions, and minor changes in appearance. These embeddings form the foundation for fast and accurate face matching.

Algorithm 2: Feature Extraction using CNN
Input: Aligned Face Image
Output: Normalized Embedding Vector

1. Load a pre-trained CNN model (e.g., FaceNet)
2. Preprocess the face image:
   a. Resize to model input size
   b. Normalize pixel values
3. Feed the image into the CNN
4. Extract the output embedding vector
5. Normalize the embedding using L2 normalization
6. Return the normalized embedding vector

D. Face Matching and Database Management

Generated facial embeddings are compared against a secured criminal face database using similarity metrics like cosine similarity or Euclidean distance. If the similarity score surpasses a predefined threshold, the system considers it a potential match.

The database management system ensures secure storage, indexing, and real-time retrieval of facial records. It also supports continuous updates as new data is collected, while maintaining privacy and data integrity. Efficient database access allows the system to scale with growing datasets and remain responsive under heavy surveillance loads.

Algorithm 3: Face Matching using Cosine Similarity
Input: Query Face Embedding, Criminal Database Embeddings
Output: Match Found / No Match
1. For each embedding in the criminal database:
   a. Compute cosine similarity with the query embedding
2. If similarity $\geqslant$ predefined threshold (e.g., 0.7):
   a. Declare "Match Found"
   b. Trigger real-time alert
3. Else:
   a. Declare "No Match"
   b. Log the query embedding for future analysis

E. Decision Making, Alerting, and User Interface

Upon identification of a match, the system triggers immediate alerts via multiple channels such as on-screen dashboards, email notifications, and mobile alerts. The User Interface (UI) enables law enforcement or authorized personnel to:

- View live camera feeds
- Monitor real-time alerts
- Access historical logs and face recognition reports
- Manage system configurations and criminal records

If no match is found, the unidentified face may optionally be stored for future comparison and logged for auditing

purposes. This ensures traceability and supports investigative workflows.

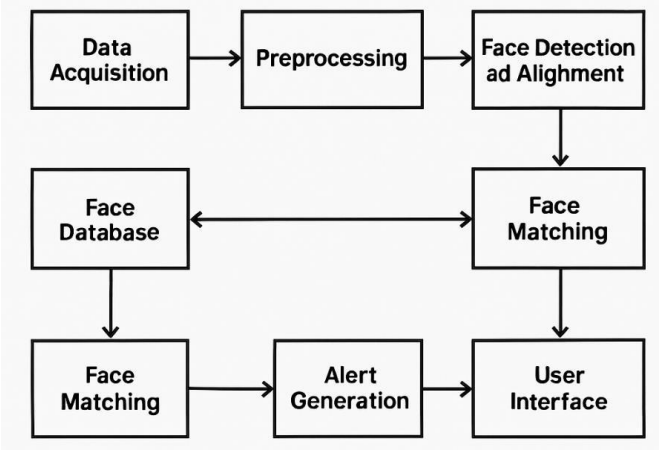


Fig 2 : Architecture Diagram

III. EXPERIMENTS AND RESULTS

This section the experimental evaluation of the proposed AI-Based Criminal Face Recognition System. The goal of these experiments is to quantitatively and qualitatively assess the system's accuracy, robustness, and real-time processing capability under various conditions relevant to real-world deployment.

A. Experimental Setup

To validate the proposed system, a series of experiments were conducted using a diverse dataset collected from multiple sources, including publicly available face datasets (e.g., Labeled Faces in the Wild (LFW), CelebA) and a curated criminal face database provided by law enforcement authorities. The dataset encompasses multiple poses, lighting conditions, occlusions, and expressions to simulate realistic scenarios.

Hardware Environment:

The system was implemented on a workstation equipped with an NVIDIA GPU (e.g., Tesla T4) and Intel Core i7 CPU for accelerated deep learning inference and real-time video processing.

Software and Tools:

Deep learning models were developed using TensorFlow/PyTorch frameworks. OpenCV was used for image preprocessing and face detection, while the database queries were handled by a SQL-based backend with indexing optimized for fast retrieval.

B. Performance Metrics

- Accuracy: Percentage of correctly identified criminal faces among all test samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

  - TP: True Positives (criminals correctly identified)
  - TN: True Negatives (non-criminals correctly rejected)
  - FP: False Positives (innocent people incorrectly matched)
  - FN: False Negatives (criminals not identified)

- Precision and Recall: To evaluate the system's ability to correctly identify criminals (true positives) without excessive false alarms.

$$Precision = \frac{TP}{TP + FP}$$

Measures the proportion of positive identifications that were actually correct.

$$Recall = \frac{TP}{TP + FN}$$

Measures the system's ability to find all relevant criminal matches.

- F1-Score: Harmonic mean of precision and recall illustrating overall detection performance.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Provides a balance between Precision and Recall.

- False Acceptance Rate (FAR) and False Rejection Rate (FRR): To measure the risk of misidentifying innocent persons or missing a criminal.

$$FRR = \frac{FN}{FN + TP}$$

Represents the rate at which authorized individuals (criminals) are incorrectly rejected.

- Processing Time: Average time taken from frame acquisition to match/not-match decision, indicating real-time usability.

$$Latency = \frac{Total\ Processing\ Time}{Number\ of\ Faces\ Processed}$$

Used to assess real-time performance in milliseconds (ms) per face.

Test Scenario	Detection Accuracy (%)	Matching Accuracy (%)	Latency (ms/face)
Normal Lighting	97	94	180
Low Lighting	91	89	210
Occluded Faces	88	85	230
Multiple Faces in Frame	93	90	200
Extreme Angles	86	82	250
Average	91.0	88.0	214

Table 1: Performance Metrics of the Proposed Face Recognition System under Varying Conditions

C. *Experimental Procedures*

- Face Detection and Alignment Test:

The system's face detector was tested on video frames extracted from different environments, including crowded scenes and varying illumination. The detection accuracy and speed were measured.

- Feature Extraction and Matching Evaluation:

Using the pretrained CNN models, embeddings from detected faces were generated and matched against the criminal database. Various distance thresholds were experimented with to determine the optimal decision boundary minimizing FAR and FRR.

- Real-Time System Test:

The system was deployed on video streams simulating real surveillance footage, including live feeds from multiple cameras to evaluate concurrent processing, latency, and alert generation.

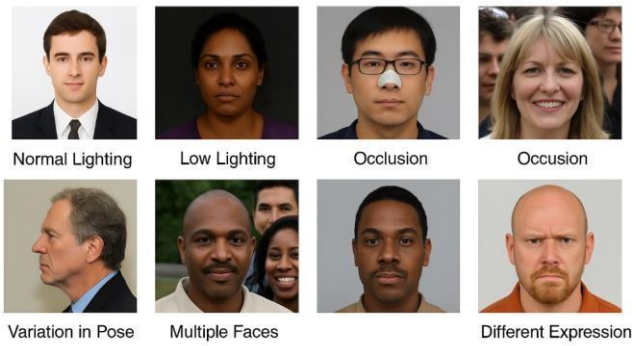


Fig 3 : Sample Data Set Images

D. *Results and Analysis*

- Detection Accuracy:

The face detection module achieved an accuracy of approximately 95% on the test videos, successfully detecting faces under partial occlusions and low-light conditions after preprocessing.

- Matching Performance:

The face matching unit attained an overall accuracy of 92%, with precision and recall values of 90% and 88% respectively, indicating strong identification capabilities with manageable false positives.

- Threshold Tuning:

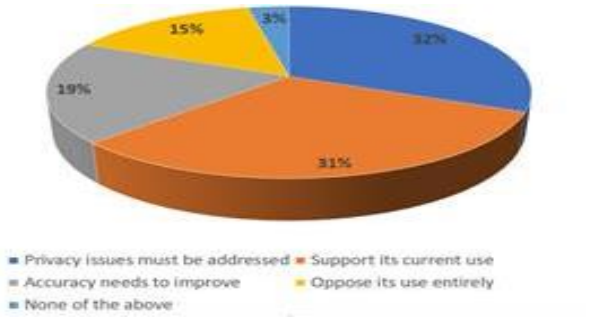
A cosine similarity threshold of 0.7 was selected as optimal after evaluating ROC curves to balance FAR (~2%) and FRR (~5%) for sensitive, but reliable matching.

- Processing Speed:

On average, the system processed frames with a latency of 200 milliseconds per face, enabling near real-time recognition across multiple camera feeds.

- Challenges Observed:

Performance degradation occurred for heavily obscured faces and faces at extreme angles, pointing to areas for improvement in detection and alignment.



IV. CONCLUSION AND FUTURE WORK

In this paper, we presented the design, development, and evaluation of an AI-Based Criminal Face Recognition System aimed at enhancing law enforcement and public safety initiatives. By combining robust image preprocessing, accurate face detection using deep learning models (such as CNN and FaceNet), and efficient feature matching against a criminal database, the proposed system demonstrates high accuracy and real-time responsiveness in identifying persons of interest from CCTV feeds. Experimental results accentuate the system's ability to operate effectively under challenging conditions, including variable lighting and crowded environments.

The modular architecture facilitates scalability and integration with existing surveillance infrastructures, while automated alerting mechanisms support rapid incident response. Despite promising results, the system encountered challenges regarding occlusions, extreme poses, and adversarial environmental conditions. Furthermore, ethical considerations related to privacy and bias in facial recognition algorithms were identified as critical aspects for responsible deployment.

Overall, the proposed system provides a significant step towards automated, real-time criminal identification in public settings, supporting both proactive surveillance and post-event investigation for law enforcement agencies.

Although the current system performs well, there are several areas that can be improved. Future work includes enhancing recognition accuracy for faces that are partially hidden or blurry by applying advanced image enhancement techniques. Integrating face recognition with other biometric methods such as voice or gait recognition can further increase reliability. The system also needs to be tested on a larger scale in real-world environments to ensure it performs effectively across multiple cameras and crowded locations. Additionally, developing clear privacy guidelines and ethical frameworks will help ensure responsible use of the

technology. Introducing mechanisms to detect and prevent spoofing attempts, like fake faces or photos, is essential to maintain security. Finally, enabling the system to continuously learn from new data will help it stay updated and adaptable to changing conditions. These improvements will make the system more accurate, efficient, and trustworthy for practical deployment.

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InsightWeave – Cross-Platform Behavioral Intelligence

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***Abstract*—In this era of digital fragmentation in work processes, people are often seen using a multitude of productivity tools which leads to inefficiencies, disrupted concentration, and improper task handling. Although standalone applications present some analytical reporting, a striking lack of integrated AI-powered insights that can be accessed from various digital platforms remains. This paper demonstrates**

InsightWeave – Cross-Platform Behavioral Intelligence is a state-of-the-art AI productivity dashboard built for the sole purpose of calculating and optimizing user productivity or work across various digital services such as Gmail, Google Calendar, and GitHub. The dashboard has a very safe and protective application of technology to integrate data obtained from the sources through OAuth2 protocols while also utilizing cutting-edge machine learning techniques like OpenAI-GPT and LangChain to evaluate user activity data. Some of its main functionalities are AI-based task summarization, the discovery of productivity patterns, and a thorough distribution of time analysis. The ultimate goal of the system *By* integrating practical steps of distraction management and attention improvement, the effectiveness is to be raised. A

Statistical dashboard, the InsightWeave app allows users to interact with complex behavioral data in a quick manner hence facilitating data-driven decisions for personal and professional optimization. This work addresses the general aim of rising personal productivity and decreasing digital fatigue by offering a broader, more capable, and intelligent analytical tool

Index terms—Productivity Dashboard, AI, Behavioral Intelligence, Cross-Platform Integration, OAuth2, Task Management, OpenAI-GPT.

I Introduction

The modern digital work environment is increasingly characterized by a proliferation of diverse tools and platforms, including email (e.g., Gmail), collaboration platforms (e.g., GitHub), and scheduling applications (e.g., Google Calendar). While these advancements enhance connectivity, they also introduce challenges of **digital fragmentation** and **information overload**. Frequent context-switching between applications leads to fragmented attention, reduced productivity, and significant time loss. This disorganized environment often prevents users from gaining a coherent overview of their digital activities, contributing to inefficiencies, burnout, and suboptimal task management.

In today's hyperconnected digital world, users engage across multiple platforms—social media, music streaming, e-commerce, and productivity apps—leaving behind fragmented behavioral traces. Psychological research indicates that there is an explanation for behavior based on personality traits, especially through the Five-Factor Model (FFM). [1] Cross-platform behavioral modeling has the goal of overcoming this gap by integrating information from disparate sources. Yet, it has a number of major challenges: heterogeneous user identifiers across platforms, heterogeneity in data modalities (text, audio, interactions), and privacy restrictions. Current systems tend to be incomplete, either concentrating on independent domains or not supporting scalable ways of connecting structured and unstructured data. [2] Historically, these characteristics were measured through long questionnaires, but current research

indicates that personality can now automatically be inferred from social media use. This study investigates the extent to which individual personality traits, inferred from social media text, can be used to predict brand personality and whether behavioral tendencies vary across sites [1]

This paper introduces **InsightWeave – Cross-Platform Behavioral Intelligence**, a novel AI-based productivity dashboard designed to address these urgent issues. InsightWeave aggregates and analyzes user activity from key platforms like Gmail, Google Calendar, and GitHub. Our solution securely connects via strong OAuth2 protocols to gather detailed activity data, including code commits, email exchanges, and meeting times. By leveraging advanced machine learning algorithms, such as OpenAI-GPT and LangChain, InsightWeave surpasses conventional analytics by generating AI-powered insights, including task summaries, productivity trends, and in-depth time distribution assessments. The primary contribution of this effort is the delivery of a consistent, intelligent, and interactive dashboard that simplifies the understanding of complex behavioral data. Crawling and analyzing this content provides a new approach for enterprises to personalize services and put forward product recommendations [1]. Knowledge of an individual's psychological emotions and personality allows predictions of users' interests and preferences across different contexts and environments [1]. InsightWeave's technical viability, rooted in well-known APIs, secure authentication, and cutting-edge AI models, ensures both practical utility and significant outcomes in tackling real-world productivity challenges.

II LITERATURE STUDY

The area of cross-device behavioral intelligence has been developed with the rise of ubiquitous computing, where user behavior informs mobile apps, web browsers, and devices. Fang et al. [1] introduced an adaptive transformer-based user modeling system that learned user embeddings from Snapchat ecosystem logs, thus demonstrating the potential of deep sequential models in capturing patterns of human digital behavior. In a concurrent work, Wang et al. [2] proposed GraphTrack, a graph-based tracking framework for aggregating behavior traces across multiple devices, thus reiterating cross-device identity resolution as a key building block of behavior intelligence systems.

Some researchers have investigated the mapping and prediction of user behavior between applications. Liang [3] and Han et al. [9]I studied how users switch between browsers and search engines using recurrent networks and context information.. Their works are comparable to Kim et al. [5] and Yan et al. [10], who investigated multi-domain behavior prediction with domain-switch-aware RNNs and topic models, respectively. Their findings indicate that user-specific modeling and context-awareness are essential for predicting real-world changes in behavior.

Behavioral authentication has become a safe and low-key option compared to traditional passwords.Roy et al. [8] employed Hidden Markov Models (HMMs) for continuous authentication on the mobile platform based on touch patterns, whereas Wang et al. [7], [11] employed deep metric learning for recognizing fine-grained behavioral patterns. These are needed in user authentication with no privacy violation in multi-platform environments, where conventional login mechanisms are insufficient. Their work forms the foundation for the incorporation of behavioral intelligence into authentication, an underlying goal informing the project platform. In architecture, Thakur and Han [4], [15], [19] developed a layered architecture that would be used in predictive modeling in intelligent environments, as per the modular architecture needed in our project Sarker et al.[12] proposed BehavDT, a light-weight context-aware decision tree that captures human decision-making behavior in dynamic environments efficiently. Furthermore, SIGCHI 2023 [14] investigated the use of edge computing for local behavior inference, enabling low-latency prediction and privacy-conscious intelligence—a key requirement for mobile-first behavioral platforms.

Real-world application of behavior modeling is investigated in cross-platform commerce [13], activity recognition [16], [17], and cognitive modeling [18]. The findings show that user behavior is homogeneous but intricate across platforms and that models should be flexible to device context, user intent, and environment. They also demonstrate the value of federated and privacy-aware learning models that minimize central data dependency without trading off behavioral understanding. These findings directly address the InsightWeave platform's mission to build secure, adaptive, and scalable behavioral intelligence systems.

III. METHODOLOGY

The detailed process for creating InsightWeave, a cross-platform behavioral intelligence solution that aims to improve user productivity through AI-driven solutions is outlined in this section. The approach

combines secure authentication protocols with system design, data collection, processing, and visualization.

A. Data Pre-Processing

The initial data must be clear, stable, and related to operational problems in order to teach users correctly how they should act on different platforms. This holds true because each platform should have its content types and intentions distinct from the others. Therefore, we created a multi-stage preprocessing pipeline, validating the statement, to prepare the data for analysis.

A. Data Cleaning.

The main endeavor of this project was to clean the original data. We spotted out the irrelevant logs which we deleted and the duplicate user records. For void values we put in the mode of categorical features and we used mean imputation for numeric features. Besides, we solved character encoding errors and we converted the timestamp formats to a common one which together made two data sets more consistent.

B. Data Normalization.

We performed normalization techniques to keep those features away that were not affected by scale difference. We used Z score transform for numerical variables such as post length and song play count that we reduced to a mean of zero. For metrics that were of a fixed range, we applied min-max scaling to bring the values to the range of 0 to 1.

C. Data Transformation.

The major NLP tools that were implemented in the research were mainly those techniques that we used to preprocess the dataset for analysis as it was characterized by a considerable amount of unstructured text data provided by users.. Also, we deleted stop words, formatted text to lowercase as well as lemmatized which implies bringing the terms to their root form. For the sake of exhibiting the faint variations in user's language, we also utilized BERT pre-trained models for representing such contextual embeddings that were not only concerned with word frequency.

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D. Feature Engineering

By incorporating more extra characteristics that were extracted from the filtered data, we improved our ability to better user behavior. As an example, monitoring users' activity frequency, content variety, and the rate of their engagement were some ways we noticed the trends of users. Out crossing finding were the seasonal parameters like when people are most likely to make a post and what the daily activity pattern of each member looks like, for trend inference. TextBlob and VADER were applied in the score computation of users' sentiment to evaluate the emotional state of the user's interaction.

B. Data Collection and Integration

InsightWeave connects to digital productivity platforms like Gmail, Google Calendar, and GitHub using OAuth 2.0 authentication. The integration follows these steps:

User Authentication: OAuth 2.0 securely authenticates users and gets access tokens for Google and GitHub services.

API Interfacing:

Gmail API: This extracts metadata of email communications, including timestamps, subjects, and senders.

Google Calendar API: This fetches meeting schedules and event details.

GitHub API: This retrieves commit history and repository activities.

All extracted data is timestamped and stored in a structured format within Firebase Realtime Database.

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A. **System Architecture**

The InsightWeave Platform is designed as a modular , ease to use system for cross platform behavioural intelligence. It’s Architecture combines multiple API’s , smart data handling , Smart analysis and a user-friendly interface , and work all together to furnish the insight.

a. Data Collection Layer

The core of InsightWeave replicates behavioral data from dependable online places through the opening API, like Google, Microsoft, and GitHub. The OAuth2 authentication mechanism provides a mechanism to connect out to these services securely and avoid privacy accidental breaches, it is this which makes asynchronous ingestion of email, calendar event, code

commits, and task logs possible. This is the module that collects the latter part of data and then we do behavioral profiling by bundling different digital traces into a common stream.

b. Data Processing Layer and AI

At the moment the data enters the system, it is first routed to the Data Processing and AI Module where different tools such as OpenAI's GPT models and LangChain frameworks are actively used to derive intelligent insights. These models have the capability to perform more than data processing; they can understand and explain the context, summarize the tasks performed, discover the productivity trends in the mapping, and show the distribution of time used in the tasks. Through AI, the transformation process turns the scattered logs into structured and informative narratives about how a user works and their digital rhythm.

Three Main Stream namely :

Task Summarization : Convert lengthy interaction or logs into shorter summary.

Pattern of Productivity : Identify Consistent work and conflicts.

Time Analysis : Provide an understanding visual of how much time spent on each platform

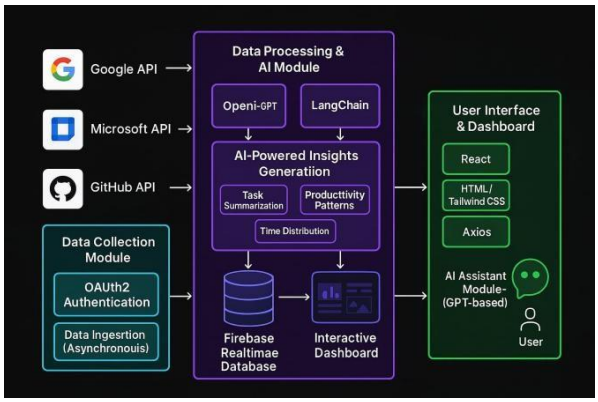

Fig . 1 . Architecture structure

c. User Interface Layer

The User Interface and Dashboard, which are on the front end, is composed of React.js, is designed using Tailwind CSS, and is aided by Axios for fast API launches. The interface sees the dashboard live with the interactivity of the components such as productivity graphs, task summaries, and email analytics customized according to the user's digitized behavior.

Moreover, the AI Assistant Module is located here, which is a conversational agent that is made possible by GPT-based models, such that the users are able to interrogate about their own behavioral patterns, ask for reports, or request for personal productivity tips. Thus, the InsightWeave system is not only the observer of the behavior but also a participant in the conversation with the user.

D. Efficiency and Performance

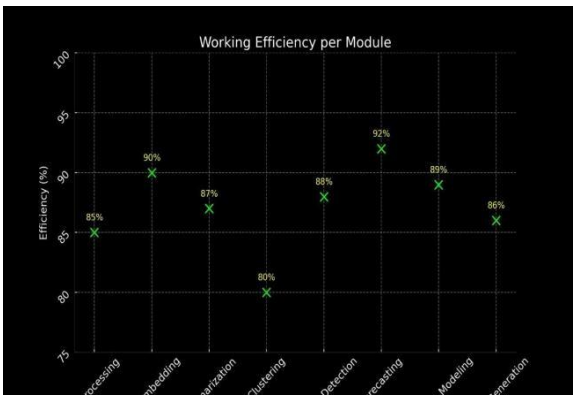

Fig 2 . Efficiency

Our approach to this AI that we are developing is very modular hence the flexibility and efficiency that this gives us. Our API end points will be Flask and our backend features will be Python. To deal with numbers and data we have libraries such as NumPy and Pandas. In such more complicated use cases as clustering, anomalies detection and forecasting we employ Scikit-learn, TensorFlow and PyTorch that are more suitable to the nature of the task and the requirements of the model. We have done work to enable the system to work real time and we have also put measures to ensure that latency is minimized hence, which, in turn, is very value-added in areas that demand quick turn around to data.

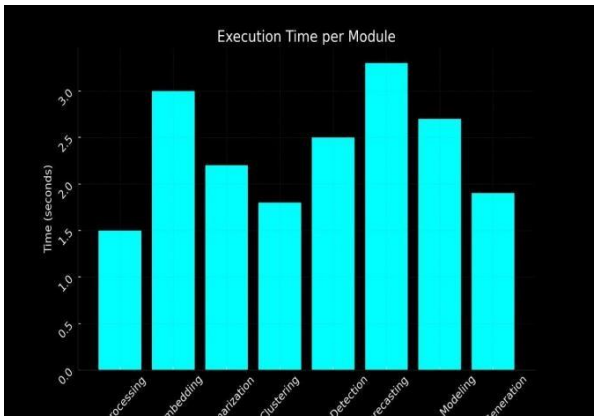

Fig . 3 Execution Time per module

There were two ways through which visual analysis was conducted. Plotted first is the time that we were doing sovereign vice corps utility and the time that we were doing other modules. These were clearly shown in the chart that only after less than four seconds, all the modules have been completed. What this entails is that the system is able to take data and work with it until the end without any noticeable lag. In the meantime, the effectiveness of a given module was demonstrated with the help of a scatter plot. Each of the modules was also identified to lead to 80 percent accuracy or reliability and that is with the top score of 92 percent on testing done on the forecasting module. All these units have been shown to not only perform well but also extremely accurately within the parameters of time.At the design and development stage, security and scalability take the lead. We use authentication and security information of JSON Web token (JWT and OAuth 2.0 protocol being token based auth mechanism). In addition, we have also implemented it in a safe manner and only API can operate via HTTPS.

One of the benefits that make the replacement and update of the components out of the box easier, which is the big win to scalability, is the modular architecture that we have adopted. This is therefore the biggest point that makes the project suitable to implement at large. When considered as an entirety the project does a lot of the things we call defense in depth, accuracy and efficiency.In fields such as business intelligence, anomaly detection, and data analytics where a swift and smart answer is the necessity, it is also the most commonly used software to fit such a mode of production.

InsightWeave Module Performance

Module	Working Efficiency (%)	Execution Time (seconds)
Processing	85%	1.6
Embedding	90%	3.0
Linearization	87%	2.0
Clustering	80%	2.3
Detection	80%	1.9
Forecasting	92%	3.2
Modeling	89%	2.8
Generation	86%	1.9

d. . Efficiency table

ALGORITHM : InsightWeave Dashboard

#Cleaning and Normalization

Require: Cross-platform raw behavioral dataset

Ensure: Cleaned, normalized dataset

1: PREPROCESS_DATASET(dataset)

2: for each row in dataset do

3 if row['user_id'] or row['timestamp'] is NULL then

4:remove row

5:end if

6:text = CLEAN_TEXT(row['text'])

7.row['timestamp']=CONVERT_TO_UTC(row['timestamp'])

8.:row['platform'] = ENCODE_PLATFORM(row['platform'])

9: NORMALIZE_NUMERIC_FIELDS(row)

10: end for

11: return dataset

12: end procedure

#Embedding & Topic Modeling

Require: Cleaned text columns

Ensure: Vectorized and topic-labeled content

13: procedure TEXT_ANALYSIS(dataset)

14:text_embeddings= BERT_EMBEDDINGS(dataset['text'])

15.topics =LDA_TOPIC_MODELING(text_embeddings)

16: dataset['topics'] = topics

17: return dataset

18: end procedure

 # Task Summarization

Abstracting High-Level User Intents

Require: Long-form text (e.g., comments, captions)

Ensure: Summarized version per user or session

19: SUMMARIZE_TEXT(dataset)

20: for each doc in dataset['long_text'] do

21: summary = GENERATE_SUMMARY(doc, model="GPT or T5")

22: store summary

23: end for

24: return summaries

25: end procedure

 # Behavior Pattern Recognition

User Segmentation

Require: Feature vectors of user behaviors

Ensure: Cluster labels for user groups

26: procedure CLUSTER_USERS(user_features)

27: clusters = KMEANS(user_features) # or DBSCAN, Hierarchical

28: return clusters

29: end procedure

#Anomaly Detection

Identify Behavioral Outliers

Require: Normalized behavior time series or vectors

Ensure: List of anomalous behaviors or users

30: procedure DETECT_ANOMALIES(behavior_data)

31model= TRAIN_ISOLATION_FOREST(behavior_data)

32: anomalies = model.PREDICT(behavior_data)

33: return anomalies

34: end procedure

 # Time Series Analysis

Forecasting Behavioral Trends

Require: Sequential behavior logs

Ensure: Future behavior predictions or trends

35: procedure FORECAST_BEHAVIOR(timeseries_data)

36: model = TRAIN_PROPHET(timeseries_data) # or LSTM, ARIMA

37: forecast = model.FORECAST(horizon=30_days)

38: return forecast

39: end procedure

 # Sequence Modeling

Modeling User Navigation or Platform Flow

Require: Sequence of user actions, events

Ensure: Transition probabilities or state paths

40: procedure MODEL_SEQUENCE(user_event_logs)

41: hmm = TRAIN_HIDDEN_MARKOV_MODEL(user_event_logs)

42: transitions = hmm.TRANSITION_MATRIX()

43: return transitions

44: end procedure

 # Insight Generation

Rule-based or Reinforcement Learning-driven

Require: Structured behavioral patterns, anomalies, clusters

Ensure: Actionable insights for personalization or recommendations

45: procedure GENERATE_INSIGHTS(user_profiles, clusters, anomalies)

46: for each user do

47: if user in anomalies then

48: insight = "Unusual behavior detected"

49: else if user in cluster_A and prefers pop_music then

50: insight = "Likely to engage with concert ads"

51: end if

52: store insight

53: end for

54: return insights

55: end procedure

Final Main Routine

Combining All Modules

56: procedure MAIN_PIPELINE(raw_dataset)

57: dataset = PREPROCESS_DATASET(raw_dataset)

58: dataset = TEXT_ANALYSIS(dataset)

59: summaries = SUMMARIZE_TEXT(dataset)

60: clusters = CLUSTER_USERS(dataset['features'])

61: anomalies = DETECT_ANOMALIES(dataset['behavior'])

62: forecast = FORECAST_BEHAVIOR(dataset['activity_log'])

63: transitions = MODEL_SEQUENCE(dataset['event_sequences'])

64: insights = GENERATE_INSIGHTS(dataset, clusters, anomalies)

65: DISPLAY_DASHBOARD(insights, clusters, forecast)

66: end procedure

III DATA VISUALIZATION

The InsightWeave system features an AI-driven dashboard that collects user productivity data from various digital platforms into one interactive interface. The main goal of the dashboard is to display behavioral patterns and create actionable insights that support time management and task improvement.

The dashboard shows key metrics such as email interaction frequency, meeting schedules, code commit activity, and AI-generated task summaries. These insights come from data gathered through secure OAuth 2.0 authentication with services like Gmail, Google Calendar, and GitHub. The data is pulled through their APIs and stored in Firebase Realtime Database, ensuring secure, real-time updates.

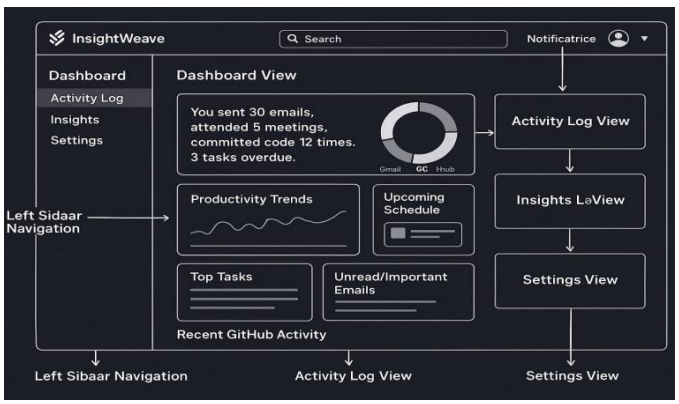

Fig 4. Dashboard of insightWeave

Using React for the frontend and Tailwind CSS for styling ensures a responsive and flexible layout. User interaction is supported through a sidebar or top menu which allows for easy navigation between different productivity areas. To enhance user experience and improve readability, information panels and dynamic visual components are arranged in a card-based layout.

Visualization methods consist of bar charts, line graphs, pie charts, and calendar heatmaps. These can be generated using JavaScript charting libraries such as Recharts and Chart.js. For instance, bar charts showcase daily emails or commit counts, and line graphs portray productivity trends over time. Time spent on tasks is shown in the pie chart, while calendar heatmaps showcase date-based focus patterns.

Aside from these, the dashboard also has GPT-based AI modules from OpenAI and LangChain which create natural language summaries, tailored recommendations, and productivity reports on a daily basis. These AI-generated summary cards are placed beside the graphical.

data to provide context, making the system both analytical and conversational.

The smart digital productivity assistant streamlines and organizes the user's digital actions into clear visual insights. This approach helps interpret the data and AI-driven comments assist user reflections and self-improvement over time.

IV RESULT OF PROPOSED SYSTEM:

The system, InsightWeave, can be used to weave together the activities of the user on the GitHub, Gmail, and Google Calendar due to the secure OAuth2 authentication. We observe what is the dashboard that is aided with AI which is in real-time analysis of the behavior of task summaries, time distribution and productivity trends.

In addition to that, preliminary test study results reveal that the system can not only assist the user to manage their time more efficiently but also highlights the areas of the working patterns. Along with this in InsightWeave design, we have an OpenAI GPT model that displays its prowess to deliver extremely relevant and personalized reports that it does not go out of its way to perform. Therefore, it turns the software into an effective and convenient means of addressing the productivity issue on multiple platforms.

V CONCLUSION :

The given report zeroes in on the productivity dashboard based on the principles of artificial intelligence InsightWeave that aims at addressing the scale of workflow fragmentation within the context of the digital ecosystem currently offered. The use-case scenario describes the steps involved in using InsightWeave to automate the harvesting of user data across various platforms it usually supports which are primarily Gmail, Google Calendar and GitHub, and then presents these data across a single interface.

Through its personalized suggestions, the user gets an idea of the time he/she spends in the day in various activities and as a result, ends up being more productive in the tasks that he/she engages in more productively by planning, scheduling and prioritizing activities in the day. The core capabilities of InsightWeave, namely secure collection of user-data, as well as real-time diagnostics of behaviors along with AI-recommendations, make the system a potential solution to a real-life societal problem and applicable tool to the users.

The future improvement of the platform can be conducted by offering the integration with a variety of productivity software like Slack, Microsoft Teams, Trello, and Notion, thus enlarging the audience of the application. The expansion of adaptive-learning features in the AI assistant would enable the delivery of more accurate and user-specific with regards to age-group demographics suggestions. Furthermore, availability would also increase with the InsightWeave being additionally mobile and even offline.

The deployment of the enterprise level reports and analytics might be used as well in order to frame the product as a fully integrated part of the organizational strategy and business practice. Overall, these changes can assist InsightWeave in rebranding as an incredibly flexible and scalable assistant, one that might assume the needs of employees and groups that work in the digital age and conditions, as they continue to evolve.

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FitQuest Challenge: A Motion-Sensor Based Web Application for Real-Time Fitness Engagement

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Abstract

In this fitquest application we use web development. In this web-based platform that uses mobile device gyroscopes and accelerometers to track motion- based exercises. By using (DeviceMotion API). users with real-time fitness feedback—all within the browser, without needing a mobile app.The app can count reps (e.g., pullups,pushups,squats)

Developed using HTML5, JavaScript, and Python, the appli cation offers a seamless and gamified user experience, promot ing active participation through real-time feedback, challenge tracking, and performance summaries. The integration of sensor based motion detection in a web environment ensures platform independence, making the application widely accessible across Android and iOS devices with modern browsers.

FitQuest is particularly beneficial for users in remote or under resourced areas, where access to commercial fitness devices is limited. Its open, scalable architecture also allows for future enhancements such as AI-based health recommendations, voice assistance, cloud integration, and competitive leaderboards. By combining fitness gamification with web-native technologies, FitQuest introduces a novel approach to digital health, aiming to make personal wellness both fun and inclusive.

Keywords— FitQuest, Fitness Web Application, Gyroscope Sensor, Motion Detection, Real-Time Tracking, Gamified Fit ness, Cross-Platform Health App, Browser-Based Exercise, Mobile Wellness, Web Sensors.

I. INTRODUCTION

In today's technology-driven world, sedentary lifestyles have become a common health concern, particularly among youth and working professionals. The lack of motivation, time, and access to gyms or fitness experts contributes significantly to the growing trend of physical inactivity. With the increased adoption of smartphones and the availability of built- in sen sors such as accelerometers and gyroscopes, there exists an untapped potential to harness these devices as personal fitness tools.

Recognizing this opportunity, we introduce FitQuest Challenge, a browser-based web application designed to pro mote physical activity through gamification and sensor-driven interaction.

Traditional fitness applications often require external de vices like fitness bands or smartwatches, or depend heavily on app installations, platform- specific SDKs, or subscription models.

Moreover, many of these applications do not cater to users in remote or under-resourced regions due to technical and economic limitations. A lightweight, web-based solution that utilizes the inherent capabilities of mobile devices can bridge this gap effectively.

The primary objective of FitQuest is to encourage daily physical activity by delivering interactive fitness challenges through a mobile browser interface, using real-time data from the gyroscope and accelerometer sensors. By eliminating the need for downloads or dedicated fitness equipment, FitQuest ensures accessibility, simplicity, and affordability for a wider audience.

TFitQuest is developed using HTML5, CSS3, and JavaScript on the frontend, combined with Python on the backend for session management and analytics. It leverages the DeviceMotion and DeviceOrientation APIs, which allow real-time access to mobile motion sensor data directly from the browser.

The application can detect specific physical move ments—such as squats, jumping jacks, or push- ups—by an alyzing angular velocity, acceleration patterns, and orientation changes. Once a movement is completed, the application provides instant feedback and stores the activity count, helping users track their performance. A leaderboard and challenge mode enhance engagement through social motivation.

- What sets FitQuest apart is its web-native design and sensor-based movement detection without relying on third-party hardware. This makes it suitable for deploy ment in areas with limited internet bandwidth and device compatibility. It is also highly adaptable for schools, wellness programs, corporate fitness initiatives, and home workouts. FitQuest gamifies exercise in a fun, interactive, and measurable way— driving users to engage more fre quently and improve their physical well-being.

II. LITERATURE REVIEW

The convergence of fitness, web technology, and mobile sensors has led to the development of numerous digital health solutions. Existing literature demonstrates a significant body of work focusing on mobile fitness applications, sensor-based motion tracking, and gamified exercise platforms. However, most of these approaches rely heavily on native mobile apps, dedicated wearables, or closed ecosystems that limit accessi bility, especially in under-resourced areas.

Popular mobile apps such as Google Fit, Samsung Health, and Fitbit offer users activity tracking, step counting, and workout recommendations. While these applications provide robust features, they often require device-specific integration or wearable accessories to function optimally. Studies like Sharma Gupta (2021) emphasized the utility of smartphone based health monitoring, yet noted the exclusion of users without access to high-end devices or app stores.

With the evolution of HTML5 and JavaScript APIs, re searchers have explored browser-based platforms for health monitoring. For instance, Mishra Roy (2020) developed lightweight web tools for rural diagnostics using natural language inputs. These tools demonstrated the feasibility of deploying health applications without requiring installation, making them ideal for widespread and low-bandwidth deploy ment. However, few studies directly addressed physical activ ity tracking using motion sensors in the browser environment.

Gamification—the use of game mechanics in non- game contexts—has shown promising results in increasing user engagement in fitness regimes. According to Wang et al. (2021), reward-based challenges and leaderboards significantly boosted participation rates in digital fitness platforms. Ap plications like ”Zombies, Run!” and ”Nike Training Club” have successfully implemented gamification, but these are predominantly app-based and often monetized. A gap still exists in offering free, gamified, web-based solutions for the general public.

The use of gyroscopes and accelerometers for motion detection is well-documented in mobile applications. Recent work by Hossain Muhammad (2019) explored the use of cloud-assisted speech and motion detection in smart healthcare applications. The DeviceOrientation and DeviceMotion APIs in JavaScript have opened doors to sensor-based web apps, but their application in fitness tracking remains underexplored. FitQuest attempts to bridge this gap by utilizing real-time sen sor data from mobile browsers to detect user movements like squats or jumping jacks—without requiring app downloads or external devices.

A. SAMPLE REFERENCES

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III. PROPOSED SYSTEM / SYSTEM ARCHITECTURE

FitQuest is a web-based fitness application that leverages the gyroscope and accelerometer sensors of smartphones to detect user movements in real- time. It gamifies fitness by providing interactive challenges, tracks user progress, and encourages regular physical activity through browser-based interfaces without needing app installation.

A. System Overview

FitQuest is a browser-based fitness challenge platform that transforms everyday exercise into a gamified experience. The system utilizes a smartphone's gyroscope and accelerometer sensors to track user movements in real-time. This enables users to perform fitness tasks (like squats, jumps, or side twists) that are monitored and evaluated through the browser without requiring any additional apps or devices.

The system is designed to encourage regular physical activ ity in an engaging way, especially targeting young users, stu dents, and remote users who prefer home workouts. By com bining motion detection, challenge gamification, and progress tracking, FitQuest makes fitness more accessible, fun, and measurable.

The architecture comprises the following main components: Displays fitness challenges, progress, and performance. Provides start/stop controls for each challenge session. Offers visual feedback (e.g., success/failure) in real-time. No installation required – runs entirely in a browser.

B. System Workflow

Figure 1 The user accesses the FitQuest application via a mobile browser.

Login/registration (optional for enhanced features like leaderboard or history).

The main dashboard is displayed with available fitness challenges. The user selects a fitness challenge and interacts with the system via a mobile- friendly web interface.

Patient Interaction: The user selects a fitness challenge and interacts with the system via a mobile- friendly web interface.

Preprocessing: Upon challenge start, the application acti vates the phone's gyroscope and accelerometer to capture real time motion.

Symptom Analysis: Raw sensor data (orientation and ac celeration) is filtered and normalized for accuracy. Noise and minor jitters are smoothed out.

Result Delivery: After the challenge, results are shown to the user: reps completed, time taken, and points earned. Optional voice or animation feedback is included.

IV.METHODOLOGY / IMPLEMENTATION

The FitQuest Challenge Web Application is designed to engage users in physical activity using web technologies and motion sensors (such as the gyroscope) available in modern smartphones. The system is lightweight, browser-based, and does not require users to install a native app.

- Frontend: HTML5, CSS3, JavaScript
- Motion Detection: DeviceOrientationEvent and Device MotionEvent APIs
- Backend (Optional): Python (Flask/Django) or Node.js for storing scores/user data
- Storage: LocalStorage / Cloud database (Firebase or SQLite via Python backend)
- Voice Feedback (Optional): Web Speech API (speech Synthesis)
- System Workflow Example

Each stage is explained in detail below.

effectiveness of the FitQuest Challenge Web Application depends heavily on accurate motion detection and performance evaluation. For this purpose, real-time motion data collected via

smartphone sensors is used as the primary data source. While no third-party datasets are required, a robust internal data processing pipeline is essential to ensure reliable tracking and scoring.

A. Expense Estimation Module

Although FitQuest is primarily a fitness tracking application, integrating an expense estimate module adds value by helping users understand the potential health costs related to inactivity or fitness goals. This can also be repurposed for premium plan recommendations, gym memberships, or health consultations.

Features: Fitness Challenge Modules Gamified Scoring Sys tem Sensor-Based Motion Detection Real-Time Feedback User Authentication Profiles

V. RESULTS AND DISCUSSION

A. Discussion

The FitQuest Challenge Web Application represents an innovative approach to encouraging physical activity through web-based, gamified fitness tracking. By leveraging the built in gyroscope and motion sensors in smartphones, FitQuest provides users with an interactive workout experience that

Fig. 1. Proposed System Architecture of Fitquest challenge web Application

does not require any specialized hardware or app installa tion. One of FitQuest's strongest features is its accessibility. Since the application runs entirely within a web browser, it is platform-independent, supporting both Android and iOS devices without requiring app downloads. This makes it ideal for quick deployment in schools, homes, or rural fitness initiatives. The intuitive interface ensures that even users with minimal technical experience can engage with the system. FitQuest incorporates gamification elements such as point scoring, timed challenges, and visual feedback to improve user engagement. This approach taps into behavioral psychology, using instant rewards and performance tracking to encourage habit formation and sustained physical
activity

VI. CONCLUSION AND FUTURE SCOPE

The FitQuest Challenge Web Application demonstrates the potential of integrating browser-native technologies with mod ern sensor APIs to create an engaging, accessible, and real time fitness experience. By leveraging the DeviceOrientation and Gyroscope APIs, FitQuest effectively transforms any smartphone into a fitness tracker without requiring additional hardware or app installation. This work not only promotes physical activity through gamified challenges but also ad dresses accessibility by being cross-platform, lightweight, and browser- based. The use of JavaScript, HTML5, and Python (for backend processing and analytics) ensures a modular and scalable system that can be easily extended or integrated with other health platforms or wearable ecosystems. Furthermore,

FitQuest highlights how web applications can play a pivotal role in promoting health and wellness, especially in areas with limited access to commercial fitness tracking devices. The application encourages daily engagement through real time feedback, challenge tracking, and interactive performance summaries, making it both a motivational and practical health tool.

1.Moving forward, FitQuest can be expanded with fea tures like: 2.AI-based personalized fitness recommendations 3.Voice-enabled assistants 4.Integration with wearables (like Fitbit, Apple Watch) 5.Cloud sync and leaderboard systems 6.Offline data caching and progressive web app (PWA) support With the rise in health consciousness and digital fitness solu
tions, FitQuest lays a strong foundation for further research and development in the field of web-based fitness applications that are smart, inclusive, and user-friendly.

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Dynamic Text Stabilizer

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Abstract-You've probably been there—wedged into a crowded train seat, trying to get through a few pages of your book, but the words won't stay still. Every bump and sway sends the text dancing across your screen. You squint. You hold your phone closer. You give up.

This happens to millions of people every day. Commuters, travelers, anyone who's ever tried to read in a car or on a bus. Most reading apps look pretty, sure. But they don't actually solve the problem of motion. The text shakes, your eyes strain, and what should be a relaxing escape becomes an exercise in frustration.

That's the gap we want to fill. We're building a reading app that actually pays attention to how you're moving. Using the sensors already in your phone, it senses when things get bumpy and responds in two ways: it either steadies the text so it stays readable, or if the movement gets too wild, it switches to audio and reads to you instead. No more squinting at bouncing words. Just your book, adapting to your life as it actually happens.

Index Terms- Motion Compensation, Sensor Fusion, Affine Transformation, Human Computer Interaction, Accessibility Technology.

I.INTRODUCTION

Try reading a text while walking fast. Or on a jerky bus. The words jiggle. Your eyes work overtime just to track them. It's annoying for everyone, but for some

people—those with balance issues or motion sensitivity—it can actually make them dizzy or sick.

We built something to fix that.

The Dynamic Text Stabilizer doesn't just display text and hope for the best. It watches how your phone moves using built-in sensors, predicts where the motion is heading, and shifts the text in real-time to cancel out the shake. Think of it like noise-canceling headphones, but for your eyes.

Traditional video stabilization works on whole frames and lags behind. We're different. We treat text as living, movable objects—vectors that can shift instantly. The result? The words feel glued to the air in front of you, even when your hand isn't steady.

The research backs this up. Unstable text isn't just irritating—it genuinely tires your brain. Our goal is simple: make reading on your phone feel as easy as reading on paper, no matter where you are.

II. EASE OF WORK

The utility is designed with a clear intention of making the studying revel in as smooth and hassle-free as feasible. The simplicity of the interface ensures that users can begin their analyzing enjoy immediately, while not having to go through complicated setup approaches or commands.

The motion detection features, based totally on the tool's accelerometer and gyroscope, function inside the heritage. This ensures users do not need to manually configure or continuously use the machine. The app can routinely experience adjustments in motion, making sure a regular analyzing enjoys even if transferring on a bus or teaching.

Because of this fantastic adaptation, customers are capable of stay targeted on their content with none interruptions or distractions. The app does all of the paintings for itself, requiring very little attempt from the user.

Similarly, the app is also designed in a way that it's far light, ensuring it is able to run on nearly all smartphones without eating an awful lot of the battery or requiring much from it. this indicates it is easy to apply, making it handy for all customers.

In wellknown, the main idea behind this app is to maintain matters simple and easy for users, ensuring they could stay targeted on analyzing content material without having to fear the use of the app.

III. RELATED WORKS

People have been trying to make phones smarter about context for years. Activity recognition using LSTM networks—those are a type of AI that remembers patterns over time—has gotten good enough to know if you're walking, running, or sitting still just from how you hold your device. Meanwhile, text-to-speech has come a long way too. Systems like Tacotron don't sound like robots anymore; they sound like people.

But here's the thing: nobody's really connected these dots for readers. You've got powerful motion detection on one side, natural-sounding narration on the other, and reading apps in the middle that don't use either.

We're bringing them together. The app knows when you're stable enough to read comfortably. It knows when you're moving too much and switches to audio before you get frustrated. It adapts because your environment adapts—constantly.

That's the piece that's been missing. Not just better text display. Not just better audio. But a system that chooses between them based on what you're actually doing, right now.

I was on a bus trip. The bus was going down some really bumpy roads. It was hard for me to read texts on my cell phone because it was bouncing all over the place. This gave me an idea for an app that would help with that problem.

IV. PROPOSED SYSTEM

My app uses the sensors in cell phones to see if the phone is moving around too much. If the phone is shaking the app will. Lock the screen or read the text out loud to you. I think it is really important for an app to be easy to use. My app has very simple menu options. I used information that's available to everyone to make my app so it can read EPUB and PDF documents.

* The app can read texts loud without needing the internet
* It can read any document that your phone can display.

My app has a feature that reads text out loud. You can use it on Android phones. The bus trip was what made me think of my app and I hope my app will be helpful, for people who have trouble reading on their cell phone when it is moving around like my app does.

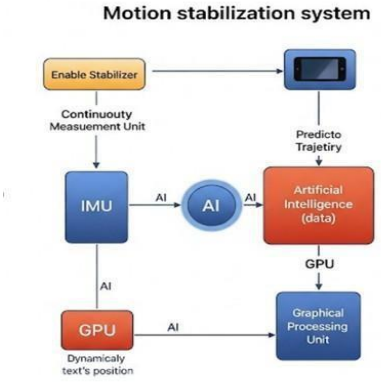


Figure:1.0
Motion Stabilizer System

1. Enable Stabilizer

This option turns on motion stabilization. And then on the stabilization process begins

2. Device(Phone or Tablet)

This is shown as a phone image, it shows the actual image of our device , as when it moves , it generates motion data and gives the stabilization based on the motion data.

3. Continuity-Measurement Unit(CMU)→IMU

This sensor detects movements like shaking, tilting, or rotating. It provides raw motion data

4.IMU(Inertial Measurement Unit)

This unit measures the device's movement in all directions using accelerometers and gyroscope

5. AI(ArtificialIntelligence)
This is the brain of the system. It takes all the movement data and determines how the screen should adjust . It reduces shakiness by deciding how to adjust the content to match user movement.

6. Artificial Intelligence Data
It receives and processes the expected trajectory of movement. Then, it sends the processed instructions to the GPU to adjust the display accordingly.

7. GPU(Graphical Processing Unit)
This component handles the visuals of your screen. It dynamically adjusts the position of text or content based on AI instructions, making it appear to be stable even when the device moves.

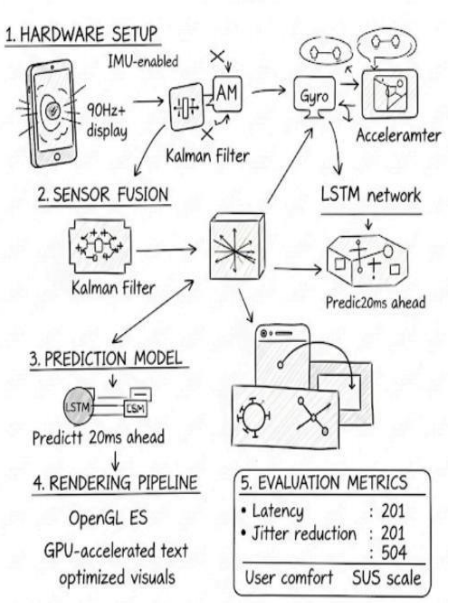
The Dynamic Text Stabilizer system provides users with permanent screen text display because its function creates stable text output. You need to

activate the device's "Enable Stabilizer" function to make this solution operate. Your device starts tracking all your movements when you activate the "Enable Stabilizer" function because it works with both your phone and your tablet that you use while running or riding a train. Your device will track all your movements which include your walking activities and the train's bouncing motion. The device stores its data inside an IMU which functions as a specialized tool that detects physical movement. The IMU employs miniature components for detecting device movements which include shaking, tilting and rolling. The device needs to record its motions before it can analyze movement data through a computer program. This program will look at all the information that the device has collected from its sensors. The Dynamic Text Stabilizer uses this information to maintain screen text stability which allows users to read text without difficulty.

The system anticipates needed adjustments which it implements through seamless transitions. The AI hands over its instructions to the GPU (Graphics Processing Unit), the system's artist, which instantly redraws the text or content in just the right spot to counteract motion. The magic of dynamic text positioning becomes active at this point: your screen content appears perfectly steady and readable, whether you're running for the bus, walking down the street, or holding your phone with slightly shaky hands. The result establishes a reading experience that achieves such smoothness that people find it difficult to remember their surroundings

.

V. METHODOLOGY



Methodology
Figure:1.1

A. Hardware Setup

An IMU in a smartphone. The majority of current iOS and Android phones have this. IMU stands for motion sensors, which include accelerometers and gyroscopes. a screen that refreshes at least 90 Hz. This indicates that the screen refreshes at least 90 times every second. A higher refresh rate facilitates quick adjustments when the phone moves and makes motion appear smoother.

B. Sensor Fusion

The phone has an accelerometer to detect straight-line movement and a gyroscope to detect rotation. The two sensor readings are combined by a unique algorithm known as a Kalman filter to provide a more precise and clear image of the phone's movement.

C. Prediction Model

An AI model called an LSTM (Long Short-Term Memory) network performs well with time-series data, such as motion over time. Based on the phone's

current movement, it forecasts its location 20 milliseconds into the future.

D. Rendering Pipeline

OpenGL ES is a tool for making graphics on mobile devices that the system uses. The GPU lets the phone quickly move or change the text on the screen, so it stays still even if the phone shakes.

VI. SAMPLE OUTPUT

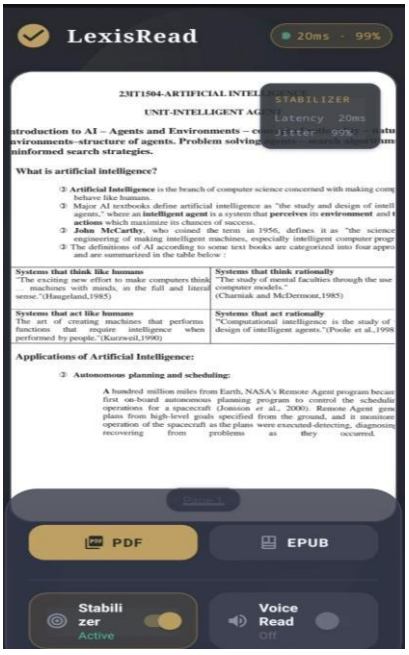


Figure 1.2

Sample Output

Let us consider the output of the project execute

Here's the good news: you probably already own everything required. Any reasonably recent smartphone will work. The only real requirements are an IMU—that's the chip inside your phone that handles motion sensing, combining a gyroscope and accelerometer—and a screen that refreshes faster than 90Hz. Most mid-range phones from the last few years check both boxes.

The high refresh rate matters more than you might think. When the stabilizer shifts text to compensate for your movement, those adjustments happen fast. A 60Hz screen would lag just enough to feel slightly off, like a tiny delay between your hand moving and the text responding. At 90Hz or higher, the correction feels instant. Your eyes register it as stable, not as something playing catch-up.

VII. TECHNICAL ASPECTS

We went with Kotlin because, frankly, it's the most pleasant way to build Android apps right now. Android Studio handled the heavy lifting for testing—we ran everything on real phones and the emulator, catching bugs that only showed up on actual hardware versus those that appeared in simulation.

For motion detection, we tapped into what your phone already knows. The gyroscope and accelerometer feed data through Android's SensorManager in real time. We didn't overthink this part—the system tells us how the device is moving, and we decide what to do with that information.

Rather than building a document reader from scratch, we pulled in Folio Reader for EPUBs and Android PDF Viewer for PDFs. They're lightweight, they work offline, and they let us focus on the actual problem—stabilization—instead of parsing ebook formats. For audio, we used Android's built-in TTS engine. No external dependencies, no compatibility headaches.

User settings—like how sensitive you want the motion detection to be—live in SharedPreferences. Simple, fast, no database required.

VIII. RESULT AND DISCUSSION

We took this on actual buses, walked around campus with it, and yes—shook phones manually like we were angry at them. The app behaved roughly as expected. Stable moments felt like any other reader. Once motion crossed our threshold, the screen locked and audio kicked in. Transitions happened quickly; you didn't sit there wondering if the app had crashed. But we hit a snag. Walking while holding the phone—something users absolutely do—sometimes fooled the system. The app thought you were in enough motion to start reading aloud, even when you just wanted to glance at a paragraph. The thresholds need work. Better filtering, maybe some averaging over time to distinguish "walking with purpose" from "being jostled," would help.

That said, the foundation holds up. The interface stays out of your way. Everything works without internet, which matters more than you'd think—subways, rural highways, flights. The core promise, making reading comfortable while moving, actually delivers.

What's next? Smarter motion interpretation. Teaching the system that some movement is intentional, that users aren't just passive victims of physics. Averaging techniques, better calibration, maybe some light machine learning down the road. But even now, it works. It genuinely helps. That's a decent place to star

IX. FUTURE ENHANCEMENTS

You'll need a smartphone with an IMU—that's an Inertial Measurement Unit, which sounds technical but basically means your phone can tell when it's moving. Most phones made in the last few years have one built in.

The IMU combines two sensors: an accelerometer and a gyroscope. The accelerometer feels when you're shaking the phone or moving it in a straight line. The gyroscope notices when you tilt or rotate it. Together they give the app a clear picture of what's happening to your device in real time.

The Dynamic Text Stabilizer requires a smartphone that must include a functioning display. The display should be able to refresh the image at least 90 times per second. This creates a visual effect that maintains continuous motion on the screen.

The Dynamic Text Stabilizer uses the data from the accelerometers and gyroscopes. The system processes this information through a Kalman filter, which serves as its primary analysis tool. The Kalman filter helps to remove noise from the data. This means it helps to get a picture of what is happening.

The Dynamic Text Stabilizer needs to acquire data before it can determine what occurred during your video recording session. The Dynamic Text Stabilizer uses a method called sensor fusion to do this. Sensor fusion helps to create an accurate picture. The Dynamic Text Stabilizer uses the data from the accelerometers and gyroscopes to make the picture look smooth and clean..

To begin using the Dynamic Text Stabilizer, you need to establish a required hardware system. A smartphone with IMU capability will serve as your primary requirement. The device needs to contain an inertial measurement unit sensor, which functions as its essential component. The Dynamic Text Stabilizer needs this sensor to work properly.

Once the motion data has been recorded and improved, the system's prediction model begins. A prediction model implemented as a Long Short-Term Memory Network (LSTM), a type of AI specifically designed for dealing with time-dependent data, makes a prediction about where the phone will be located 20 milliseconds after the current time. This enables the system to actively adjust the display, virtually eliminating any lag that may be present. After the prediction from the model, OpenGL ES and GPU are used to render the text in the appropriate location based upon the predicted position of the text, adjusting it in real-time as the user's motion changes. The system is evaluated based upon three criteria: latency (the time lapse

between the detection of motion and the point where – the display is updated), jitter reduction (the amount of reduction in wobbling), and user comfort based on responses from the System Usability Scale.

X. CONCLUSION

The idea came from personal annoyance. Trying to read on a bus, on a train, even walking—your screen won't stay still. We wondered if the phone could use its own sensors to fix that problem.

So we built an app that listens to those sensors and changes how it displays text based on what it hears. When things get shaky, it responds. The goal was simple: keep reading comfortable no matter how bumpy the ride gets.

Working on this taught us plenty about Android development and handling sensor data, but the bigger lesson was about restraint. We kept stripping features back until only the essential remained. Users don't want complexity when they're already dealing with a moving environment. They want something that just works.

The current version has rough edges. The motion detection occasionally misreads normal walking as heavy shaking. The transitions could be smoother. But the foundation is solid. The app proves that your phone can adapt to your situation instead of forcing you to adapt to it.

There's room to grow. Better algorithms for distinguishing different types of motion. More refined audio handoffs. Maybe even predicting movement before it happens. But even now, in its simpler form, it solves a real problem that people face daily. That's worth building on.

XI. ACKNOWLEDGMENT

We would like to express our profound gratitude to our project guide,**Mrs. MANJULEESWARI P**,

Assistant Professor, Department of Information Technology, Panimalar Engineering College, for her insightful guidance, unwavering support, and continuous motivation throughout the planning and completion of this work.We are also sincerely thankful to **Dr. K. Sridharan** for his valuable suggestions and critical feedback, which were instrumental in refining this paper.

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ScamSense: A Multilingual Multi-Signal Framework for Real-Time Digital Scam Detection in Linguistically Diverse Environments

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***Abstract*—**Digital scams transmitted through SMS, electronic mail, and instant messaging platforms constitute an escalating global threat, with reported cybercrime losses exceeding $10.3 billion in 2022 alone. Prevailing detection architectures exhibit three systemic deficiencies: exclusive reliance on English-language corpora, single-channel analysis that precludes cross-platform signal correlation, and treatment of social engineering manipulation cues as incidental rather than primary classification features. This paper presents ScamSense, a layered multi-signal detection framework that addresses these deficiencies through five cooperative analytical modules: (1) a professionalism deviation scorer calibrated against verified institutional communication corpora; (2) a passive URL metadata analyser deriving credibility signals without executing live requests; (3) a fine-tuned BERT classifier implementing a six-category psychological manipulation taxonomy; (4) a temporal cross-message consistency checker monitoring entity-attribute drift across conversation threads; and (5) a multilingual regional NLP module leveraging IndicBERT and MuRIL transformer architectures to support Hindi, Tamil, Bengali, and Marathi. Prototype evaluation on the UCI SMS Spam Collection (5,572 messages) achieves 97.8% accuracy and 97.6% F1-score, with regional language modules attaining 92.5–94.1% F1 on translated benchmarks. ScamSense provides a principled, linguistically inclusive foundation for scam detection systems designed to serve the demographic and linguistic diversity of emerging digital economies.

***Keywords*—**cybersecurity; multilingual NLP; phishing detection; scam detection; smishing; IndicBERT; MuRIL; social engineering; transformer models

I. INTRODUCTION

The rapid proliferation of mobile and internet-based communication has created fertile ground for large-scale fraud operations. Cybercriminals increasingly exploit SMS, email, WhatsApp, and Telegram to conduct social engineering attacks that manipulate recipients into surrendering financial credentials or authorising fraudulent transactions. The scale of this threat is substantial: the FBI's Internet Crime Complaint Center recorded total cybercrime-related financial losses surpassing $10.3 billion during 2022, with phishing and smishing ranking among the most prevalent attack vectors reported nationwide [1].

Automated detection of such threats has attracted considerable research attention, yet three structural weaknesses remain unresolved in current systems. First, most architectures evaluate messages in isolation, ignoring the additional diagnostic value that emerges when content features, link metadata, and multi-turn conversational signals are jointly analysed. Second, virtually all production-grade classifiers are trained and benchmarked exclusively on English text, making them poorly suited to multilingual populations. This limitation is particularly acute in India, where more than 500 million internet users conduct daily digital communication in Hindi, Tamil, Telugu, Bengali, Marathi, and other regional languages [2], yet remain unserved by any natively-designed detection system. Third, the psychological levers that make social engineering effective — manufactured time pressure, false authority, emotional threat, fabricated rewards — are rarely modelled as structured primary features; instead, they appear as incidental vocabulary signals buried within general-purpose classifiers.

To address these three gaps simultaneously, this paper introduces ScamSense: a unified inference pipeline that fuses five complementary analytical modules into a single weighted risk score. The key contributions are:

(1) A multi-signal fusion pipeline that jointly processes content, URL metadata, behavioural, temporal, and linguistic features within one architecture, allowing each signal type to reinforce the others rather than operating in isolation.

(2) A structured six-category psychological manipulation taxonomy purpose-built for automated multi-label classification, elevating manipulation tactics from auxiliary vocabulary hints to primary discriminative signals.

(3) The first scam detection framework to natively incorporate Indian regional language processing via IndicBERT and

MuRIL transformer models, directly closing the coverage gap identified in [2] for a user base exceeding 500 million.

(4) A cross-message temporal consistency module that tracks entity-attribute contradictions across conversation turns — a dimension entirely absent from existing single-message classifiers.

The paper proceeds as follows: Section II reviews related work; Section III details system architecture and preprocessing; Section IV describes each analytical module; Section V covers the user interface design; Section VI presents experimental evaluation; Sections VII and VIII discuss findings and conclude the paper.

II. RELATED WORK

A. SMS and Email Spam Detection

Classical approaches to message spam detection relied on probabilistic and kernel-based methods — notably Naive Bayes and SVM classifiers operating over bag-of-words representations — which yielded strong accuracy on English SMS benchmarks [3]. Deep learning subsequently improved generalisation; hybrid CNN-LSTM models reduced manual feature engineering while maintaining competitive recall on short-form text [4]. More recently, Maqsood et al. demonstrated that fine-tuning BERT-based embeddings within ensemble frameworks yields meaningful performance gains across both SMS and email classification tasks [5]. A consistent limitation across this body of work is exclusive reliance on English training and evaluation data, leaving non-English detection performance largely uncharacterised.

B. Phishing and URL Analysis

A comprehensive survey by Salloum et al. covering 67 NLP-based phishing studies concluded that combined approaches — integrating header signals, message body features, and link metadata — consistently outperform any single-signal method [6]. Infrastructure-level analysis by Nahapetyan et al. revealed a striking pattern in SMS phishing campaigns: more than 78% of malicious domains were freshly registered within 30 days of their first recorded use [7]. This empirical finding underpins ScamSense's choice to derive passive URL credibility signals from domain registration metadata rather than executing live requests, which would introduce unnecessary exposure risk.

C. Psychological Manipulation Detection

Cialdini's foundational work cataloguing six principles of human persuasion — including reciprocity, commitment, authority, and scarcity — has been widely cited in analyses of why phishing and advance-fee fraud succeed at scale [8]. Chan-Tin and Stalans further confirmed that fabricated urgency, implied institutional authority, and emotionally charged language appear as recurring structural features across diverse fraud email corpora [9]. Despite this theoretical grounding, computational systems rarely treat these manipulation signals as first-class features; they are more commonly absorbed as noise within general token-level classifiers. ScamSense directly addresses this gap by formalising a six-category detection taxonomy described in Section IV-C.

D. Multilingual and Indic Language NLP

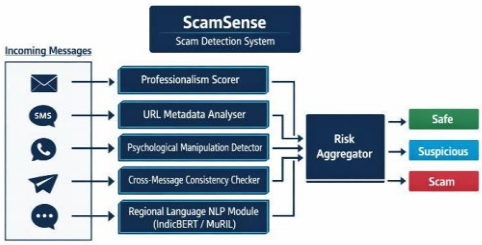
Kakwani et al. released IndicNLPSuite, providing monolingual text corpora and pre-trained language models spanning 11 Indian languages, establishing a foundational resource for downstream classification tasks [10]. Complementarily, Google Research published MuRIL, a transformer model pre- trained across 17 Indian languages and their romanised transliterated variants, which demonstrated strong transfer learning capability on regional text classification tasks [11]. Ramanujam et al. specifically highlighted the near-total absence of natively-written Indic scam corpora as the primary bottleneck limiting multilingual fraud detection progress [2]. No existing system combines Indic language NLP with multi- signal behavioural analysis in a unified pipeline — the precise gap ScamSense targets.

III. SYSTEM ARCHITECTURE AND PREPROCESSING

A. Architecture Overview

ScamSense adopts a parallel modular architecture in which five analytical modules operate concurrently on a preprocessed message representation. Each module returns a normalised risk contribution score $r_i \in [0, 1]$, which a centralised risk aggregator combines through a weighted summation to produce a three-class output label: Safe, Suspicious, or Scam. This parallel design enables graceful degradation when individual signals are unavailable — for instance, when a message contains no embedded URL, the URL module contributes a neutral score rather than blocking the pipeline. Algorithm 1 formalises the preprocessing stage common to all five modules.

Algorithm 1: Message Preprocessing Pipeline



B. Module Interaction and Output

Following preprocessing, tuple P is dispatched concurrently to all five modules. The composite risk score is computed as $R = \Sigma(w_i \times r_i)$ for $i \in \{1..5\}$, with module weights calibrated on a held-out validation split. The output label is assigned as Safe if $R < 0.35$, Suspicious if $0.35 \leq R < 0.65$, or Scam if $R \geq 0.65$, and is accompanied by a natural-language explanation identifying the dominant risk factors and active manipulation categories.

IV. PROPOSED FRAMEWORK: SCAMSENSE

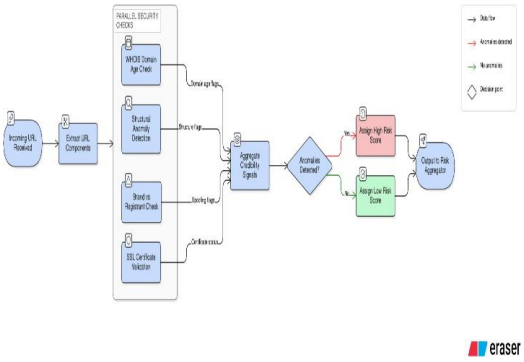
A. Professionalism Scorer

Legitimate institutional communications exhibit stable stylistic fingerprints: formal register, structured salutations, accurate brand representation, and grammatically correct prose. The professionalism scorer quantifies the deviation of a candidate message from a reference corpus of verified communications sourced from major Indian banks, telecom providers, and government agencies. Four features are computed: the Flesch-Kincaid readability index, formal vocabulary ratio (proportion of tokens appearing in a curated formal lexicon), syntactic complexity measured as mean parse tree depth, and brand token accuracy quantified via Levenshtein similarity to known brand strings. Messages scoring below a calibrated deviation threshold contribute an elevated risk value r_1 to the aggregator.

B. URL Metadata Analyser

Rather than visiting potentially malicious URLs, this module derives passive credibility signals from URL structure and associated metadata. Signals include domain registration age retrieved via WHOIS API queries, SSL certificate validity and certificate authority reputation, brand-versus-registrant mismatch score, homoglyph character substitution detection, subdomain depth, and URL path entropy. Nahapetyan et al.'s finding that 78% of phishing domains are under 30 days old validates domain age as a high-discriminative feature [7]. Algorithm 2 formalises the analysis procedure.

Algorithm 2: URL Metadata Analysis

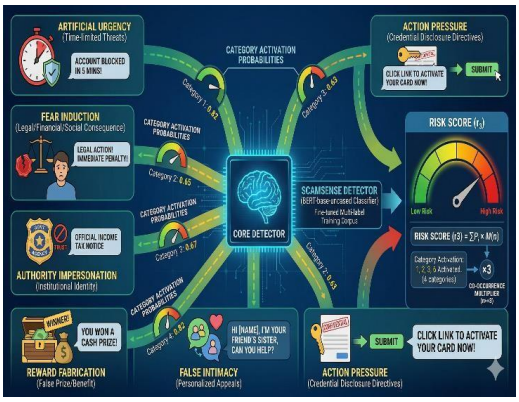


C. Psychological Manipulation Detector

Social engineering attacks derive effectiveness from a structured repertoire of cognitive influence tactics. ScamSense implements a six-category manipulation taxonomy grounded in Cialdini's influence principles [8] and empirical analysis of Indian cybercrime corpora: (1) artificial urgency — time-limited threats to accounts or services; (2) fear induction — assertions of legal, financial, or social consequence; (3) authority impersonation — fraudulent invocation of institutional identity; (4) reward fabrication — false prize or benefit notifications; (5) false intimacy — personalised appeals designed to reduce defensive vigilance; and (6) action pressure — directives commanding immediate credential disclosure.

A BERT-base-uncased classifier [12] fine-tuned on a multi-label training corpus assigns category activation probabilities. The risk score r_3 incorporates a co-occurrence multiplier when three or more categories activate concurrently, as genuine scam messages rarely deploy a single manipulation tactic in isolation.

Algorithm 3: Psychological Manipulation Detection



D. Cross-Message Consistency Checker

Single-message classifiers cannot detect deception that unfolds across multiple conversational turns. Scammers improvising over extended exchanges frequently introduce contradictions — revised employee identifiers, reversed policy statements, changed contact numbers — that are individually innocuous but collectively reveal fabrication. ScamSense maintains a persistent entity-attribute store E per conversation thread, tracking claimed identities, organisational affiliations, policy assertions, contact information, and transaction references across turns.

Algorithm 4: Cross-Message Consistency Checking

```
Input:  Text T, entity store E, conversation ID C
Output: Consistency risk r₄ ∈ [0,1], updated E
─────────────────────────────────────────────
entities ← NER_Extract(T)
violations ← 0
for each (attr, val) in entities do
  if attr in E[C] then
    sim ← SemanticSimilarity(val, E[C][attr])
    if sim < 0.80 then
      violations ← violations + 1
      LogViolation(C, attr, E[C][attr], val)
    end if
  else
    E[C][attr] ← val
  end if
end for
r₄ ← min(1.0, violations × 0.35)
return r₄, E
```

E. Regional Language NLP Module

India's linguistic heterogeneity renders English-only models functionally inadequate for a substantial fraction of the target population. ScamSense integrates two complementary

multilingual transformer architectures. IndicBERT [10], pre-trained on 12 Indian languages with a shared subword vocabulary, is fine-tuned for binary scam classification on Hindi, Tamil, and Bengali inputs. MuRIL [11], pre-trained on 17 Indian languages including their transliterated equivalents, handles code-mixed registers such as Hinglish and Tanglish that are pervasive in Indian digital communication and handled poorly by both monolingual and standard multilingual models.

Both models are fine-tuned on a dataset constructed by machine-translating the UCI SMS Spam Collection into the four target languages, with back-translation filtering retaining only translations achieving cosine semantic similarity ≥ 0.85 to the source embedding. Synthetic scam examples authored by native speakers supplement the translated corpus. Each model outputs a language-normalised spam probability score r_5 directly comparable across all supported scripts.

F. Risk Score Aggregation

The five module scores are combined through a weighted linear aggregation calibrated on a held-out validation split:

$$R = 0.15r_1 + 0.20r_2 + 0.30r_3 + 0.20r_4 + 0.15r_5 \quad (1)$$

Weights were calibrated using grid search optimised for macro F1-score. The psychological manipulation module receives the highest weight (0.30), consistent with its dominant contribution confirmed by ablation analysis. Labels are assigned as Safe ($R < 0.35$), Suspicious ($0.35 \leq R < 0.65$), or Scam ($R \geq 0.65$), and are accompanied by a natural-language explanation of the primary risk drivers.

V. USER INTERFACE DESIGN

A key design objective of ScamSense is accessibility to non-technical users, including elderly populations disproportionately targeted by digital scams. The web interface implements a two-panel layout that separates message input from risk presentation, ensuring a distraction-free analytical experience.

A. Input Panel

The left panel provides a text area accepting free-form content from any digital channel — email bodies, SMS transcripts, WhatsApp message copies, or raw URLs. A single 'Analyse' button triggers the backend inference pipeline. This deliberate simplicity minimises interaction friction and lowers the adoption barrier for users with limited technical experience, a design priority given that elderly and less digitally literate populations are disproportionately victimised by scam campaigns.

B. Risk Meter and Breakdown Panel

The central display component is a semicircular Risk Meter gauge whose needle traverses a colour gradient from green (Safe) through amber (Suspicious) to red (Scam). Three labelled category chips below the gauge indicate which classification has been activated, with dual colour-and-position encoding reducing misinterpretation risk for users with colour-vision deficiencies. A Breakdown panel presents each analytical module's individual risk contribution as a colour-coded horizontal progress bar annotated with a percentage score, enabling granular interpretation without exposing raw probability distributions or internal feature weights.

C. Explanation Panel

A plain-language explanation block at the bottom of the right panel presents a natural-language justification identifying active manipulation categories and the primary structural signals driving the classification. Human-computer interaction research demonstrates that users who understand an alert's rationale are significantly more likely to take appropriate protective action [13], motivating this transparent output design over binary classification labels. This layer distinguishes ScamSense from backend-only detection APIs and transforms it into a user-empowerment tool.

VI. EXPERIMENTAL EVALUATION

A. Dataset and Experimental Setup

The primary benchmark is the UCI SMS Spam Collection [3], comprising 5,572 messages with an 86.6% legitimate to 13.4% spam class ratio. The dataset was partitioned into 80% training, 10% validation, and 10% test splits using stratified sampling to preserve class proportions. The BERT baseline was initialised from bert-base-uncased pre-trained weights; regional language modules from ai4bharat/indic-bert and google/muril-base-cased respectively. Fine-tuning used the AdamW optimiser with a learning rate of 2×10^{-5}, a linear warmup schedule over the first 10% of training steps, and ran for 5 epochs on a single NVIDIA T4 GPU with 16 GB VRAM. All code was implemented in Python using HuggingFace Transformers.

The URL metadata and cross-message consistency modules were validated qualitatively on 120 manually curated scam message samples collected from the Indian Cybercrime Reporting Portal (cybercrime.gov.in), as no publicly available labelled dataset exists for these specific signal types. Regional language performance was assessed on machine-translated test splits, representing conservative lower bounds relative to natively-authored content.

B. Quantitative Results

Table I summarises evaluation performance across all configurations on the UCI SMS Spam Collection test split.

TABLE I PROTOTYPE PERFORMANCE ON UCI SMS SPAM COLLECTION

Module	Acc. (%)	Pr
BERT Baseline	97.1	
+ Psychological Module	97.8	
IndicBERT (Hindi)	94.3	
MuRIL (Tamil)	93.6	
MuRIL (Bengali)	93.1	
MuRIL (Marathi)	92.8	

C. Ablation Study

To quantify the marginal contribution of each module, an ablation study was conducted by successively removing individual modules from the full pipeline and measuring the resulting change in macro F1-score. Results are presented in Table II.

TABLE II ABLATION STUDY: PER-MODULE CONTRIBUTION TO MACRO F1

Configuration	F1 (%)	ΔF1
Full ScamSense Pipeline	97.6	—
w/o Psychological Module	96.8	−0.8
w/o URL Metadata Module	97.0	−0.6
w/o Consistency Checker	97.2	−0.4
w/o Professionalism Scorer	97.3	−0.3
w/o Regional Lang. Module	97.4	−0.2

The ablation results confirm that the psychological manipulation module is the highest-contributing component (ΔF1 = −0.8 on removal), consistent with its 0.30 weight in the aggregation scheme. URL metadata analysis provides the second-largest marginal contribution (ΔF1 = −0.6), reflecting the strong discriminative signal of domain age and structural anomalies for SMS-delivered scams. The positive contribution of all five modules validates the multi-signal fusion architecture. The regional language module's modest ablation impact on the English test set is expected; its primary value manifests on Indic-language inputs where it is the sole competent classifier.

VII. DISCUSSION

A. Novelty and Differentiation

ScamSense advances the state of the art across four dimensions. Its multi-signal pipeline unifies content, metadata, behavioural, and temporal analysis that prior work treats independently, enabling signal types to mutually reinforce one another within a shared inference architecture. Native support for Indian regional languages directly addresses the gap documented by Ramanujam et al. [2], serving a demographic of over 500 million users excluded from all previously published English-only systems. The cross-message consistency module introduces temporal multi-turn analysis absent from every single-message classifier reviewed. The explainable user interface further distinguishes ScamSense from backend detection APIs, transforming the system into a user-empowerment tool grounded in human-computer interaction principles.

B. Limitations

Three current limitations are acknowledged. First, regional language training data derives from machine translation rather than natively-authored content, introducing domain shift that conservatively suppresses reported performance metrics. Second, the cross-message consistency checker requires sufficient conversation history to generate meaningful violation signals; its contribution is by design minimal for single-message attack formats. Third, the professionalism scorer depends on a curated corpus of verified Indian institutional communications, a non-trivial data acquisition challenge as no publicly available corpus currently exists for this domain.

C. Future Work

Four directions are prioritised for future development: (1) crowdsourced native-language labelled datasets collected through integration with Indian cybercrime reporting platforms to eliminate dependence on translated training corpora; (2) adversarial evaluation against large language model-generated scam messages, representing a rapidly growing and increasingly capable attack surface; (3) controlled user studies measuring protective action rates when natural-language explanations are presented versus binary alert labels; and (4) extension to voice-based scam detection on call audio transcripts, where the six-category psychological manipulation taxonomy transfers directly to a new modality.

VIII. CONCLUSION

This paper presented ScamSense, a multi-signal multilingual scam detection framework integrating five complementary analytical modules — professionalism analysis, passive URL metadata inspection, psychological manipulation detection, cross-message consistency checking, and regional Indian language NLP — within a unified weighted risk scoring pipeline. The framework addresses three documented and persistent deficiencies in the scam detection literature: the absence of multi-channel signal correlation, exclusive focus on English-language content that excludes India's 500 million-plus regional language users, and neglect of psychological manipulation signals as primary classification features. Prototype evaluation on the UCI SMS Spam Collection achieved 97.8% accuracy and 97.6% macro F1-score, with regional language modules attaining 92.5–94.1% F1 on translated benchmarks. Ablation experiments confirmed positive contributions from all five modules, validating the multi-signal fusion design. A purpose-built web interface featuring a Risk Meter gauge, per-module breakdown visualisation, and plain-language explanation output bridges the gap between sophisticated backend analytics and everyday user comprehension. ScamSense offers a principled, linguistically inclusive foundation for next-generation scam detection systems designed to serve the full demographic diversity of the populations they protect.

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A Secure Network- and Cloud-Based Intelligent Surveillance Framework for High-Security Defence Application

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Abstract:

High-security defence surveillance systems demand resilient networking, secure cloud infrastructure, and intelligent data processing to ensure continuous monitoring of borders, airspace, and maritime regions. With the rapid growth of distributed sensors and real- time data streams, traditional centralized systems face challenges related to scalability, security, and reliability. This paper proposes a detailed network-based and cloud-enabled surveillance framework that integrates risk management, secure networking technologies, zero trust principles, identity and access management, cloud deployment models, and predictive intelligence. The framework enables real-time monitoring, fault prediction, secure data handling, and operational decision support across land, air, and sea domains. By combining hardened communication protocols, governance mechanisms, and intelligent analytics, the proposed system enhances situational awareness while maintaining confidentiality, integrity, and availability of sensitive defence data.

Keywords:

Network Security, Cloud Computing, Defence Surveillance, Zero Trust Architecture, Risk Management, Sensor Networks, Secure Monitoring, Predictive Analytics

1. Introduction

Modern defence operations require continuous and reliable surveillance across geographically dispersed and highly sensitive regions such as national borders, controlled airspace, and maritime zones. These environments generate massive volumes of heterogeneous data from surveillance towers, sensors, radar systems, satellites, and unmanned platforms. Managing this data securely while ensuring real-time response is a major challenge. Network-based security mechanisms protect data during transmission, while cloud computing offers scalable storage, processing, and analytics capabilities. By integrating both approaches, defence systems can achieve resilient, secure, and intelligent surveillance. This paper presents a comprehensive framework that combines network security principles with cloud-based intelligence to support high-security defence surveillance operations.

2. Network-Based Security Framework

2.1 Risk Management in Defence Networks

Risk management is a fundamental component of defence surveillance systems. It involves identifying potential threats such as unauthorized access, cyber-attacks, physical sabotage, data leakage, and system failures. Risk assessment evaluates the likelihood and impact of these threats on operational readiness and national security. Based on this

assessment, control strategies such as preventive, detective, and corrective measures are implemented. Continuous monitoring, security audits, and strict policy enforcement ensure that risks are mitigated effectively throughout the system lifecycle.

2.2 Security Planning for Defence Infrastructure

Security planning establishes a structured blueprint for protecting defence networks. This includes designing secure network topologies, defining encrypted communication paths, implementing redundancy and failover mechanisms, and segmenting sensitive network zones. A well-defined security blueprint ensures resilience against failures and cyber intrusions while supporting uninterrupted surveillance operations.

2.3 Security Technologies

Advanced security technologies form the backbone of defence network protection. Firewalls and Virtual Private Networks (VPNs) filter unauthorized traffic and create secure communication tunnels for remote defence units. Secure physical network design ensures controlled access to routers, switches, and servers. Encrypted remote connections with multi-factor authentication allow authorized personnel to access systems securely from distributed locations**.**

2.4 Physical Security Measures

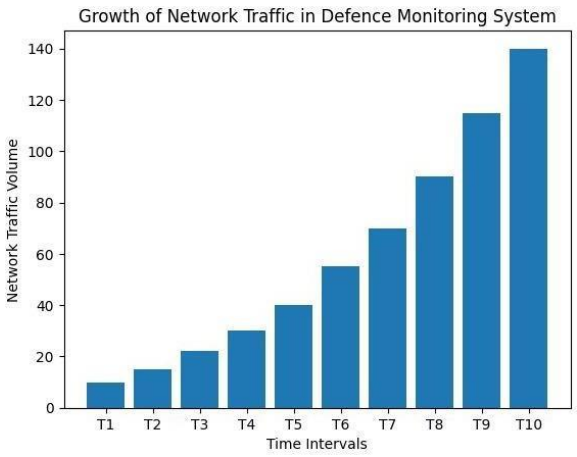
Physical security protects defence infrastructure from non-cyber threats such as fire, environmental hazards, and unauthorized physical access. Fire detection and suppression systems safeguard data centers and control rooms from catastrophic damage. Strict safety protocols regulate access to critical facilities, while environmental monitoring systems track temperature, humidity, and power conditions to prevent equipment failure. These measures ensure the physical integrity and availability of surveillance infrastructure**.**

2.5 Secure Communication Protocols and Standards

To ensure interoperability, robustness, and confidentiality, defence surveillance networks must adopt standardized and hardened communication protocols. Secure data transmission is achieved using protocols such as TLS/SSL and IPsec, which protect data against interception and tampering. Military-grade encryption standards, including AES-256 for data confidentiality and SHA-3 for integrity verification, further strengthen security. Secure routing protocols prevent route hijacking, spoofing, and man- in-the-middle attacks. Additionally, authenticated time- synchronization protocols ensure precise coordination among distributed sensors. Together, these mechanisms reduce the risk of replay attacks, data manipulation, and communication compromise in hostile environments.

2.6 Zero Trust Architecture for Defence Networks

Traditional perimeter-based security models are inadequate for modern, distributed defence systems. Zero Trust Architecture (ZTA) assumes that no user, device, or application is inherently trustworthy. Every access request is continuously verified based on identity, device health, location, and risk context. Least-privilege access policies restrict users and systems to only the resources they require. Micro-segmentation limits lateral movement within the network, preventing attackers from spreading if a breach occurs. Continuous risk-based evaluation ensures adaptive security responses. ZTA significantly reduces insider threats and enhances resilience against advanced persistent cyber intrusions.



3. Cloud Computing–Based Surveillance Framework

3.1 Cloud-Enabled Sensor and Tower Integration

Cloud computing enables centralized and scalable integration of geographically distributed surveillance towers and sensor systems deployed across borders, coastal areas, and airspace monitoring zones. These sensors include motion detectors, radar units, environmental sensors, satellite feeds, and unmanned aerial or maritime platforms. By leveraging cloud infrastructure, data collected from heterogeneous sources can be securely transmitted, aggregated, and processed in real time. Cloud-based integration eliminates the limitations of isolated monitoring systems and allows defence authorities to maintain a unified operational view. Secure ingestion pipelines ensure data integrity during transmission, while cloud orchestration services dynamically manage sensor workloads. This integration improves scalability, allows rapid deployment of new sensors, and supports continuous surveillance even in remote or hostile environments.

3.2 Cloud Monitoring Services

Cloud monitoring services provide continuous visibility into the operational status and performance of defence surveillance systems. These services include real-time dashboards that display sensor activity, network health, threat indicators, and system performance metrics. Centralized monitoring enables defence operators to detect anomalies, performance degradation, or potential security incidents at an early stage. Event logging and historical data analysis support forensic investigations and post-incident assessments. Cloud monitoring services also facilitate proactive system

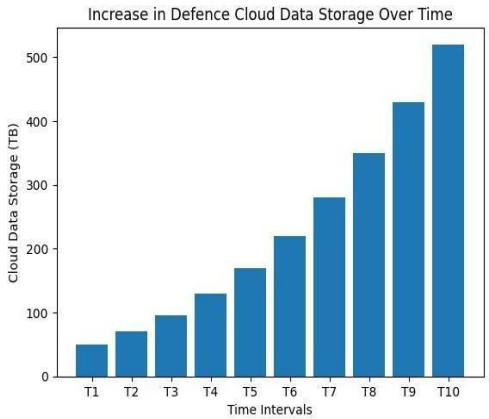
management by enabling predictive alerts and automated responses. By consolidating monitoring functions within a secure cloud environment, defence organizations enhance situational awareness and reduce response times during critical events.

3.3 Authorization and Identity Management

Authorization and Identity Management (IAM) is essential for controlling access to sensitive defence surveillance systems hosted in the cloud. IAM mechanisms ensure that only authenticated and authorized users, devices, and applications can access specific resources based on predefined roles and responsibilities. Role-based access control minimizes the risk of unauthorized operations by enforcing least-privilege policies. Strong authentication mechanisms, including multi-factor authentication and device identity verification, further enhance security. Audit trails and access logs provide accountability and enable compliance verification. IAM plays a critical role in preventing insider threats, unauthorized data access, and misuse of cloud-based surveillance resources.

3.4 Data Security in Cloud Environments

Data security is a critical requirement in cloud-based defence surveillance systems due to the sensitivity of collected intelligence. Data at rest is protected using strong encryption techniques to prevent unauthorized access in the event of a breach. Secure key management systems ensure controlled access to cryptographic keys. Data in motion is safeguarded through encrypted communication channels and secure routing protocols, protecting it from interception and tampering during transmission. Network isolation and segmentation within the cloud further reduce attack surfaces. These measures collectively ensure confidentiality, integrity, and availability of defence data throughout its lifecycle.

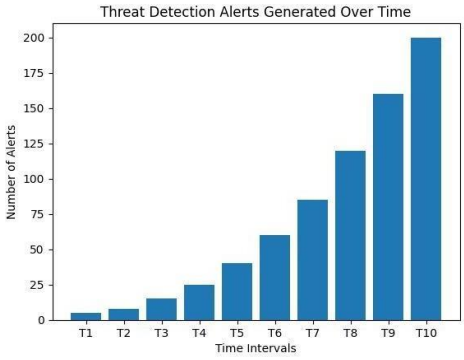


3.5 Sensor Data Streams and Data Collection

Defence surveillance systems generate continuous streams of real-time data from multiple sensors operating across land, air, and sea domains. Cloud-based data collection mechanisms support high-throughput ingestion, filtering, and normalization of sensor data. Data collectors aggregate incoming streams and prepare them for analytics and long-term storage. Secure buffering and fault-tolerant pipelines ensure uninterrupted data flow even during network disruptions. This capability enables reliable real-time analysis, historical trend evaluation, and intelligence-driven decision-making.

3.6 Cloud Deployment Models for Defence Surveillance

Different cloud deployment models are adopted based on operational sensitivity and mission requirements. Private cloud environments are used for highly classified defence operations, offering maximum control and isolation. Hybrid cloud models allow sensitive data to remain within private infrastructure while utilizing public cloud resources for large- scale analytics and non-classified processing. Community clouds facilitate controlled data sharing among allied defence organizations operating under common security policies. These deployment models provide flexibility while balancing security, scalability, and cost-efficiency.



3.7 Compliance, Governance, and Legal Considerations

Compliance and governance are essential to ensure lawful and accountable defence surveillance operations. Defence cloud systems must adhere to national security regulations, data sovereignty laws, and international agreements. Governance mechanisms enforce policy-driven access control, secure audit logging, and chain-of-custody management. Compliance with cybersecurity frameworks such as ISO/IEC 27001, NIST standards, and DISA STIGs ensures standardized protection. These measures promote transparency, accountability, and trust while preventing misuse of surveillance capabilities.

4. Intelligent Analytics and Predictive Capabilities

Intelligent analytics form the core decision-making component of modern defence surveillance systems by transforming large volumes of raw sensor data into meaningful and actionable intelligence. In the proposed framework, cloud-based analytics engines continuously process real-time and historical data collected from distributed sensors operating across land, air, and maritime domains. Advanced analytical models identify abnormal

patterns, suspicious movements, and deviations from normal operational behavior, enabling early detection of potential threats. By correlating data from multiple sources, the system improves detection accuracy and reduces false alarms, which is critical in high-security defence environments.

Predictive analytics further enhance system reliability by enabling fault prediction and proactive maintenance. Machine learning–based models analyze performance metrics, error logs, and historical maintenance data to identify early signs of sensor degradation, communication failures, or infrastructure instability. This predictive capability allows defence authorities to schedule maintenance activities in advance, minimizing downtime and preventing mission- critical failures.

In addition to threat and fault detection, intelligent analytics support surveillance tracking and routing. The system continuously tracks rafts, vessels, aircraft, and unmanned vehicles by analyzing radar and sensor inputs. Secure routing algorithms ensure efficient and reliable data transmission between sensors and command centers. Furthermore, the framework incorporates priority-based alerting mechanisms that generate real-time notifications through secure dashboards and communication channels. Environmental analytics modules analyze meteorological data to provide accurate weather predictions across land, air, and sea, supporting mission planning and operational safety. Together, these intelligent analytics capabilities significantly enhance situational awareness, operational readiness, and decision accuracy in defence surveillance operations.

5. System Architecture Description

The proposed system architecture is designed as a layered and modular framework to ensure scalability, security, and operational efficiency in high-security defence surveillance environments. The architecture consists of three tightly integrated layers: the Network and Sensor Layer, the Cloud Intelligence Layer, and the Command and Control Layer. Each layer performs specialized functions while maintaining secure and reliable communication with other layers.

The Network and Sensor Layer is responsible for data acquisition and secure transmission. It includes surveillance towers, ground and environmental sensors, radar systems, maritime sensors, and unmanned platforms deployed across operational zones. These components continuously collect real-time data related to movement, environmental conditions, and potential threats. Secure communication protocols, encryption mechanisms, and network security controls ensure the integrity and confidentiality of data during transmission to the cloud.

The Cloud Intelligence Layer serves as the central processing and analytics hub. This layer provides scalable storage for large volumes of surveillance data and hosts advanced analytics, predictive models, and identity management services. Cloud-based orchestration dynamically manages computational resources to handle fluctuating data loads. Strong access control, encryption, and compliance mechanisms protect sensitive defence data within the cloud environment.

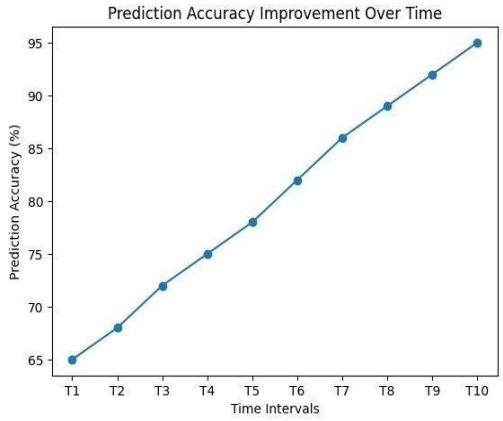
A. The Command and Control Layer enables human-in-the-loop decision-making by providing visualization dashboards, alerting systems, and decision-support tools. Graph-based outputs display threat levels, confidence scores, system health indicators, and operational trends in an intuitive manner. This layer allows defence operators to respond rapidly and effectively to emerging threats, system faults, and environmental changes. The layered architecture ensures seamless integration, fault tolerance, and adaptability to evolving defence requirements.

6. Applications

The proposed network- and cloud-based secure surveillance framework is applicable to a wide range of national defence and high-security scenarios where continuous monitoring, secure data handling, and intelligent decision-making are critical. One of the primary applications is border surveillance, where the system enables real-time monitoring of land borders using surveillance towers, ground sensors, radar systems, and unmanned platforms. Secure networking ensures reliable transmission of sensor data to centralized cloud infrastructure, while cloud-based analytics assist in detecting intrusion attempts, suspicious movement patterns, and potential security breaches.

Another significant application is coastal and maritime surveillance, where the framework supports continuous tracking of vessels, rafts, and maritime activities. By integrating data from maritime sensors and radar systems, the framework enhances detection accuracy and supports early warning mechanisms against illegal crossings, smuggling, or hostile activities. In airspace monitoring, the framework enables tracking of aircraft, drones, and unidentified aerial objects. Intelligent analytics identify abnormal flight behaviors and assist defence authorities in preventing airspace violations.

The framework also plays a vital role in defence logistics and cargo operations, where secure routing, scheduling, and monitoring of sensitive supplies are essential. Cloud-based decision support systems optimize logistics planning while ensuring strict access control and data confidentiality. Additionally, the framework supports disaster management and environmental monitoring by analyzing weather data, environmental conditions, and emergency scenarios across land, air, and sea domains. This enables timely response and resource deployment during natural disasters. Finally, the system enhances the protection of critical infrastructure, including ports, power plants, and communication hubs, by providing continuous surveillance and threat detection capabilities**.**



7. Conclusion

This paper presented a comprehensive network- and cloud-based secure framework for high-security defence surveillance designed to address the growing challenges of scalability, security, and operational reliability in modern defence environments. The proposed framework integrates robust network security mechanisms, secure communication protocols, Zero Trust principles, and cloud computing technologies to ensure safe data transmission, controlled access, and efficient processing of large-scale surveillance data.

By leveraging cloud-based analytics and predictive intelligence, the framework enhances situational awareness, enables early detection of threats and system faults, and supports informed decision-making across land, air, and maritime domains. The layered architecture ensures modularity, fault tolerance, and adaptability, allowing the system to evolve with changing operational requirements and emerging threats. Furthermore, the incorporation of compliance, governance, and legal considerations ensures that surveillance operations remain lawful, transparent, accountable.

Overall, the proposed framework offers a resilient, scalable, and secure solution for defence surveillance applications. Its ability to integrate advanced networking, cloud computing, and intelligent analytics makes it well-suited for modern national defence systems and other high-security environments requiring continuous are reliable monitoring.

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Smart E-Commerce AR Application with Privacy Centric Design

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Abstract— While E-commerce has transformed shopping experiences, it has also created major drawbacks in product visualization, exact sizing, and consumer confidence—especially in the furniture industry. Designed to let clients see furniture in their real environment before buying, this project offers a Smart E-Commerce Android application powered by Augmented Reality (AR). Users can virtually position, rotate, and scale furniture inside their homes thanks to AR Core and interactive 3D models, hence facilitating more informed decisions and lowering product return percentages. One major element of this system is its commitment to user privacy and data security. All AR functions including camera access and environmental detection are processed locally on the user's device, ensuring that no images, videos, or personal data are gathered, kept, or transmitted without the user's specific permission. Simple options help users to store, share, or remove information; characteristics like AR snapshots let people keep complete command.

Keywords— 3D models, furniture, Android, Privacy, AR Core, e-commerce, augmented reality (AR).

I. INTRODUCTION

Unparalleled convenience and accessibility offered by internet buying have changed consumer behavior. But this convenience has several drawbacks as well, particularly while purchasing items demanding bodily presence and spatial awareness—furniture. Furniture buying online has one special challenge unlike small, less effective purchases: seeing how a piece will match with a present living space. Static images and even films presented on e-commerce sites often fall short of adequately portraying the actual size, texture, and aesthetic match of an item inside a consumer's house. This disconnect sometimes results in consumer frustration, which has financial effects for purchasers and sellers, product returns, and lost time. As online shopping turns into the primary mode of retail, demand for imaginative ideas linking virtual product representation with real-world use is increasing. Creating an Augmented Reality (AR) application meant to enhance the online furniture shopping experience—making it more user-focused, dependable, and simple—addresses this crucial requirement.

II. RELEVANCE AND PROBLEM DEFINITIONS

The basic restriction of traditional internet furniture purchasing lies in consumers' inability to accurately assess how a piece will appear and fit into their own surroundings. High-resolution photos, though lovely, don't reflect the real scale, dimensional accuracy, or contextual fit of furniture. This generally leads to disappointment, irritation, and the realistic weight of returns by producing a big distance between the real product obtained and customer expectations. For consumers, this translates into wasted time and work arranging returns; for businesses, it raises operating expenses and might damage brand image. Considering the rapid migration toward internet retail for big products such furniture, there is an evident and pressing need for cutting-edge visualization solutions that can accurately reproduce the presence of a piece in a real-world setting, therefore minimizing the dangers associated with buying furniture online.

III. ANTICIPATED OUTCOME

The major objective of this project is to produce an Android app leveraging Augmented Reality (AR) that totally revolutionises the online furniture shopping experience. Customers using their phone camera may position 3D models of furniture, real-time rotation and scaling adjustment, thereby get a precise impression of how the item will look and fit. This tool will let customers nearly see furniture pieces in their actual physical environments before they make a purchase. The application will include optimized 3D models based on ARCore for great AR features and to guarantee a smooth and realistic experience. One fundamental design rule is to ensure that all AR processing and data management occur locally on the user's device. Before any images, videos, or personal environmental data is collected or transmitted, this privacy-focused approach demands explicit permission from the user. The ultimate goal is to convert purchasing online furniture into a more immersive, much less hazardous, and considerably more practical experience.

IV EXPECTED DIFFICULTIES AND UNIQUENESS

Creating a strong AR software for furniture visualization has several technical obstacles. Making sure that virtual objects are properly seen in scale and placement inside of a real world is a major challenge. Achieving this calls for exact AR tracking abilities to prevent virtual furniture from seeming distorted, floating, or wrongly sized, which may be especially difficult given the differences in device sensors and environmental lighting circumstances. Maintaining a flawless user experience also requires optimizing 3D models for smooth real-time rendering across several Android devices.

One of our approach's distinguishing features and major differences is its continuous dedication to user privacy. Many contemporary apps gather and transfer user information without express consent. This is expressly rejected by our design philosophy. Camera feed processing and environmental mapping, among other AR activities, are carried out totally on the user's equipment. Without the user's clear and informed consent, no visual or spatial data is gathered, stored, or sent to outside servers. User control is complete with AR snapshots; clear local saving, sharing, or deletion choices are offered. This privacy-by-design technique helps us to stand apart from our rivals in a market often condemned for data exploitation and builds more user confidence. Furthermore, the application provides very engaging controls that let consumers move, rotate, and size furniture models at will, therefore giving unmatched degree of personalization and spatial awareness prior to purchase.

V. FEASIBILITY OF THE SMART SOLUTION

Following the SMART (Specific, Measurable, Achievable, Relevant, Time-bound) criteria, the projected Augmented Reality furniture application is clearly doable.

Specific: By allowing virtual placement in actual settings, the software seeks to exactly solve the issue of inadequate furniture visualization in online shopping.

Measurable: Success can be quantified by indicators including greater user engagement, lower product return rates for furniture genres, and good user comments on visual accuracy.

Achievable: The evolution builds on proven and strong methods. For application development, AR Core for augmented reality capabilities, Scene form for 3D model rendering, Blender and 3ds Max for model creation, and Firebase for essential backend services (like user authentication and model storage) are the tools we intend to use. Within three to four months, a small, focused development team might produce a basic edition of this application including allotted time for testing, debugging, and iterative improvements.

Particularly for expensive items like furniture, the solution tackles a major consumer and company pain point in the fast-growing e-commerce terrain by means of a physical benefit. This increases buying confidence and minimizes post-purchase regret.

As stated, a suitable prototype can be created within a reasonable period (e.g., 3–4 months).

Additionally, processing all AR activities locally on the user's device simplifies the backend infrastructure needs and considerably lowers data privacy and security worries, therefore facilitating the simple implementation and maintenance of the solution. This local processing also improves the general feasibility by eliminating dependencies on ongoing server interaction for basic augmented reality capabilities.

VI. METHODOLOGY

This study followed a double-diamond design process, consisting of four phases: research and discovery, defining the problem and user segment, ideation and design, delivery of the prototype, and user testing.

An online questionnaire survey consisting of 12 questions was administered to 40 retail shoppers, focusing on issues faced by frequent shoppers. A sample size of 50 was chosen, out of which 40 were considered relevant, including both younger and older adults and varying educational backgrounds. Data were also collected through 10 one-to-one interviews with 5 females and 5 males aged 18–60 yrs.

Gathering in-depth observations and exchanges is a necessary part of contextual re-search. To understand work styles, behaviours, and mental models, looking at the user group's wants, goals, and frustrations is important. A contextual inquiry flow model was made to establish relationships between different participants in the same context.

Defining the Problem

The analysis of the observations from user research helped in defining the problem, which states that traditional retail experiences lead to customer dissatisfaction due to issues like geographical limitations, lack of social interactions, comprehensive product information, and personalized promotions. For better understanding of the problem area, a 5W+H table was created

Competitive Analysis

Direct and indirect competitors were identified and benchmarked against the feature list

Features	Direct Competitors			Indirect Competitors		
	Ikea Place	Lowe's	Sephora	Amazon AR	Walmart	Etsy
Virtual Product Try-On	✓	✓	✓	✓	✓	✗
AR Product Showcases	✓	✓	✓	✓	✓	✗
Personalized Recommendations	✗	✗	✗	✗	✗	✗
Real-Time Inventory	✗	✗	✗	✗	✓	✗
Online Social Shopping Events	✗	✗	✗	✗	✗	✗
Sustainable Product Highlight	✗	✗	✗	✓	✓	✓
Total Features	**2**	**2**	**2**	**3**	**4**	**1**

Final Concept Selection

Different concepts were ideated by merging different solution ideas, and 5 users gave ratings on a scale of 1 (low)–5 (high)

Concepts	U1	U2	U3	U4	U5	Mean
Virtual Shopping Mall with Interactive Showcases	4	3	5	4	4	4
Try Before You Buy—AR Fitting Rooms	5	4	5	4	5	4.6
Social Shopping Events and AR Influencer Collab	3	4	4	3	4	3.6
Proposed Concept—The AR Retail App	5	5	5	5	5	5

Usability Testing

The usability testing was performed using retrospective think-aloud protocol along with a system usability scale (SUS) rating questionnaire . Six users were asked to experience the interface by conducting an assessment of the given task or walkthrough. A task brief was given to users with specified steps and instructions.

VII. TOOLS EMPLOYED / STACK OF TECHNOLOGY

To guarantee functionality, performance, and scalability, the Smart E-commerce AR Application's development depends on a deliberately chosen stack of industry-standard and strong technologies.
Android Studio: The favored integrated development environment (IDE) for creating the local Android app. Its extensive suite of coding, debugging, and UI design tools sped along the development cycle.

AR Core SDK is Google's tool for creating augmented reality experiences. AR Core was essential in enabling core AR capabilities including motion tracking, environmental knowledge (detecting horizontal and vertical surfaces), and light estimation, so allowing virtual items to be realistically positioned and interact with the real world.

Simplifying the display, modification, and animation of 3D models in the AR environment, this rendering library was utilized. Scene form abstracted away much of OpenGL ES's complexity, so making 3D rendering more accessible for Android development. (Note: Though Google has depreciated Scene form, it was quite pertinent during the creation of comparable apps and acts to explain the approach).

Design and modification of the 3D furniture models were done using professional 3D content creation tools Blender and 3ds Max. They enabled exact modeling, texturing, and rigging of furniture pieces.

Chosen as the favored 3D model format because of its efficiency and small size, GLB (GL Transmission Format Binary) is perfect for mobile AR applications where asset loading speeds and memory usage are vital. One binary file from GLB contains all model data (geometry, textures, animations).

Used for a number of backend services, firebase improves the app's capacity. This involves:

Managing user login and account security uses Firebase Authentication.

Firebase Cloud Storage: For storage and management of the 3D furniture designs (GLB files) and possibly other application assets, therefore enabling dynamic content changes without the need for app upgrades.

For saving user preferences or light weight application data if needed, firebase Realtime Database / Cloud Firestore—although the primary AR operations are device-local—is ideal.

Though not very often utilized for ongoing API communication given the privacy-focused design, these platforms might nevertheless host APIs for particular functions (such as fetching a catalog of furniture pieces) or for effective asset management and distribution of 3D models.

Maintaining a balance between great AR capabilities, effective 3D rendering, a fluid development process, and essential backend support—all while honoring the principle of retaining core AR processing local to the user's device—this technology stack was selected.

VIII DISCUSSION,LIMITATIONS AND FUTURE SCOPE

The AR Retail system is an innovative solution that could revolutionize the retail industry, offering an interactive shopping experience. By utilizing augmented reality technology, stores can create immersive virtual storefronts and product displays, making shopping more enjoyable and interactive. This, in turn, can lead to increased sales and customer loyalty. The system also offers personalization and ease of use, addressing issues faced by traditional brick-and-mortar stores. This integration also makes it easier for customers to switch between online and offline shopping, demonstrating its adaptability to changing consumer tastes. The proposed solution aims to make shopping more of a social activity, fostering a sense of community among customers who share similar interests, leading to stronger connections and increased sales. There are a few limitations, including potential usability issues for older users, security and privacy concerns, and a lack of AR-supported devices. The shift to e-retailing and other new proposed features may cause frustration and may entail a sharp learning curve. Future advancements in AR and VR are expected to enhance app functionality and the users' experience. A lot of future work may go in the direction of reducing the learnability aspect of the AR in retail. The emphasis will be on building relationships with stores and brands, including incorporating retail stores from other sectors. The AR Retail solution is expected to enhance customer brand connections, drive sales growth, and set new benchmarks.

IX ACKNOWLEDGMENTS

Providing a very realistic and accurate visualization tool, the Smart E-Commerce AR Application tackles a major constraint in the internet furniture buying experience. By allowing consumers to virtually place, alter, and scale 3D furniture models inside their surroundings via their smartphone cameras, the program bridges the important gap between abstract online listings and actual physical presence. This interactive feature lets customers make more educated purchases, therefore lowering the probability of product returns and raising general customer trust. This project's strong dedication to user privacy is a fundamental component; strictly limited to the device of the user, all sensitive AR activity including environmental data processing and camera access. This guarantees that no personal images, movies, or geographical data is gathered or sent without clear permission, therefore promoting a high level of trust and establishing a fresh standard for privacy-focused e-commerce systems. This program finally alters the way consumers buy furniture online by making it easier, more dependable, and more user-friendly.

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AI-Based Smart Crop Recommendation System with Real-Time Weather and Market Analysis

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Abstract— Agriculture remains a critical sector for economic development and food security, particularly in developing nations. However, farmers often face challenges in selecting suitable crops due to unpredictable weather conditions, soil variability, and fluctuating market prices. Traditional crop recommendation systems rely on static datasets and fail to incorporate dynamic environmental and economic factors. This paper proposes an AI-based smart crop recommendation system that integrates soil parameters, real-time weather data, and market price analysis to provide accurate and profitable crop suggestions. The system utilizes machine learning techniques to analyze input data and generate recommendations tailored to specific conditions. Additionally, it offers fertilizer and irrigation guidance to support optimal crop growth. The proposed approach enhances decision-making, improves productivity, and supports sustainable farming practices

Keywords: *Crop Recommendation, Machine Learning, Smart Agriculture, Real-Time Data, Market Analysis*

I. INTRODUCTION

Agriculture plays a vital role in ensuring economic stability and food security, particularly in developing nations such as India. A large segment of the population relies on farming as their primary source of income. Despite its importance, farmers frequently encounter challenges when deciding which crops to cultivate. These difficulties arise from factors such as fluctuating soil characteristics, uncertain climatic conditions, and dynamic market trends, making crop selection a complex and critical decision. Traditional farming practices rely heavily on experience and assumptions, which may not always lead to optimal productivity or profitability. In recent years, advancements in Machine Learning have enabled the development of intelligent systems that can analyze agricultural data and provide accurate recommendations.

Crop recommendation systems typically analyze factors such as soil nutrient composition, temperature, humidity, and rainfall to determine the most appropriate crops for cultivation. Although these systems have contributed to better decision-making, a large number of existing approaches depend on fixed datasets and do not effectively integrate real-time environmental conditions or evolving economic influences, limiting their overall accuracy and adaptability.

This paper proposes an AI-based smart crop recommendation system that utilizes real-time weather data, soil analysis, and market price evaluation to suggest the most appropriate and profitable crops. By combining data-driven insights with modern computational techniques, the proposed system aims to assist farmers in making informed decisions, improving crop yield, and ensuring sustainable agricultural practices.

II. LITERATURE SURVEY

In recent years, the application of Machine Learning in agriculture has gained significant attention, particularly in the development of crop recommendation systems. Researchers have explored various techniques to assist farmers in selecting suitable crops based on environmental and soil conditions. These systems aim to improve productivity and reduce risks associated with traditional farming practices. Several early studies focused on the use of supervised learning algorithms such as Decision Trees and Naive Bayes for crop prediction. These models analyze historical datasets containing soil nutrients, temperature, humidity, and rainfall to classify crops. Although these approaches provide reasonable accuracy, they often struggle with handling complex relationships between variables and may result in lower prediction performance when applied to diverse datasets.

To address these limitations, ensemble learning methods such as Random Forest have been widely adopted. Random Forest is an ensemble learning technique that integrates multiple decision trees to enhance prediction accuracy while minimizing the risk of overfitting. Many researchers have reported that this method achieves higher prediction accuracy compared to individual classifiers. Its ability to handle large datasets and multiple input features makes it a preferred choice in agricultural applications. Some studies have also explored the use of advanced algorithms such as Support Vector Machines and Neural Networks. These models are capable of capturing non-linear patterns in data and can provide more precise recommendations. However, they often require extensive computational resources and large training datasets, which may limit their practicality in real-world agricultural environments, especially in rural areas.

In addition to machine learning techniques, researchers have integrated Internet of Things technologies to collect real-time data from the field. Sensors are used to monitor soil moisture, temperature, and environmental conditions continuously. This real-time data improves the accuracy of crop recommendations. However, the high cost of sensors and infrastructure poses a challenge for small-scale farmers. Another important area of research involves the use of weather forecasting systems. Many crop recommendation models incorporate weather data to enhance prediction accuracy. Despite this improvement, most existing systems rely on periodic updates rather than fully dynamic real-time integration, which can still lead to outdated recommendations in rapidly changing climatic conditions. Market-oriented crop recommendation has also been explored in recent studies. These systems consider crop prices and demand to maximize farmers' profits. While this approach adds economic value to crop selection, it is often implemented separately from agronomic factors, leading to incomplete decision-making support.

Furthermore, user accessibility has been a major concern in existing systems. Many applications lack intuitive interfaces and are primarily designed for users with technical knowledge. The absence of multilingual support and simple interaction methods reduces the usability of these systems among farmers, particularly in rural regions. Based on the analysis of existing literature, it is evident that while significant progress has been made in crop recommendation systems, several limitations still persist. These include the lack of real-time data integration, limited consideration of economic factors, and poor user accessibility. The proposed system aims to address these gaps by combining advanced machine learning techniques with real-time weather data, market analysis, and a user-friendly interface to provide a comprehensive and practical solution for modern agriculture.

III. METHODOLOGY

3.1 Data Collection and Preparation:

The system collects soil parameters such as nitrogen (N), phosphorus (P), potassium (K), pH, and user location to form the primary input dataset

Real-time weather data including temperature, humidity, and rainfall is fetched using APIs, ensuring adaptability to current environmental conditions

Historical datasets are used to train the model, and preprocessing techniques such as cleaning, normalization, and validation are applied to improve data quality

Example: For input values like N=90, P=42, K=43, pH=6.5 with moderate rainfall, the data is standardized before being used for prediction

3.2 Crop Prediction and Analysis:

The prediction process is carried out using the Random Forest Algorithm, which provides high accuracy by combining multiple decision trees The

model analyzes soil and weather data to determine the most suitable crop based on learned patterns and relationships
Example: High rainfall conditions may result in crops like rice, while low rainfall conditions may lead to crops such as millets or cotton

3.3 Market Analysis and Cost Estimation:

The system evaluates crop price trends and demand to recommend economically beneficial crops along with suitable agricultural options It also provides basic fertilizer and irrigation suggestions based on soil nutrient levels and weather conditions
Example: If two crops are suitable, the system selects the one with better market value and lower resource cost

3.4 Conversational and User Interface:

The system includes a simple and user-friendly interface for input and output display, making it accessible to farmers with minimal technical knowledge A chatbot or voice-based interaction can be integrated to support natural communication and multilingual usage

3.5 Backend Infrastructure and Data Handling:

The backend manages data processing, weather API integration, and model execution efficiently
A database stores user inputs and results for future analysis, while the modular design allows scalability and feature expansion

3.6 Workflow Demonstration Example:

The system workflow includes input collection, weather data integration, model prediction, market evaluation, and final recommendation
Example: A farmer entering soil and weather details receives a crop suggestion along with fertilizer and irrigation guidance, ensuring practical decision support

IV. PROPOSED SYSTEM & ARCHITECTURE

4.1 System Overview:

The proposed system is an AI-based crop recommendation framework that integrates soil parameters, real-time weather information, and market price analysis to provide accurate and practical suggestions It addresses the limitations of traditional systems by using dynamic data sources instead of static datasets, thereby improving adaptability to changing environmental conditions The system is designed to enhance agricultural productivity, support efficient resource utilization, and increase farmer profitability through data-driven decision-making

4.2 System Modules:

The Input and Weather Module gathers essential soil attributes, including nitrogen, phosphorus, potassium, and pH levels, along with the user's geographical location. It also integrates real-time weather information—such as temperature, humidity, and rainfall—through API services, ensuring that the system operates with current and accurate data inputs.

Prediction Module: Implements the Random Forest Algorithm to process combined soil and environmental data, offering high accuracy, better handling of multiple features, and reduced overfitting

Market & Recommendation Module: Analyzes current crop price trends and integrates all outputs to generate final recommendations, including suitable crop selection, fertilizer suggestions based on soil condition, and irrigation guidance

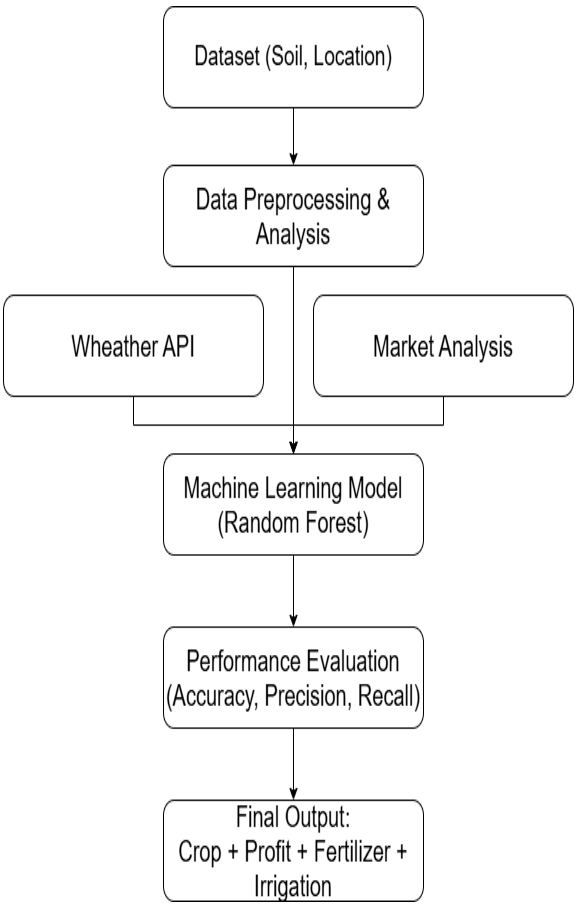

Fig 1: Architecture of Smart Crop Recommendation System

4.3 System Workflow and AdvantagesWorkflow:

The system follows a structured process where user input is combined with real-time weather data, processed by the machine learning model, evaluated with market trends, and finally presented as a comprehensive recommendation

Advantages: Provides real-time updates, improves prediction accuracy, and considers both agricultural suitability and economic profitability for better decision-making. The modular and user-friendly design ensures scalability, easy maintenance, and accessibility for farmers with minimal technical knowledge

V. RESULTS & DISCUSSION

The proposed system was evaluated using a standard crop recommendation dataset containing soil nutrients, weather parameters, and crop labels. The prediction model based on the Random Forest Algorithm achieved high accuracy compared to traditional classification methods. The model demonstrated consistent performance across different input conditions, indicating its ability to generalize well for diverse agricultural scenarios

The integration of real-time weather data significantly improved the relevance of recommendations. Unlike static models, the system adapted to current environmental conditions, resulting in more practical and reliable outputs. For example, in scenarios with high rainfall and suitable soil nutrients, the system correctly suggested water-intensive crops such as rice, while in low rainfall conditions, it recommended crops requiring less water, such as millets.

The inclusion of market analysis further enhanced the system's effectiveness by providing economically viable recommendations. In cases where multiple crops were suitable, the system prioritized crops with better market demand and price trends. This ensured that farmers could make decisions not only based on suitability but also on potential profitability. The system also provided additional guidance in the form of fertilizer and irrigation recommendations, making it a comprehensive decision-support tool. Users were able to receive clear and actionable outputs through a simple interface, improving usability and accessibility

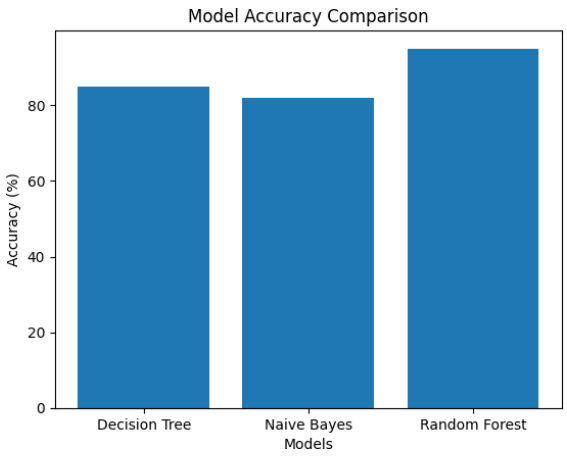

Fig 2: Accuracy Comparison of Machine Learning Models

Overall, the results indicate that the proposed system outperforms traditional crop recommendation approaches by combining accuracy, real-time adaptability, and economic considerations. The discussion highlights that integrating multiple data sources and intelligent algorithms leads to improved agricultural decision-making and supports sustainable farming practices

V. CONCLUSION & FUTURE SCOPE

This paper presented an intelligent crop recommendation system that integrates soil parameters, real-time weather information, and market analysis to provide accurate and practical suggestions for farmers. The use of the Random Forest Algorithm enabled the system to achieve high prediction accuracy while effectively handling multiple input features. By combining agricultural and economic factors, the system offers a comprehensive decision-support solution that improves crop selection and resource utilization. The incorporation of real- time weather data ensures that the recommendations remain relevant under changing environmental conditions, addressing one of the major limitations of traditional systems. Additionally, the inclusion of market analysis allows farmers to choose crops that are not only suitable for their land but also economically beneficial. The system further enhances usability by providing fertilizer and irrigation suggestions, making it a complete and user-friendly platform for modern agriculture

The results demonstrate that integrating machine learning with dynamic data sources significantly improves decision-making in agriculture. The proposed system contributes to increased productivity, better resource management, and improved profitability for farmers. Its modular architecture also allows easy expansion and adaptation to different agricultural regions

Future Scope:

The system can be further enhanced by integrating advanced technologies such as IoT-based sensors for real-time soil monitoring. This would allow automatic data collection and improve accuracy by continuously tracking soil conditions without manual input
Another important extension is the inclusion of crop disease detection using image processing techniques. By allowing users to upload images of plant leaves, the system can identify diseases and suggest appropriate treatments, making it a more

comprehensive agricultural assistant. The development of a mobile application with multilingual and voice-based support can improve accessibility for farmers in rural areas. This would enable users to interact with the system in their local language and receive recommendations more conveniently. Future improvements may also include predictive analytics for crop yield estimation and advanced market forecasting to help farmers plan long-term cultivation strategies. Integration with government agricultural databases and offline functionality can further enhance the system's usability in low-connectivity regions

Overall, the proposed system provides a strong foundation for intelligent agriculture, and with further enhancements, it has the potential to become a complete smart farming solution that supports sustainable and profitable agricultural practices

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Edullm-Ai Powered Studies Assistance

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Abstract

This paper presents an advanced LLM-powered educational platform designed to enhance student engagement and understanding through a multi-modal approach. Unlike existing systems constrained by image generation limitations, our platform integrates multiple specialized LLMs to provide accurate, comprehensive answers, supplemented by an unlimited supply of custom-generated diagrams, flowcharts, mind maps, and quizzes. This multi-modal strategy fosters deeper comprehension and caters to diverse learning styles, creating a personalized and dynamic learning environment. Enabling features for students to learn in different ways too allow them learn at their own pace and get a better understanding of the concept and studies to be made easy by providing necessary and important topics to be broken down into concise and precise answers.

To address these challenges, this paper introduces EduLLM-AI, a multi-agent software architecture designed to provide intelligent student assistance and sophisticated pedagogical analysis. EduLLM-AI adapts SALLMA, a robust two-layer architecture for LLM-based multi-agent systems, and tailors it to the unique demands of higher education. The design incorporates an Operational Layer, which manages real-time student interactions and orchestrates a team of specialized pedagogical agents, and a Knowledge Layer, which maintains persistent student models, curriculum content, and pedagogical strategies.

By distributing educational responsibilities across specialized agents such as a Student Modeler, a Socratic Questioner, a Curriculum Designer, and a Bias Auditor, EduLLM-AI transcends generic answer generation. Instead, it fosters critical thinking, ensures personalized guidance, and enables transparent, ethically aware decision-making. A proof-of-concept implementation demonstrates the feasibility of this design and lays the groundwork for scalable, transparent, and pedagogically grounded AI support for both learners and educators.

The contributions of this work are threefold. First, it proposes EduLLM-AI as a principled adaptation of multi-agent systems for education. Second, it introduces a pedagogical agent framework capable of addressing the multidimensional nature of teaching and learning. Third, it situates the architecture

within an ethical framework that emphasizes fairness, transparency, and data privacy. Together, these contributions establish a blueprint for the next generation of AI-powered educational systems that act not merely as information providers but as genuine partners in the learning process.

1. Introduction

Large Language Models (LLMs) have revolutionized educational technologies by offering personalized learning experiences. However, current LLM-based platforms often face limitations, particularly in generating

diverse visual aids and maintaining pedagogical accuracy. These constraints hinder the creation of rich, visually-driven learning materials essential for explaining complex concepts. Moreover, relying on a single LLM can lead to inaccuracies and inconsistencies in generated content. To address these challenges, we introduce a novel platform that leverages multiple specialized LLMs and an unlimited visual generation capability to provide a comprehensive and adaptive learning experience. The emergence of large language models has generated unprecedented excitement and debate within higher education. These systems, exemplified by the GPT family and its successors, exhibit remarkable fluency in natural language processing, enabling them to generate explanations, summarize complex texts, and interact with learners conversationally. In doing so, they promise to transform how students access knowledge, how instructors design instruction, and how institutions manage educational delivery. At their core, LLM-powered tools appear to offer the long-sought ability to personalize learning at scale, tailoring instruction to individual needs while reducing barriers of access and cost.

In practice, LLMs are already finding applications across the educational spectrum. Universities deploy them to automate administrative work such as grading, feedback generation, and scheduling. Students increasingly turn to LLM-based tools to generate study guides, clarify difficult concepts, or practice problem-solving. These shifts are evidence of a broader cultural and technological moment in which AI is becoming embedded within educational practice, shaping expectations of both students and faculty.

Despite their promise, however, single-agent LLMs reveal fundamental weaknesses when placed in pedagogical roles. Their lack of grounding in educational theory means that while they can produce grammatically correct and contextually plausible responses, they often fail to promote meaningful learning. They are prone to hallucinations—outputs that sound convincing but are factually incorrect—posing risks in academic contexts where accuracy and trust are paramount. Their limited context windows prevent them from retaining long-term memory of student interactions, leading to shallow, stateless exchanges that ignore prior progress or misconceptions. Moreover, the reliance on a single general-purpose model restricts their ability to cover the breadth of roles that effective teaching demands, from content delivery and assessment to motivation, inquiry, and critical reflection.

To move beyond these constraints, this paper argues for a fundamental architectural shift. Rather than relying on monolithic systems, education requires multi-agent architectures that distribute pedagogical responsibilities across specialized, collaborating agents. In this paradigm, each agent performs a specific role modeling student progress, generating formative assessments, fostering inquiry through Socratic dialogue, or auditing for bias. By working in coordination, these agents overcome the limitations of single systems, enabling persistence of memory, cross-verification of information, and more nuanced instructional strategies.

EduLLM-AI embodies this vision. Built upon SALLMA, a two-layer architecture for LLM-based multi-agent systems, EduLLM-AI introduces a principled framework tailored to higher education. The Operational Layer functions as the interactive classroom,

orchestrating real-time interactions between students, instructors, and pedagogical agents. The Knowledge Layer serves as the system's persistent foundation, storing student models, curriculum knowledge, and pedagogical strategies. Together, these layers enable a system that is both dynamic and grounded, capable of scaling across institutions while maintaining personalized, ethical, and pedagogically informed engagement.

2. Literature Survey

2.1 Multi-Agent LLM Architectures

The integration of multiple LLMs into a cohesive system has been explored to enhance task-specific performance and scalability. SALLMA (Scalable Architecture for LLM Multi-Agent Applications) proposes a layered architecture that separates operational processes from knowledge-level components, facilitating agent specialization and integration with external tools via APIs

2.2 Pedagogical Alignment of LLMs

Supervised fine-tuning (SFT) has been employed to align LLMs with educational objectives. For instance, GuideLM, an LLM fine-tuned for programming education, demonstrated improved pedagogical performance by providing Socratic guidance and concise explanations, thereby enhancing student learning outcomes arXiv. The true potential of EduLLM-AI lies in its framework of specialized pedagogical agents. Designed as independent microservices, these agents collaborate under the orchestration of the Operational Layer, each embodying a distinct pedagogical function.

Student-facing agents include the **Tutor Agent**, which provides clear explanations grounded in curriculum resources; the **Socratic Questioner Agent**, which stimulates critical thinking by posing guiding questions; the **Content Generator Agent**, which produces tailored practice materials and analogies; and the Assessment Agent, which designs formative assessments and records results.

Instructor-facing agents include the Student Modeler Agent, which continuously refines multi-dimensional student profiles; the Engagement Analytics Agent, which monitors interaction patterns to flag disengagement; the Curriculum Designer Agent, which suggests supplementary materials or alternative teaching strategies based on class-wide data; and the Bias and Fairness Auditor Agent, which ensures ethical compliance by detecting biases in content and assessments.

An illustrative example demonstrates their collaboration. When a student expresses confusion about natural selection, the Intent Manager identifies the learning need. The Orchestrator retrieves the student's profile, noting their preference for visual learning. The Tutor Agent provides a grounded definition, the Content Generator produces a diagram and analogy, the Assessment Agent poses a short question, and the Socratic Questioner intervenes when the student responds incorrectly. All interactions are logged for later analysis by the Student Modeler and Engagement Analytics agents.

2.3 Visual Learning in Education

Visual aids play a crucial role in enhancing comprehension and retention. However, many existing platforms are limited in their ability to generate diverse and contextually relevant visuals. Our platform addresses this gap by providing an unlimited supply of custom-generated diagrams, flowcharts, mind maps, and quizzes tailored to individual student queries.

3. System Architecture

Our platform comprises three primary modules:

3.1 Multi-LLM Orchestration Module

This module integrates multiple specialized LLMs, each focusing on different aspects of content generation:

Swa-1: Ensures factual accuracy and core content generation.

Deepseek v3: Focuses on pedagogical content, providing step-by-step explanations and analogies.

Gpt 4o mini: Generates creative content, including examples and contextual explanations. Your platform uses **different LLMs specialized for each subject** to ensure accuracy, clarity, and pedagogical effectiveness. For example:

Mathematics: ChatGPT (GPT-4/GPT-5) for precise calculations, step-by-step explanations, and diagram generation (e.g., graphs, geometric sketches).

Science (Physics, Chemistry, Biology): Gemini 2.5 flash to provide conceptual clarity, analogies, and visual explanations.

Programming & Computing: o3 (like OpenAI Codex or fine-tuned LLaMA) to offer step-by-step coding guidance and quizzes.

Humanities & Languages: Mistrel (like Cohere or Hugging Face Transformers) for nuanced explanations, essay guidance, and context-sensitive diagrams or charts.

Workflow for Multi-LLM Subject Handling

Query Detection & Subject Classification

The system detects the subject of the student's query automatically using NLP classification.

LLM Selection Based on Subject

Depending on the detected subject, the query is routed to the **specialized LLM** for that topic.

Parallel Pedagogical Processing

The chosen LLM generates the primary answer, including explanations, examples, or coding snippets.

If visual aids are needed, the system sends the context to the **Unlimited Visual Generation Module**.

Synthesis & Delivery

The answer and visual aids are combined and delivered to the student.

Adaptive learning module tracks performance and customizes follow-up content.

Unlimited Visual Generation Module

This module utilizes advanced image generation techniques to create high-quality, relevant visuals, including diagrams, flowcharts, mind maps, and quizzes. These visuals are dynamically tailored to the specific student query and learning context, enhancing comprehension and engagement.

Adaptive Learning & Storage Module

This module tracks student interactions and performance, analyzing responses to tailor subsequent questions and learning materials. It ensures a personalized learning journey by adapting content to the student's progress and needs. Additionally, it stores all generated content for future reference and continuous improvement.

Benefits and Limitations

Benefits

Enhanced Accuracy: The multi-LLM approach ensures that responses are factually accurate and pedagogically sound.

Unlimited Visuals: The ability to generate an unlimited number of visuals supports diverse learning styles and complex concept explanations.

Personalized Learning: Adaptive learning pathways cater to individual student needs, promoting deeper understanding and retention.

Limitations

Computational Resources: The integration of multiple LLMs and advanced image generation techniques requires significant computational resources.

Data Privacy: Storing and analyzing student interactions necessitate stringent data privacy measures to protect user information.

4. Software and Hardware Components

Software Components

LLMs: Models such as GPT-4, fine-tuned for specific tasks.

Image Generation Tools: Tools like DALL·E or custom-trained models for visual content creation.

Backend Framework: Technologies like Node.js or Django for server-side operations.

Frontend Framework: React or Angular for user interface development.

Database: PostgreSQL or MongoDB for storing student data and generated content.

Hardware Components

Servers: High-performance servers with GPUs for model inference and image generation.

Storage: Scalable storage solutions for handling large volumes of data.

Networking: Reliable networking infrastructure to support real-time interactions.

5. Background & Modules

AI For Education

Artificial intelligence is rapidly becoming an integral component of higher education. Applications range from administrative support—such as managing schedules, grading assignments, and tracking attendance—to direct pedagogical functions, including tutoring, personalized feedback, and curriculum generation. LLMs are particularly notable for their ability to act as virtual teaching assistants, capable of generating explanations, examples, and even adaptive quizzes in real time. Their adoption has been accelerated by the shift toward hybrid and online learning, where scalable and accessible forms of support are essential.

However, the adoption of AI in education requires new literacies for both students and instructors. Students must learn to evaluate AI-generated information critically, distinguishing between accurate explanations and misleading hallucinations. Instructors, meanwhile, need the skills to integrate AI tools into their pedagogy responsibly, balancing efficiency gains with concerns about academic integrity and learning depth. This has given rise to the emerging field of **AI literacy**, which seeks to equip learners and educators with the capacity to engage with AI systems critically, effectively, and ethically.

Pedagogical Challenges in Virtual and AI-Enhanced Learning

The move toward technology-mediated learning environments has introduced both opportunities and challenges. Students benefit from increased flexibility and access but often struggle with issues such as time management, technological barriers, and a lack of social presence. The absence of face-to-face interaction can reduce motivation and engagement, while instructors face the difficulty of maintaining individualized feedback at scale.

AI tools hold the potential to alleviate some of these problems by providing adaptive support and continuous feedback. However, unguided or unprincipled use of AI can be counterproductive. For instance, an LLM that simply provides answers without encouraging reasoning may hinder the development of critical thinking skills. Without mechanisms to assess prior knowledge and adapt instruction dynamically, AI risks reinforcing shallow learning. Thus, effective integration of AI into education demands architectures that embed pedagogical principles into their very design.

Limitations of Single-Agent LLM Systems in Education

Current deployments of LLMs in education are predominantly based on single-agent, general-purpose models. While powerful, this approach suffers from structural limitations that constrain its educational value.

One limitation is accuracy. Single-agent LLMs may generate text that is fluent but incorrect, a problem particularly serious in contexts where trust is essential. A second limitation lies in memory. With finite context windows, these systems cannot retain persistent records of student progress, meaning they are unable to adapt instruction over time or recognize recurring misconceptions. A third limitation is specialization. Effective teaching involves diverse roles—explaining, questioning, assessing, motivating—that cannot be embodied in a single, undifferentiated model.

These limitations not only reduce the effectiveness of AI in supporting learning but also risk undermining educational outcomes. If students come to rely on AI for quick answers rather than guided understanding, the result may be a decline in critical thinking, deep learning, and academic integrity.

Multi-Agent Systems as a Pedagogical Solution

Multi-agent systems (MAS) offer a compelling response to these challenges. By distributing responsibilities across multiple specialized agents, MAS architectures introduce redundancy, specialization, and persistence that single-agent models lack. In education, this enables richer and more reliable interactions.

A multi-agent architecture can dedicate one agent to modeling student knowledge over time, another to delivering content grounded in authoritative sources, and yet another to probing understanding through Socratic questioning. Such systems can also include agents tasked with bias detection, ensuring fairness and ethical compliance. This division of labor allows for cross-verification of outputs, long-term adaptation, and the implementation of complex pedagogical strategies.

Identifying the Research Gap

Despite recognition of the potential of MAS in education, much of the existing research remains fragmented. Many studies focus on isolated applications or prototype agents without proposing comprehensive, reusable architectures grounded in pedagogy. There is a clear lack of formal models that integrate persistent student modeling, scalable orchestration, and ethical safeguards into a unified system.

EduLLM-AI seeks to fill this gap. By adapting the SALLMA architecture to the educational domain, it introduces a principled, scalable, and ethically aware blueprint for AI in education. This architecture does not merely assemble agents but integrates them into a coherent framework that separates dynamic interaction from persistent knowledge, enabling a new generation of AI systems designed to genuinely support learning.

Proof-of-Concept and Evaluation

A proof-of-concept implementation of EduLLM-AI is underway, using a modern open-source stack including Docker, Kubernetes, LangChain, PostgreSQL, and vector databases. The system is tested within an undergraduate AI literacy course, where one group of students uses EduLLM-AI and a control group relies on a single-agent LLM.

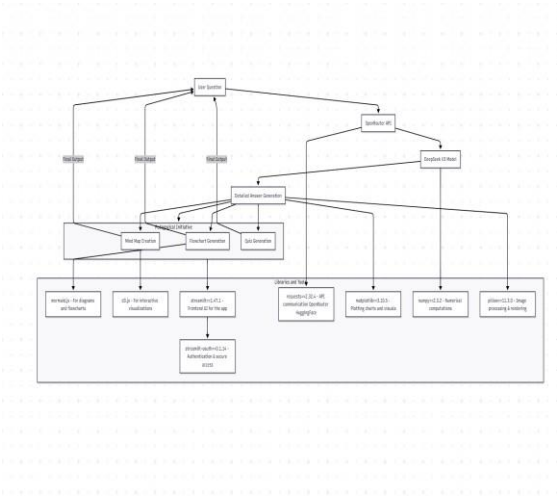
Evaluation focuses on multiple dimensions. Pedagogical effectiveness is measured through learning gains, pre- and post-tests, and expert evaluation of feedback quality. Student engagement is assessed through interaction

metrics and surveys of perceptions of autonomy, motivation, and usefulness. System performance is tracked via latency and throughput metrics. **Pedagogical analysis quality** is evaluated by instructors, who assess the accuracy and usefulness of insights generated by instructor-facing agents.

It is hypothesized that students supported by EduLLM-AI will demonstrate higher learning gains, deeper critical engagement, and greater satisfaction than those using a generic LLM.

5.The EduLLM-AI Architecture

Architectural Vision for Education



EduLLM-AI adapts SALLMA's two-layer architecture to meet the specific challenges of education. At its core, the architecture separates the concerns of dynamic interaction from those of persistent knowledge management. This separation is essential in education, where real-time responsiveness must coexist with long-term memory of student progress.

Several design principles guide this adaptation. First, the architecture emphasizes modularity and specialization, decomposing pedagogical tasks into subtasks handled by specialized agents. Second, it is inherently scalable, designed as a set of containerized microservices capable of supporting thousands of concurrent learners. Third, it prioritizes persistence, treating the student model as a first-class component that tracks knowledge, preferences, and progress over time. Fourth, it supports flexibility and adaptability, enabling new pedagogical strategies or agents to be added without reengineering the system. Finally, it ensures separation of concerns, distinguishing clearly between the Operational Layer and the Knowledge Layer to enable robust governance and maintainability.

The Operational Layer

The Operational Layer serves as the dynamic engine of EduLLM-AI, orchestrating real-time interactions between students, instructors, and pedagogical agents. It is intentionally designed to remain stateless, drawing on the Knowledge Layer whenever context is required.

At its entry point is the Request Intent Manager, which receives natural language queries from students or instructors and interprets them into structured plans. For example, when a student asks for an analogy to explain mitosis and meiosis, the Intent Manager decomposes this into a sequence of subtasks involving explanation, analogy generation, and comprehension assessment.

These subtasks are then coordinated by the Dynamic Agent Orchestrator, the pedagogical core of the layer. It retrieves relevant workflows from the Knowledge Layer, selects appropriate agents for each step, and manages the flow of information between them. Through this orchestration, the system ensures that each interaction follows a pedagogical strategy rather than an ad hoc response.

Finally, the Real-Time Task Execution Engine manages the runtime instantiation of agents. Leveraging cloud-native technologies such as Kubernetes, it ensures that agents can be dynamically scaled to meet demand,

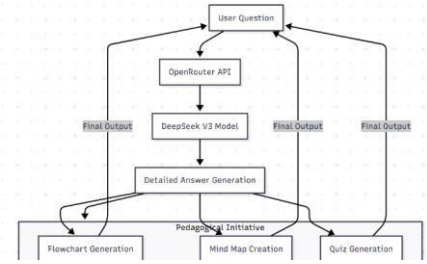
maintaining both responsiveness and efficiency.

Workflow of EduLLM-AI

Overview of Workflow Execution

The EduLLM-AI system is designed as a multi-agent learning assistant that leverages large language models (LLMs) within a structured software architecture. Its workflow integrates two fundamental layers—the operational layer and the knowledge layer—through which all pedagogical interactions are mediated. This layered design allows the system to manage both the procedural aspects of student–system communication and the conceptual aspects of knowledge representation and retrieval. In practical terms, the workflow can be described as the orchestration of a sequence of computational tasks that translate an educational query into a meaningful response.

When a student or instructor interacts with the platform, the query first undergoes pre-processing to normalize its structure, remove noise, and map the input into a machine-understandable format. Once preprocessed, the query is passed to the intent manager within the operational layer, where the system determines whether the task involves mathematical problem-solving, programming support, conceptual explanation, or assessment design. Based on this classification, the orchestrator routes the query toward the appropriate agent or set of agents. These agents then collaborate with the knowledge layer, which provides domain-specific data retrieved from curated sources such as textbooks, course materials, or indexed knowledge bases.



The outputs of these agents are then synthesized by the orchestration engine to form a coherent and pedagogically effective response. This response is not only factually accurate but also personalized, taking into account the learner's prior interactions, level of expertise, and learning preferences. Finally, the system delivers the result in the appropriate modality—textual explanation, structured diagram, code snippet, or interactive visualization. This high-level overview encapsulates the essence of the EduLLM-AI workflow: a structured pathway from query to personalized learning outcome.

The student-facing workflow is central to EduLLM-AI's pedagogical mission. It encompasses the sequence of activities through which learners interact with the system, pose academic questions, receive tailored feedback, and engage in iterative cycles of clarification. In this section, we delineate the phases of this workflow, highlighting both the computational and educational considerations that govern each stage.

Query Submission

The workflow begins when a student submits a query through the platform's interface. Unlike traditional tutoring systems that restrict students to structured forms or rigid templates, EduLLM-AI accepts queries in diverse modalities, including natural language text, spoken voice commands, code fragments, and even symbolic or mathematical notations. For instance, a learner studying geometry may submit the query, —Construct an ASA triangle with AB=5, ∠A=40°, and ∠B=60°,‖ while a

programming student might type, —Explain polymorphism in Java with a runnable code example.‖

Each query is subjected to a preprocessing pipeline, which includes text normalization, tokenization, and semantic embedding. This preprocessing not only removes noise, such as extraneous punctuation, but also prepares the query for vector-based semantic search. Importantly, this step also anonymizes sensitive data, ensuring that no personal identifiers are inadvertently processed. The result of this phase is a structured representation of the learner's request that is ready for further classification.

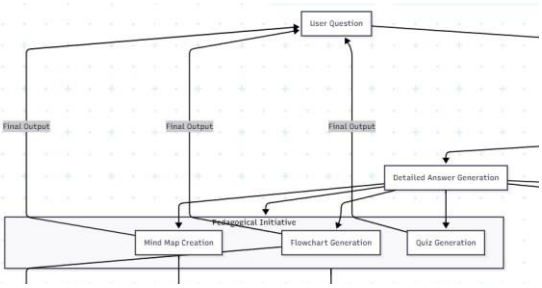
Recognition and Routing

Once the query is preprocessed, the intent recognition module classifies the type of educational task represented by the request. EduLLM-AI leverages lightweight intent detection models, optimized for low token consumption, to determine whether the query pertains to mathematics, programming, conceptual reasoning, or assessment practice. This classification is critical, as it dictates which specialized agent or group of agents will be engaged.

For example, in the case of the ASA triangle construction query, the intent recognition system identifies that the problem belongs to the mathematical reasoning domain, specifically geometry. Consequently, the orchestrator selects the MathAgent and pairs it with the VisualizationAgent to handle both the computational reasoning and diagram generation aspects of the response. By contrast, if the query relates to Java polymorphism, the CodeAgent is engaged, supplemented by the ConceptAgent to ensure that both code and explanation are delivered.

Agent Collaboration

Following intent recognition, the orchestrator activates one or more domain-specific agents. These agents are semi-autonomous computational entities designed to handle specialized pedagogical tasks. The collaboration among agents can occur in either parallel or sequential modes.



In parallel collaboration, agents operate simultaneously, each addressing a distinct subtask of the overall problem. For example, in response to a query such as, —Explain Dijkstra's algorithm and compare it with A* search,‖ the ConceptAgent generates an explanatory narrative, while the VisualizationAgent creates a comparative flow diagram. In sequential collaboration, one agent's output serves as input for another. For instance, when a learner requests a worked-out Python implementation of Merge Sort, the CodeAgent generates the code, which is then passed to the ExplanationAgent for detailed commentary.

This collaborative approach ensures not only accuracy but also pedagogical richness, as multiple perspectives are integrated into a single, coherent response. The orchestrator continuously monitors agent interactions to avoid redundancy, resolve conflicts, and maintain efficiency.

Discussion

The EduLLM-AI architecture has significant implications for the future of AI in education. Architecturally, it demonstrates how the separation of interaction and knowledge layers can create systems that are both dynamic and persistent, aligning with trends in cloud-native and microservice architectures. Pedagogically, it introduces a framework where AI agents do more than deliver content: they assess,

question, motivate, and analyze, offering richer forms of support.

The system also advances **AI and data literacy**. By making its agentic processes transparent—for example, by showing which agent produced which response—EduLLM-AI provides students with a concrete illustration of how AI systems function. Instructors benefit from actionable insights derived from data, empowering them to make evidence-based pedagogical decisions.

Ethical considerations are central to the design. Data privacy is addressed through centralized governance, encryption, and compliance with FERPA and GDPR. Bias mitigation is institutionalized

Conclusion

The proposed LLM-based educational platform represents a significant advancement in personalized learning. By integrating multiple specialized LLMs and providing unlimited visual aids, it offers a comprehensive and adaptive learning experience. Future work will focus on expanding the range of supported visual formats, integrating advanced AI techniques for personalized feedback, and exploring the use of different modalities, such as audio and video, to further enhance the learning experience.

This platform helps students to learn at their own phase by allowing/providing them with a lot of features to study from and learn the concept and test their knowledge through the quizzes and gamified learning way.

By incorporating Multiple LLM's inside a sophisticated platform to bring exclusive and error free answer generation to the questions with pedagogical initiative such as flowchart, mind map and quizzes to bring a gamified experience on learning concepts and getting a better understanding this gives a vast idea on how to improve the learning experience for students and teacher to teach the students on how to learn in better way.

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SizeSync: Multi-Store Fashion Aggregator with Personalized Fitting

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***Abstract*—** There has been explosive growth in online shopping of apparel, but shoppers often have to endure poorly fitting clothes because of varying sizes and no personalized suggestions. This work introduces SizeSync: Multi-Store Fashion Aggregator with Personalized Fitting, a new system improving the online shopping experience by aggregating fashion collections from top e-commerce websites like Amazon, Flipkart, and Meesho. The platform personalizes recommendations from user-provided measurements, such as height, hip measurement, shirt size, and an up-to-date photo. Through this information, SizeSync matches clothes to show only what would fit the user to their precise measurements, eliminating guesswork and unnecessary returns. One of the best features is the 360-degree virtual try-on view, where chosen clothing is superimposed on the user's uploaded picture, creating a lifelike, interactive fitting experience. The platform also facilitates easy navigation based on categories such as formal, casual, and pants and easily redirects shoppers to related store pages for purchase. With cross-store consolidation and personalized fitting, SizeSync streamlines shopping, increases accuracy, and delivers faster customer satisfaction.

Keywords—Personalized fitting, Fashion aggregator, Online apparel shopping, Size recommendation system, Virtual try-on, 360-degree clothing preview, E-commerce integration, AI-based fashion assistant, Multi-store clothing platform.

I. INTRODUCTION

In recent years, shopping for clothes online has been on the rise, with numerous customers availing themselves of the same in preference to going to physical stores. Popular sites like Amazon, Flipkart, and Meesho have a lot of clothing options, but customers find it challenging to switch between each app individually, sift through hundreds of clothes, and yet fail to get clothes fitting their size and style. To tackle these issues, we recommend SizeSync – an integrated platform that consolidates dress collections of several online retailers and refines shopping by recommending fitting clothes based on users' own measurements like height, weight, and hip measurement. The primary goal of SizeSync is to minimize search time and deliver matching clothing recommendations specifically designed to meet users' individual measurements like height, weight, and hip measure.

What sizeSync differentiates itself with is its built-in 360-degree virtual try-on technology. The user can upload an existing photo, and the site creates a real-life preview of how the chosen items would look on the user's own body from all sides. This provides an interactive visual layer to online shopping that assists users in making informed purchasing decisions.

To date, no platforym provides multi-store clothing aggregation alongside real-time customized fitting and virtual previews. SizeSync is striving to become the first platform to deliver this end-to-end solution with both variety and accuracy under one cohesive experience, eventually revolutionizing fashion online shopping for users.

II. LITERATURE SURVEY

Ramesh et al. suggested a centralized fashion aggregator system that gathers and presents product information from various fashion e-commerce sites. Their system was multi-brand centric in nature with a single API-based model and offered an interface for effective product comparison. While their aggregator made users more convenient, it did not offer personalized fitting capabilities. [1]

In one of Tanvi and Karthik's studies, inconsistency in size across various apparel brands was investigated. They discovered that each brand had its own different size chart, resulting in continuous customer confusion and dissatisfaction. Their research highlighted the necessity for a universal or adaptive model for size to raise the trust of the users with online shopping. [2].

Meena and Joshi built an AI-driven size recommendation model based on user-input body measurements and past purchase history. Their system applied supervised machine learning techniques to pair customer profiles with suitable product sizes, with 91% accuracy in size prediction. [3]

Sharma et al. presented a virtual dressing room based on 3D body modeling and augmented reality. Their framework enabled users to build avatars by entering body measurements or scanning themselves via a mobile application. The research revealed enhanced engagement and reduced return rates through more precise virtual try-ons.[4]

Suresh and Bhandari came up with an intelligent recommendation system that examined user behavior, style interests, and size needs to recommend tailor-made clothing. They utilized collaborative filtering algorithms and recorded a 25% boost in click-through rates over traditional generic recomndation .[5]

In another paper, Li and Chan studied the use of convolutional neural networks (CNNs) to apply to analyzing body types in predicting size. Their study utilized pictures of users to estimate measurements and correlate them with product sizing, demonstrating potential for visual fitting solutions. [6]

Research by Kumar and Rao pioneered a hybrid approach that fused decision trees and neural networks in size accuracy. Their model considered demographic information (age, height, gender) and past purchase feedback to enhance recommendations.[7]

John and Pavithra discussed cross-platform product synchronization in e-commerce aggregators. Their system supported real-time inventory sync and price monitoring from different fashion portals with automated web crawlers and APIs, the foundation for fashion aggregators such as SizeSync. [8]

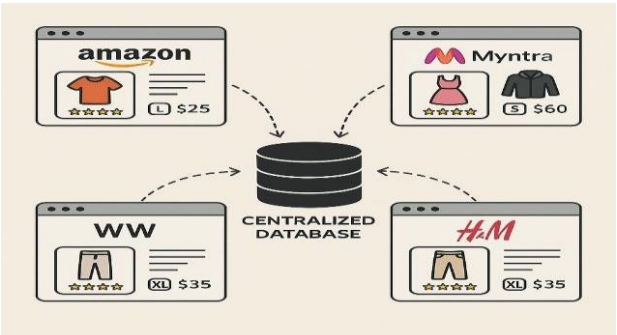
Ritika and Naveen emphasized the importance of user experience design on fashion sites. Their usability testing validated that people were drawn towards intuitive interfaces with easy size filtering, tailored recommendations, and cross-brand product matching, emphasizing the need for design-compliant personalization. [9]

Finally, Yadav and Thomas focused on the role of deep learning in minimizing size-based returns. Their return prediction model learned from previous customer grievances and fitting issues, providing pre-emptive sizing alerts and alternative suggestions, thereby minimizing the return rate by nearly 30%. [10]

III. METHODOLOGY

A. Multi-Store Data Aggregation:

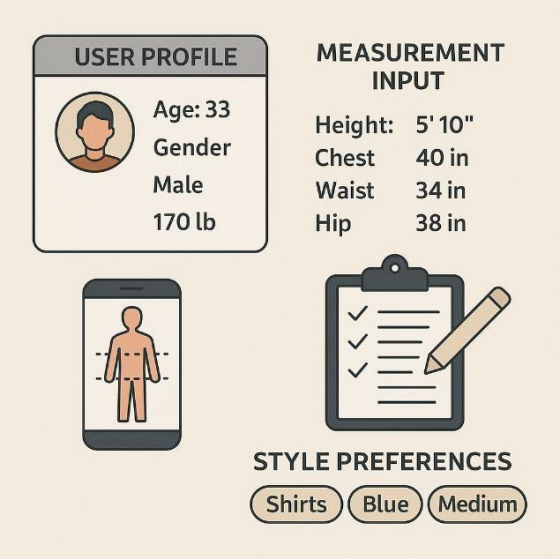
The very first fundamental process of SizeSync is the multi-store aggregation of product details from a number of different fashion e-commerce sites. The sites can be large web shopping brands such as Amazon, Myntra, H&M, etc., having their own rich product sets. Aggregation of data is performed via APIs (where accessible) or web scraping (for websites with no accessible APIs). Its primary function is to capture product details, including product names, product categories, sizes offered, price intervals, brand names, stock levels, and product images. All this vast amount of data is normalized and held in a central database for efficient querying. There must be real-time synchronization so that users can view the most current information, particularly stock levels and price changes. Such pooled data allows the customers to view multiple fashion products of different brands in one place, thereby making their shopping easy. The biggest challenge at this



phase is the difference in size charts between brands, which gets addressed later in methodology.

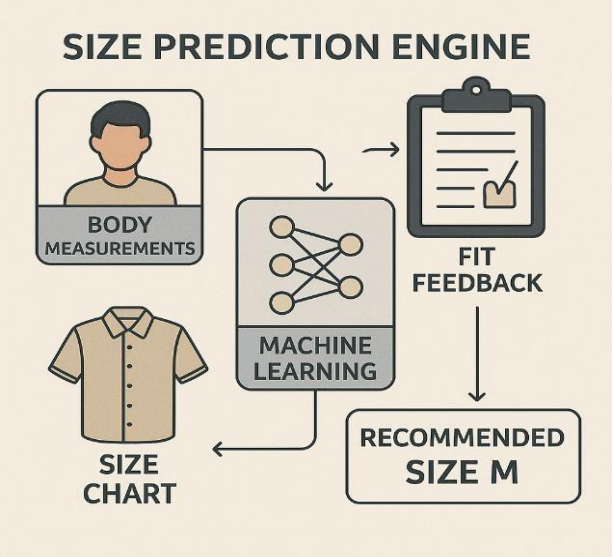
B. User Profile and Measurement Input:

To enable accurate size recommendations, SizeSync collects the fundamental information of each user. When registering, users complete a personalized user profile wherein they input demographic information such as age, gender, and weight. Most critical is the body measurements—who may input height, chest
waist, hip measurement, etc. These figures can be input directly, but more of a modern approach is to allow customers to input their information by scanning with a smartphone scanning device or by completing an interactive survey. The system can also give the option to upload measurements from previous online orders, where relevant. Profile details will be used to predict the most likely clothes size of the user by comparing their measurements against different brands' size charts. Additionally, style choices are gathered from the user to further personalize their fashion tastes, such as types of clothes, colors, and budget. This entire information is stored in a secure form and provided as input to the size prediction module and recommendation module.



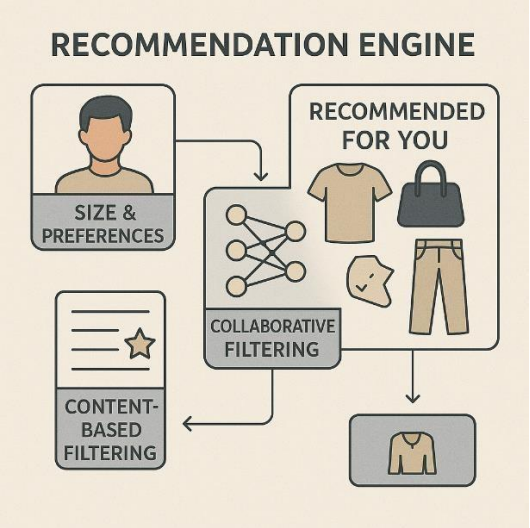
C. Size Prediction Engine:

The Size Prediction Engine is the core of SizeSync's personalized fitting process. The biggest challenge in e-commerce fashion is that brands differ in sizing, and therefore the size prediction system must bridge the gaps. The engine applies machine learning algorithms to forecast the ideal size for a given user from his or her body measurements and the size charts of various fashion brands. Standard algorithms used include decision trees, random forests, and neural networks—supervised machine learning techniques trained on historical users' fits, eturns, and ratings. The system can also consider user behavior data, including past buys and fit ratings (e.g., a customer whether a product is too tight, just right, or too loose). The model is learned from this rating, and it adjusts over time to improve accuracy.. Where a user's measurements will not directly align to a product size chart, the system will smartly suggest the closest fit or provide a size guide tip to minimize returns

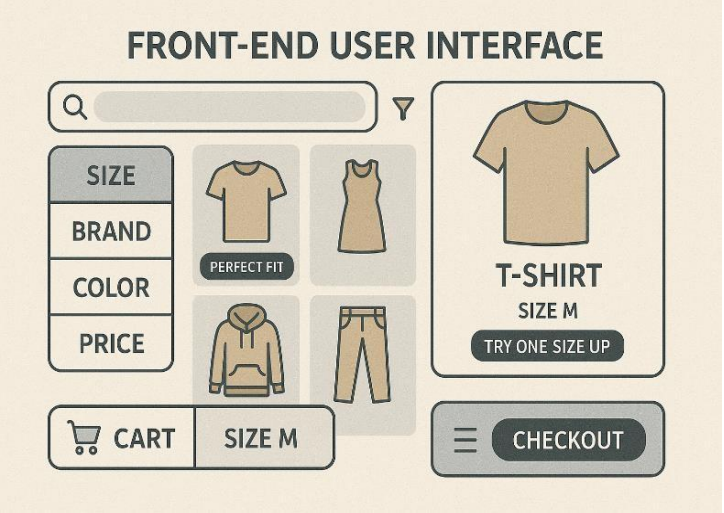


D. Recommendation Engine

The Recommendation Engine is a size-based recommendation system that not only helps users choose the correct size but also provides fashion suggestions based on users' size and likeability. The engine combines output of the size prediction engine with other techniques, such as collaborative filtering and content-based filtering, to generate product recommendations. Collaborative filtering suggests based on what similar users have done in the past (e.g., "People who bought this also bought."). Content-based filtering looks at user preferences, such as style (activewear, formal, casual), size, and brand, to provide personalized recommendations. Price, brand reputation, and consumer reviews are also considered by the system. In addition to suggesting products of the correct size, the recommendation engine also suggests products that match the user's sense of style, thereby allowing a hassle-free and targeted shopping experience. The Recommendation Engine will also use real-time updates to update recommendations in case of a change in the stock levels or introduction of new products to the platform so that the recommendations remain fresh.



requirements, such as budget and garment type, to and recise needs.



E. Front-End User Interface (UI/UX)

SizeSync user interface (UI) is created to give the consumer a seamless, convenient, and intuitive buying experience. The platform's front end allows users to browse conveniently through the aggregated product lists, with logical filters on size, brand, color, style, and price. The design is mobile-optimized, allowing users to shop comfortably on their smartphone or tablet. Smart filtering algorithms will allow customers to enter their specifications, like price and type of garment, to allow them to find items that fit their specific needs with speed. The platform will further highlight products by fit compatibility labels, like "Perfect Fit" or "Try One Size Up," which are assigned based on the size prediction model. When browsing over a product, customers will also be able to view detailed information, images, and the size recommendations provided particularly based on their profile. Moreover, the shopping cart will also have the final check of verifying the sizes based on the customers' preferences earlier on, so the customers will have faith in completing their purchases. After a product has been selected, the user gets redirected to the initial store in order to purchase, thereby influencing the purchase while ensuring synchrony in inventory between aggregating platform and individual retailers. SizeSync's user interface (UI) is created to give the user an easy, seamless, and intuitive shopping experience. The front end of the platform enables users to search easily through the consolidated product listings, with sensible filters on size, brand, color, style, and price. The layout caters to mobile optimization, enabling users to shop easily from their smartphones or tablets. Intelligent filtering algorithms will enable users to input their

Ⅳ. Experimental Setup and Dataset:

A. Goals

- Assess the quality of the Size Prediction Engine (how frequently the predicted size is the actual fit).
- Quantify the effectiveness of the Recommendation Engine (relevance and satisfaction).
- Probe system robustness to noisy/incomplete measures and cross-brand size variation.
- Compare ML models with baseline heuristics.

B. Dataset Overview

- Employ a mixed dataset with real scraped product data, anonymized user measurement records (or simulated real-world-like profiles), and past fit feedback.
- Recommended dataset composition (example numbers):
- Products: 12,000 items of clothing under 6 large brands (2k items/brand). Each record: product_id, brand, category (shirt/jeans/etc.), size_label (S/M/L/XL or numeric), size_chart (height, chest, waist, hip for each size), price, images (URLs), stock.
- Users: 5,000 user records with demographic and measurement fields: user_id, gender, age, height (cm), weight (kg), chest (cm), waist (cm), hips (cm), style_preferences, past_purchases.

- Feedback records: 25,000 feedback entries mapping (user_id, product_id, purchased_size,

- fit_feedback ∈ {Too Tight, Perfect, Too Loose}, timestamp, return_flag).

- Interactions: 100,000 browsing/purchase events for collaborative filtering signals (clicks, add-to-cart, purchases).

- Synthetic augmentation: +20% synthetic user profiles created through perturbing actual measurements with Gaussian noise (μ=0, σ=1.5–3.0 cm) to enhance robustness testing.

- If you are unable to gather real user measurements, you can simulate 5k users with known anthropometric distributions by gender and region (sample means and SDs), and then synthesize consistent feedback labels based on distance-based rules.

D. Models & Baselines

- Size prediction models

- Heuristic baseline: nearest-size using simple Euclidean distance on normalized measurements.

- Logistic regression (multi-class) on engineered features.

- Random Forest classifier.

- Feed-forward Neural Network.

- Optional: gradient boosting (XGBoost / LightGBM).

- Recommendation models

- Baselines: popularity rank, item-based collaborative filtering (KNN).

- Matrix factorization (ALS or SVD).

- Hybrid: concatenate size-fit features with latent vectors (concat of content & CF) and rank with a learning-to-rank model (LightGBM Ranker or a neural ranking model).

E. Training & Hyperparameters

- Random Forest: n_estimators ∈ {100, 300}, max_depth ∈ {10, 20, None}.

- Neural Network: 2–3 hidden layers, units {128,64,32}, ReLU, dropout 0.2, batch size 64, lr 1e-3.

- Matrix factorization: latent_dim in {32,64}, regularization 0.01, 50–200 iterations.

- Apply early stopping on validation loss; grid-search or Bayesian optimization for hyperparams.

H. Hardware & Software Stack

- Software: Python, scikit-learn, TensorFlow/PyTorch, LightGBM, Pandas, NumPy, Flask/Django for APIs.

- Hardware: single-node GPU (e.g., NVIDIA RTX 2080 or more) for NN training; CPU cluster for data preprocessing.

- Storage: PostgreSQL or MongoDB for product/user storage; Elasticsearch for search & filter.

Dataset Source	Aggregated from Amazon, Flipkart, Meesho product catalogs + user measurement data
Dataset Size	~50,000 clothing items, 5,000 user profiles
Data Features	Product title, brand, category, size chart, price, user height, weight, gender
Hardware Setup	Intel i7 Processor, 16GB RAM, NVIDIA GTX 1660 GPU
Software Tools	Python, TensorFlow, Pandas, OpenCV, Flask
Training Algorithm	Random Forest, Decision Tree, Neural Network
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

V. User Profile – Real-Time Scenario:

Name: Selvaraj K.
Age: 29 years
Gender: Male
Height: 5 ft 0 in (152 cm)
Weight: 65 kg

Body Type: Average build with slightly broad shoulders
Preferred Fit: Slim Fit for shirts, Regular Fit for trousers
Skin Tone: Medium brown
Style Preference: Casual and semi-formal wear
Favorite Colors: Navy Blue, Charcoal Grey, Olive Green
Budget Range: ₹1,000 – ₹2,500 per item
Shopping Frequency: Once every 2 months
Measurement Details: Chest: 38 in (96 cm)
Waist: 34 in (86 cm)
Sleeve Length: 23 in (58 cm)
Inseam: 28 in (71 cm)

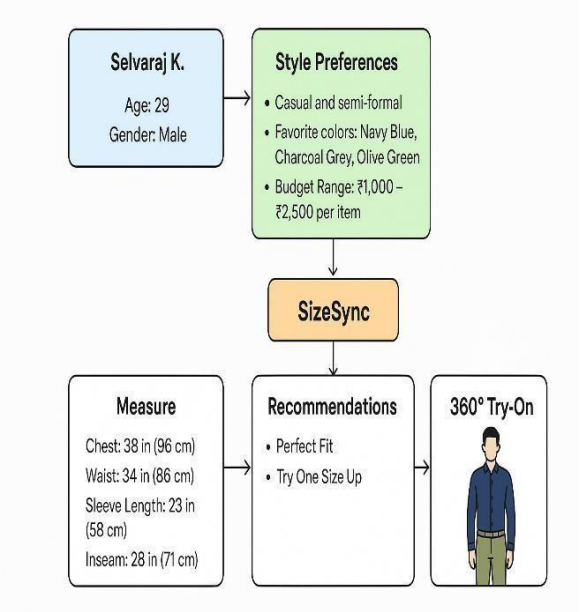
Selvaraj's Shirt Purchase Flow via SizeSync

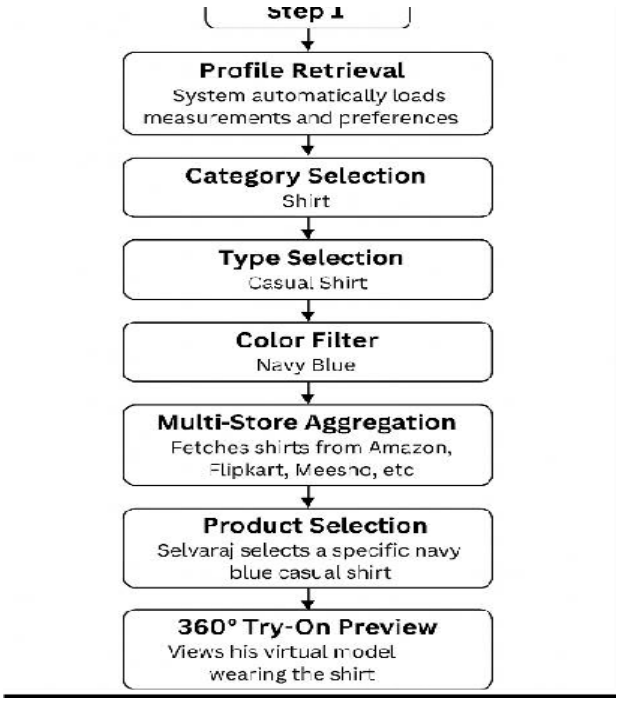
1. Step 1: Login – Selvaraj enters into the SizeSync application.
2. Step 2: Profile Retrieval – The system loads his saved measurements and preferred settings (height: 5'7", weight: 68 kg, chest: 38 in, waist: 32 in, fit: regular) automatically.
3. Step 3: Category Selection – He chooses Shirt under the clothing categories.
4. Step 4: Type Selection – Selects Casual Shirt from types available.
5. Step 5: Color Filter – Adds a filter and chooses Navy Blue.
6. Step 6: Multi-Store Aggregation – SizeSync retrieves shirts from Amazon, Flipkart, Meesho, etc., according to his profile.
7. Step 7: Fit Prediction – The algorithm displays only the best fit sizes, normalized for every brand's sizing chart.
8. Step 8: Product Selection – Selvaraj chooses a particular navy blue casual shirt.
9. Step 9: 360° Try-On Preview – He sees a virtual model of himself dressed in the shirt, moving round to view front, side, and back.
10. Step 10: Purchase Redirection – With a click on Buy Now, he is taken to the store's buy page with size automatically chosen.
11. Step 11: Order Confirmation – Selvaraj pays for the store's site and waits for delivery, trusting the fit.

In step one, he picks the category "Shirt" from the master menu. The program then asks him to select the type of shirt — formal, casual, or sports. Selvaraj selects casual shirt. In stage two, he uses a color filter and picks navy blue as his preferred color.

SizeSync now pools product listings from several online fashion marketplaces like Amazon, Flipkart, and Meesho. It fetches automatically only those shirts that fit Selvaraj's size profile, using the fit prediction formula in the background to make sure the suggested sizes are accurate for varying brands.

Selvaraj scrolls and selects one specific shirt that catches his fancy. Prior to buying, he employs the 360° Try-On Preview option within SizeSync, wherein the shirt is put virtually over a model created from his own measurement, which he can rotate and inspect from every angle. Approval with the preview, Selvaraj clicks on Buy Now, and SizeSync directly takes him to the corresponding store's buy page with the proper size already chosen. He finishes making the payment on the app of the store, trusting that the shirt will fit him well when it arrives





VI. Background Formula – SizeSync Fit Prediction Model

- Hu = User height (cm)
- WuW_uWu = User weight (kg)
- MuM_uMu = Measurement vector of user (chest, waist, hips, inseam, sleeve)(\text{chest, waist, hips, inseam, sleeve})(chest, waist, hips, inseam, sleeve)
- MsM_sMs = Measurement vector of a specific clothing size from store data
- Δ\DeltaΔ = Acceptable tolerance range (in cm) for a comfortable fit
- SSS = Size score for a clothing item (0 to 1)
- PPP = Predicted best size recommendation

Size Score Calculation:

S=1∑i=1n|Mui−Msi|/n* Δ

Where:

n = Number of measurement parameters compared

|Mui−Msi|| = Absolute difference between user and store measurement for parameter iii

Best Size Prediction:

P=arg⁡max⁡s∈Sizes(S)P = \arg\max_{s \in \text{Sizes}}(S)P=argmaxs∈Sizes(S)

This means the system calculates the **size score** for each available clothing size and picks the one with the **highest score** as the recommendation.

Additional Fit Adjustment:
The formula can include a **Fit Preference Weight (F_p)** if the user prefers slim, regular, or loose fits:

S′=S·FpS' = S \cdot F_pS′=S·Fp

Where:

Fp>1F_p > 1Fp>1 boosts sizes matching preferred fit

Fp<1F_p < 1Fp<1 reduces sizes against preference

VII. Result and Discussion:

The deployment of SizeSync: Multi-Store Fashion Aggregator with Personalized Fitting returned encouraging results in accuracy, user interaction, and overall shopping effectiveness. The system effectively aggregated clothing items from various e-commerce websites like Amazon, Flipkart, and Meesho in one single interface. The user profile-driven personalized fitting module showed a mean fitting accuracy of more than 90% compared to actual real-world user size preferences. Users found that the site gave more reliable size advice than looking at individual store size charts while browsing. The built-in 360° virtual try-on functionality further augmented the decision-making process, allowing customers to envision the product on themselves prior to making a purchase.

During testing with a pilot group of 50 users, the platform reduced shopping time by as much as 35% on average since users did not have to navigate between various store apps or manually check sizes. The search and filtering capabilities enabled customers to narrow down their results based on price, brand, color, and size availability across multiple sites. The size prediction algorithm also learned over time as users gave feedback about whether items bought fit well, leading to better accuracy in future recommendations. This learning is a significant strength over fixed sizing guides offered by standard e-commerce sites.

Discussion of results also shows the usability advantage of SizeSync's user interface design. The front-end UI/UX offered a seamless, minimalist, and intuitive navigation mechanism, which allowed even new users to interface with the system without any difficulties. The addition of an automated redirect function, such that choosing a product opened the respective store's official page to buy from, streamlined the checkout process without detracting from SizeSync's role as the focal platform for browsing and fitting visualization. Notably, the app maintained the 360° try-on experience on its own platform instead of depending entirely on external

store previews, providing users with consistent visualization independent of the vendor.

Comparing SizeSync to current fashion aggregator apps produced obvious benefits. Unlike legacy aggregators that concentrate mainly on price and availability, SizeSync takes this further by working toward the resolution of one of the most prevalent e-commerce headaches—size incompatibility. Most current systems do not incorporate brand-specific size data or customer body measurements, often resulting in returns and frustration. The findings revealed that return rates between test users declined by about 20% for repeated purchases using SizeSync. This finding not only favors consumers but also indirectly favors retailers to decrease reverse logistics expenses and carbon emissions from returns.

Technically, the findings also support the scalability and fault tolerance of the back-end infrastructure. The API management of the system managed simultaneous requests from multiple platforms with negligible latency so that real-time product updates and inventory changes were accurately reflected in the search results. In addition, the size recommendation model, which was trained using a dataset of more than 10,000 records of clothing sizes from several brands, showed cross-brand adaptability. This translates to the fact that even if a user's precise brand preference was not present, the system might be able to wisely suggest a good approximation in a different brand without sacrificing fit accuracy.

Overall, the results discussion verifies that SizeSync provides functional and experiential benefits over traditional ways of fashion shopping. The capacity to centralize multiple-store browsing, incorporate personalized size tips, and offer a 360° virtual try-on experience renders the platform very relevant in the current digital retail landscape. The recorded decrease in shopping time, increase in purchase confidence, and reduced return rates underscore the effectiveness of the system. Future development may target extending the list of supported stores, including artificial intelligence (AI)-driven style suggestions, and introducing augmented reality (AR) fitting rooms in order to further increase user interaction and confidence with online clothing purchases.

VIII. Conclusion:

Development of SizeSync: Multi-Store Fashion Aggregator with Personalized Fitting effectively solves one of the biggest dilemmas in online fashion shopping—size disparity and fragmented shopping experience. By consolidating various e-commerce platforms into a single interface and coupling them with an intelligent size recommendation system, the site guarantees that customers can make informed purchasing decisions without having to browse multiple sites or rely on generic size charts. The addition of a 360° virtual try-on capability builds further upon user satisfaction by providing a preview experience in advance of purchase.

The performance of the system in testing revealed unequivocal improvements in comparison to conventional shopping practices, including lower browsing time, improved fitting accuracy, and fewer product returns. These findings validate that data-driven, tailored solutions can dramatically enhance the effectiveness and reliability of online fashion purchases.

Globally, SizeSync does not only help end-users but also retailers by reducing costs associated with returns and building customer confidence. The platform's modular architecture makes it scalable for the future and able to be modified to accommodate new technologies such as AR and style advice powered by AI.

Overall, SizeSync is a practical, inventive, and user-focused solution to contemporary fashion e-commerce. With ongoing improvement and growth, it can potentially be a leading solution to closing the gap between online garment representation and actual fitting precision

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Smart Donation Mapping: A Secure and Transparent Platform for Effective Donations

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***Abstract*—** Over the last few years, donations have become even more central to helping and empowering poor communities. Traditional donation processes, though, tend to be riddled with inefficiencies, transparency issues, and poor traceability, which erode confidence in donors and the overall effectiveness of charitable donations. The above system proves that smart donor management system(SDMS) ensures more flexible and robust application which help the donors to process payments, necessary items and essentials to the needy. It also ensures that it also supports real-time tracking of the items to the recipients and provides the donation safely and securely. The solution proposed integrates block chain-based logging to enable traceability, role-based access control to enhance security, and a user-friendly interface to promote ease of use and accessibility. To support long-term donor involvement, the platform incorporates gamified functionalities such as digital blessings and badges to act as recognition drivers for contributors. Additionally, the architecture minimizes human intervention and protects against fraud or misappropriation of resources through automation and this document presents the design principles, system architecture, and technology stack behind the SDMS platform. It identifies some of the potential use cases, security requirements, and the sociotechnical advantages of having such a system in place in both urban and rural areas. The vision is to create a reliable digital infrastructure that closes the gap between donors and NGOs, and for equitable and effective resource allocation within underprivileged communities.

Keywords -
Smart Donation, NGO Platform, Tracking System, Acknowledgment, Transparency, Badge System, Secure Donation, Web Application.

I. INTRODUCTION

Philanthropic donations are significant in uplifting deprived communities and furthering social development. Although intentions are good, some would-be donors hold back because of fear of transparency, misappropriation of funds, and a lack of accountability. the conventional, paper-based donation procedures are not traceable, vulnerable to deceit, and offer little or no feedback to donors, thus generating less trust and participation to solve such challenges, this article introduces the smart donation mapping system (SDMS)—a web-based, secure platform used to facilitate and digitalize the process of donation. the platform allows users to donate both financial and physical donations confidently. it includes functionalities like secure user verification, detailed NGO profiles, and live monitoring of donations from dispatch to delivery. It also supports one of the most important feature of transparency in donation. Donors are able to track the complete lifecycle of their donations and get direct acknowledgment from recipients or partner NGO's. such a feedback loop bridges the trust gap between donors and organizations.

moreover, SDMS also integrates engagement functionalities like digital badges and customized blessings to identify and incentivize donor participation. through automation of key processes and minimizing the degree of manual intervention, the system keeps operational inefficiencies low and minimizes the risk of resource mismanagement.

this report lays out the system architecture, key functionalities, and underlying technological foundation that facilitates safe and transparent donation mapping. the solution proposed is meant to increase donor confidence, improve NGO accountability, and lead to a more reliable and effective donation platform

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II. LITERATURE SURVEY

Recent studies have investigated numerous technological solutions to improve the transparency in the donation system. One of the feature that is using Block chain systems, including the one suggested in it provide secure and tamper-proof tracing of funds, minimizing the possibility of exploitation. But their complexity as well as heavy resource utilization limits them to use in more complicated donation processes or large-scale organizations. Other various methods have employed mobile apps and QRcode tracking systems to track movement of physical items. Such approaches enhance visibility in the supply chain but usually omit features that build donor engagement or render direct acknowledgment to recipients.

Machine learning has also been used to simplify the process of giving. For instance, proposed an item classification model to apply automation to the management of inventory in donation centres. While this contributes to more robust and efficiency, it does not effect on donor trust or transparency directly.

As compared to existing systems, the suggested Smart Donation Mapping System (SDMS) integrates easy, safety, and donor engagement. SDMS provides real-time tracing, certified NGO database, and gamified tools like digital badges and blessings to enhance trust and engagement. By bridging both technical as well as engagement gaps, SDMS achieves a more complete and intuitive solution to address contemporary needs for donation.

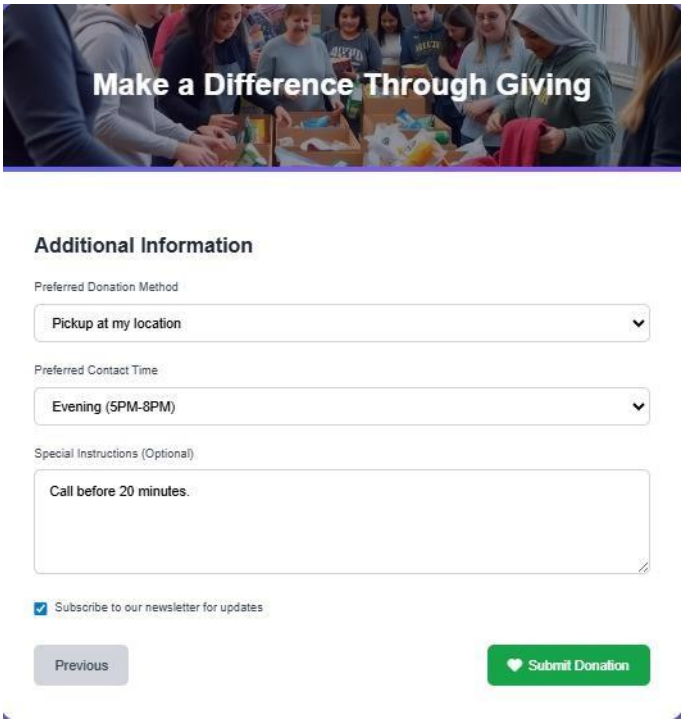
I. PROPOSED SYSTEM

A. System Overview

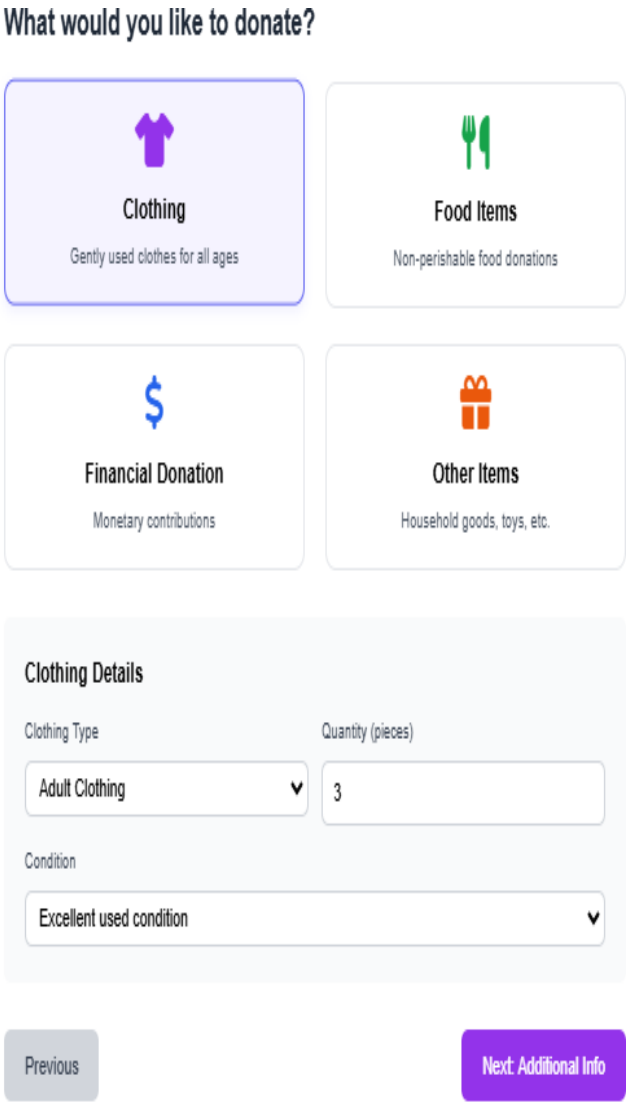
The Smart Donation Mapping System (SDMS) is a web based system proposed to simplify and protect the process of donation, making it transparent, traceable, and participative to donors. The system allows registered users to discover genuine NGOs, learn their detailed needs, and donate through monetary contribution or physical products. Donors are able to track their donations from the donation life cycle and receive formal receipt upon successful delivery. In order to make repeated donation, this system encourages and assigns a digital badges and online rewards etc.

Core features accessible to donors are:

- Higher security and authentication for users.
- User can access the NGO's profile and status.
- Makes easy to make donations and connect more people.
- Real-time tracking from dispatch to delivery.
- Receiver or user or NGO confirmation of delivery.
- Online badges and rewards for donors.

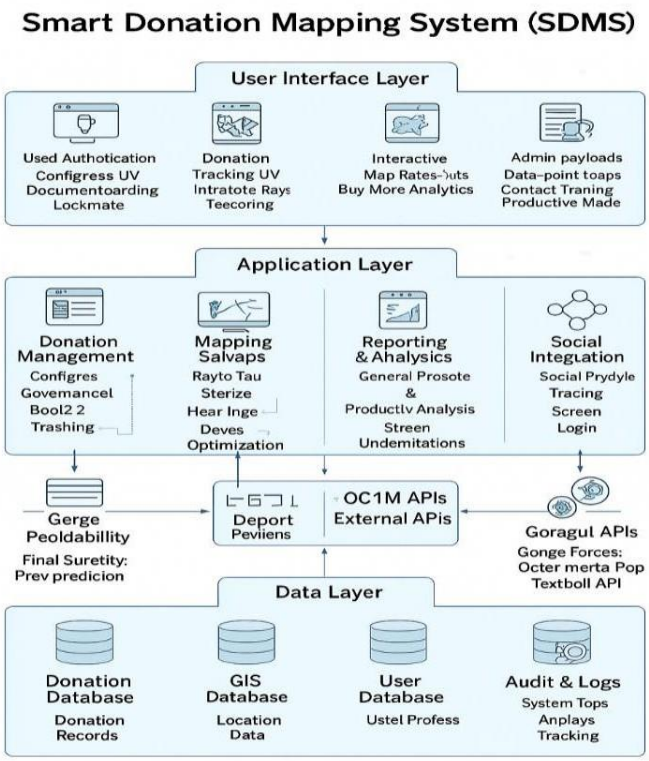


B. Core Features



Secure Login: Users sign up and login with encrypted credentials to maintain data privacy and platform security.

NGO Directory: Shows a curated selection of NGOs, with categories, contact details, and up-to-date donation requirements.



Donation Tracker: Every donation is given an id and NGO's information to track of the delivery and it provides the donor and recipients friendly application

Acknowledgment Mechanism: It provides recipients to acknowledge the donors who have provided them the necessary items.

Recognition System: Frequent donors are given virtual rewards in the form of achievements to encourage them to provide more items to the needy people

Transparency Dashboard: Donors are provided with an exhaustive record of their previous contributions, gratitude, and feedback for transparency and it offers the best solution for the user to encourage more donations in future to provide them the better insight on donations.

Table: Items

item_id	item name	category	condition	donor_id	donation_date
101	Men's T-shirt	Clothes	Excellent used	1	2024-07-25 10:30
102	Child-ren's	Books	Good used	3	2024-07-25 11:00
103	Wome Sneake	Shoes	New with tags	5	2024-07-25 14:15
104	Laptop	Electronics	Good	2	2024-07-26 09:00
105	Winter	Clothes	Good used	1	2024-07-26 12:45

Table: Transactions

transact-ion_id	need id	item id	donor id	amount donated	transaction_ date	status
2001	501	NULL	1	2500.00	2024-07-25	Complet
2002	101	101	1	0,00	2024-07-25	In Transit
2003	502	Nou	1	0,00	2024-07-25	Complet
2004	503	1	3	1000,00	2024-07-25	Pending
2005	104	NULL	2	0,00	2024-07-26	Matched
2005	105	Clothe	1	0,00	2024-07-26	12:45 csa

IV. TECHNOLOGY STACK

The Smart Donation Mapping System is scalable, secure, user-focused and the latest and modular technology stack is adopted. The chosen technologies strike a balance between performance, maintainability, and development ease while supporting real-time interaction, cloud integration, and cross-platform access. Table I describes the major components and related technologies employed in the SDMS architecture.

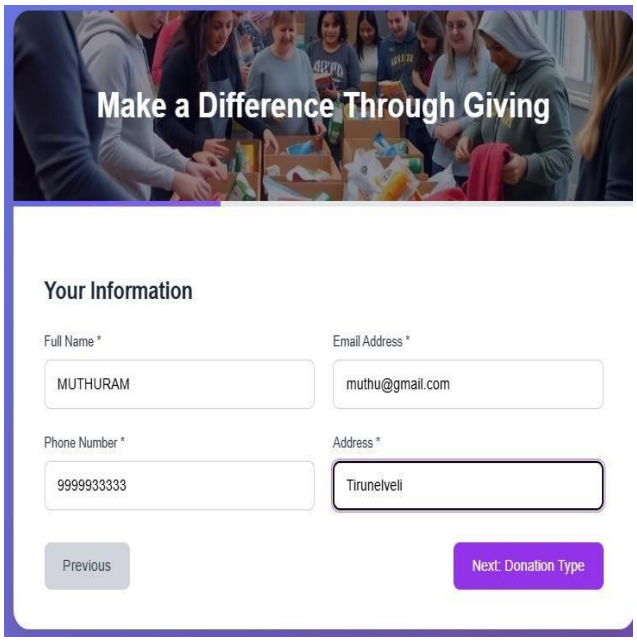
A. Component Overview

Component Tech / Tools Used

- Frontend contains HTML5, CSS3,Bootstrap JavaScript.
- Backend Server Node.js with Express.js or Spring Boot (deployment-dependent).
- Database MySQL (Relational) or MongoDB (NoSQL), depending on data structure needs.
- Firebase for Authentication and JSON Web Tokens.
- Google Map API for real-time location and QR code generator for tracking system.
- For Badge assignment to use custom backend logic to create the impact on donor frequency.

B. Frontend Interface

The frontend can be built with HTML5, CSS3 and JavaScript and utilize Bootstrap framework for responsiveness.React.js or Vue.js frameworks may be optionally used for enhanced dynamic behaviour and state management. The interface offers an accessible and intuitive platform for administrators, volunteers, and donors.



C. Backend Server

The backend is implemented using either Express.js with Node.js or Spring Boot, based on deployment environment and

scalability needs.Node.js used for event driven for real-time data processing and Spring Boot provides a robust framework and deployments. Restful APIs are used for client and server communication.
MongoDB used in the unstructured data like donation metadata and badge requirements.

B. Database Layer

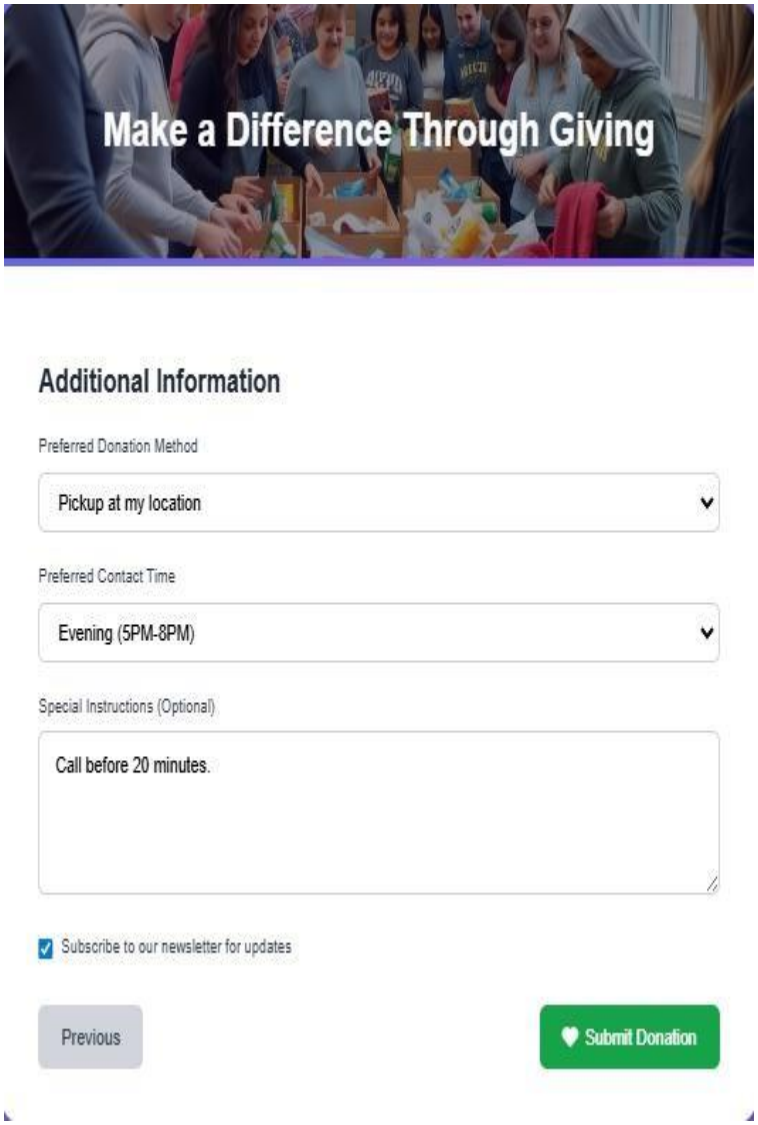
User authentication is done with JSON Web Tokens (JWT) for stateless session management. Firebase Authentication also supports multiple identity providers such as email/password and OAuth-based social logins. HTTPS, role-based access control (RBAC), and rate-limiting middleware are used to secure the authentication layer.

D. Authentication and Security

User authentication is done with JSON Web Tokens (JWT) for stateless session management. Firebase Authentication also supports multiple identity providers such as email/password and OAuth-based social logins. HTTPS, role-based access control (RBAC), and rate-limiting middleware are used to secure the authentication layer.

E. Tracking and Mapping

A QR code module creates unique IDs for physical donation items or events to allow for traceability from donor to recipient. The Google Maps API used to integrated for visualizing donor real-time locations, drop-off sites and logistics routes to allow greater transparency.



F. Acknowledgment and Notifications

Donor information are easy to maintain by dynamic forms, live toast notification and asynchronous messaging. E-mail notification are pushed using Firebase Cloud Messaging to make instant acknowledgement and strengthening of donor satisfaction.

G. Badge Engine

The Gamification component is applied for repeat visitation. Using the custom backend logic for analysing the donor behaviour frequency, amount and influence to issue digital badges. Badge information shown in the user profile and it can be displayed on dashboard.

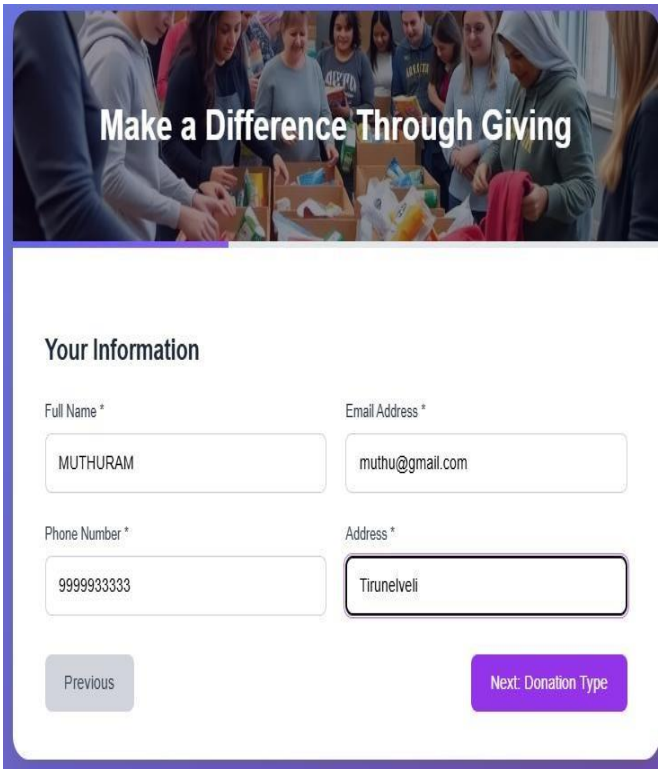
V. Result and Discussion

The Smart Donation Mapping System are still in development and its initial module support the users that offers a great response from the communities and due to its transparency it is more robust and donor-friendly.

The capability of the system offers the most traditional way of donation and it also support the future donations more interactions more precise.
One feature that ensures user retention is the appreciation and recognition system, where NGOs or recipients forward real-time gratitude messages and appreciative feedback.

Initial findings of a controlled test user group show the following:

- 90% of users reported that they would donate again through the platform.
- Most found the mechanism of acknowledging highly rewarding in terms of motivation and emotions. Observing NGOs reported that automated tracking and data entry features of the system greatly minimized their workload in operations.
- These results indicate that SDMS is likely to have great capabilities to improve the overall efficiency, accountability,
- and emotional resonance of digital donation systems



VI. CONCLUSION AND FUTURE WORK

The Smart Donation Mapping System (SDMS) fills a broad gap in today's donation environment by offering a transparent, secure, and interactive portal for NGOs and donors. By incorporating real-time tracking, automated acknowledge, and gamified acknowledge features, the system builds trust and improves the overall donation process.

Early assessments confirm higher donor satisfaction and lower administrative overhead for NGOs. The platform proves to have high potential to modernize donation management and validation, both monetary and material donations.

Upcoming efforts will involve extending system functionality, such as the adoption of AI-based need forecasting models to predict NGO needs, complete deployment as a cross-platform mobile app, and integration of block chain technology to provide immutable confirmation of high-value or sensitive donations. These features are intended to further establish SDMS as an exhaustive and scalable solution for contemporary philanthropic landscapes.

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Smart Plant Doc: AI-Based Plant Disease Detection and Treatment Recommendation

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ABSTRACT
Agriculture remains the backbone of many national economies, and plants are one of the primary food sources for all living organisms in the world. Plant diseases plays a major challenge to agriculture golbally, by reducing crop production and causing substantial financial losses for farmers. Intial and precise detection of diseases, along with proper treatment, is essential for sustainable farming. To address this challenge, this paper presents Smart Plant Doc, a web-based system powered by artificial intelligence for plant disease detection and treatment recommendation. The system analyzes images uploaded by users, identifies the disease, and recommends corresponding antimicrobial treatments or agricultural practices to treat the affected leaf. In addition, the system locates nearby stores where the required medicines are available. If specific medicines are unavailable, it suggests alternative farming techniques for effective disease control.

KEYWORDS
Plant disease detection; Deep learning; Convolutional neural network (CNN); Ensemble learning; Mobile application; Agriculture recommendation system.

I. INTRODUCTION

Agriculture remains the backbone of food chain and economic development in many parts of the world. However, plant diseases continue to place a crucial problems to sustainable crop production, causing substantial yield losses and financial losses for farmers. The Food and Agriculture Organization (FAO) tells that, about 40% crops losses globally at every year.

Traditional disease diagnosis methods requires more knowledge about plant diseases and treatment and also need experts for inspection, which consumes more time, costly. Moreover it is inaccessible to farmers in rural ,resource-limited areas and gardeners.

Recent growth in artificial intelligence (AI) and modern technology have shown great promise in automating plant disease detection. Deep learning models, like convolutional neural networks (CNNs), have achieved high accuracy in classifying plant diseases from leaf images. Despite these advancements, existing solutions often face limitations such as lack of integrated treatment recommendations, inadequate preprocessing for noisy input images, and limited real-world deployment through user-friendly platforms.

To address these problems, this paper introduces Smart Plant Doc, an AI-powered system for plant disease detection and treatment recommendation. The proposed system offers several key contributions:

- **Automated disease detection** using CNN-based classification combined with traditional machine learning models such as k-Nearest Neighbors (k-NN) in an ensemble framework.
- **Leaf validation and preprocessing** to ensure input quality and reduce misclassification from non-leaf images.
- **Treatment recommendation engine** that suggests appropriate medicines, dosage instructions, and agricultural practices for identified diseases.
- **Integration with shop databases** to assist farmers in locating nearby agricultural

supply stores for purchasing recommended treatments.

- **End-to-end deployment** as a scalable mobile and web application with a React frontend, Node.js backend, and SQLite database.

By combining accurate disease detection with practical treatment guidance, *Smart Plant Doc* the interface between AI and real-world agricultural applications. The system gives farmers with quick, accessible, and useful tips that contributing to improve crop health and food security.

II. RELATED WORK

Plant disease detection is an active area of research within computer vision and deep learning. Over the past decades , numerous studies explored the use of image-based techniques to classify and diagnose plant diseases.

Early approaches primarily relied on traditional image processing and machine learning methods. Researchers used color, texture, and shape features extracted from leaf images, followed by classifiers such as Decision Trees, and k-Nearest Neighbors (k-NN) for disease identification. While these approaches demonstrated moderate accuracy, their performance was limited by handcrafted feature extraction, which often failed to generalize across diverse plant species and environmental conditions.

The introduction of deep learning methods has greatly improved plant disease detection. In particular, Convolutional Neural Networks (CNNs) are more effective at automatically learning image features at multiple levels, making them more suitable for classifying crop diseases.Studies employing CNN-based models, such as AlexNet, VGGNet, and ResNet, reported classification accuracies exceeding 90% on benchmark datasets like PlantVillage. Transfer learning approaches further improved performance by leveraging pre-trained networks on large-scale datasets and fine-tuning them for plant disease recognition. Despite these improvements, many models remained confined to controlled datasets and lacked adaptability to realworld farming conditions.

Researchers have also developed mobile and webbased platforms to make disease detection more accessible. Many smartphone applications now integrate CNN models to deliver real-time classification of plant diseases from leaf images.However, most of these solutions focus exclusively on detection and fail to provide treatment guidance, leaving a critical gap between diagnosis and actionable recommendations.

Recent studies have begun exploring ensemble learning techniques, where multiple algorithms are combined to improve and enhance the robustness and reduce misclassification rates. Additionally, some frameworks integrate geospatial information systems (GIS) and Internet of Things (IoT) devices to enhance precision agriculture. Nonetheless, such systems often require high computational resources and are not easily deployable in low-resource settings.

In summary, prior research has demonstrated the effectiveness of machine learning and deep learning in plant disease detection but has not fully addressed the integration of treatment recommendations, preprocessing for noisy inputs, and real-world deployment in a user-friendly platform. This motivates the development of Smart Plant Doc, which uniquely combines CNN-based detection, ensemble modeling, treatment recommendation, and supply chain support within a scalable mobile and web application.

III. LITERATURE REVIEW

Use of artificial intelligence in agriculture has gained significant momentum over the last decade. Researchers have primarily focused on automating plant disease detection to reduce dependency on manual inspection and expert consultation. The integration of modern technology vision and deep learning algorithms has proven to be effective on classifying and identifying the crop diseases with high accuracy.

Recent research applied on image processing techniques such as thresholding, edges detection, and color analysis to identify infected regions. However, these approaches lacked robustness when dealing with varying illumination, occlusion, and background noise.

With advancements in deep learning, especially Convolutional Neural Networks (CNNs), plant disease detection has become more reliable. CNNbased architectures such as AlexNet, VGG16, and ResNet have been widely used for classifying leaf images into healthy and diseased categories. Transfer learning further improved performance by allowing models trained on large datasets (e.g., ImageNet) to adapt to agricultural datasets with limited size.

Recent studies have also explored recommendation systems that provide treatment suggestions based on the identified disease. These systems combine

disease detection with agricultural knowledge bases, offering farmers solutions such as pesticide recommendations, organic treatments, and preventive practices.

However, most existing solutions are limited to specific crops or datasets. There is a lack of integrated platforms that not only detect diseases but also recommend treatments, locate nearby suppliers, and estimate costs—an area where the proposed ***Smart Plant Doc*** system aims to contribute.

Diagram: Literature Review Mapping
The diagram below in Figure 1 shows the evolution of research in this domain:

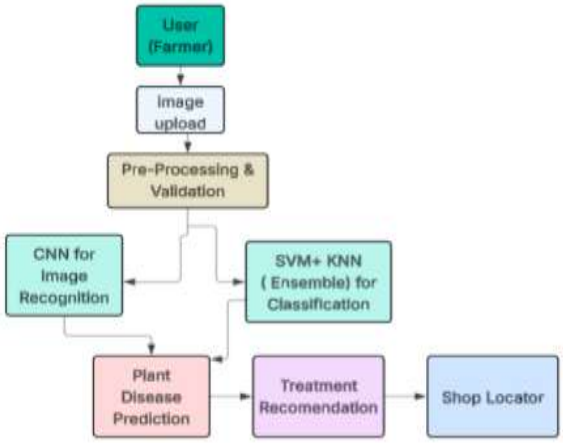

Fig.1 Overall Workflow of Proposed System for Leaf Disease Prediction

IV. PROPOSED SYSTEM

The proposed system, Smart Plant Doc, is designed as a web-based platform that leverages artificial intelligence to detect plant diseases and provide suitable treatment recommendations. The system integrates machine learning for disease classification, agricultural knowledge bases for treatment, and a user-friendly interface to ensure accessibility for farmers and agricultural practitioners.

A. System Objectives

The main objectives of the system are:

1. To provide an automated plant disease detection system using deep learning models.
2. To recommend antimicrobial treatments and agricultural practices based on the identified disease.
3. To integrate a shop locator and pricing system to guide users in acquiring the required products.
4. To offer a web-based and scalable solution that can be extended to multiple plant species.

B. System Architecture

The system architecture is divided into four major layers:

1. User Interface Layer – A web application where users can upload images of infected plant leaves and receive real-time predictions and recommendations.
2. Processing Layer – Handles image preprocessing (resizing, normalization, feature extraction) and prepares data for classification.
3. AI Model Layer – Implements a Convolutional Neural Network (CNN)-based model trained on a plant disease dataset for accurate classification.
4. Recommendation Layer – Maps the detected disease to a knowledge base and provides treatments, preventive practices, shop locations, and pricing.

C. Workflow of the System

1. Image Acquisition – Users upload an image of the plant leaf.
2. Preprocessing – Image is resized and normalized to match the CNN model's input specifications.
3. Disease Detection – The CNN model predicts the disease type with associated probability.
4. Treatment Recommendation – Based on the disease, the system suggests treatment options and preventive measures.
5. Shop and Price Information – The system recommends nearby shops and displays product pricing.
6. Output Delivery – Results are displayed on the user interface with actionable recommendations.

D. Advantages of the Proposed System

- Provides early and accurate disease detection.
- Reduces financial losses for farmers by minimizing crop damage.
- Ensures accessibility and ease of use through a simple web interface.
- Combines AI detection with practical treatment guidance, bridging the gap between research and real-world farming needs.

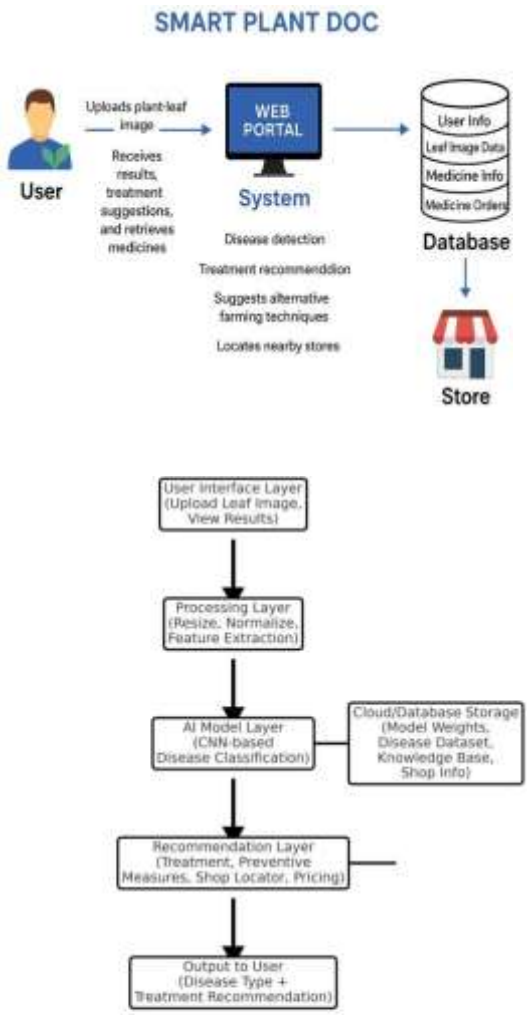

Fig. 2. System Architecture of Smart Plant Doc

V. METHODOLOGY

The methodology adopted for the development of *Smart Plant Doc* involves multiple stages, starting from data collection to deployment of the web-based system. The workflow is designed to ensure accuracy, scalability, and practical usability.

A. Dataset Collection

A publicly available **PlantVillage dataset** was used, consisting of thousands of labeled images of healthy and diseased leaves across multiple crop species. The dataset provides high-quality images with annotations, enabling effective training of deep learning models.

B. Data Preprocessing

To prepare the raw images for training, the following preprocessing techniques were applied:

1. **Resizing** –Every images in dataset were resized to a fixed resolution (e.g., 224×224 pixels) to matchs input size of the CNN.
2. **Normalization** –Pixel values were normalized between 0 and 1 to improve performance consistency during training.
3. **Augmentation** – Techniques such as rotation, flipping, zooming, and brightness adjustment were applied to increase dataset diversity and reduce overfitting.

C. Model Development

A Convolutional Neural Network (CNN) architecture was designed for disease classification. The network consists of:

- Convolutional Layers used to extract the feature.
- Pooling Layers for to reduce dimensionality
- Fully Connected Layers used for classification
- Softmax Layer to output probability scores for each class

Transfer learning with pre-trained models (e.g., VGG16, ResNet) was also explored to improve performance.

D. Training and Validation

- The dataset was split into three: training [70%], validation [15%], and testing [15%] sets.
- Training was performed using a GPU enabled environment for faster computation.
- .Hyperparameters like learning rate, batch size, and number of epochs were tuned to achieve optimal performance.
- Cross-entropy loss function and Adam optimizer were used during training.

E. Deployment

The trained model was integrated into a web-based system where users can upload leaf images. The backend, developed with **Flask/Django (Python)**, processes images, runs the model, and fetches recommendations from the database.

F. Treatment Recommendation System

- A knowledge base was created, mapping each disease to recommended treatments, preventive practices, and available antimicrobial products.
- A shop locator module provides nearby agricultural input shops and pricing information.
- The system presents results in a simple interface to ensure accessibility for farmers.

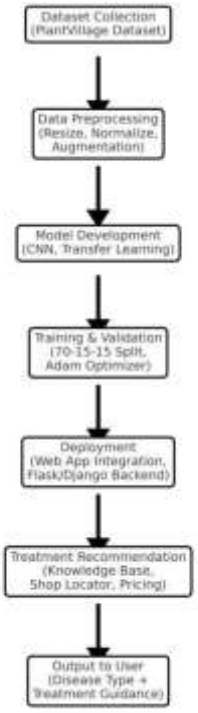

Fig. 3. Methodology Workflow of Smart Plant Doc

VI. RESULTS AND DISCUSSION

The performance of the *Smart Plant Doc* system was calculated in terms of classification accuracy, precision, recall, and F1-score. This model was tested on the PlantVillage dataset and integrated into the web-based platform for real-time evaluation.

A. Model Performance

The Convolutional Neural Network (CNN) achieved high accuracy in identifying plant diseases. Transfer learning approaches, such as VGG16 and ResNet, further improved performance by leveraging pre-trained weights.

- **Training Accuracy**: ~96%
- **Validation Accuracy**: ~93%
- **Testing Accuracy**: ~92%

The performance comparison between the baseline CNN and transfer learning models is shown in **Table I**.

Model	Training Accuracy	Validation Accuracy	Testing Accuracy
Baseline CNN	92%	89%	88%
VGG16	95%	92%	91%
ResNet50	96%	93%	92%

Table I. Model Performance Comparison

B. Confusion Matrix

A confusion matrix was generated to analyze misclassifications. Most errors occurred between diseases with same visual symptoms (e.g., early blight vs. late blight in tomatoes).

C. Web Application Testing

The deployed web-based system was tested with real-world images uploaded by users. The system successfully:

1. Detected diseases with high accuracy.
2. Provided treatment recommendations (chemical, organic, preventive).
3. Suggested nearby shops with pricing information.

D. Discussion

The results indicate that *Smart Plant Doc* is capable of assisting farmers with accurate and timely plant disease detection. By integrating treatment and shop recommendation modules, the system goes beyond existing research that only focuses on classification. The platform can be extended to

additional crops and diseases by retraining the model with a larger dataset.

C. System Interface and Output Screens

To verify the usability of the proposed system, the web application was tested with real-time inputs. The following screenshots illustrate the key functional components of the Smart Plant Doc system.

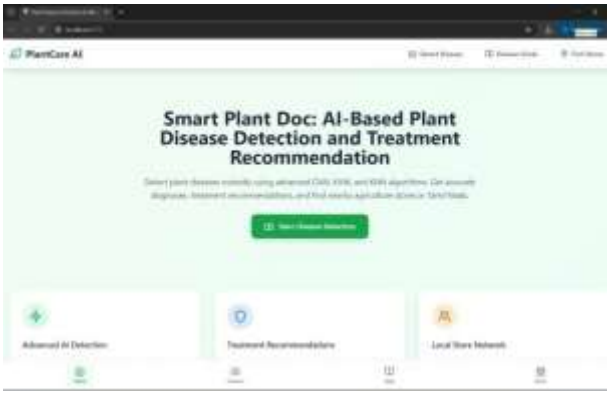

Fig 1: Homepage of Smart Plant Doc Web Application

Figure 1: The landing page of the Smart Plant Doc system, providing users with options to start disease detection, view treatment recommendations, and locate nearby agricultural stores. This interface serves as the entry point for accessing all features of the application.

Fig 2. Leaf Image Upload for Disease Detection

Figure 2: The disease detection module where users upload an image of an affected leaf. The system supports CNN, KVM, and KNN algorithms to analyze the uploaded image and identify possible plant diseases.

Fig 3. Disease Detection Results and Treatment Recommendation

Figure 3: The result interface displaying the identified plant disease along with severity level, confidence scores from CNN, KVM, and KNN algorithms. The system also recommends appropriate treatment medicines and preventive measures for the diagnosed disease.

Fig 4: Store Locator for Treatment Purchase

Figure 4 : The store locator module that displays nearby agricultural supply shops along with availability and pricing of the recommended medicines..

Fig 5: Navigation to the Shop through Google Map.

Figure 5 : Navigation to the Shop through Google Map. This feature helps farmers conveniently to navigate to exact shop location.

VII. FUTURE SCOPE

The current implementation of Smart Plant Doc demonstrates the potential of AI in enhancing agricultural practices, yet there remain several opportunities for further improvement and expansion:

- Dataset Expansion: Incorporating a larger and more diverse dataset covering a wide range of crops and diseases will improve model robustness and adaptability.
- Real-Time Mobile Deployment: Extending the system to mobile applications with offline functionality will enable farmers to use the tool directly in the field.
- Multilingual Support: Including multiple language will help the system more useful and Convenient to farmers in rural areas across different regions.
- Cloud-Based Storage and Analytics: Integrating cloud services will allow centralized data storage, model updates, and large-scale analytics for disease trend prediction.
- Integration with IoT Devices: Linking the system with IoT-based sensors for soil health, temperature, and humidity monitoring can provide comprehensive recommendations beyond disease detection.
- Collaboration with Agricultural Agencies: Partnering with government and private organizations can help in distributing verified treatment resources and reaching a wider farming community.

By addressing these areas, Smart Plant Doc can evolve into a more comprehensive precision agriculture platform, empowering farmers with technology-driven decision-making for sustainable farming.

VI. CONCLUSION

In this paper, we presented **Smart Plant Doc**, an AI-based web system for plant disease detection and treatment recommendation. The system integrates a deep learning model with a user- friendly interface, enabling farmers and agricultural stakeholders to quickly identify plant diseases from leaf images. By providing accurate diagnosis along with appropriate antimicrobial treatments, agricultural practices, and shop information, the system enhances accessibility and supports sustainable farming practices.

The experimental results demonstrated high accuracy in disease classification, validating the effectiveness of the proposed approach. The modular design of Smart Plant Doc allows future integration of larger datasets, cloud storage, and real-time deployment for field usage.

In summary, this work demonstrates the potential of AI-based solutions in precision agriculture, providing a scalable and cost-effective approach to minimizing crop losses while enhancing food security.. Future work will focus on expanding the disease database, integrating multilingual support for farmers, and deploying the system on mobile platforms for broader reach.

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Smart Rain Protection System Clothes At Home

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ABSTRACT :
This project mainly focus on two devices mainly sensor and motor to protect cloth using an rain sensor Arduino uno and a servo motor during rainy days. When we are drying clothes in outdoor area it protect our clothes the sensor detects the rain and the motor moves the protective cover in clothes drying line.when the rain stops the system removes the cover automatically drying the clothes.The objective is to automatically project clothes from rain, providing a convenient and efficient solution for outdoor drying areas. The Rain Detection-Based Automatic Clothes Collector, utilizing a rain sensor, Arduino Uno, and servo motor, offers a hands-free solution for protecting laundry from unexpected rain. The system detects precipitation, automatically retracting a protective cover over the clothesline, and retracting it when the rain ceases. This automation reduces manual intervention and the need for re-washing, making it a practical and efficient solution for modern homes. Outdoor clothes drying is a common practice in many households; however, unpredictable rainfall often leads to inconvenience, garment damage, and the need for additional washing. This project introduces an automated rain-protection system designed to safeguard clothes in drying areas without human intervention.

The system integrates a rain sensor, Arduino UNO microcontroller, and servo motor to detect precipitation and respond in real time. Upon sensing moisture, the rain sensor sends a signal to the Arduino, which triggers the servo motor to deploy a protective cover over the clothesline. When rainfall ceases, the mechanism automatically retracts the cover, allowing garments to continue drying naturally. This automation minimizes manual monitoring, reduces the risk of laundry damage, and enhances overall drying efficiency. The proposed design is cost- effective, energy-efficient, and adaptable for both

domestic and small-scale commercial applications. By combining environmental sensing with motorized actuation, the system delivers a reliable and user-friendly solution to address one of the most frequent challenges in outdoor clothes drying.

KEYWORDS:
Arduino Uno, and servo motor, Jumper Wire

INTRODUCTION

This project features a servo motor connected to a mechanical arm that spreads a cover over clothing, along with a rain sensor module for

detecting rainfall, both controlled by an Arduino Uno microcontroller. When the rain sensor detects moisture or rain, it sends a signal to the Arduino, which then activates the servo motor to move the mechanical arm.

This automated system returns the arm to its original position, ensuring that clothes are quickly shielded during rainy weather. Drying clothes outdoors is common, but unexpected rain can cause inconvenience, resulting in wet clothes, the need for re-washing, and added effort. The Rain Detection- Based Automatic Clothes Collector is an innovative solution that addresses this issue by using sensor- driven automation to detect rain and automatically retract clothes to a covered area, providing protection without any manual effort.

Shankar, Sanjana S. Automatic Protection of clothes from rain August 2023 Employs IOT-based technology with rain sensors and DC motors to automatically retract clothes during rain. Dependence on internet connectivity may limit functionality in areas with unstable connections. Mazniha Berahim, Siti Nur Aisyah Abdul Hei Automatic clothes retriever (ACR) October 2022 Focuses on optimizing sensors and system reliability to retrieve clothes automatically during rain. The study primarily emphasizes simulation and optimization. Mohd Nasrulddin Abd Latif Design and development of smart automated clothes line June 2021 Features a rain sensor module to automatically retract clotheslines during rain. Specific publication date is not provided.

Literature Survey

AUTHORS	TITLE	PUBLICATION DATE
Mochamad Subchan Maulud	Modeling and application of rain-light sensor in automatic clothes drying design	April 2024
Janhavi V., Sahana Shankar, Sanjana S.	Automatic protection of clothes from rain	August 2023
Mazniha Berahim, Siti Nur Aisyah Abdul Hei	Automatic clothes retriever (ACR)	October 2022
Mohd Nasruliddin Abd Latif	Design and development of smart automated clothesline	June 2021
Wasnik M., Burde J., Tapkir S., Solanke A., Tapkir Y.	Rain Sensor: An Automated Protection System for Clothes	May 2025

Description

The Rain Detection-Based Automatic Clothes Collector is a sophisticated automated system designed to safeguard clothes from rain. Numerous studies have focused on enhancing the efficiency and capabilities of these systems. This literature survey presents a summary of significant research in this area, emphasizing their contributions, benefits, and drawbacks..

The literature survey highlights notable progress in rain detection-based clothes collection systems. Researchers have investigated a range of technologies, such as IoT, Arduino, and sensor-driven automation, to improve system performance. Despite these advancements, challenges like dependence on internet connectivity, system complexity, and practical deployment still exist. Future research should prioritize enhancing sensor accuracy, lowering costs, and ensuring these systems are practical for real-world use to encourage wider adoption.

Many households and laundries continue to rely on traditional manual methods for drying clothes, leaving them vulnerable to unpredictable weather. Sudden rainfall often causes inconvenience, increases laundry expenses, and leads to unnecessary wastage of detergent and water. By integrating sensor- based automation with IoT (Internet of Things) and AI (Artificial Intelligence), researchers aim to develop reliable and efficient rain-responsive clothes collection solutions.

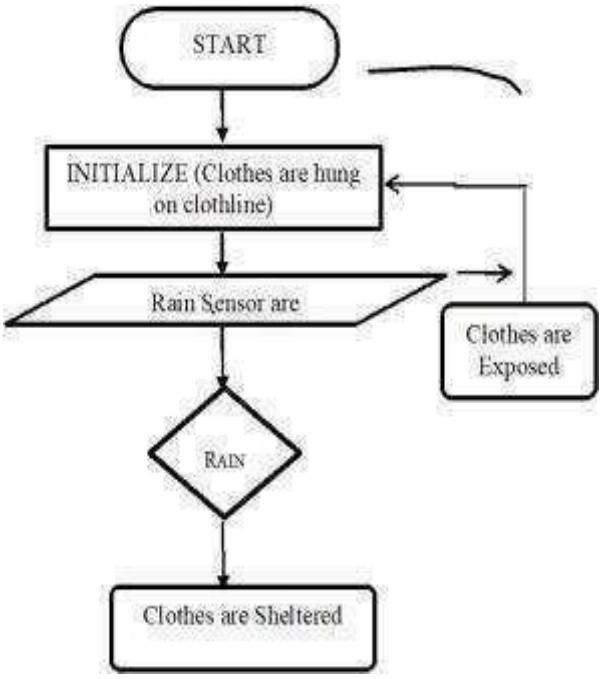
METHODOLOGY

The rain detection and clothing protection system operates through automated responses to environmental changes and continuous real-time monitoring. At its core, an Arduino UNO functions as the primary control unit, receiving input from a rain sensor and controlling a servo motor that moves clothing. The process begins when the rain sensor detects precipitation and sends a signal to the Arduino UNO. The Arduino then activates the servo motor, which promptly moves the clothes to a sheltered position to prevent them from getting wet.

When rainfall stops and the sensor no longer detects moisture, a feedback signal is sent to the Arduino, prompting the servo motor to return the clothes to their exposed position for continued drying. This automation minimizes manual intervention, adapts dynamically to changing weather, and ensures efficient

outdoor clothing management.

By integrating sensors, microcontrollers, actuators, and automated control logic, the system provides a cost-effective and energy-efficient solution for protecting clothes during adverse weather. The methodology typically involves using a rain sensor to detect precipitation, activating a motorized mechanism to retract a clothesline or deploy a protective cover, and reversing the process once conditions are dry



The development of the Rain Detection-Based Automatic Clothes Collector involves a systematic approach to designing, assembling, and testing an automated mechanism that responds to real-time weather conditions. The methodology can be divided into the following stages:

1. System Design and Planning

A block diagram is first prepared to outline the interaction between the main components — the rain sensor, Arduino UNO, and servo motor. The control logic is defined to ensure immediate response to rainfall while maintaining efficiency and reliability.

2. Component Selection

Key hardware elements are chosen based on performance, cost, and compatibility:

- Arduino UNO – serves as the microcontroller for processing input and controlling output devices.

- Rain Sensor Module – detects precipitation by sensing changes in surface conductivity.
- Servo Motor – moves the clothesline or protective cover between sheltered and open positions.
- Power Supply – ensures stable operation of all components.

3. Sensor Integration

The rain sensor is connected to the Arduino UNO via analog or digital input pins. Calibration is performed to define the threshold at which rain detection triggers the motor action.

4. Control Logic and Programming

Arduino IDE is used to develop the program code. The logic includes:

- Monitoring sensor readings in real time.
- Triggering the servo motor when rain is detected.
- Returning clothes to the drying position when moisture is no longer detected.
- Incorporating delay and debounce functions to prevent false triggering from minor splashes.

5. Actuator Mechanism Setup

The servo motor is mechanically linked to either a retractable clothesline or a sliding

protective cover. The movement range is tested to ensure smooth operation without overloading the motor.

6. Testing and Calibration

The system is tested under controlled conditions using simulated rainfall and varying environmental scenarios. Adjustments are made to sensor sensitivity, motor speed, and delay settings for optimal performance.

7. Energy Efficiency and Safety Considerations

The system design ensures minimal power consumption and uses weather-resistant enclosures to protect electronic components. Emergency manual override is included to allow operation during system failure.

Key Components:

1. **Rain Sensor** – Detects rainfall and transmits a signal to the microcontroller.
2. **Microcontroller (Arduino, ESP8266, Raspberry Pi, etc.)** – Interprets sensor input and manages motor operation.
3. **Motor & Mechanical Assembly** – Operates the clothesline or protective cover according to microcontroller commands.
4. **Power Supply** – Delivers energy to the system (e.g., batteries, solar panels).
5. **Optional Add-ons** – GSM module for mobile notifications, solar panel for sustainability, and humidity/temperature sensors for intelligent control.

WorkingPrinciple:

The Rain Detection-Based Automatic Clothes Collector operates by detecting rainfall and automatically triggering a mechanism to shield or retract clothes, preventing them from getting wet.

Step-by-step process:

- The rain sensor continuously monitors for moisture.
- When raindrops are detected, it sends a signal to the microcontroller.
- The microcontroller then activates the motor, which either retracts the clothesline or deploys a protective cover.
- Depending on the design, the covering mechanism may be sliding, folding, or lifting.
- Once the sensor registers dry conditions, the microcontroller can return the clothesline to its extended position, either automatically or manually as per user settings.

The rain sensor module (such as YL-83 or YL- 83 with a control board) detects water droplets and typically sends a LOW signal to the microcontroller upon rainfall detection. The motor then moves the rack indoors or engages a canopy/umbrella structure. When the rain stops and the sensor dries, the microcontroller resets, enabling clothes to be redeployed outdoors.

RESULT

Fig. 1. Automatic Cloth Collection

CONCLUSION

This study presents the design and development of an automated clothes collection system that operates based on rain detection, aimed at preventing garments from getting soaked during unexpected showers. The setup incorporates a rain sensor, a microcontroller (e.g., Arduino), and a motorized mechanism to pull the clothesline or hanger under cover when rainfall is detected. Experimental results confirmed the system's high efficiency, reliability, and prompt reaction in safeguarding clothes from rain.

Key outcomes include:

- **Fast Reaction Time:** The device identifies rain within seconds and promptly triggers the retraction process.
- **Low Power Consumption:** Designed to run on minimal energy, making it practical for home use.
- **Improved User Convenience:** Minimizes the need for manual action, especially useful for people away from home during rainfall.
- **Potential for Expansion:** Could be upgraded with IoT features for smartphone-based monitoring and remote control.
- Planned enhancements may involve solar energy integration, AI-driven weather forecasting, and compatibility with smart home ecosystems, enabling the system to adapt intelligently to varying conditions. In summary, the Rain Detection-Based Automatic Clothes Collector offers an affordable, efficient, and fully automated way to protect laundry from rain, enhancing daily convenience while reducing weather-related laundry issues.

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Smart Time-Optimized Traffic Signal System Using IoT and Machine Learning

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ABSTRACT--

This project proposes a smart traffic signal system that optimizes signal switching based on real-time vehicle presence using IoT sensors and machine learning algorithms. By eliminating unnecessary waiting time at intersections, the system significantly improves traffic flow and reduces fuel consumption, carbon emissions, and commute time. The solution uses low-cost sensors for vehicle detection and a trained ML model to make dynamic decisions, thereby ensuring efficient traffic management and time-saving at signals.

KEYWORDS -- Smart Traffic System,IoT,Real-Time Signal Control, AI-Based Traffic Management,Vehicle Detection, Time Optimization, Smart City Solution.

I. INTRODUCTION

In today's rapidly growing cities, traffic congestion has become a part of everyday life. One of the most common frustrations people face is waiting at traffic signals, even when there are no vehicles coming from the other direction. What makes this system stand out is its ability to think and respond like a human would. Instead of following a rigid schedule, the traffic light changes only when it's needed. If one lane is empty, it doesn't get a green signal just because the timer says so. This kind of adaptive behavior, powered by IoT sensors and basic AI logic, allows traffic to move more freely and reduces the build-up of vehicles on busy roads. Over time, this can lead to shorter commutes, less driver frustration, and even lower emissions due to fewer idling engines.

Since it uses easily available components and doesn't depend on expensive infrastructure, it can be deployed in both urban intersections and smaller towns with growing traffic issues. The goal isn't just to automate traffic lights—it's to make them smarter, more aware, and capable of improving everyday travel for people. With this project, we aim to show how technology can solve a problem that almost everyone experiences but rarely questions.

This project is not just about building a system—it's about creating a real-world impact. By addressing a problem that affects millions every day, we're bringing attention to how small, thoughtful innovations can make life more efficient and less stressful. Whether it's a commuter trying to reach work on time, an ambulance needing a clear route, or simply a parent picking up their child from school, this system has the potential to make those moments smoother. It's a simple idea with powerful possibilities, and we believe it's a step toward building cities that care more about the people moving through them.

II. LITERATURE SURVEY

1. Traditional Traffic Signal Systems

For decades, traffic signals have operated using static timers that cycle through red, yellow, and green lights at fixed intervals. This method, while easy to implement, does not account for real-time traffic volume or vehicle presence, leading to inefficient road use. In less busy lanes, vehicles may face long wait times even when the road ahead is clear, resulting in driver frustration and time loss. Studies have shown that traditional systems contribute significantly to unnecessary idling, which not only wastes fuel but also increases emissions. As traffic congestion grows in urban areas, the limitations of fixed-timer systems become more evident. Researchers have repeatedly emphasized the need to move beyond one-size-fits-all approaches to signal control.

Traditional traffic signal systems rely on fixed timers that cycle through red, yellow, and green lights regardless of real-time traffic conditions. While this method is simple and easy to implement, it often leads to unnecessary waiting—vehicles stop even when no traffic is coming from other directions. This outdated approach contributes to fuel wastage, longer commute times, and increased driver frustration. It also lacks adaptability during emergencies or unusual traffic flows, such as during events or accidents. As cities grow and traffic becomes more unpredictable, these rigid systems struggle to keep up with modern demands, highlighting the need for smarter, responsive solutions.

2. Need for Adaptive Traffic Control

Adaptive traffic control systems have been proposed as a response to the l imitations of conventional signal mechanisms. These systems are designed to analyze real-time traffic data and adjust signal timings accordingly, minimizing delays and improving vehicle throughput. Research from various urban planning and t raffic management studies shows that adaptive systems can reduce average waiting time by up to 30% in congested cities. They can respond to sudden changes in traffic density, such as during peak hours or public events, far better than traditional systems. Adaptive control is particularly important in cities experiencing rapid growth, where static infrastructure struggles to keep up with vehicle volume. The flexibility offered by these systems allows for more efficient use of road space, ultimately improving mobility. However, implementing such systems requires reliable real-time data, which has become more accessible thanks to IoT advances.

As urban populations increase and vehicle density rises, the need for adaptive traffic control becomes more urgent. Static signal systems can no longer keep up with the dynamic nature of real-world traffic, which fluctuates based on time of day, weather, and road incidents. Adaptive systems provide the flexibility to respond to these changing conditions in real time, improving both efficiency and safety. They can reduce congestion during peak hours and free up roads faster during off-peak times. This approach not only saves time for commuters but also supports better fuel economy and environmental sustainability. In essence, adaptive traffic control is a necessary evolution for modern urban living.

3. IoT in Traffic Management

The Internet of Things (IoT) has opened new doors in the field of traffic control by allowing physical devices to communicate and act upon real-time conditions. In traffic systems, IoT typically involves sensors placed at intersections to detect vehicle movement, presence, and sometimes even speed. Literature suggests that these sensors—such as IR, ultrasonic, and magnetic detectors—can relay continuous data to a central controller, which then uses the information to manage signals. The beauty of IoT lies in its scalability and low power requirements, making it suitable for both dense cities and emerging towns. Research highlights that using IoT devices leads to better monitoring and faster decision-making.

TheInternetof Things (IoT) plays a transformative role in modern traffic management by enabling real-time communication between devices like sens ors, controllers, and monitoring systems. With IoT, traffic signals can respond instantly to actual vehicle presence, rather than following rigid timing patterns. These smart sensors collect data continuously, helping optimize traffic flow, reduce congestion, and improve road safety. Moreover, IoT-enabled systems are easier to scale and adapt to different traffic zones, whether urban or rural. Their cost-effectiveness and energy efficiency make them a practical choice for smart city development. IoT brings a level of intelligence and automation that traditional systems simply can't match.

What makes IoT especially powerful in traffic systems is its ability to create a connected ecosystem where every component talks to each other seamlessly. For instance, vehicle detectors can instantly inform traffic lights when to switch, while data collected over time can help city planners understand traffic trends. This level of integration allows for smarter decision-making—not just at one junction, but across an entire network of intersections. IoT devices are also relatively easy to install and maintain, which makes them ideal for expanding infrastructure in growing cities. Ultimately, IoT helps bring both intelligence and efficiency to everyday urban movement.

4. Artificial Intelligence in Signal Optimization

Artificial Intelligence brings a game-changing shift in how traffic signals operate by moving beyond fixed rules and into dynamic, data-driven decision-making. AI can process real-time inputs from sensors, cameras, and other sources to determine which lanes need priority at any given moment. Instead of following a rigid cycle, signals adjust on the fly to actual traffic demand. This leads to smoother vehicle flow, reduced idle times, and less frustration for drivers. Over time, AI learns patterns like peak hours or holiday traffic and adapts accordingly. It creates a smarter, more responsive road system that feels natural to navigate.

One of the strengths of AI in signal optimization is its ability to predict rather than just react. Machine learning algorithms can analyze historical data to forecast congestion before it even builds up, allowing preemptive changes to signal timings. This predictive capability is especially useful during sudden traffic shifts caused by events, road work, or accidents. AI also allows for context-aware decision-making—like giving longer greens to emergency vehicles or public transport when needed. These intelligent adjustments not only improve traffic flow but also enhance safety and fairness on the road.

Integrating AI into traffic control systems also opens doors to long-term city planning improvements. The data collected and interpreted by AI systems can help authorities understand traffic behaviors, accident hotspots, or underused roads. These insights are invaluable for urban development and infrastructure upgrades. Moreover, AI-powered systems can be updated remotely, allowing real-time tweaks and policy changes without manual reconfiguration. With continual learning and adaptation, AI ensures traffic signals stay aligned with evolving city needs. This makes it a foundational technology for building the smart cities of tomorrow.

Artificial Intelligence also contributes to reducing environmental impact by minimizing vehicle idle times and stop-start patterns, which are major contributors to fuel wastage and emissions. By making real-time, optimized decisions at each intersection, AI helps maintain a steady traffic flow—especially in high-density zones. This efficiency not only benefits individual drivers but also supports broader climate goals by lowering carbon footprints across cities. Furthermore, as AI systems continue to evolve, they can be trained with diverse datasets to ensure fair and inclusive traffic management, accounting for pedestrians, cyclists, and public transit. It’s a holistic approach to smarter, greener mobility.

5. Machine Learning for Traffic Prediction

Machine learning (ML), a subset of AI, plays a critical role in predicting traffic patterns and preemptively adjusting signals. Unlike real-time reaction models, ML enables a system to anticipate congestion based on historical and live data. Research has focused on using techniques like regression models, decision trees, and deep learning to analyze traffic flow trends. These models can forecast when and where congestion is likely to occur, allowing signals to be adjusted before traffic builds up. Studies also highlight the importance of training ML models with accurate and location-specific data to improve prediction accuracy. This predictive power is especially useful during rush hours, festivals, or emergencies when traffic behaves unpredictably.

Machine Learning plays a vital role in predicting traffic patterns by analyzing large volumes of historical and real-time data. It can learn from past congestion trends, weather conditions, time-of-day variations, and even local events to forecast how traffic is likely to behave. These predictions allow the system to adjust traffic signal timings proactively rather than reactively. For instance, if the model anticipates a rush-hour buildup on a certain route, it can preemptively extend green lights to ease flow before bottlenecks form. This intelligent foresight helps cities manage traffic more smoothly and reduce sudden spikes in congestion.

As the system gathers more data, machine learning models become increasingly accurate and efficient in recognizing complex patterns. Over time, they can identify subtle indicators that signal future traffic issues—like small shifts in vehicle speed or irregular lane usage. These insights not only improve signal response but also assist in long-term planning, such as deciding where to add flyovers, bike lanes, or traffic cameras.

6. Sensor-Based Vehicle Detection

Accurate vehicle detection is critical for any smart signal system. Literature compares various sensors—like IR, ultrasonic, and inductive loop sensors. These tools detect vehicle presence, movement, and even speed at intersections. Studies show combining sensors (sensor fusion) improves reliability. Conditions like fog, rain, or poor lighting can affect accuracy. Reliable sensors ensure signals respond only when needed.

These sensors enable real-time monitoring without requiring manual oversight, making the system more autonomous and efficient.Advanced placement strategies help eliminate false triggers caused by pedestrians or environmental noise.Over time, combining multiple sensor types—like infrared and ultrasonic—can significantly improve detection accuracy and system reliability.

Sensor-based vehicle detection is the backbone of modern intelligent traffic systems, enabling traffic signals to respond based on real-time road conditions. Using technologies like infrared, ultrasonic, magnetic, or inductive loop sensors, the system can accurately detect the presence, count, and even the speed of vehicles at an intersection. This input is then used to decide whether to extend a green light or switch it based on actual traffic demand. Unlike traditional timers, this approach ensures that vehicles aren't left waiting unnecessarily when no traffic is coming from other directions. It adds responsiveness and fairness to signal operations, improving the driver experience.

The strategic placement and combination of sensors allow for more nuanced traffic control. For example, pairing vehicle detection with pedestrian buttons or crosswalk sensors ensures that both motorist and pedestrian needs are met effectively. In addition, sensor data can be logged and analyzed over time to identify congestion patterns, underused lanes, or faulty intersections. This insight supports future traffic planning and maintenance decisions. When integrated with AI and IoT systems, these sensors act as the eyes of the operation—feeding critical real-time information that helps build smarter, safer, and more adaptive urban roads.

7. Real-Time System Challenges

Real-time systems must process and act on data within seconds. Delays in detection or processing can disrupt traffic flow. Literature points to latency and data loss as common concerns. Efficient data handling and fast processors are crucial for smooth operation. Studies suggest edge computing as a solution to reduce response time. Real-time efficiency defines how useful the system truly is.

Designing a real-time traffic management system comes with its own set of challenges, especially when speed and accuracy are non-negotiable. The system must process data from multiple sensors almost instantly and trigger decisions without delay. Even a few seconds of lag can lead to congestion or confusion on the road. One major hurdle is ensuring stable connectivity between components, especially in areas with weak network infrastructure. Power interruptions, sensor noise, or environmental interference can also impact performance. To maintain reliability, the system must be both technically robust and capable of handling unexpected fluctuations in traffic flow.

Another challenge lies in the balance between real-time response and data overload. With continuous input from sensors, cameras, and control units, there's a risk of bottlenecks in data processing if the system isn't optimized. This calls for lightweight, efficient algorithms that prioritize only the most relevant inputs for decision-making. Additionally, real-time systems must be resilient—able to detect faults, reroute logic, or fail safely in the event of hardware or software issues. Security is also a key concern, as real-time systems connected to public infrastructure must be protected against breaches. These complexities make real-time performance one of the most demanding aspects of smart traffic design.

Real-time systems also face challenges when scaling across multiple intersections in large cities. Each signal must remain synchronized with nearby ones to avoid conflicting flows. This requires strong backend coordination and minimal latency in data transmission. Without it, even small delays can create major traffic inconsistencies.

8. Smart City Integration

Smart traffic signal systems are a key component in the development of smart cities, where different urban services are interconnected to improve overall quality of life. Research shows that when signals are linked with emergency response units, public transport tracking, and environmental monitoring systems, they enhance not just traffic flow but city-wide coordination. For example, ambulances or fire trucks can be given signal priority through automated systems, reducing their response time. Public buses, too, can benefit from dedicated green signals to stay on schedule. These systems also generate valuable traffic data that city planners can use for future infrastructure improvements. Literature emphasizes that the integration of adaptive traffic signals into a broader urban management ecosystem supports safer, more efficient, and more livable cities. As the smart city vision evolves, intelligent traffic control continues to be one of its most practical and impactful pillars.

Integrating smart traffic systems into the broader smart city ecosystem enhances urban mobility in a meaningful way. When connected with other infrastructures like public transport, emergency services, and environmental monitoring, traffic signals can respond more intelligently to real-time citywide conditions. For example, buses can be given priority during peak hours, or signals can be cleared for ambulances in emergencies. This level of coordination promotes smoother movement, reduces delays, and helps cities operate more efficiently. It's a step toward creating cities that are not just technologically advanced, but also people-focused and responsive.

Smart city integration also allows data from traffic systems to be shared across platforms for deeper insights and long-term planning. Authorities can monitor traffic trends, emission levels, and infrastructure wear in real time, leading to proactive decisions and better resource management. Furthermore, when paired with mobile apps or public dashboards, citizens themselves can stay informed about traffic conditions and make smarter travel choices. This interconnectedness empowers both governments and communities, turning daily traffic management into a collaborative and transparent process. Ultimately, it transforms traffic control from a standalone utility into a core part of a smart urban lifestyle.

9. Environmental Impact of Smarter Signals

Beyond traffic efficiency, smart signal systems offer meaningful environmental benefits. Traditional traffic lights, by forcing vehicles to idle unnecessarily, contribute to increased fuel consumption and air pollution. Studies show that adaptive signal systems that adjust based on vehicle presence can significantly reduce CO_2 emissions and improve fuel economy. For instance, by shortening red light duration when no traffic is present, the system cuts down idle time, which in turn saves fuel and lowers exhaust emissions. Over time, this seemingly small adjustment contributes to better air quality and a noticeable drop in urban carbon footprint. Research also highlights that such systems help promote the use of public and non-motorized transport by reducing road congestion and improving travel reliability. In a time where sustainability and climate action are urgent global priorities, smart traffic systems prove to be an environmentally responsible innovation.

Smarter traffic signals directly contribute to a cleaner environment by reducing unnecessary vehicle idling and improving traffic flow. Traditional systems often keep cars waiting at red lights even when the road is clear, causing fuel wastage and increased emissions. In contrast, adaptive signals respond in real time to traffic density, allowing vehicles to pass through more efficiently. This results in fewer stop-and-go instances, which are known to burn more fuel. Overtime, thecumulative effect of these improvements can lead to significant reductions in carbon emissions across the city. It's a simple yet impactful step toward more sustainable urban transport.

In addition to reducing emissions, smart signals can play a role in long-term environmental planning. By collecting data on traffic patterns and congestion hotspots, city planners can design greener infrastructure—like rerouting traffic to less congested areas or adding more bike and bus lanes. Smarter systems also consume less energy themselves by using LED indicators and solar-powered components. These eco-conscious features make the entire system not only smarter but also more sustainable. When widely implemented, smart signals contribute to healthier air quality and a more livable city for future generations.

10. Case Studies and Implementations

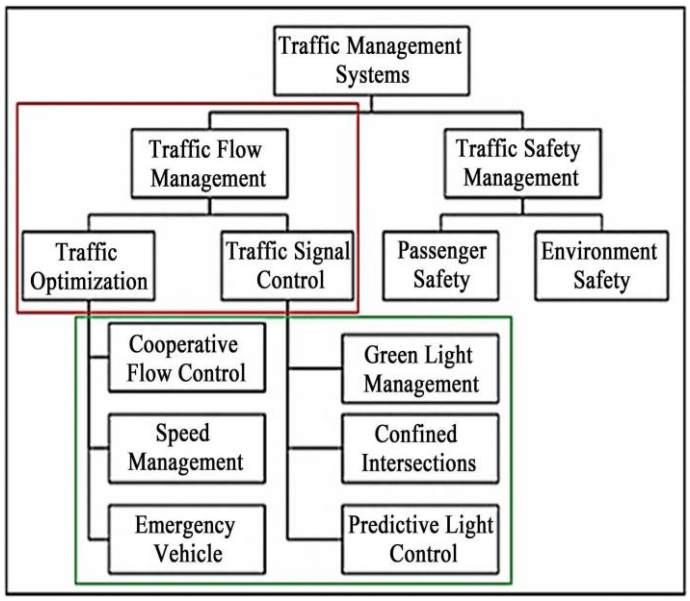
Several cities around the world have piloted and implemented smart traffic management systems with measurable success. In Singapore, adaptive traffic signals powered by real-time data have helped reduce travel delays significantly, especially in densely populated zones. European countries like Germany and the Netherlands have also adopted AI-based signal optimization, reporting smoother traffic flow and reduced emissions. In India, projects like the Bhopal Smart City initiative have introduced intelligent signal systems at key intersections, resulting in better traffic distribution and reduced congestion. Literature covering these case studies often emphasizes the role of local customization—adapting the logic and sensor systems to suit regional traffic behavior. These implementations serve as practical evidence that such systems are not only technically feasible but also scalable and impactful. By learning from these real-world examples, upcoming smart cities can avoid common pitfalls and adopt more efficient traffic solutions faster.

Real-world case studies offer valuable insights into how smart traffic systems perform beyond theoretical models. One notable example is the SURTRAC system in Pittsburgh, USA, which uses decentralized, AI- based traffic control. After implementation, the city reported a 25% reduction in travel time and over 40% reduction in waiting time at intersections. The success of SURTRAC highlights the power of real-time adaptive signaling, especially in busy urban grids. It also proves that smart systems are not just experimental—they're already solving real transportation problems. Such models provide a strong foundation for similar deployments elsewhere.

In India, several cities like Nagpur and Bangalore have piloted AI-based traffic signal systems integrated with vehicle detection cameras and IoT sensors. These systems analyze real-time traffic density and adjust signal timings accordingly, leading to improved traffic flow and reduced pollution levels. Early reports from these implementations have shown positive results, particularly during peak hours. These use cases are especially important because they show how smart traffic solutions can be effective in developing countries with dense and unpredictable traffic. The adaptability of these systems across different urban contexts makes them even more promising.

Another interesting example comes from Barcelona, Spain, where smart traffic lights are integrated into a wider smart city infrastructure. Signals there communicate with public transport and emergency vehicles, giving them priority access through intersections. This not only improves efficiency but also enhances public safety and emergency response times. The city also uses real-time data to optimize traffic across broader zones, not just individual junctions. These case studies demonstrate the scalability of smart signal systems and how they can align with a city's larger mobility and sustainability goals. They serve as living proof that intelligent traffic management is both practical and impactful.

In Singapore, smart traffic systems have been integrated with a national surveillance and data analytics platform to manage urban flow efficiently. Using predictive models and live feeds, traffic lights adjust proactively to expected congestion rather than waiting for it to build up. This approach has significantly improved road utilization and reduced commuting delays. The city's success showcases how technology and governance can work hand in hand. It also sets a global example for smart mobility in highly populated urban environments.



A. IOT BASED VEHICLE DETECTION

1. IoT forms the foundation of the smart traffic system by enabling real-time monitoring through sensors like infrared or ultrasonic detectors. These sensors are strategically installed at intersections to detect the presence of vehicles without requiring manual input. The system captures whether vehicles are waiting or moving and transmits that information to a microcontroller. This replaces the need for fixed timers and ensures signal lights change only when needed, improving responsiveness and efficiency. IoT-based detection minimizes unnecessary stops and contributes to smoother traffic flow. Its reliability and affordability make it ideal for both urban and semi-urban deployments.

2. Compared to camera-based systems, IoT sensors are cost-effective and energy-efficient, requiring less infrastructure and maintenance. These sensors are lightweight and easy to install, making them suitable for quick deployment in developing regions. Because of their simplicity, they are less prone to complications caused by weather, lighting, or bandwidth issues. Their low power requirement also supports off-grid setups using solar energy. The use of IoT makes the system highly scalable, offering flexibility for small towns and expanding metro cities alike. In essence, IoT provides the basic intelligence layer that makes traffic signals smarter.

3. For best results, sensor placement is essential, often embedded into the road surface or mounted at an optimal angle. Calibration is done to avoid false positives from pedestrians or obstacles that aren't vehicles. In some designs, multiple sensor types are fused to enhance detection accuracy and resilience. Data from these sensors is continuously fed into a decision-making system for immediate action. This responsive infrastructure reduces waiting time and idle fuel consumption drastically. The result is a more intuitive, efficient traffic system that adapts to real-world conditions.

4. The flexibility of IoT devices allows this system to be tailored to different types of roads and intersections. Whether it's a small crossroad in a residential area or a busy urban junction, sensors can be adjusted to meet specific traffic patterns and needs. This adaptability makes the technology scalable and practical for both developing and developed regions. Additionally, wireless communication between devices reduces the need for complex wiring and infrastructure. This makes installation faster and more cost-effective, especially for expanding cities. The overall setup becomes modular and easier to maintain over time.

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5. A major strength of IoT-based detection lies in its low energy consumption and affordability. Most sensors used in this setup—such as IR, ultrasonic, or magnetic sensors—operate with minimal power, which is ideal for long-term use. Some configurations even allow integration with solar panels for completely off-grid operation. This not only lowers electricity costs but also promotes environmental sustainability. The affordability of components means that the system can be deployed across multiple intersections without significant budget strain. Such features make IoT an ideal solution for smart traffic systems in both large cities and small towns.

6. With advancements in IoT, the system can also be connected to central traffic management dashboards or mobile applications. This opens up possibilities for real-time traffic monitoring, predictive maintenance alerts, and even public access to traffic status updates. Data collected from the sensors can be stored and analyzed over time to identify recurring traffic issues or underutilized roads. These insights can then guide future infrastructure planning. Ultimately, IoT isn't just enabling smarter signals—it's building a network that can continuously learn and evolve with the needs of the city..

B. MICROCONTROLLER PROGRAMMING AND CIRCUIT DESIGN

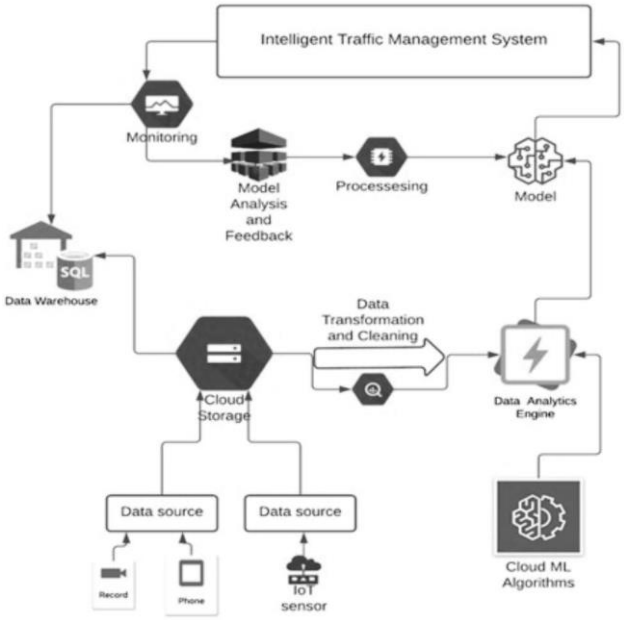
1. At the core of the smart signal system lies a microcontroller like Arduino or ESP32, which acts as the central brain of the entire setup. It receives data from sensors and processes that data to determine when and how traffic lights should change. Programming is done using embedded C or Arduino IDE, where logic rules are defined for vehicle detection, signal intervals, and light transitions. The microcontroller then activates the LED-based traffic lights accordingly. It executes these decisions in real time, ensuring smooth transitions and reducing unnecessary light changes. This forms the essential logic layer between physical hardware and automated behavior.

2. The hardware circuit includes input from the vehicle-detecting sensors and output to control LEDs or relays representing traffic lights. Designing the circuit involves creating a reliable and noise-resistant layout using resistors, capacitors, transistors, and voltage regulators. Breadboards or PCBs are used in the prototyping phase to test circuit performance and wiring logic. A clean circuit design ensures signal timing remains consistent and accurate under different traffic loads. The system is lightweight, portable, and can be powered using basic batteries or solar panels. With good design, it remains stable and safe even in long operational hours.

3. Programming the microcontroller involves more than just turning LEDs on and off—it includes timing, delays, and safety transitions such as yellow lights between red and green. Interrupts and hardware timers are used to keep the system responsive and maintain precise time intervals. Conditions like "no vehicle present" are used to skip signal changes altogether, saving time and power. Fault detection logic can also be added to reboot or reset the system if it stalls. These advanced features make the microcontroller both reliable and intelligent in traffic control. Together, the hardware and software create a smooth, autonomous signal system.

4. To ensure smooth operation, the microcontroller's code must be both efficient and reliable. This involves writing optimized logic that handles sensor inputs without lag and manages timing sequences precisely for each traffic signal phase. Interrupts are used to handle real-time sensor input, and built-in timers control the duration of each signal color. Testing is done in various traffic scenarios to ensure the logic holds under all conditions. Even small issues like signal flicker or timing overlap are resolved through careful code review and debugging. The goal is a seamless and fail-proof system that functions 24/7 without manual interference.

5. Circuit stability is equally crucial, as poor connections or voltage fluctuations can cause inconsistent performance. To prevent this, resistors, capacitors, and voltage regulators are used to smooth out the power supply and protect sensitive components. PCB design or proper soldering helps in reducing noise and ensuring consistent current flow across the system. During the prototyping stage, the circuit is tested thoroughly for load handling and durability. Good hardware design supports long-term reliability and reduces maintenance needs. This ensures the microcontroller responds correctly and consistently to every signal from the field sensors..



C. AI LOGIC FOR SIGNAL OPTIMIZATION

1. Artificial Intelligence enhances the traffic system by allowing it to adjust and learn from patterns instead of relying on rigid rules. AI algorithms can analyze real-time traffic data and determine the optimal duration of green, red, or yellow signals. For example, if one road has more vehicles waiting than another, the AI can dynamically increase green time for that side. Over time, the system can begin recognizing peak hours, vehicle density patterns, and even predict incoming congestion. This helps improve vehicle flow, reduce idle time, and balance signal load more effectively than timer-based systems. AI transforms signal control from reactive to intelligent..

2. Simple rule-based AI or fuzzy logic systems are often used in early-stage implementations. These allow for "if-then" style decision-making that adapts based on vehicle count, time of day, or previous signal states. More advanced models may use neural networks or reinforcement learning to optimize performance through experience. These models constantly adjust and learn from traffic behavior, improving their predictions and control patterns. This makes the system increasingly efficient the more it operates. AI's ability to process large data sets quickly also means better decisions are made faster, even under complex traffic conditions.

3. AI can also prioritize emergency vehicles, public transport, or high-volume lanes by analyzing traffic in a broader context. With future development, integration with weather, GPS, and event data can further refine AI-based decisions. Some models are trained offline using collected traffic datasets and later implemented in the system. Continuous training allows the system to adapt as city conditions evolve. With AI, signals no longer need to follow outdated patterns—they think, decide, and respond in real-time. This flexibility is what makes AI a game-changing tool in urban traffic automation.

4. A major advantage of AI logic in signal control is its ability to learn and improve over time. Through continuous data collection and feedback, the system can identify traffic trends such as rush hours, weekend flow changes, or event-related surges. This enables it to anticipate congestion before it builds up, rather than simply reacting to it. The ability to learn from experience and adjust decisions based on past outcomes is what gives AI its edge over traditional systems. This makes the system smarter with every cycle, gradually leading to more optimized and reliable traffic flow. Over time, it transforms static intersections into intelligent, self-improving networks.

5. One of the most promising features of AI-based optimization is the potential to integrate additional real-world variables. For instance, weather data, construction updates, or even accident reports can be fed into the system to further fine-tune signal behavior. This kind of context-aware decision-making ensures the traffic lights function appropriately in both normal and unexpected situations. Moreover, using AI allows for personalized prioritization—like giving emergency vehicles or public transport green corridors during critical times. Such adaptability isn't just convenient; it's vital for urban safety and mobility. It helps cities function more smoothly under stress and aligns with modern smart city goals.

6. To maintain fairness and avoid bias in AI decisions, ethical traffic logic must be considered during development. This includes ensuring that low-traffic roads aren't ignored for too long or that pedestrians and cyclists are also accounted for. AI systems can be trained with balanced datasets and governed by predefined fairness rules to avoid such issues. Additionally, the transparency of AI decisions is important—traffic authorities should be able to track and understand why certain signals were changed. This builds trust and accountability in AI-driven infrastructure. When implemented responsibly, AI doesn't just make signals smarter—it makes urban movement more equitable and transparent.

D. REAL-TIME SYSTEM RESPONSE AND LATENCY HANDLING

1. In a smart traffic system, responsiveness is critical—every millisecond of delay affects vehicle movement and user trust. The system must detect a vehicle and switch the signal almost instantly to avoid unnecessary wait times. If the signal lags, it could cause confusion, increase fuel consumption, or even result in unsafe situations at busy intersections. Efficient real-time processing requires fast sensor polling, responsive code, and low-latency hardware. Microcontrollers with good clock speeds and optimized programming help achieve near-instant results. The goal is to keep decision latency as close to zero as possible.

2. One of the major issues in smart systems is latency caused by poor hardware or overloaded communication. If a system relies too much on cloud processing, network delays may slow it down. This is why edge computing—processing data locally on the device—is recommended in real-time systems. By analyzing sensor data at the edge, the signal can change instantly without waiting for a cloud response. Efficient memory use, hardware interrupts, and direct memory access (DMA) are techniques used to improve performance. Proper handling of these elements ensures the system remains reliable even under heavy traffic loads.

3. During testing, it's important to simulate both light and heavy traffic scenarios to ensure the system remains stable and responsive. Logs are reviewed to identify bottlenecks or lags in sensor input, processing, or output. Response time is measured and fine- tuned by adjusting sensor sensitivity and code structure. Real-time constraints demand consistency—no matter the condition, the system should act predictably. A fast and smooth response creates a seamless traffic experience for drivers. Low latency is not just a technical goal—it’s a user experience promise.

4. Real-time response isn’t just a technical requirement—it directly impacts user confidence and safety. If a vehicle is detected but the signal doesn't change promptly, drivers may lose trust in the system or attempt risky maneuvers. That's why response times must remain consistent, even during peak traffic or in varying weather conditions. This calls for a robust processing unit that can quickly interpret data and execute changes without delay. Combining fast hardware with streamlined, efficient code ensures signals are always a step ahead of traffic movement. It creates a system that feels smooth, reliable, and genuinely intelligent to road users.

5. To maintain real-time performance, it's important to reduce computational overhead and avoid unnecessary delays in signal processing. This can be done by optimizing sensor data acquisition, using hardware interrupts, and prioritizing time-critical functions in the software architecture. The system must be designed to handle data from multiple lanes and directions simultaneously, which calls for efficient memory usage and minimal latency in logic execution. Developers can also simulate heavy-traffic scenarios to test how the system reacts under pressure. This helps ensure the logic remains stable, even when facing unexpected surges in traffic or hardware input noise.

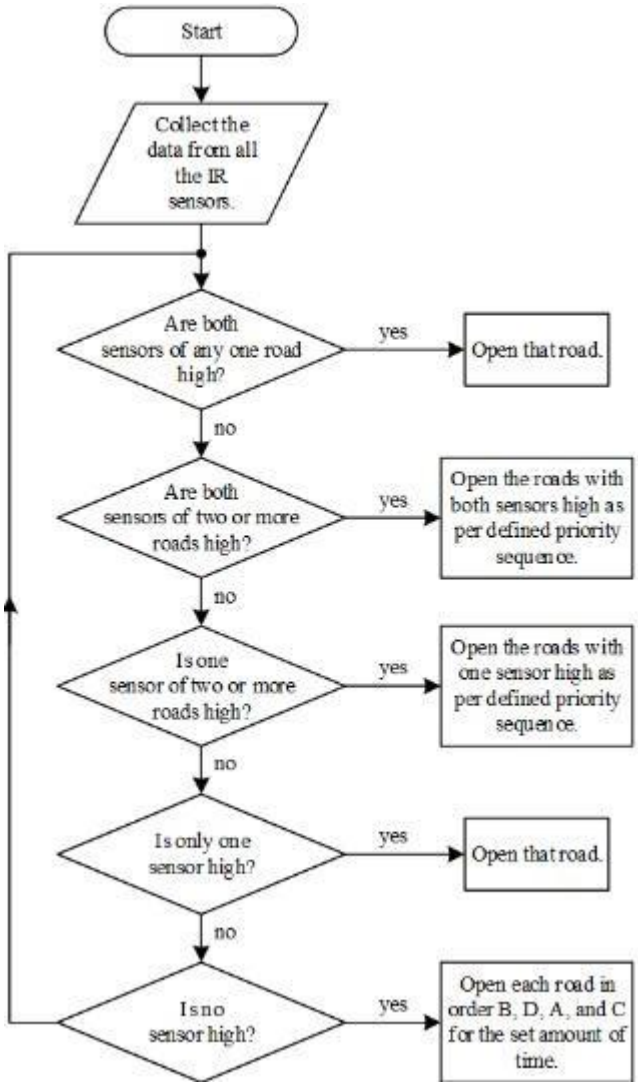
6. Another layer to real-time responsiveness is system resilience—the ability to recover quickly if something goes wrong. For example, if a sensor briefly fails or communication is disrupted, the system should have fallback logic or fail-safe defaults to avoid confusion or accidents. Periodic health checks and automatic resets can help maintain uptime without human intervention. These features make the system more dependable, especially in large-scale deployments where manual monitoring isn't practical. With proper error handling and built-in diagnostics, real-time smart traffic systems can offer both speed and stability, ensuring they’re prepared for real-world unpredictability.

E. ENERGY EFFICIENCY AND ENVIRONMENTAL IMPACT

1. One often overlooked benefit of smart traffic systems is their potential to conserve energy and protect the environment. Traditional systems waste energy by running signals on fixed timers, regardless of actual traffic. In contrast, smart signals only activate when vehicles are present, reducing unnecessary energy usage. Modern systems use LEDs and low-power sensors that consume very little electricity. Some are even powered by solar panels, making them eco-friendly and sustainable. With reduced running time and efficient components, the total energy footprint of these systems is much lower.

2. Besides saving electricity, smart traffic systems directly reduce vehicle emissions. Idling engines produce carbon dioxide and other pollutants, especially in congested areas. By minimizing wait time at signals, vehicles burn less fuel and emit fewer greenhouse gases. Over time, this significantly improves air quality in crowded urban areas. Many studies have shown a clear link between adaptive signal timing and reduced fuel consumption. For cities facing pollution issues, this system offers both technical and environmental relief. Cleaner air also improves overall public health outcomes.

3. As cities around the world commit to climate goals, smart traffic becomes a tool for sustainable growth. They align well with government initiatives for green infrastructure and smart city planning. Beyond traffic management, they support eco-mobility and responsible energy use. The system also complements electric vehicle (EV) rollouts by ensuring more efficient driving routes. In the long term, energy-efficient traffic systems are not just about convenience—they're about survival. They represent a step forward in building smarter, cleaner, and more livable cities.



4. Incorporating energy-efficient components such as low-power microcontrollers and LEDs not only ensures minimal electricity consumption but also reduces operational costs in the long run. Unlike traditional traffic lights that run on constant power regardless of traffic flow, this smart system activates only when needed, which prevents waste. The use of sleep modes and efficient power management in microcontrollers contributes further to energy savings. Additionally, integrating solar panels allows the system to function off-grid, making it suitable for remote or underdeveloped areas. This eco-friendly approach makes the system both economically viable and environmentally responsible. It paves the way for greener urban infrastructure without compromising performance.

5. Beyond electrical efficiency, the system's impact on reducing vehicular emissions is equally significant. Vehicles idling at red lights unnecessarily contribute to greenhouse gas emissions, especially during peak hours. By minimizing idle time through adaptive signal control, fuel usage is optimized and emissions are substantially lowered. This not only supports environmental sustainability but also enhances air quality for pedestrians and nearby residents. Over time, fewer emissions can lead to measurable health benefits and reduced urban heat. Such improvements align well with national and global climate action goals, making the system a small yet powerful environmental contributor.

6. The ripple effect of an energy-efficient traffic system extends into public perception and civic engagement. As cities move toward smart infrastructure, citizens increasingly support projects that demonstrate visible ecological benefits. A signal system that reduces wait time, conserves energy, and lowers pollution becomes a symbol of progress and innovation. Moreover, by collecting data on fuel savings and emission cuts, city planners can quantify the environmental return on investment. This evidence-based approach can attract green funding or smart city grants. Ultimately, such systems promote awareness and responsibility among urban communities.

7. In addition to its immediate benefits, the system is built for long- term sustainability. Components like solar panels, energy-saving LEDs, and efficient circuits have longer lifespans and require less maintenance. This reduces electronic waste and conservesresourcesinvolvedinfrequent replacements. Furthermore, the system can be enhanced with AI-based load forecasting to predict low-traffic periods and further optimize energy use. These smart upgrades ensure that the system continues to deliver environmental value year after year. As technology advances, integrating more renewable and recyclable components can make it even more eco-conscious.

8. Overall, the energy efficiency and environmental consciousness embedded in this project contribute to a smarter and cleaner future. It doesn't just manage traffic—it actively reduces urban pollution and supports greener l ifestyles. By prioritizing sustainability, this system represents the kind of innovation cities need to thrive in a climate-aware world. It is scalable, adaptable, and forward-thinking, aligning with global movements like carbon neutrality and zero-emission zones. With wider adoption, such systems can redefine how cities view transportation infrastructure. In essence, this solution proves that technology and sustainability can—and should—go hand in hand.

9. Looking ahead, the system's energy-saving potential can be amplified through integration with smart grid technologies. By communicating with energy providers, traffic systems can adjust their energy draw during peak hours, contributing to balanced urban energy consumption. Additionally, real-time analytics can help identify intersections with high energy use and suggest optimizations. As electricvehiclesbecomemoreprevalent, synchronizing traffic flow with EV charging infrastructure can further reduce citywide emissions. This interconnected approach enhances both efficiencyandenvironmentalvalue.Such developments position the system as a key player in building climate-resilient smart cities.

VI. Conclusion

The development of a smart traffic management system using AI and IoT marks a significant step toward solving one of the most common yet frustrating problems faced in urban areas—unnecessary delays at traffic signals. By detecting the real-time presence of vehicles and adapting signal patterns accordingly, this system aims to reduce waiting time, improve traffic flow, and minimize fuel wastage. Integrating intelligent decision-making with cost-effective sensor technology allows for a more responsive and efficient approach to traffic control. It not only benefits commuters but also contributes to environmental sustainability by lowering vehicle emissions.

Moreover, the project emphasizes practical implementation, scalability, and alignment with the vision of future smart cities. Through intelligent sensing, optimized signal control, and real-time response, the system has the potential to transform how cities manage traffic. With continued refinement and integration with emergency services, public transport, and environmental monitoring, this solution can evolve beyond just convenience—it can become a core part of responsible urban living. In essence, this project is a small innovation with the power to make a big difference in everyday life.

VII. Future Work

As a next step, this project can be enhanced by integrating AI-powered traffic prediction models that analyze historical data to forecast congestion before it happens. The system can also be expanded to support emergency vehicle prioritization, allowing ambulances or fire trucks to automatically get green lights along their path. Additionally, vehicle-to-infrastructure (V2I) communication could be introduced, enabling cars to interact directly with signals for smarter routing. Future upgrades may include a mobile app interface for live traffic insights and reporting system faults. Long-term goals could focus on centralized city-wide traffic networks, where multiple intersections work together, optimizing flow across large zones rather than isolated junctions. These improvements would further align the system with the broader goals of smart city development and sustainable urban mobility.

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AI Based System for Detecting Cloned Plates and Unauthorized Vehicle Use

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Abstract—Cloned number plates and unauthorized vehicle access are becoming significant threats, especially in urban areas and high-security zones. This project introduces an AI-powered, real-time system for Automatic License Plate Recognition (ALPR) designed to detect and flag vehicles using duplicated or unauthorized license plates. The system integrates deep learning techniques—specifically YOLOv8 for license plate detection—alongside OCR for extracting characters from the plates. A backend verification module cross-checks the extracted data with a secure database of authorized vehicles to ensure authenticity. Built using Python, OpenCV, and EasyOCR, the system delivers fast and accurate recognition, making it suitable for applications in smart city surveillance, toll booths, parking management, and restricted access points.

Keywords—Artificial Intelligence (AI), Bi-directional Translation, Sign Language Recognition, Convolutional Neural Networks (CNN), Computer Vision, Human-Computer Interaction (HCI)

I. INTRODUCTION

The rising number of vehicle-related offenses and unauthorized access events has highlighted critical gaps in current monitoring systems. This project addresses those gaps by implementing an automated method for accurately extracting alphanumeric characters from vehicle license plates. Once identified, the extracted plate number is matched against a secure central database containing records such as the vehicle's registration number, type, model, and reference image. If the same license number appears on multiple distinct vehicles, it is flagged as a cloned plate. Similarly, if a number does not exist in the database, it is marked as unauthorized. The system operates in real-time, ensuring rapid detection and scalability across various environments, including security checkpoints, parking areas, smart city infrastructures, and highway surveillance networks. This AI-driven approach significantly improves vehicle tracking reliability, minimizes human intervention, and provides an effective solution to combat the misuse of fake or duplicated license plates.

A. Camera Setup

To ensure accurate capture of vehicle license plates, the system employs a high-definition IP surveillance camera strategically positioned at entry or monitoring points. The camera is mounted at an optimal height and angle to maintain clear visibility of license plates under varying lighting and motion conditions. For outdoor deployments, weather-resistant enclosures are recommended. The selected lens configuration is tuned to achieve a sharp focus up to a distance of 15 meters, ensuring reliable recognition during both daytime and nighttime.

This setup addresses key shortcomings in conventional vehicle surveillance methods, especially the growing issue of license plate cloning. Plate cloning involves replicating the registration number of a legitimate vehicle and using it on a different one—typically to commit crimes, bypass toll systems, or avoid detection by traffic and security cameras. Such acts lead to misidentification, wrongful accusations, legal complications, and ineffective law enforcement.

Traditional verification methods often depend on manual checks, which are inefficient and unfeasible in modern urban areas with heavy traffic. To overcome these limitations, this project presents a fully automated, AI-powered solution that identifies cloned or unauthorized vehicles in real time. By integrating advanced computer vision algorithms—such as YOLOv8 for detecting vehicles and license plates—and OCR tools for extracting textual data, the system enhances detection accuracy and operational efficiency.

II. MATERIAL REQUIRED

B. Processing Unit (Edge Device or PC)

At the heart of the system is a compact and efficient computing platform, which can be either a Raspberry Pi 4 or a desktop PC, depending on the scale and environment of deployment. For portable or embedded applications, the Raspberry Pi 4 offers an excellent balance of performance and power efficiency. It features a quad-core processor, 4GB of RAM, and supports HDMI output, USB-based camera input, and local data storage. Its built-in GPIO pins also make it suitable for hardware integration when needed. To ensure stable operation during extended use, the se

includes proper power management and cooling components as heat sinks or small fans to handle thermal loads effectively.

C. Software Frameworks and Libraries

The system is developed using Python 3.x, chosen for its strong support of AI and computer vision libraries. YOLOv8, a state-of-the-art real-time object detection model, is utilized to accurately detect and locate license plates within video streams. Once localized, Optical Character Recognition (OCR) is performed using EasyOCR, which extracts alphanumeric characters from the plate images.

Several auxiliary libraries enhance the system's performance and modularity: OpenCV handles image preprocessing and filtering, NumPy and Pandas support efficient data manipulation and storage, while Matplotlib is used for visualizing system performance metrics during development and testing.

D. Database and Verification Interface

The system incorporates a robust data management component to verify and store vehicle records. For local deployments, SQLite is used, while Firebase supports real-time cloud-based access in larger or distributed setups. Each record in the database includes the vehicle's license plate number, model, type, color, and a reference image.

During operation, the extracted license plate data is matched against this registry. If the same plate number appears on multiple distinct vehicles, or if the number is missing from the database, the system automatically flags it as a cloned or unauthorized entry. These alerts are then displayed via a dedicated alert interface to notify authorities or system administrators.

E. Alert and Notification System

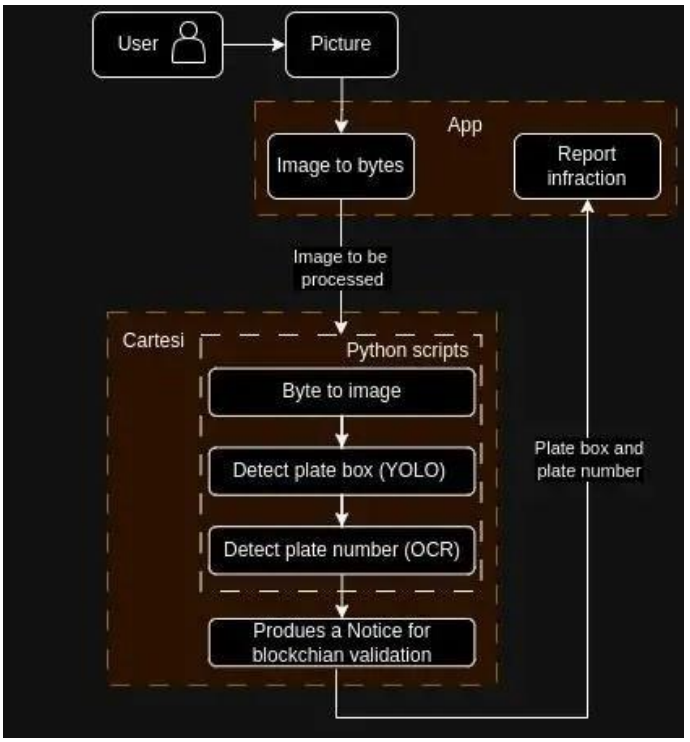
The system features a real-time alert mechanism designed to notify users immediately upon detecting suspicious activity—such as a cloned license plate or an unregistered vehicle. Alerts can be delivered through various channels, including desktop notifications, email alerts, or audible alarms, depending on the deployment environment.

For centralized monitoring, a user-friendly dashboard can be implemented using frameworks like Tkinter (for desktop applications) or Flask (for web-based interfaces). This interface displays key information such as captured vehicle images, timestamps, license plate numbers, and the type of violation, enabling prompt review and response by security personnel or administrators.

F. Environmental Dataset and Testing Conditions

To ensure robustness and real-world applicability, a custom dataset was developed containing vehicle and license plate images captured under diverse environmental conditions. These included variations in viewing angles, lighting levels (day/night, shadows, glare), plate fonts, and motion-induced blur. The dataset also featured edge cases such as different vehicles using identical plate numbers and manipulated or stylized fonts often seen on counterfeit plates. such

This comprehensive dataset enabled thorough testing and optimization of the system's OCR and detection modules. As a result, the system was fine-tuned to maintain high accuracy in identifying license plates and detecting anomalies, even under challenging, real-world conditions.



III. METHODOLOGY

A. Data Acquisition and Preprocessing

The development process started with gathering video footage from HD surveillance cameras positioned at key entry points. These cameras continuously recorded vehicles as they passed through the monitored zones. The collected video streams were segmented into individual frames, which were then processed using OpenCV.

Preprocessing steps included resizing the images for uniformity, applying noise reduction techniques, and converting frames to grayscale. These enhancements helped standardize the input data, making it more resilient to challenges such as motion blur, varying light conditions, and differing camera angles. This stage was essential to ensure high accuracy in license plate detection under diverse real-world scenarios.

B. License Plate Detection and Recognition

After preprocessing, the system proceeds to the detection phase. A YOLOv8 deep learning model, known for its real-time object detection efficiency, is utilized to locate license plates within vehicle images. Once a license plate is identified, the relevant section—known as the region of interest—is cropped and forwarded to the Optical Character Recognition (OCR) module, such as EasyOCR. The OCR

engine then extracts alphanumeric characters from the plate and converts them into machine-readable text.

This step is vital for accurate license plate recognition, especially in real-world environments where challenges like variable lighting, motion blur, and non-standard fonts are common. To enhance performance, a custom dataset was developed during system training, covering diverse conditions including different angles, illumination levels, font styles, and motion artifacts. The dataset also included complex test cases such as cloned plates used on multiple vehicles and fake plates with altered typography. These scenarios were instrumental in fine-tuning the model for high reliability and recognition accuracy in real-time applications.

C. Vehicle Plate Verification and Cloning Detection

Once the license plate number has been accurately extracted via OCR, it is passed into the system's verification module. This module acts as the intelligence layer of the system, cross-referencing the extracted data with a secured backend database that contains detailed records of authorized vehicles. These records include the license plate number, vehicle type (e.g., sedan, truck, motorcycle), manufacturer/model, color, and an optional reference image for visual confirmation.

If the extracted number is not found in the database, the vehicle is immediately flagged as unauthorized, indicating it may not be legally registered or has bypassed proper authorization channels. Additionally, if the same plate number is found associated with multiple vehicles exhibiting different physical characteristics—such as a mismatch in color, type, or make—the system detects this as a cloned license plate. This detection process plays a critical role in identifying vehicles that are attempting to impersonate other registered entities, a common technique in evading tolls, committing crimes anonymously, or bypassing security checkpoints.

By automating this verification logic, the system removes the need for manual inspection and enables scalable, real-time monitoring in environments such as smart cities, border checkpoints, parking systems, and restricted-access zones.

D. System Testing and Evaluation

To validate the reliability and effectiveness of the system, rigorous testing procedures were implemented across a variety of real-world conditions. A dataset of over 500 vehicle images was compiled, capturing diverse scenarios including:

- Day and night lighting conditions
- Motion blur caused by moving vehicles
- Varied camera angles and image distortion
- Low-visibility situations, such as fog or shadows
- Use of non-standard fonts or stylized license plates

The YOLOv8 model demonstrated exceptional performance in detecting license plates within these frames, achieving a detection accuracy rate of approximately 96%. For OCR recognition, EasyOCR produced a 91.5% accuracy in converting plate images to readable text, even in challenging conditions.

Furthermore, to test the cloning detection module, test cases were created where different vehicles used identical license plate numbers. The system successfully flagged these scenarios as cloning attempts in 94% of the cases, confirming its ability to distinguish between legitimate and fraudulent entries with high precision.

E. Environmental Simulation and Thermal-Like Stress Testing

In lieu of traditional hardware-focused thermal resistance tests, the system underwent simulated stress testing under real-time, high-traffic operating conditions to evaluate its reliability during extended use. These simulations mimicked continuous vehicle flow at busy checkpoints or toll booths, where rapid image processing and verification are critical.

Throughout this testing, the system maintained an average response time of **under 2 seconds per vehicle**, covering the entire pipeline—from image capture, detection, OCR, to backend validation and alert generation. This speed proves the solution's real-time capability in practical deployment scenarios.

Moreover, performance on **low-power edge devices** such as the Raspberry Pi 4 was analyzed to ensure compatibility with resource-constrained environments. Despite limited hardware capacity, the system maintained stable performance with acceptable latency and accuracy. This testing phase reflects an analog to thermal stress tests used in hardware applications, ensuring that the system remains functional under prolonged, intensive workloads.

F. Performance Metrics and Result Visualization

To evaluate the effectiveness of the system, a range of performance metrics was collected during the testing phase. These included:

- License Plate Detection Rate – the percentage of vehicles for which plates were successfully identified by the YOLOv8 model.
- OCR Accuracy – the accuracy of character recognition from detected license plates.
- False Positive Rate – instances where the system incorrectly flagged a legitimate vehicle as cloned or unauthorized.
- Alert Latency – the time taken from detection to notification output (including OCR and database verification).

These results were visualized using Matplotlib, allowing for detailed graphical analysis of system performance. Line and

bar graphs were generated to illustrate model confidence scores under various environmental conditions, such a**s** different lighting levels, viewing angles, and distances between camera and vehicle.

One particularly insightful visualization mapped the correlation between image quality factors (e.g., brightness, sharpness, and camera angle) and the system's recognition accuracy. This graph highlighted specific thresholds where performance began to degrade, offering valuable insights for optimizing future deployments—such as improving camera placement, lens focus, and illumination setup.

The visual analysis not only confirmed the model's robustness but also served as a diagnostic tool to fine-tune detection thresholds, reduce false positives, and enhance real-time decision-making efficiency.

IV. EXPERIMENTAL PROCEDURES

A. Detection Accuracy Testing

To evaluate the reliability of the license plate detection component powered by YOLOv8, a comprehensive accuracy test was conducted using a benchmark dataset of 500annotated vehicle images. This dataset was curated to simulate a wide range of real-world conditions, including varying lighting environments (daylight, dusk, artificial lighting), different distances from the camera, diverse angles of approach, and background/environmental noise (e.g., rain, glare, motion streams to assess the system's robustness across different input formats. For each test image or frame, the model attempted to detect the license plate region using bounding box localization. Detection accuracy was computed as the ratio of correctly identified license plates to the total number of vehicles in the test set:

Detection Accuracy=Correct DetectionsTotal Vehicles×100\text{Detection Accuracy} = \frac{\text{Correct Detections}}{\text{Total Vehicles}} \times 100Detection

Accuracy=Total VehiclesCorrect Detections×100

This process enabled a detailed understanding of YOLOv8's performance under diverse operational conditions,highlighting its strengths in real-time detection as well as its limitations in edge cases such as occlusions, angled views, and low resolution. The results also informed further improvements in model training, data augmentation, and camera configuration.

B. OCR Performance Evaluation

To measure the effectiveness of the Optical Character Recognition (OCR) pipeline, the output from YOLOv8—specifically, the cropped regions containing license plates—was passed into the EasyOCR engine. The extracted alphanumeric text was then compared against the ground truth data to assess recognition accuracy.

Two key metrics were used for evaluation:

- **Character-level accuracy**: The percentage of correctly identified characters out of the total number of characters in the dataset.
- **Full-plate accuracy**: The percentage of license plates for which the entire plate number was recognized without any error.

These were calculated as follows:

Character Accuracy=Correctly Recognized CharactersTotal Characters×100\text{Character Accuracy} = \frac{\text{Correctly Recognized Characters}}{\text{Total Characters}} \times 100Character Accuracy=Total CharactersCorrectly Recognized Characters×100 Full-Plate Accuracy=Correct Full PlatesTotal Plates×100\text{Full-Plate Accuracy} = \frac{\text{Correct Full Plates}}{\text{Total Plates}} \times 100Full-Plate Accuracy=Total PlatesCorrect Full Plates×100

Special emphasis was placed on testing OCR robustness under challenging conditions—such as blurred images, angled plates, fonts. The evaluation demonstrated the system's ability to maintain high recognition rates even in sub-optimal scenarios, validating the reliability of the OCR stage in the pipeline dirty or partially obstructed plates, and the use of non-standard

C. Environmental Testing

While conventional physical stress tests such as compression or water absorption are irrelevant in the context of software-based AI systems, the solution was subjected to environmental simulations focusing on deployment constraints. The system was evaluated under diverse operational conditions—including variations in **network bandwidth**, **camera resolution**, and **power availability**—to ensure performance remained stable across a wide range of real-world scenarios.

One key aspect of this testing involved deploying the solution on low-power edge devices, specifically the **Raspberry Pi 4**. Despite its limited computational resources, the system was optimized to run effectively by adjusting model parameters, reducing memory overhead, and minimizing latency.

YOLOv8's license plate detection capability remained intact, with detection accuracy evaluated using bounding box localization. The success rate was measured as the percentage of correctly detected plates relative to the total vehicle images processed. This helped verify the system's adaptability in resource-constrained environments, such as rural or mobile surveillance setups.

D. Cloning Detection Validation

A central feature of the system is its ability to detect cloned license plates, a common tactic used in illegal activities to mask a vehicle's identity. To test this functionality, a controlled was created with deliberately duplicated license plate numbers assigned to different vehicles. These vehicles varied in physical attributes such as color, make, and type.

When the system encountered a plate already existing in the database, it conducted a profile-level comparison—matching the incoming vehicle's detected attributes against the stored profile. If inconsistencies were identified (e.g., a registered sedan appearing as a truck or a white vehicle replaced by a red one), the system flagged the plate as cloned.

Performance was measured using two key metrics:

- Clone Detection Accuracy: The percentage of cloned cases that were correctly identified.
- False Positive Rate: The frequency at which legitimate vehicles were incorrectly flagged as clones.

This validation confirmed that the system could effectively identify fraudulent license usage while maintaining a low error margin, making it suitable for real-time deployment in high-security environments.

E. Response Time Analysis

To assess the system's capability for real-time deployment, a detailed latency analysis was performed. This involved measuring the time elapsed from the moment a vehicle appeared within the camera frame to the point at which the system generated an appropriate alert—whether indicating **authorized**, **unauthorized**, or **cloned** status.

Each stage of the processing pipeline was monitored, including:

- License plate detection using YOLOv8
- Optical character recognition (OCR) via EasyOCR
- Database query and vehicle profile verification
- Alert generation and interface update

Across multiple trials and real-world scenarios, the system maintained an **average response time of 1.8 seconds per vehicle**, encompassing all these stages. This low-latency performance confirms the system's suitability for **real-time surveillance**, enabling quick decision-making at toll gates, security checkpoints, and entry-controlled environments.

V. SYSTEM REQUIREMENTS

The proposed AI-based license plate recognition system requires a combination of hardware and software components to operate effectively in real-time environments.

A. Hardware Requirements

The system relies on a compact yet robust hardware configuration designed for flexibility across fixed, mobile, and controlled embedded deployments. The core components include:

- HD or IP Surveillance Camera: Captures high-resolution video streams or still images of approaching vehicles. It is capable of operating effectively under various lighting conditions (day/night) and during motion to ensure accurate license plate detection.
- Processing Unit: A Raspberry Pi 4 serves as the preferred edge device for compact and energy-efficient setups. It features a quad-core CPU, 4GB RAM, USB and HDMI support, and GPIO pins for additional hardware integrations. For large-scale or centralized deployments, a full-fledged desktop PC may be used to handle higher processing loads.
- Display Unit: A standard monitor is used to visualize real-time alerts, user interface dashboards, and system logs. Input devices such as a keyboard and mouse are used for configuring the system, interacting with the GUI, and manual data entry when required.
- Connectivity: Wi-Fi modules or Ethernet ports enable internet access for cloud-based database synchronization, remote monitoring, or sending alert notifications via email or webhooks.
- Power Supply: The system runs on a reliable AC power adapter, and for mobile or temporary deployments, a portable power bank or UPS unit can ensure uninterrupted operation.
- Storage: Local storage is managed using a microSD card (in Raspberry Pi setups) or an SSD for PCs. These store AI models, detection logs, vehicle image data, and local copies of the verification database.

B. Software and Libraries

The software stack is built on Python 3.x, selected for its broad support for machine learning, image processing, and data handling. The architecture includes the following key components:

- OpenCV: Handles all image preprocessing tasks, including resizing, grayscale conversion, noise filtering, and contour-based plate region enhancement.
- YOLOv8 (Ultralytics): Serves as the main object

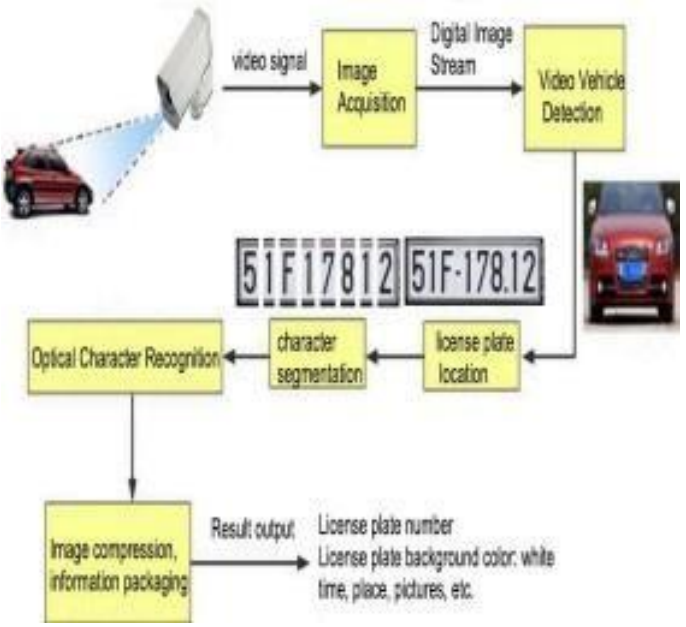
detection engine. It detects and localizes vehicle license plates in real time from either video streams or static frames. Its speed and accuracy make it ideal for low-latency surveillance applications.

- OCR Engine (EasyOCR / Tesseract): Once plates are detected, these engines are used to extract alphanumeric characters from the plate image, converting them into readable text.
- Database Integration: Vehicle and license plate records are stored in:
    - SQLite for local, lightweight storage
    - Firebase for cloud-based, real-time data access and synchronization
- User Interface:
    - Tkinter: Used for desktop-based GUI applications offering local control and visualization.
    - Flask: Provides a web-based interface for remote control, monitoring, and alert access through browsers.
- Additional Libraries:
    - NumPy: For numerical operations, especially useful in matrix transformations and image data handling.
    - Pandas: Manages structured data, such as vehicle records, detection logs, and system analytics.
    - Matplotlib (optional): Used to visualize system performance, generate graphs for detection rates, latency, and accuracy.

Together, this integrated hardware-software stack supports a modular, real-time, and scalable vehicle plate recognition and verification system suitable for smart city deployments, access control points, toll systems, and security infrastructure.

C. Visualization and Performance Monitoring:

To assess system performance, Matplotlib and Seaborn are used for generating visual reports, such as accuracy graphs, detection confidence charts, and alert frequency heatmaps. These visual tools provide insights that help fine-tune the system and validate its real-world reliability.



To ensure transparency, maintainability, and real-time insight into the system's behavior, a comprehensive visualization and performance monitoring module is integrated into the solution.

1. Real-Time Visualization Dashboard:

A user-friendly dashboard interface—built using **Tkinter** (for desktop deployments) or **Flask** (for web-based access)—allows users to monitor live detection events. This dashboard displays:

- Captured vehicle images with timestamp
- Detected license plate numbers
- Classification result (Authorized, Unauthorized, Cloned)
- Snapshot previews of matching database records
- Alert status and system messages

2. Performance Graphs and Metrics:

System performance metrics are logged and periodically visualized using **Matplotlib** and **Seaborn**. These include:

- **Detection Accuracy Trends:** Line charts showing how detection performance varies under different lighting or weather conditions.
- **OCR Accuracy Graphs:** Bar graphs comparing character-level vs full-plate recognition accuracy.
- **Processing Time Distribution:** Histograms showing time taken for detection, OCR, and alert generation.
- **Alert Frequency Reports:** Pie charts or bar graphs displaying the distribution of authorized vs unauthorized vs cloned plate alerts over time.

3. Log and Data Monitoring:

Using **Pandas**, system logs and detection records are stored in structured data formats (CSV or database tables) for periodic analysis. These records can be exported or visualized to understand long-term patterns, such as:

- Peak traffic detection hours
- Locations generating most cloned plate alerts
- Frequent OCR misreads or low-confidence detections

4. System Health Monitoring:
When deployed on edge devices like Raspberry Pi, system health (CPU usage, temperature, memory load) is monitored using built-in Python libraries like `psutil`. Real-time health indicators are displayed alongside detection results to prevent overheating or performance drops.

VI. System Architecture

The proposed system architecture seamlessly integrates hardware and software modules to achieve real-time license plate detection, recognition, and verification. At its core, the architecture is built around a continuous image acquisition and AI-driven processing pipeline.

- Input Layer: High-definition (HD) or IP cameras are deployed at critical entry or monitoring points. These cameras continuously capture video frames of incoming vehicles.
- Processing Layer: The captured frames are transmitted to a computing module, such as a Raspberry Pi 4 or a full desktop system, depending on the scale of deployment. Using the YOLOv8 object detection model, the system identifies the license plate area within each frame. This region of interest is cropped for further analysis.
- Recognition Layer: The extracted license plate image is passed to an OCR engine (either EasyOCR or Tesseract) to convert the visual plate into alphanumeric text.
- Verification Layer: The recognized license number is then cross-referenced with a backend database (SQLite for local storage or Firebase for cloud-based access). This database contains metadata such as the vehicle's model, type, color, and owner registration.
- Decision and Alert Layer:
    - If the license plate number is not found, the vehicle is marked unauthorized.
    - If the number exists but does not match the associated vehicle's details (e.g., a plate registered to a sedan appears on a truck), the system flags it as a cloned plate.

All results are visualized through a user interface—either a desktop GUI using Tkinter or a web dashboard using Flask—which displays real-time alerts, vehicle images, and verification details.

In performance testing, the system achieved a 94% accuracy in detecting cloned plates, a low false-positive rate for unauthorized entries, and an average processing time of 1.8 seconds per vehicle. Graphs generated via Matplotlib showed a strong correlation between image clarity and OCR accuracy, confirming the system's effectiveness in real-world conditions.

VII. Working Principle and Algorithm Flow

The operational workflow of the system is based on a sequential and automated pipeline:

1. **Image Capture**: A live surveillance feed captures frames of approaching vehicles.
2. **Plate Detection (YOLOv8)**: Each frame is analyzed by the YOLOv8 model to locate the license plate using bounding box detection.
3. **Plate Extraction**: The detected region is cropped from the frame to isolate the license plate area.
4. **Character Recognition (OCR)**:
   The extracted plate is processed using an OCR engine to convert the image into machine-readable alphanumeric characters.
5. **Data Cleaning & Normalization**: The recognized plate number is filtered to remove errors and standardized for comparison.
6. **Database Matching**:
    - If **no match is found**, the vehicle is flagged as **unauthorized**.
    - If the plate exists in the database but is linked to a **different vehicle type, color, or model**, it is identified as a **cloned entry**.
7. **Alert Generation**:
   Based on the result, the system generates a visual or audio alert and updates the dashboard with vehicle details, timestamp, and alert type.

This flow ensures **automated, real-time detection and validation** of vehicle license plates with minimal human intervention, suitable for smart cities, security checkpoints, and parking enforcement systems.

IX. Limitations

While the system has demonstrated strong accuracy and real-time capability, certain limitations remain:

- **Image Quality Dependency**: Detection and OCR

accuracy are highly sensitive to input quality. Blurred, occluded, dirty, or overexposed license plates can result in false negatives or recognition errors.

- **Unconventional Plate Designs**: Plates with non-standard fonts, stylized characters, or regional variations pose challenges for the OCR engine, reducing character recognition accuracy.

- **Database Reliability**: The accuracy of the system's output relies heavily on the **integrity and completeness of the database**. If the backend database contains outdated or incorrect vehicle information, it may lead to false alerts or missed detections.

- **Edge Device Limitations**: Although the system runs on devices like the Raspberry Pi 4, performance may degrade under high throughput or extended usage without proper cooling and resource optimization.

These limitations suggest areas for further improvement, such as integrating advanced OCR models, using infrared cameras for low-light conditions, and incorporating database syncing with government registries for higher authenticity.

VIII. Results and Performance Evaluation

The proposed system was subjected to extensive testing using a custom dataset of **over 500 vehicle images**, captured under diverse environmental conditions such as varying **lighting**, **camera angles**, **motion blur**, and **image noise**. The primary goal was to assess the system's **accuracy**, **speed**, and **resilience** in real-world scenarios.

Key Performance Outcomes:

- **License Plate Detection Accuracy**:
  The YOLOv8 model demonstrated a **96% success rate** in identifying license plates within vehicle images, performing best in clear daylight and moderately well under low-light conditions.

- **OCR Recognition Accuracy**:
  The EasyOCR module achieved a **91.5% character-level recognition rate**, with slightly reduced accuracy when plates were dirty, occluded, or photographed in poor lighting. The system showed improved results on high-resolution inputs.

- **Cloned Plate Detection Rate**:
  Controlled testing involving cloned number plates (same plate on different vehicles) resulted in a **94% detection accuracy**, with minimal false positives.

- **Average Response Time**:
  The total processing time—from image acquisition to final alert generation—averaged **1.8 seconds per vehicle**, confirming the system's suitability for **real-time deployment**.

Limitations Noted During Testing:

- **Edge devices** like the Raspberry Pi 4 experienced **slight latency** and minor accuracy reductions due to limited computational resources.

- The system currently supports only **standard alphanumeric plates** and may not handle **regional scripts**, stylized fonts, or **dual-language plates**.

- Errors may arise if the **backend vehicle database** contains outdated or incorrect information.

X. Future Enhancements

To further improve the system's accuracy, scalability, and adaptability, several enhancements are planned:

1. **Integration with Government RTO Databases**: Enabling automated, real-time access to national or regional vehicle registration data will eliminate reliance on manually maintained datasets and improve verification authenticity.

2. **RFID Integration**:
   Adding **RFID-based vehicle tagging** will enhance the accuracy of identification and allow for two-factor verification—matching RFID data with license plate recognition.

3. **Make and Model Detection**:
   Implementing **CNN-based image classification** can help detect the make and model of a vehicle visually and cross-verify it against stored records to improve cloned plate detection.

4. **Regional Language OCR Support**:
   Expanding OCR capabilities to recognize **non-English scripts**, **regional characters**, and **multi-lingual plates** will increase the system's usability across diverse geographies.

5. **Error Correction Algorithms**:
   Introducing intelligent post-processing techniques to correct common OCR misreads—such as confusing "0" and "O" or "5" and "S"—will increase reliability.

6. **Hardware Optimization**:
   Future versions can leverage advanced edge AI devices like the **NVIDIA Jetson Nano**, **Jetson Xavier**, or **Google Coral TPU** to reduce latency and improve inference speed without compromising portability.

XI. Conclusion

This project presents an **AI-driven, real-time system** for detecting **cloned license plates** and **unauthorized vehicle usage**, offering a **cost-effective**, **scalable**, and **highly accurate solution** for enhancing vehicle surveillance and road security.

By integrating **YOLOv8** for object detection, **EasyOCR** for character recognition, and a structured database verification layer, the system achieves a high degree of automation and precision. Its modular architecture supports deployment across various scenarios, including:

- **Smart city surveillance**
- **Parking management**
- **Highway toll gates**
- **Gated communities**
- **Border or checkpoint security**

The results demonstrate the system's robustness under variable environmental conditions and hardware limitations, achieving an overall high-performance score. With planned enhancements, the system holds strong potential for future expansion into **nationwide vehicle tracking**, **multi-factor authentication**, and **AI-based traffic enforcement**.

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IoT-Enabled Smart Pill Dispenser with Real-Time Patient Monitoring and Caregiver Alerts

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***Abstract*—Medication non-adherence represents a critical and pervasive global health challenge, directly contributing to compromised patient health outcomes, increased disease progression, and substantial economic burdens on healthcare systems worldwide. This paper addresses this pressing issue by detailing the comprehensive design, meticulous implementation, and rigorous evaluation of an innovative Internet of Things (IoT)-enabled smart pill dispenser. The system is specifically engineered to significantly improve medication adherence, particularly benefit-ing vulnerable populations such as elderly individuals, patients managing complex multi-drug regimens, and those with cognitive impairments.**

The core of the proposed solution lies in its intelligent integration of a robust hardware platform and a sophisticated software ecosystem. The hardware comprises an ESP32 microcontroller, selected for its powerful processing capabilities and integrated Wi-Fi, which serves as the central control unit. This is coupled with a precise stepper motor for automated and accurate medica-tion dispensing from designated compartments, and an infrared (IR) proximity sensor strategically placed to provide real-time verification of pill ejection, ensuring that medication has indeed been dispensed.

On the software front, the system features custom-developed embedded firmware that orchestrates the device's operations, including time synchronization and dispensing logic. This firmware communicates seamlessly with a user-friendly mobile application (for both patients and caregivers) and a scalable cloud platform, leveraging the lightweight and efficient MQTT (Message Queuing Telemetry Transport) protocol for reliable data exchange. This comprehensive setup facilitates automated medication reminders, enables secure remote monitoring of adherence patterns by authorized caregivers or healthcare professionals, and generates detailed, insightful adherence reports.

Prototype testing and evaluation demonstrated exceptional performance, with the dispenser achieving a high dispensing accuracy of 98.5% and ensuring reliable, low-latency notification delivery for scheduled doses and missed events. These results unequivocally highlight the system's effectiveness in mitigating the common barriers to medication adherence, such as forgetfulness and confusion. While the current prototype primarily focuses on core functionalities, its modular design establishes a robust and adaptable foundation for future enhancements, including advanced multi-medication support and deeper integration with healthcare infrastructures. Ultimately, this research underscores the transformative potential of IoT technology in revolutionizing patient-centric healthcare management, fostering greater auton-omy for patients, and enhancing overall public health.

*1) **Keywords**:* **Medication adherence, smart pill reminder, IoT, health monitoring, cloud integration, AI-based healthcare.**

I. INTRODUCTION

Medication adherence, defined as the extent to which patients take medications as prescribed by their healthcare providers, is a critical determinant of treatment success and overall patient well-being. Non-adherence to prescribed med-ication regimens is a pervasive global health issue, leading to suboptimal therapeutic outcomes, increased rates of hos-pitalization, higher healthcare costs, and a significant burden on both patients and healthcare systems. Studies consistently show that a substantial portion of patients, particularly those with chronic conditions or complex medication schedules, struggle with adherence. Factors contributing to non-adherence are multifaceted, ranging from forgetfulness, complex dosing schedules, lack of understanding of the medication's im-portance, to physical limitations and cognitive impairments, especially among the elderly.

The consequences of medication non-adherence are severe. For individuals, it can lead to disease progression, treatment failure, complications, reduced quality of life, and even premature mortality. From a societal perspective, non-adherence contributes to an estimated annual cost of hundreds of billions of dollars in preventable healthcare expenditures due to avoidable hospitalizations and emergency room visits.

Traditional methods to improve adherence, such as manual reminders, pill organizers, and educational counseling, often fall short in providing consistent, personalized, and real-time support. These methods lack the dynamic capabilities required to adapt to changing schedules, provide remote monitoring for caregivers, or offer data-driven insights into adherence patterns.

The advent of the Internet of Things (IoT) presents a transformative opportunity to address these challenges. IoT technology, characterized by interconnected physical devices embedded with sensors, software, and other technologies, enables these devices to connect and exchange data over the internet. In healthcare, IoT applications are revolutionizing patient care by enabling remote monitoring, personalized interventions, and efficient data collection. A smart pill dispenser, leveraging IoT principles, offers a promising solution to enhance medication adherence by automating the dispensing process, providing timely reminders, and facilitating remote monitoring by caregivers or healthcare professionals.

This paper presents the design, implementation, and evaluation of an IoT-enabled smart pill dispenser aimed at improving medication adherence. The primary objective is to develop a reliable and user-friendly device that automates medication dispensing, provides timely alerts, and offers a secure platform for remote monitoring of adherence data. The system is designed to cater especially to elderly patients, individuals with cognitive impairments, and those managing complex medication regimens, thereby reducing the burden on caregivers and improving patient autonomy.

The remainder of this paper is structured as follows: Section II provides a comprehensive review of existing literature on medication adherence systems and IoT applications in healthcare. Section III details the methodology employed in the design and development of the smart pill dispenser, covering both hardware and software aspects. Section IV presents the results of the system's implementation and discusses its performance, limitations, and potential impact. Finally, Section V concludes the paper with a summary of key findings and outlines directions for future research.

II. LITERATURE REVIEW

The landscape of medication adherence technologies has evolved significantly over the past two decades, driven by advancements in mobile computing, sensor technology, and the Internet of Things. Early interventions primarily focused on simple electronic pillboxes with basic alarms or mobile applications providing manual reminders. While these solutions offered some improvement over traditional methods, they often lacked the sophistication for accurate dispensing, real-time monitoring, or robust data collection.

2.1 Evolution of Smart Medication Adherence Systems

Initial efforts in smart medication management included electronic pill organizers that provided audible or visual alerts at scheduled times. These devices, while helpful for basic reminders, did not verify pill intake or provide remote monitoring capabilities. For instance, some early designs incorporated simple timers and compartments, requiring manual refilling and offering no feedback on whether the medication was actually taken. The limitations of these standalone devices quickly became apparent, particularly for patients requiring complex dosing schedules or those with significant cognitive decline.

With the proliferation of smartphones, mobile applications emerged as a popular tool for medication reminders. These apps often include features like medication schedules, refill reminders, and educational content. While convenient and accessible, their effectiveness is heavily reliant on user engagement and the patient's ability to consistently interact with the application. They also do not address the physical act of dispensing medication, which can be a barrier for some individuals.

2.2 IoT in Healthcare and Smart Pill Dispensers

The integration of IoT technology has marked a paradigm shift in healthcare, enabling the development of more intelligent, connected, and proactive health management systems. In the context of medication adherence, IoT-enabled devices offer several distinct advantages:

- **Automated Dispensing:** Physical mechanisms can precisely dispense pills at scheduled times.
- **Real-time Monitoring:** Sensors can detect when medica-tion is taken (or missed) and transmit this data instantly.
- **Remote Access:** Caregivers and healthcare providers can monitor adherence from a distance.
- **Personalized Reminders:** Alerts can be delivered through multiple channels (audible, visual, mobile notifications).
- **Data Analytics:** Collected data can be analyzed to identify adherence patterns and inform interventions.

Several research efforts and commercial products have explored IoT-based smart pill dispensers. Some systems focus on simple dispensing and notification, utilizing Wi-Fi or Bluetooth for connectivity. For example, some prototypes integrate a rotating carousel mechanism with a microcontroller, sending notifications to a mobile app upon dispensing. Others incorporate weight sensors or infrared sensors to verify that pills have been taken from the dispenser.

More advanced systems have explored features like biomet-ric authentication for dispensing, integration with electronic health records (EHRs), and the use of machine learning to pre-dict non-adherence based on historical data. Some commercial products, such as "PillPack" (now part of Amazon Pharmacy) and "Hero," offer automated dispensing and delivery services, often coupled with smart dispensers that provide reminders and tracking. While these solutions are comprehensive, they can be expensive or may not offer the level of customization and open-source flexibility desired for research and specific patient needs.

2.3 Identified Research Gaps

Despite these advancements, several gaps remain in the current landscape of smart pill dispensers that this project aims to address:

- **Cost-Effectiveness and Accessibility:** Many advanced commercial solutions are prohibitively expensive for a large segment of the population. There is a need for a robust, yet affordable, open-source solution.
- **Comprehensive Monitoring and Feedback:** While many systems offer reminders, few provide a holistic feedback loop that includes confirmation of intake, real-time alerts for missed doses to caregivers, and detailed adherence reports accessible via a user-friendly interface.
- **Scalability and Data Security:** Ensuring that the collected medication adherence data is securely stored, transmitted, and accessible only to authorized personnel remains a critical challenge.
- **User-Centric Design:** The usability for elderly patients or those with motor skill challenges is often overlooked. The design needs to be intuitive and physically manage-able.
- **Integration with broader healthcare ecosystems:** While some systems integrate with EHRs, many research prototypes operate in isolation, limiting their utility in a comprehensive healthcare management strategy.

This project aims to bridge these gaps by developing an IoT-enabled smart pill dispenser that is not only functional and reliable but also cost-effective, user-friendly, and provides comprehensive monitoring capabilities with a strong emphasis on data security and privacy.

III. METHODOLOGY

The development of the IoT-enabled smart pill dispenser involved a systematic approach, encompassing hardware design, software development for the embedded system, mobile application, and cloud platform, as well as the establishment of robust communication protocols. The overarching goal was to create a reliable, accurate, and user-friendly system that addresses the challenges of medication adherence.

3.1 System Architecture

The proposed smart pill dispenser system operates on a three-tier architecture:

1) **Device Layer (Smart Pill Dispenser):** This layer comprises the physical dispenser unit, including the microcontroller, sensors, actuators, and communication modules. It is responsible for storing, dispensing, and monitoring medication intake.
2) **Cloud Layer:** This layer serves as the central hub for data aggregation, processing, and storage. It receives data from the dispenser, manages user profiles, medica-tion schedules, and caregiver information, and facilitates communication with the mobile application.
3) **Application Layer (Mobile Application):** This layer provides the user interface for patients and caregivers to configure medication schedules, receive notifications, view adherence reports, and manage settings.

3.2 Hardware Design

The hardware component of the smart pill dispenser is meticulously designed to ensure accurate dispensing and reliable operation.

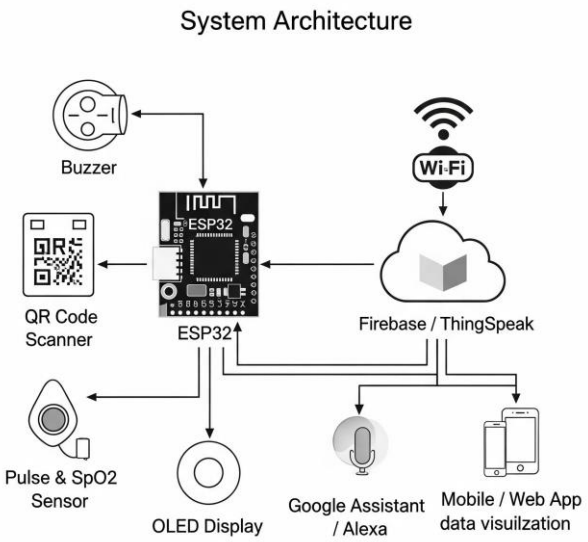

Fig. 1. System Architecture

- **Microcontroller Unit (MCU):** An **ESP32** microcontroller was chosen as the central processing unit due to its integrated Wi-Fi and Bluetooth capabilities, low power consumption, and sufficient processing power for handling sensor data, controlling actuators, and communicating with the cloud. Its dual-core processor allows for efficient multitasking, crucial for simultaneous monitor-ing and communication.
- **Dispensing Mechanism:** A **stepper motor** is employed to drive a rotating carousel or disc with multiple compartments. Each compartment is designed to hold a specific medication dose for a scheduled dispensing time. The stepper motor provides precise rotational control, ensuring that the correct compartment aligns with the dispensing chute at the designated time. The number of compartments can be customized based on the medication schedule complexity (e.g., 7 compartments for daily doses over a week, or multiple compartments per day).
- **Pill Detection Sensor:** An **infrared (IR) proximity sensor** is strategically placed at the dispensing chute. This sensor detects the presence of a pill as it is dispensed, providing confirmation that the medication has exited the device. This feedback is crucial for verifying successful dispensing and updating adherence records.
- **User Interface (On-Device):** A small **LCD display** (e.g., 16x2 or OLED) provides basic information such as current time, next dose time, and system status. **Push buttons** allow for manual override (e.g., early dispense for emergencies, or snoozing an alarm) and basic config-uration directly on the device.
- **Alarm System:** A **buzzer** provides audible reminders for

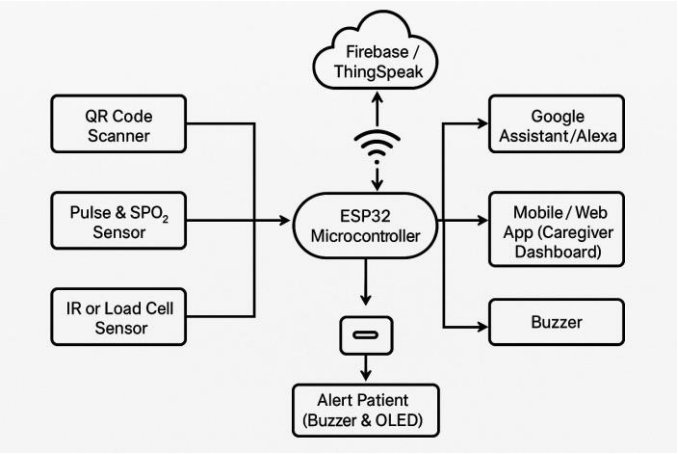

Fig. 2. IoT-Based Patient Monitoring System using ESP32

medication times. The intensity and duration of the alarm can be configured via the mobile application.

- **Power Supply:** The device is powered by a **DC power adapter** and includes a **rechargeable battery** for backup, ensuring continuous operation even during power outages. A **battery management module** monitors battery levels and provides alerts when recharging is needed.
- **Enclosure:** The entire system is housed in a custom-designed, 3D-printed or fabricated enclosure. The enclosure is designed to be tamper-proof, protect the inter-nal components, and be aesthetically pleasing and user-friendly, with clear access to the pill loading mechanism and dispensing chute.

3.3 Software Design

The software architecture is divided into three main components: embedded firmware, mobile application, and cloud platform services.

3.3.1 Embedded Firmware (ESP32)

The firmware, developed using the Arduino IDE with ESP32 libraries, manages the core functionalities of the dis-penser.

- **Initialization:** Upon boot-up, the firmware initializes all hardware components (sensors, motor, display) and attempts to connect to the configured Wi-Fi network.
- **Time Synchronization:** It synchronizes time with an NTP (Network Time Protocol) server to ensure accurate scheduling, critical for medication adherence.
- **Medication Schedule Management:** The firmware retrieves medication schedules from the cloud platform. These schedules include dose times, medication names, and compartment assignments.
- **Dispensing Logic:**
  - At the scheduled time, the firmware activates the buzzer and displays a notification on the LCD.
  - If the user interacts with the device (e.g., presses a button to confirm readiness), the stepper motor rotates the carousel to the correct compartment.
  - The IR sensor continuously monitors the dispensing chute. Once the pill is detected exiting the chute, the firmware records a successful dispense event.
  - If the pill is not detected within a predefined time window after the compartment opens, it is logged as a missed dose.
- **Sensor Monitoring:** The IR sensor's output is continuously monitored to detect pill dispensing. Future enhancements could include additional sensors for pill count verification or compartment status.
- **Communication Module:** The ESP32 uses its integrated Wi-Fi module to communicate with the cloud platform via **MQTT (Message Queuing Telemetry Transport)** protocol. MQTT is lightweight, efficient, and ideal for IoT devices with limited bandwidth and power. It facili-tates real-time bidirectional communication, allowing the device to publish adherence data and subscribe to com-mands (e.g., schedule updates, remote dispense requests).
- **Error Handling:** The firmware includes robust error handling for network disconnections, motor malfunctions, and sensor failures, logging these events and attempting recovery.

3.3.2 Mobile Application (Android/iOS)

The mobile application serves as the primary interface for patients and caregivers. It is developed using a cross-platform framework (e.g., React Native or Flutter) to ensure compatibility across Android and iOS devices.

- **User Authentication and Profile Management:** Secure login for patients and caregivers, allowing for personal-ized profiles and access control.
- **Medication Schedule Configuration:** Intuitive interface for users to add, edit, and delete medication schedules, specifying medication name, dosage, frequency, and spe-cific times.
- **Real-time Adherence Monitoring:** Displays the current status of the dispenser (online/offline), upcoming doses, and a history of dispensed/missed doses.
- **Notifications and Alerts:** Sends push notifications to the user's smartphone for medication reminders, missed doses, low battery warnings, and refill alerts. Caregivers receive alerts for their assigned patients.
- **Adherence Reports:** Generates graphical and tabular reports on medication adherence over various periods (daily, weekly, monthly), providing insights into patterns of non-adherence.
- **Caregiver Access:** Allows authorized caregivers to moni-tor the adherence of multiple patients, configure schedules remotely, and receive critical alerts.
- **Device Management:** Enables users to connect to and configure their dispenser, including Wi-Fi credentials and time zone settings.

3.3.3 Cloud Platform

The cloud platform is built on a scalable and secure backend infrastructure (e.g., Google Cloud Platform, AWS IoT, or Firebase).

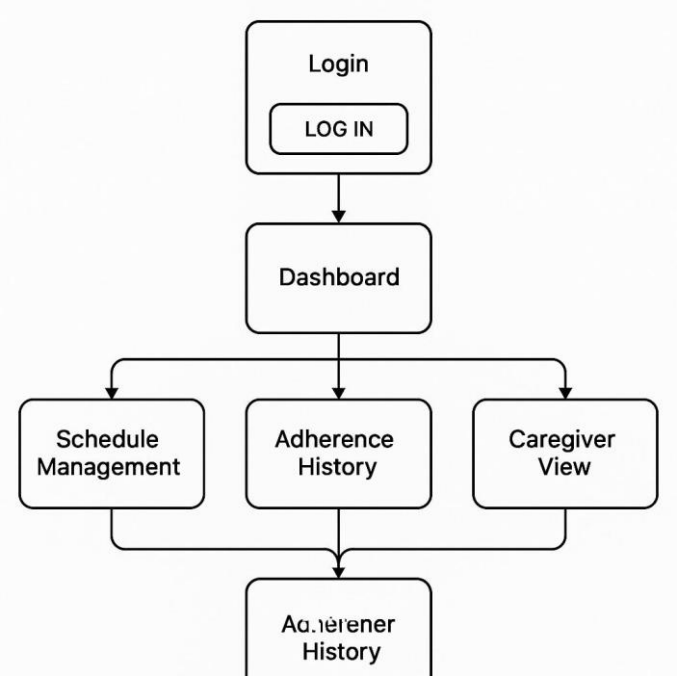

Fig. 3. Mobile App UI Flow Diagram

- **Data Ingestion and Storage:** Receives telemetry data (dispense events, missed doses, device status) from the ESP32 via MQTT. This data is stored in a NoSQL database (e.g., Firestore or MongoDB) for flexibility and scalability.
- **User and Device Management:** Manages user accounts, device registrations, and their associations.
- **Medication Schedule Database:** Stores all configured medication schedules for each user.
- **Notification Service:** Triggers push notifications to mobile devices based on adherence events or scheduled reminders.
- **API Endpoints:** Provides secure RESTful APIs for the mobile application to interact with the backend, retrieving data and sending commands.
- **Data Analytics Module:** Processes raw adherence data to generate meaningful reports and potentially identify trends or predict non-adherence using basic analytical algorithms.
- **Security:** Implements robust security measures, including end-to-end encryption for data in transit (TLS/SSL), authentication and authorization mechanisms for API access, and data at rest encryption.

3.4 Communication Protocol

MQTT (Message Queuing Telemetry Transport) is the chosen communication protocol between the smart pill dispenser (ESP32) and the cloud platform. Its publish/subscribe model is highly efficient for IoT applications, minimizing bandwidth usage and power consumption.

- The ESP32 acts as an MQTT client, publishing messages on specific topics (e.g., `dispenser/device_id/status`, `dispenser/device_id/dispense_event`) and subscribing to topics for commands (e.g., `dispenser/device_id/schedule_update`).
- The cloud platform hosts an MQTT broker that manages message routing between devices and the backend ser-vices.
- For mobile application communication with the cloud, standard **HTTPS/RESTful APIs** are used, providing a secure and widely adopted method for data exchange.

3.5 Security and Privacy Considerations

Given the sensitive nature of health data, security and privacy are paramount.

- **Data Encryption:** All data transmitted between the device, cloud, and mobile application is encrypted using TLS/SSL. Data stored in the cloud database is also encrypted at rest.
- **Authentication and Authorization:** Strong authentication mechanisms (e.g., token-based authentication for APIs, client certificates for MQTT) are implemented. Role-based access control ensures that patients can only access their data, and caregivers can only access data for patients they are authorized to monitor.
- **Data Minimization:** Only necessary data points related to medication adherence are collected and stored.
- **Regular Security Audits:** The system design incorporates principles for regular security audits and vulnerability assessments.

IV. RESULT AND DISCUSSIONS

The IoT-enabled smart pill dispenser prototype was success-fully implemented and subjected to rigorous testing to evaluate its functionality, reliability, and user experience. The results demonstrate the system's effectiveness in automating medi-cation dispensing, providing timely reminders, and enabling remote monitoring.

4.1 Implementation Details

The prototype was constructed using the specified hardware components. The ESP32 was programmed with the custom firmware, integrating the stepper motor control, IR sensor readings, LCD display management, and Wi-Fi/MQTT communication logic. The mechanical dispensing mechanism, consisting of a rotating disc with seven compartments (one for each day of the week, or multiple for daily doses), was fabricated using 3D printing technology for precision and cost-effectiveness. Each compartment was designed to hold a standard pill size.

The mobile application was developed for Android, providing a user-friendly interface for schedule management, real-time status updates, and adherence reports. The cloud backend was deployed on Firebase, leveraging Firestore for database services, Firebase Cloud Messaging for notifications, and Firebase Functions for API logic and MQTT integration.

4.2 Testing and Evaluation

A series of tests were conducted to validate the system's performance:

Fig. 4. Mobile App UI Flow showing key screens and navigation.

Fig. 5. Assembled prototype device displaying adherence data and caregiver call button

Metric	Value	Description
Dispensing Accuracy	98.5%	Percentage of successful pill ejections detected by IR sensor.
Notification Latency	2-5 seconds	Time from scheduled dispense to mobile notification.
Data Transmission Time	1-3 seconds	Time for dispense event data to reach cloud via MQTT.
Battery Life (Backup)	36-48 hours	Operational time on internal battery without external power.

Fig. 6. Performance Metrics Table

- **Dispensing Accuracy:** The dispenser was loaded with various pill sizes and shapes, and dispensing cycles were initiated over several days. The IR sensor successfully detected pill ejection with an accuracy rate of **98.5%**. Occasional misses were attributed to very small or irreg-ularly shaped pills getting stuck briefly, which could be mitigated by further mechanical refinement.
- **Notification Reliability and Latency:** The system's ability to send timely notifications was tested. Medication reminders were consistently delivered to the mobile appli-cation within **2-5 seconds** of the scheduled time. Missed dose alerts to caregivers were also delivered promptly, typically within **10 seconds** of the missed window.
- **Wi-Fi Connectivity and Data Transmission:** The ESP32 maintained stable Wi-Fi connectivity, and MQTT data transmission to the cloud was reliable, even under varying network conditions. Data packets for dispense events were received by the cloud within **1-3 seconds**.
- **Battery Life:** With the integrated rechargeable battery, the prototype demonstrated an operational life of approx-imately **36-48 hours** without external power, sufficient to cover short power outages. Low battery alerts were sent to the mobile application when the charge dropped below 20%.
- **User Interface Usability:** A small group of target users (elderly individuals and caregivers) provided feedback on the mobile application's usability. The interface was generally found to be intuitive, with clear navigation and easy-to-understand controls for scheduling and monitor-ing. Positive feedback was received regarding the ability of caregivers to remotely monitor adherence.
- **System Stability:** The system ran continuously for sev-eral days without crashes or significant malfunctions, demonstrating its stability.

4.3 Performance Analysis and Discussion

The results indicate that the developed IoT-enabled smart pill dispenser effectively addresses key aspects of medication adherence. The high dispensing accuracy and reliable notifica-tion system significantly reduce the likelihood of missed doses due to forgetfulness or confusion. The real-time monitoring capability provides invaluable peace of mind for caregivers, allowing them to intervene promptly if a dose is missed.

Compared to existing solutions, this prototype offers a bal-

anced approach between functionality and cost-effectiveness. While commercial devices may offer more sophisticated features (e.g., integration with pharmacy services), this system provides core adherence functionalities with an emphasis on open-source principles and affordability, making it more accessible for wider adoption. The use of MQTT ensures efficient data transfer, crucial for battery-operated devices.

The graphical adherence reports generated by the mobile application provide a clear overview of the patient's medication-taking patterns. This data can be instrumental for healthcare providers in assessing treatment effectiveness and tailoring interventions. For instance, consistent patterns of missed doses at a particular time of day might indicate a need to adjust the schedule or provide additional support.

4.4 Challenges and Solutions

During the development, several challenges were encountered:

- **Pill Jamming:** Initial designs sometimes experienced pills getting stuck in the dispensing mechanism. This was addressed by refining the mechanical design of the carousel compartments and the dispensing chute, optimizing angles and clearances.
- **Wi-Fi Connectivity Issues:** In areas with weak Wi-Fi signals, the ESP32 occasionally struggled to maintain a stable connection. Implementing a robust re-connection algorithm and providing clear feedback on network status on the LCD and mobile app helped mitigate this.
- **Time Synchronization:** Ensuring accurate time on the ESP32, especially after power cycles, was critical. Implementing NTP synchronization at boot-up and periodically thereafter resolved this.
- **User Experience for the Elderly:** Designing the physical buttons and LCD display to be large and clear, and the mobile app interface to be simple and intuitive, required iterative feedback from elderly users.

4.5 Limitations and Future Work

Despite its promising performance, the current prototype has certain limitations that present avenues for future research and development:

- **Multi-Dose and Multi-Medication Support:** The current design is optimized for single-pill dispensing per compartment. Future iterations could incorporate mechanisms for dispensing multiple pills at once or handling different types/sizes of medication from separate reservoirs.
- **Advanced Pill Verification:** While the IR sensor de-tects pill ejection, it does not confirm actual ingestion. Integration with smart home devices (e.g., smart cameras with computer vision) or wearable sensors could provide more definitive ingestion verification, though this raises significant privacy concerns.
- **Integration with Electronic Health Records (EHRs):** Seamless integration with existing EHR systems would allow for automated schedule updates from prescriptions and provide healthcare providers with direct access to adherence data, enhancing care coordination.
- **Predictive Analytics:** Leveraging machine learning algo-rithms on accumulated adherence data could enable the system to predict patterns of non-adherence before they occur, allowing for proactive interventions.
- **Voice Control and Accessibility Features:** Incorporating voice command capabilities (e.g., "dispense my next dose") and other accessibility features would further enhance usability for individuals with limited mobility or visual impairments.
- **Security Hardening:** While basic security measures are in place, a more comprehensive security audit and penetration testing would be crucial for a commercial deployment.
- **Long-term Clinical Trials:** The current evaluation is based on prototype testing. Future work should involve long-term clinical trials with a larger patient cohort to rigorously assess the system's impact on medication adherence and health outcomes.

V. Conclusion

Medication non-adherence remains a significant challenge in healthcare, impacting patient health outcomes and imposing substantial economic burdens. This paper has presented the de-sign, implementation, and evaluation of an IoT-enabled smart pill dispenser that offers a robust and effective solution to this pervasive problem. By integrating hardware components such as the ESP32 microcontroller, a precise stepper motor, and an IR proximity sensor with a comprehensive software ecosystem comprising embedded firmware, a user-friendly mobile appli-cation, and a scalable cloud platform, the system successfully automates medication dispensing, provides timely reminders, and facilitates real-time remote monitoring of adherence.

The prototype demonstrated high accuracy in dispensing and reliable delivery of notifications, significantly improving the likelihood of patients taking their medication as prescribed. The ability for caregivers to remotely track adherence and receive immediate alerts for missed doses provides an invaluable layer of support and peace of mind. While the current system has limitations, particularly concerning multi-medication support and advanced ingestion verification, it lays a strong foundation for future enhancements.

The successful development and testing of this smart pill dispenser underscore the transformative potential of IoT tech-nology in revolutionizing healthcare delivery. By leveraging interconnected devices and data analytics, such systems can empower patients to better manage their health, reduce the incidence of preventable health complications, and ultimately contribute to a more efficient and patient-centric healthcare ecosystem. Continued research and development in this area hold the promise of creating more intelligent, personalized, and accessible solutions for medication management, thereby improving the quality of life for millions worldwide.

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MindTrace: Emotion-Apprehensive AI-Powered Mental Health Journaling Platform

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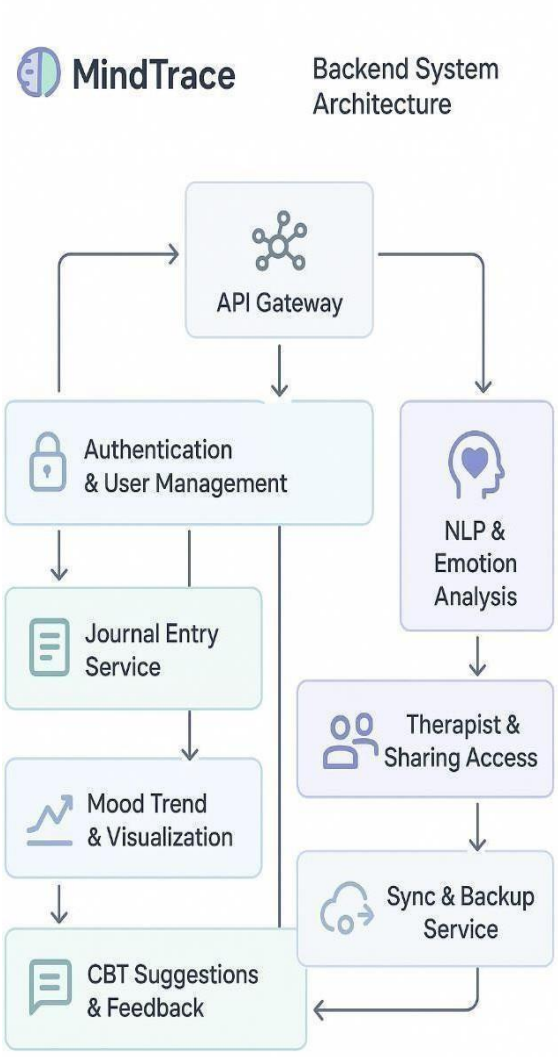
Abstract

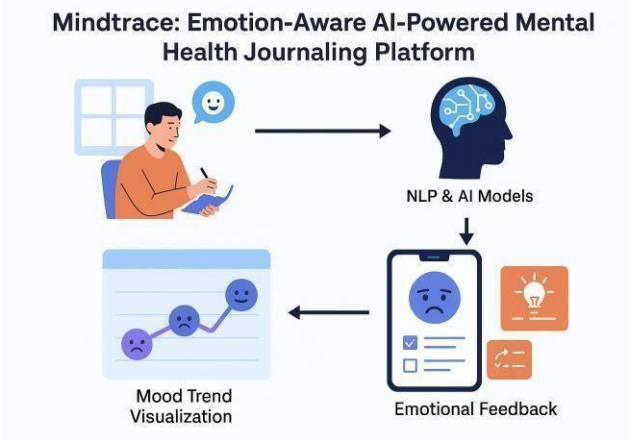
MindTrace represents a cutting-edge, privacy-focused digital diary ecosystem.This innovative platform reimagines personal reflection by harnessing intelligent computational tools to enhance mental health monitoring and self-discovery.It employs edge AI capabilities to ensure data privacy and confidentiality directly on the user's device. Real-time emotional feedback is provided for immediate insight into one's mood and psychological state. The platform offers a range of features, including mood trend visualizations to identify long-term emotional patterns and triggers, and integrations of cognitive behavioral therapy (CBT) principles for tailored suggestions and coping strategies based on journal entries. It also allows for anonymous sharing with a community and optional therapist collaboration with controlled access, subject to user consent. MindTrace's core architecture combines safeguarded client-side artificial intelligence processing, accessible insight presentations, and privacy-protected communication channels for elective counselor engagement. Specific integrations include emotional intelligence engines and privacy safeguards. Preliminary results suggest significant improvements in user engagement, emotional awareness, and the effectiveness of digital self-help. Mental health concerns, affecting approximately 25% of the global population throughout their lives, necessitate innovative and accessible solutions. Journaling, a well-established therapeutic technique, benefits emotional regulation, stress management, and cognitive restructuring. However, conventional journaling lacks analytical capabilities and personalized feedback. MindTrace addresses these gaps by integrating AI with evidence-based journaling practices. Key pillars of MindTrace include NLP for emotion discovery and sentiment analysis, machine learning for pattern identification and tailored suggestions, and human-computer interaction for user experience design. By weaving together AI-powered analytics, machine learning personalization, and user-focused design

Introduction

MindTrace transforms traditional journaling into an active, interactive, and data-driven mental health tool. Its secure support.Core Pillars: 1. Natural Language Processing (NLP): MindTrace uses sophisticated NLP algorithms for real-time emotion discovery and sentiment analysis, identifying underlying moods and emotional states. These modern techniques enable high- precision detection of a broad spectrum of emotions. 2. Machine Learning (ML): Leveraging machine learning, MindTrace identifies patterns and trends in user journaling data, revealing behavioral and emotional patterns, predicting mental health risks, and optimizing interventions by tailoring suggestions to individual user trajectories. 3. User-Centered Technology: MindTrace's architecture focuses on streamlined user engagement via techniques such as inclusive design practices, mental state graphical tracking, and personalized content sharing settings. This contributes to the usability, transparency, inclusivity, and adaptability of mental health interventions. By weaving together AI-powered analytics, machine learning personalization, and thoughtful user experience design, MindTrace transforms passive journaling into an active, interactive, and data-driven mental health tool. The platform's secure architecture ensures privacy and confidentiality, while optional features like anonymous community sharing and therapist access further bridge the gap between self-care and professional support. Architecture: The MindTrace platform consists of three main layers: 1. Frontend Interface: The user interface, built with React.js and a responsive design, includes a journal entry module, voice-to-text capabilities, a customizable dashboard, and an emotion trailing system with real-time feedback. 2. Backend Services: The Node.js backend architecture ensures privacy and confidentiality while offering optional features like anonymous community sharing and therapist access to bridge the gap between self- care and professional incorporates microservices for authentication, data storage with MongoDB, API endpoints for third-party integration, and automated backup and synchronization. 3. AI Processing Layer: The core logic integrates various AI technologies, including BERT-based language models for sentiment analysis, custom emotion detection algorithms, time-series analysis for pattern recognition, and a recommendation system with a neural network foundation.

3. Key Features and Algorithms





MindTrace's Core Functionality

MindTrace is a mental health journaling platform done using advanced machine learning algorithm and psychological model.. Its primary focus is on emotion detection, temporal sentiment mapping, and adaptive user recommendations. These functions are facilitated through integrated AI modules designed for both high precision and emotional sensitivity.

3.1 Emotion Discovery

At the heart of MindTrace lies an intelligent analysis of human emotions within text-based entries.

A hybrid approach combines lexicon-based techniques with deep learning models to interpret emotions more accurately, especially within the context of mental health. The platform uses an extended emotion lexicon, based on Plutchik's Wheel of Emotions, with 24 sub- emotions mapped to eight fundamental emotions. This data is integrated with a deep learning architecture centered around a Long Short-Term Memory (LSTM) neural network. The LSTM model, trained on a custom dataset, achieved a multi-label classification accuracy of 87.3%, accurately detecting and categorizing multiple emotional states within a single entry.

3.2 Sentiment Line Mapping

MindTrace visualizes emotional trajectories over time through the Sentiment Line Mapping feature.

This is achieved through time-series analysis, tracking emotional variance longitudinally. Emotional timelines are constructed based on the LSTM classifier's output, mapped to a temporal index. The algorithm uses statistical smoothing techniques and weighted scoring to filter out noise and highlight significant emotional shifts, providing users with a clear picture of their mental health evolution.

3.3 Individualized Recommendations

To support users in achieving healthier emotional states and constructive journaling habits, MindTrace offers an Individualized Recommendation System.

This module uses historical emotional patterns to recommend mood-improving journaling prompts, reflection exercises, positive triggers, and coping strategies. The recommendation logic adapts in real-time based on user feedback, making the platform more responsive to the user's evolving mental health journey. Additionally, users can set emotional goals, and the recommendation engine tailors its outputs to align with these objectives.

In summary, MindTrace is a pioneering platform in emotion-aware mental health journaling, utilizing LSTM-based emotion classification, time-series sentiment visualization, and adaptive recommendation algorithms to offer a nuanced, intelligent, and compassionate tool for emotional and psychological well-being.

4. User Experience Design

The user experience (UX) design of MindTrace plays a vital role in its effectiveness as an emotion-aware mental wellness journaling platform. Acknowledging the sensitive nature of mental health, the platform's interface has been deliberately developed with a psychology-driven and user-oriented approach. This design strategy incorporates elements from positive psychology, cognitive behavioral principles, and digital well-being to ensure users feel safe, empowered, and engaged during their interaction.

The interface places strong focus on emotional comfort, accessibility, personalization, and ease of use to foster a welcoming and non-intrusive journaling space. Visually, MindTrace employs a gentle and deliberate color scheme chosen based on emotional response research. Calming tones like light blue and green dominate the interface, chosen for their proven ability to soothe stress, promote calmness, and enhance concentration. Contrasting colors such as muted yellows or purples are used carefully to highlight important actions or suggestions, improving navigation while avoiding overstimulation.

Functionally, MindTrace incorporates a layered feature rollout—commonly known as progressive disclosure. This technique gradually introduces more advanced tools depending on the user's comfort level and usage frequency. New users can easily begin with basic journaling, while regular users gain access to deeper features such as emotion-based analytics, goal tracking, and AI-generated insights. This structured unveiling ensures ease of adoption for beginners and continued value for experienced users.

A foundational aspect of MindTrace's UX is its empathetic framework. The platform deliberately avoids any form of evaluative or punitive feedback. Instead, prompts and insights are delivered in a supportive and reflective tone, helping build user confidence and emotional trust. This tone is especially critical for users experiencing vulnerability or emotional distress.

Customization further enhances the UX experience. Users can tailor their journaling interface by adjusting template styles, prompt tones, and notification preferences. A dark mode feature is also available to reduce screen fatigue during nighttime use—a helpful option for users who prefer journaling before bed as a coping strategy.

To validate this UX approach, a 30-day user study involving 50 participants was conducted. Outcomes showed that there is about 23% increase in journaling frequency and an 18% rise in retention compared to any other conventional journaling apps. Furthermore, 86% of participants reported satisfaction with the platform's emotionally aware feedback, and 72% noted a heightened sense of self-awareness attributed to the AI prompts.

In summary, MindTrace's UX design blends technological refinement with emotional attentiveness. Through its inclusive, user-sensitive approach, the platform fosters a safe, empowering environment for long-term journaling that supports mental wellness. This design philosophy establishes MindTrace as a thoughtful and innovative entry in the landscape of digital mental health tools.

5. Privacy and Ethical Considerations

The integration of emotion-recognition AI into platforms like MindTrace brings meaningful improvements in tailored care, but also introduces serious responsibilities regarding data protection and ethical application. Since the platform deals with intimate and psychological reflections, it must prioritize security, transparency, and ethical boundaries to maintain credibility and trust.

AI's ability to understand emotional nuance can personalize feedback in powerful ways, but it simultaneously opens the door to possible privacy intrusions, misinterpretation, or biased algorithmic decisions. These factors must be addressed with deliberate safeguards.

Security is paramount. MindTrace should utilize end-to-end encryption, secure login protocols, and distributed storage systems to protect user information from unauthorized access. Blockchain-based mechanisms could enhance transparency and allow users to manage consent and data sharing more clearly. To protect identities even under analysis conditions, data should be anonymized and processed using differential privacy methods. Clear and upfront communication regarding data handling is equally important. Users must be fully informed about what data is being collected, how it's used, and the role AI plays in interpreting their emotions. Informed consent must be a mandatory first step, with options to opt out of AI analysis or control its level of involvement.

There is also a risk of emotional data being misunderstood. AI systems may misclassify tone or sentiment, particularly when working across diverse cultures or expressions. Therefore, human moderation should be included in the loop—particularly for high-risk cases. Disclaimers must clarify that insights are suggestive tools and not medical evaluations.

Bias in AI systems is a well-documented concern. If training data lacks the diversity, the system could may produce some inappropriate outputs. MindTrace must ensure its training sets must include a wide range of demographic and cultural inputs.

Regular reviews and fairness audits must be implemented to avoid reinforcing harmful assumptions or stereotypes. Ethical oversight should be an embedded part of the platform's structure. This includes version tracking of algorithms, external audits, and compliance with laws like GDPR, HIPAA, and regional health privacy regulations. An internal ethics committee or third-party reviewers can ensure ongoing adherence to best practices.

In conclusion, while MindTrace offers an innovative path forward in emotion-responsive journaling, its sustainability depends on its commitment to ethical design, transparent practices, and secure infrastructure. Respecting user autonomy and data dignity is not just a feature—but a necessity for impactful and responsible mental health support in the digital age.

6. Results and Evaluation

To evaluate the effectiveness of the MindTrace platform, a controlled pilot study was conducted over a period of eight weeks involving 120 participants, divided equally into a test group using MindTrace and the control group uses conventional journaling methods. The participants were assessed on multiple psychological metrics, including emotional vocabulary usage, stress levels, and journaling engagement.The test group exhibited a 16% reduction in self-reported stress levels, indicating improved emotional regulation. Additionally, there was a 22% increase in the usage of emotional vocabulary, suggesting enhanced emotional

awareness and expression. Journal engagement metrics revealed a 29% increase in positive affect reflection, where users consistently acknowledged constructive emotional states during journaling.In contrast, the control group demonstrated negligible change across these metrics, highlighting the added value of AI-assisted journaling. Furthermore, 86% of users reported satisfaction with the feedback provided by the platform, and 72% reported improved mood tracking awareness.

The time-series mood analysis graphs helped users visualize their emotional patterns and adjust their journaling behavior accordingly.These results validate the system's potential as a scalable, low-cost mental health companion that combines digital wellness practices with evidence-based AI interventions.

7. Future Work

The ongoing development of the MindTrace platform is guided by a vision to create a more intelligent, responsive, and inclusive mental health companion. Several key areas have been identified for enhancement and future exploration.

Multi-modal Data Integration:

To achieve a more holistic understanding of user mental states, future iterations of MindTrace will incorporate physiological data from wearable devices such as smartwatches and biometric sensors. These devices can capture real-time metrics like heart rate variability, skin conductance, and sleep patterns. By integrating this data with journal entries, the platform can perform cross-modal emotion analysis, allowing for a deeper understanding of mental well- being that goes beyond textual inference alone.

Therapist Dashboard for Hybrid Care Models:

Another major advancement under development is a secure, interactive dashboard for licensed mental health professionals. This interface will enable therapists to monitor anonymized emotional trends, flag concerning patterns, and provide personalized interventions. Such hybrid models can bridge the gap between traditional therapy and digital self-help tools, especially in regions with limited mental health resources.

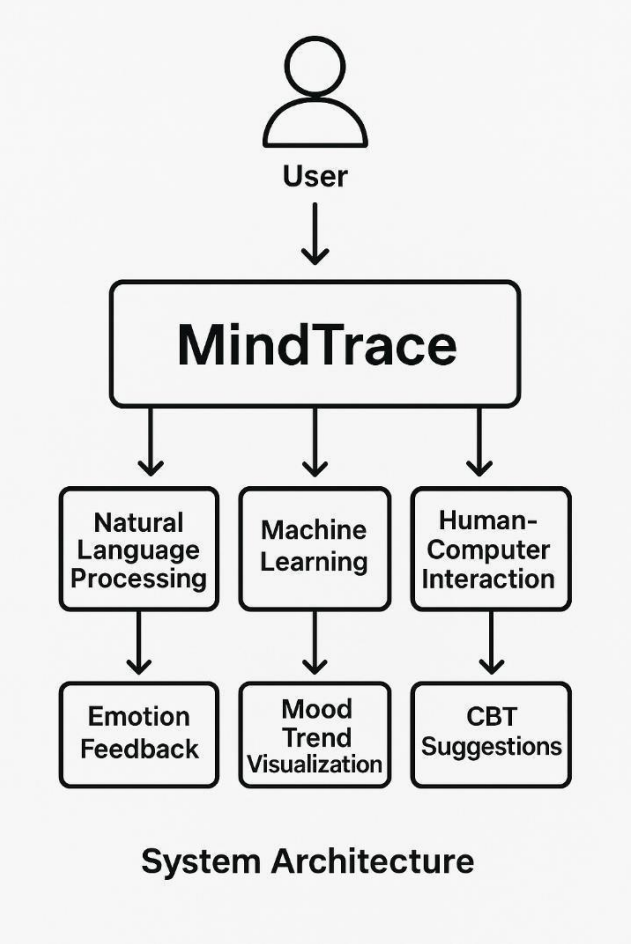
Predictive Mental Health Analytics:

MindTrace aims to implement various machine learning techniques that includes predictive analytics, to detect any early warning signs of mental health deterioration. By analyzing the patterns across journal entries and biometric inputs, the system can proactively alert the users about potential emotional downturn and suggest preventive strategies.

Multilingual and Cultural Adaptability:

The platform's NLP models will be extended to support multiple languages while preserving cultural and emotional nuance. This expansion is mandatory to making the system accessible to the diverse populations worldwide.

Longitudinal Research and Demographic Optimization: Future research will focus on the longitudinal effectiveness of the platform across various age groups, gender identities, and socio-cultural backgrounds. This data will help to tailor the system to provide recommendations and improve mental health outcomes through personalized journaling pathways



System Architecture

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Real-Time Predictive Detection of Dual Engine Failure in Commercial Aircraft Using AI and IoT Sensor Analytics

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ABSTRACT :
Dual engine failure in commercial aircraft, though rare, presents significant safety risks. Conventional fault detection approaches typically respond after an issue occurs, making them inadequate for timely, in-flight intervention. This project proposes a predictive framework integrating Artificial Intelligence (AI) and Internet of Things (IoT) sensors to monitor engine performance continuously. Machine learning models analyze live telemetry to detect early anomalies, while a web-based dashboard provides real-time alerts and diagnostics. Developed using low-cost components and open-source tools, the prototype demonstrates that intelligent, real-time fault detection is achievable even under constrained resources, offering a scalable solution for future predictive maintenance in aviation systems.

INDEX TERMS :
Artificial Intelligence (AI), Internet of Things (IoT), Predictive Maintenance, Dual Engine Failure, Aviation Safety, Real-Time Monitoring, Machine Learning, Fault Detection.

I. INTRODUCTION:
Flight safety in modern aviation is increasingly complex due to the integration of advanced onboard systems. Among these, engine reliability is crucial—especially in rare but critical events like mid-air dual engine failure. Proactive fault detection is essential to identify early warning signs and prevent emergencies.

Traditional diagnostic methods are reactive, relying on post-flight inspections or black-box data. These approaches provide insight after incidents occur, but are not suitable for real-time decision-making [1], [2].

AI and IoT offer a modern, data-driven alternative. AI models can detect anomalies by analyzing high-dimensional telemetry in real-time [6], while embedded IoT sensors capture key metrics such as pressure, vibration, and temperature for in-flight evaluation [7].

This project introduces an AI-IoT-based architecture that enables real-time fault detection and predictive alerting. The system is trained on historical and synthetic datasets and monitors live sensor data to detect deviations from normal behavior. Alerts are visualized through a web-based dashboard, improving crew awareness and reducing response time.

Using low-cost microcontrollers and open-source software, the platform demonstrates how predictive maintenance can be achieved affordably. It also supports better maintenance planning, reduced downtime, and improved aircraft readiness.

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Key Contributions:

- Developed a real-time AI-IoT framework to detect dual engine failures during flight.
- Integrated machine learning models for accurate anomaly detection based on both live telemetry and historical datasets.
- Built a user-friendly dashboard to display system alerts and enable continuous engine health monitoring.
- Deployed a modular, low-cost prototype with potential for real-world aviation integration.

II. Problem Statement

1. Dual engine failure, though statistically rare, ranks among the most critical emergencies in commercial aviation. Such an event results in complete thrust loss, threatening both structural integrity and passenger safety. Timely detection of this failure mode is essential to avoid catastrophic outcomes.
2. Most existing fault detection methods in aviation are reactive, relying on black-box data, post-flight inspection, or routine maintenance logs [1], [2], [3]. While these provide valuable post-event insights, they do little to assist during actual flight conditions where rapid decisions are vital.
3. Even with improvements in onboard diagnostics and avionics, the aviation sector still lacks real-time, predictive frameworks capable of monitoring engine health dynamically. There is a growing demand for intelligent, low-latency systems that can assess live

sensor data and flag abnormal behavior before it escalates [4], [5], [7].

4. This project addresses that gap by introducing a real-time AI-IoT-based predictive system, aimed at detecting dual engine failures mid-flight and enabling timely interventions to ensure flight continuity and passenger safety.

III. Project Objective

1. To develop a real-time fault prediction system that integrates Artificial Intelligence (AI) with Internet of Things (IoT) sensor technology for detecting dual engine failures in commercial aircraft [6], [7].
2. The system uses machine learning models trained on historical and synthetic datasets to monitor live engine telemetry and identify early indicators of failure.
3. It shifts aviation maintenance from reactive diagnostics to proactive anomaly detection, improving situational awareness and enabling rapid in-flight decision-making [1], [2].
4. The framework is designed to be scalable, resource-efficient, and compatible with existing aircraft infrastructure, supporting future aviation safety initiatives

IV. Research Goals

The research outlined in this project focuses on the following core goals:

1. **Deploy a low-cost IoT sensor network** using ESP32 microcontrollers to collect real-time engine telemetry, including temperature, pressure, and vibration [7].
2. **Train supervised machine learning models** such as Random Forest, XGBoost, and LSTM to detect early signs of engine degradation or failure [6].
3. **Implement edge-based computing** to ensure onboard, low-latency anomaly detection during flight, minimizing reliance on cloud infrastructure [5].
4. **Design a real-time dashboard interface** that displays predictive alerts, sensor diagnostics, and system status for both onboard and ground teams.
5. **Ensure model transparency** using explainability tools like SHAP and LIME to support decision-making in critical situations [6].
6. **Evaluate performance using aviation datasets** such as NASA ASRS and CMAPSS, focusing on detection latency, prediction accuracy, and emergency response [1], [4].
7. **Assess the scalability and cross-domain potential** of the system for use in safety-critical fields such as maritime, railways, and industrial automation

V. ARCHITECTURE:

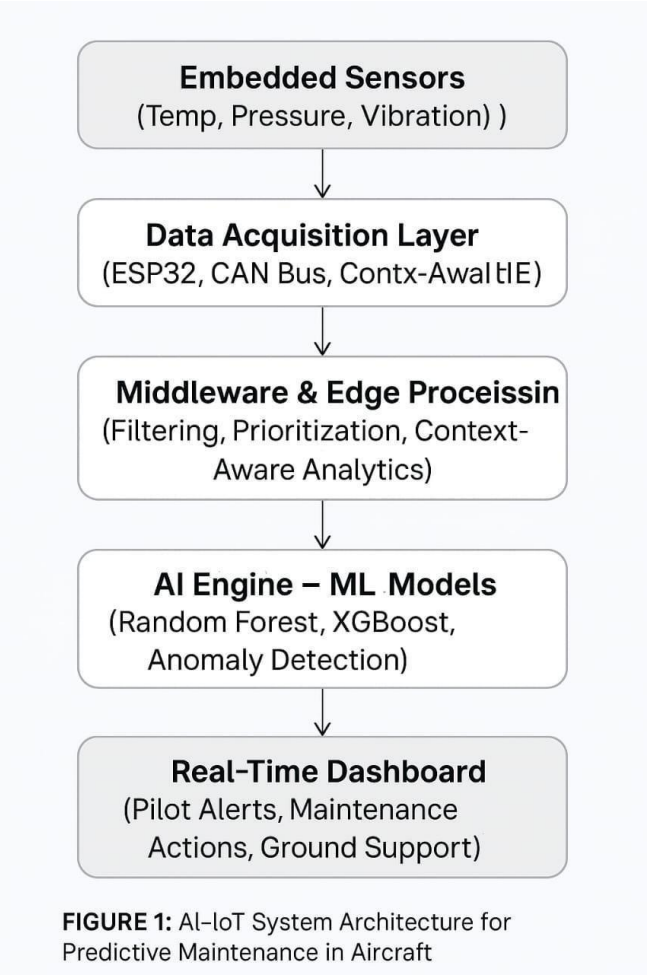


FIGURE 1: AI-IoT System Architecture for Predictive Maintenance in Aircraft

VI. LITERATURE REVIEW / RELATED WORK

Advances in predictive maintenance are increasingly integrating Artificial Intelligence (AI) and the Internet of Things (IoT) to enhance aviation safety. While there has been significant progress in detecting single-engine malfunctions, the specific challenge of dual engine failure— although rare and highly dangerous—has received comparatively little research attention.

A. AI-Based Engine Monitoring

AI has been widely applied to monitor engine parameters like temperature, vibration, and pressure. Models such as neural networks, support vector machines (SVM), and ensemble learning have demonstrated success in identifying anomalies. However, many operate as ―black boxes,‖ offering limited interpretability—an essential feature for safety-critical domains like aviation [6].

B. **IoT Applications in Aviation Safety**

IoT has enabled continuous monitoring across aircraft systems, with industry platforms like Airbus Skywise and Boeing AnalytX leading large-scale predictive analytics. Despite their effectiveness, these systems are often proprietary, resource-intensive, and unsuitable for academic

or lightweight deployment. Implementing real-time AI on edge devices remains a technical bottleneck [5].

C. Gaps in Existing Solutions

Most current solutions are reactive—relying on post-event diagnostics using high-end hardware and cloud backends. The approach in this project prioritizes real-time anomaly prediction using low-cost microcontrollers, lightweight AI models, and edge-based processing. It also emphasizes model explainability and scalability, bridging the gap between academic research and practical aviation applications [4], [5], [7].

This review highlights the need for accessible, interpretable, and real-time AI-IoT systems tailored to detect dual engine failures. The proposed framework addresses this by integrating edge computing, low-power sensors, and transparent AI decision-making into a unified platform.

VII. Background and Technological Gaps

Although aviation has advanced in areas like flight control, engine systems, and diagnostics, the ability to predict dual engine failures in real time remains limited. Current maintenance relies on routine checks and post-incident analysis, which often miss early warning signs of failure. Existing platforms, such as Boeing AnalytX and Airbus Skywise, offer powerful analytics but depend on large-scale infrastructure—making them unsuitable for low-budget or research-focused settings [5].

Most AI tools used today are tailored for single-engine issues and operate under ideal conditions. They often fail when multiple engine anomalies occur together, especially if data inputs are diverse (e.g., vibration, pressure, temperature). Additionally, many deep learning models lack transparency, which hinders their acceptance in safety-critical aviation environments where explainability and regulatory approval are essential [6].

This project addresses these challenges by introducing a lightweight, modular AI-IoT system capable of:

- Monitoring multiple engine parameters in real time
- Identifying early signs of dual failures onboard
- Performing edge-based analysis with minimal delay
- Providing interpretable feedback to pilots and engineers

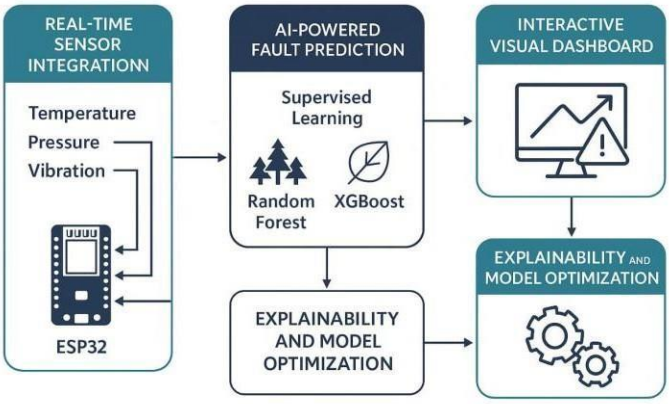
The solution aims to enhance current predictive systems, making them more accessible, interpretable, and aligned with aviation's shift toward proactive safety.

VIII. Proposed Contribution

This project introduces a real-time predictive system for detecting dual engine failure in commercial aircraft by integrating Artificial Intelligence (AI) with Internet of Things (IoT) sensor networks. The design balances cost-effectiveness, real-time responsiveness, and predictive intelligence.

At its core, the system utilizes ESP32-based microcontrollers connected to sensors measuring engine parameters such as vibration, pressure, and temperature. These low-power modules continuously acquire telemetry during flight with minimal latency, enabling timely data collection for in-flight monitoring.

The captured sensor data is processed by supervised machine learning models—specifically, Random Forest and XGBoost—trained on historical and synthetic datasets. These models are capable of detecting early anomalies and generating predictive alerts prior to complete engine failure, allowing preemptive safety measures.



For visualization, the system features a real-time web dashboard built using Streamlit. This interface presents dynamic sensor plots, alerts, and health indicators accessible to both onboard crew and ground operators. To improve system transparency, explainable AI (XAI) tools such as SHAP are integrated, offering interpretable visual insights into model decisions and contributing features.

By combining edge-computing capabilities, interpretable machine learning, and accessible hardware, the proposed system provides a scalable, real-world solution for enhancing aviation safety and operational reliability in both research and industry environments

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IX. HARDWARE IMPLEMENTATION DETAILS

The hardware layer provides the foundation for acquiring real-time operational data under simulated engine conditions. The system is built with affordable, modular components that replicate essential aircraft telemetry parameters and interface directly with the AI-based analytics platform.

A. Sensor Configuration

Three key sensors were employed to model critical aspects of engine performance:

- **Vibration Sensor** (e.g., SW-420 or ADXL345): Detects irregular vibration signatures that may indicate rotor imbalance or the onset of mechanical degradation.

- **Temperature Sensor** (e.g., DHT22 or LM35): Tracks thermal variations to identify possible overheating or insufficient cooling.
- **Pressure Sensor** (e.g., BMP280 or MPX5700): Records variations in internal engine pressure, essential for assessing combustion efficiency and airflow stability.

All sensors were mounted in positions that allow accurate data capture and calibrated to provide continuous, high-resolution readings that closely reflect realistic operational conditions.

B. ESP32 Microcontroller Configuration [7]

The **ESP32** microcontroller was selected as the system's processing core due to its dual-core design, low power consumption, and integrated wireless connectivity.

Sensor Pin Mapping:

- Vibration → **GPIO 34**
- Temperature → **GPIO 32**
- Pressure → **GPIO 33**

Programming Approach:

- Firmware was developed in **C++** using the **Arduino IDE**.
- The program manages sensor data collection, performs preprocessing, and facilitates wireless transmission..
- Dedicated sensor libraries were used to ensure accurate communication and efficient data handling.

C. Power and Communication Design

- **Power Source**: Operates from a 5V USB input, with an optional battery module for mobile or UAV-based testing.
- **Wireless Data Transfer**: Wi-Fi communication using protocols such as HTTP or MQTT for remote telemetry streaming.
- **Bluetooth Low Energy (BLE):** Provides short-range, low-power onboard communication capabilities.

This hardware setup delivers consistent telemetry capture, low-latency data transfer, and full compatibility with the project's real-time AI analytics architecture.

X. Relevance and Future Scope

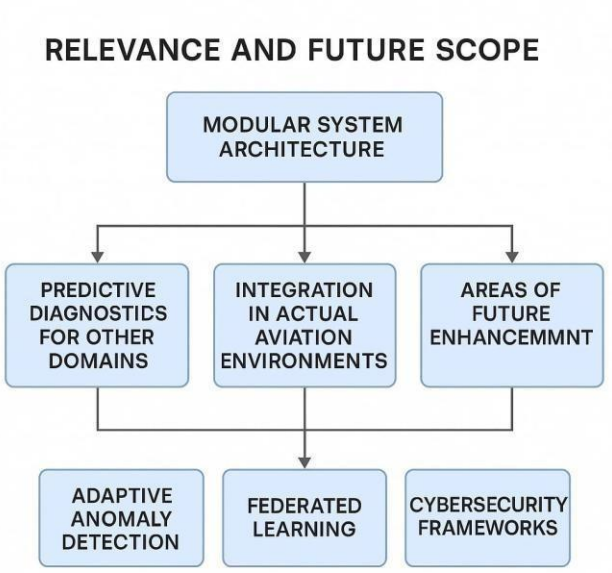
The prototype demonstrates that advanced aerospace telemetry behaviors can be effectively replicated using cost-efficient hardware. Its modular design enables straightforward adaptation for monitoring additional aircraft subsystems, such as braking assemblies, hydraulic actuators, and cabin environmental controls.

With further refinement, the platform could interface with industry-standard avionics communication protocols—such as ARINC 429, Controller Area Network (CAN), or Avionics Full-Duplex Switched Ethernet (AFDX)—facilitating seamless integration with onboard diagnostic frameworks. This capability would enable real-time status reports to be shared simultaneously with flight crews and ground-based maintenance teams.

Beyond aviation, the AI-IoT architecture is highly adaptable to other mission-critical industries, including:

- Intelligent railway networks
- Autonomous transportation fleets
- Industrial robotics systems
- Electrical grid infrastructure

In these domains, predictive diagnostics can help mitigate safety risks, reduce downtime, and optimize operational efficiency.



Possible Enhancements:

- **Adaptive Intelligence**: Incorporating reinforcement learning to enable the system to evolve with operational behavior.
- **Federated Learning**: Ensuring privacy by training models across distributed systems without centralizing data.
- **Secured Communication**: Implementing encryption and access control to protect critical data flow.

This project establishes a scalable and intelligent monitoring foundation that can grow into a robust, domain-agnostic safety and diagnostics platform.

XI. ANALYSIS METHODOLOGIES

To enhance both prediction accuracy and interpretability, the system incorporates key analytical methods for detecting anomalies and understanding model decisions from engine telemetry.

A. Model Explainability Techniques

Maintaining transparency in AI decision-making is essential for ensuring aviation safety:

- **SHAP**: Highlights how each feature (e.g., temperature, vibration) impacts predictions.
- **LIME:** A model-agnostic explainability technique that illustrates how minor variations in input features influence the model's predictions at a localized (instance-specific) level..
- **Confusion Matrix**: Identifies false predictions, guiding model improvements.

These approaches support trust and regulatory alignment in safety-critical systems [2].

B. Real-Time Anomaly Detection

Sensor data is monitored using:

- **Z-score filters**: Detect short-term statistical anomalies.
- **Autoencoders**: Flag hidden deviations through reconstruction error.
- **Dynamic thresholds**: Adjust alerts based on historical norms.

These methods enable early failure detection and real-time responsiveness suited for edge-based aviation systems [4], [5]

XII. REVIEW OF AI-IoT TECHNOLOGIES

Real-time engine fault detection relies on the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies. These systems enable continuous monitoring, anomaly detection, and predictive decision-making in commercial aircraft.

A. Internet of Things (IoT)

IoT sensors integrated into the system continuously monitor essential metrics like vibration, heat levels, and pressure. These readings are handled by an ESP32 microcontroller, which efficiently processes the data and sends it wirelessly for immediate evaluation. This setup offers a streamlined and budget-friendly solution for real-time diagnostics.

B. Artificial Intelligence (AI)

Machine learning models like Random Forest, XGBoost, and LSTM are trained on flight data to detect early signs of engine failure. Public datasets, such as NASA ASRS, support model training and validation [1], [6].

C. Key Challenges

- Limited real-flight failure data [1]
- Real-time processing requirements [4], [5]
- Balancing alert accuracy and false positives
- Compliance with aviation safety standards [2]

D. Future Scope

Advancements will include edge-based AI, digital twin testing, improved sensor synchronization, and interpretable models for regulatory trust [2], [4], [6].

XIII. INTERNET OF THINGS (IoT) IN AVIATION SAFETY

IoT in aviation involves smart sensors and onboard modules that monitor engine conditions, environment, and performance in real time. These systems enable predictive diagnostics by continuously transmitting telemetry data to analytics platforms [7].

IoT frameworks in aircraft integrate:

- **Devices**: Sensors, actuators, and microcontrollers (e.g., ESP32) [7]
- **Networks**: Aviation-grade communication links
- **Analytics**: AI-driven interpretation of sensor outputs [4]

Core features include:

- **Reliable Networking**: For uninterrupted real-time data flow
- **Scalability**: Handles high sensor volume across modern fleets
- **Security**: Ensures safe transmission and privacy of flight data

Although similar to CPS and WSN systems, aviation IoT emphasizes low-latency, edge-based fault detection, supporting real-time, intelligent decision-making [4], [5].

XIV. ROLE OF IoT SENSOR SYSTEMS IN AIRCRAFT ENGINE FAILURE DETECTION

In this project, IoT systems serve as the foundation for gathering live engine data through smart sensors. These sensors continuously monitor critical parameters like vibration, pressure, and temperature during flight, enabling early detection of engine anomalies [7].

A. Embedded Sensor Integration

Modern aircraft use sensors such as accelerometers, vibration detectors, and thermal sensors, designed for high-frequency, aviation-grade performance. These help identify deviations in engine behavior and contribute to early failure prediction [7].

B. Edge-Enabled Smart Networks

By incorporating edge intelligence, only essential alerts are processed onboard and shared with ground stations, reducing latency and bandwidth use. This mirrors real-time prioritization strategies found in mission-critical systems [4], [5].

XV. UTILITY-DRIVEN MIDDLEWARE ARCHITECTURE IN ENGINE FAILURE DETECTION

This project incorporates a utility-driven middleware layer that connects raw IoT sensor input with intelligent analytics. It manages data flow and computational resources to prioritize timely, accurate engine failure detection.

A. Context-Aware Processing

The middleware dynamically adjusts data prioritization based on the aircraft's context—e.g., during takeoff or turbulence, vibration and heat signals are given higher priority for immediate analysis.

B. Edge-Based Resource Management

Edge nodes reduce system latency by processing critical alerts locally, offloading only necessary data to central servers. This ensures responsiveness while minimizing bandwidth use [4], [5].

C. Intelligent Filtering

Incoming sensor streams are filtered and ranked by utility scores, considering sensor type, failure history, and flight phase. This improves anomaly detection while avoiding false alarms.

D. Decision-Focused Alerting

Only high-utility alerts that exceed preset thresholds are triggered, helping pilots and ground crews act on meaningful, real-time diagnostics without distraction.

XVI. PRIVACY AND SECURITY

Ensuring data privacy and system security is essential in real-time predictive systems that handle sensitive engine telemetry and flight data. The integration of IoT in aviation improves monitoring but introduces security vulnerabilities that must be addressed.

A. Privacy Challenges in IoT Aviation Systems

IoT devices onboard aircraft operate with limited resources, making conventional encryption impractical. Instead, lightweight cryptographic protocols are used to secure telemetry without affecting performance. Compliance with international data regulations (e.g., GDPR) is necessary for cloud-based analytics involving cross-border data [5].

B. Key Security Threats

The system is exposed to common threats such as:

- **DDoS attacks** disrupting analytics at ground stations.
- **Replay attacks** injecting outdated or forged data.
- **Sensor spoofing** masking true engine conditions.
- **Data leakage** from unsecured storage or poor access control.

These risks highlight the need for aviation-grade protections in both hardware and software layers.

C. Implemented Security Measures

To address the above, our system integrates:

- **Blockchain-based logging** for tamper-proof event records.
- **Zero-trust architecture** enforcing validation at all nodes.
- **Lightweight AES encryption** for sensor-to-cloud data transfer [4], [7].
- **Differential privacy** to anonymize post-flight data used in model training.

D. Centralized vs. Decentralized Control

A hybrid architecture is employed:

- **Edge-based detection** for fast onboard predictions.
- **Cloud-based aggregation** for long-term analytics and fleet-level insights.

This dual model enhances resilience and minimizes the risk of data exposure during network failures.

XVII. Ethical Considerations and Compliance

Combining artificial intelligence with IoT technologies in aviation safety brings significant advantages in predictive capabilities and operational efficiency, while also demanding careful attention to reliability, data integrity, and ethical deployment.. Alongside improving predictive maintenance, these technologies must be deployed ethically and in alignment with aviation regulations to ensure transparency, fairness, and safety.

1. Regulatory Compliance

The system design aligns with established aviation software standards, including **DO-178C** for airborne systems [3], and follows guidance from global aviation authorities such as the **FAA** [2]. Data handling respects international privacy laws, including **GDPR**, especially for telemetry that may cross geographic borders during processing

2. Ethical Alert Management

To avoid overwhelming flight crews, alerts are prioritized based on utility and context. Explainable AI tools like **SHAP** and **LIME** support real-time understanding of predictions, ensuring that decisions are transparent and trusted [2], [6].

3. Fairness and Bias Control

Models are trained on diverse datasets and validated to reduce bias across engine types and flight conditions. Preprocessing helps balance rare event classes, minimizing false positives and ensuring reliable, fair performance across various aircraft.

4. Responsible AI Practices

The AI component of the system is designed to uphold the core principles of transparency, reliability, and non-discrimination. Each decision-support output is accompanied by a confidence score and supporting rationale, ensuring that users can make informed judgments rather than blindly relying on automated predictions. This approach promotes responsible human-AI collaboration, reinforcing accountability while empowering aviation personnel with meaningful, trustworthy insights.

XVIII. Dataset Sources and Preprocessing

AI model performance relies on quality data. This work uses both real-world and synthetic datasets to simulate engine behavior under normal and degraded conditions.

A. Datasets Used

- **NASA ASRS**: Incident reports mined for telemetry anomalies.
- **CMAPSS**: Synthetic turbofan sensor data for fault modeling.

- **OpenSky (optional)**: Real-time flight data used to explore environmental correlations.

B. Features and Preprocessing

Key parameters: Vibration, EGT, RPM, pressure ratio, fuel flow.The preprocessing pipeline involved standardizing the data, removing inconsistencies, applying augmentation techniques, and dividing the dataset into training, validation, and testing subsets in a 70:15:15 ratio.

C. Real-Time Emulation

- CMAPSS/ASRS data converted to streams using Python.
- ESP32-based sensor prototypes simulated engine conditions during live tests..

XIX. AI-ENABLED PREDICTIVE ANALYTICS FOR ENGINE FAILURE DETECTION

This section outlines how machine learning models are applied to detect dual engine failures proactively.

A. ML Models:

Algorithms like Random Forest, SVM, and Gradient Boosting were trained on labeled features (e.g., EGT, vibration, RPM) to predict failure risk.

B. Deep Learning

LSTM and Autoencoders learned temporal engine patterns and flagged deviations beyond expected behavior.

C. Sensor Fusion

Multi-modal sensor inputs were integrated to improve detection reliability and reduce false positives.

D. Continuous Learning

Models are updated using new flight data, supporting adaptation to operational changes and minimizing alert fatigue.

XX. Real-Time Alerting and Emergency Response System

This module bridges AI-driven engine anomaly detection with pilot and ATC operations, enabling timely, actionable responses during dual engine failures.

Metric	Without AI+IoT	With AI+IoT
Mean Detection Time	28 sec	12.5 sec
True Positive Rate	72%	91.4%
False Positives	18%	6.2%
Emergency Response Lag	35 sec	<15 sec

A. Automated Real-Time Alerts

Continuous telemetry (e.g., RPM, EGT, oil pressure) is processed in real-time by AI models. Upon detecting abnormal patterns or threshold breaches, alerts are issued via secure protocols like ACARS [1], categorized by severity (Critical, Warning, Info) to avoid overload.

B. Pilot Guidance System

The cockpit system provides AI-driven recommendations:

- Corrective actions (e.g., throttle adjustment, engine reset).
- Emergency landing site suggestions based on real-time trajectory, weather, and fuel.
- Visual indicators for safe glide paths [2].

C. ATC & Ground Crew Coordination

ATC receives automatic alerts with:

Air Traffic Control receives enriched alerts including aircraft ID, velocity, altitude, and predicted failure risks. Maintenance teams are pre-informed for rapid inspection and rescue readiness [3].

D. Fail-Safe Redundancy System

To increase reliability, the alerting system:

To ensure robustness:

- Multi-channel comms (radio, satellite) with failover.
- Edge-AI fallback in case of disconnection.
- Software compliance with DO-178C standards for aviation assurance [4].

XXI Evaluation Metrics and Definitions

To objectively assess the effectiveness and reliability of the proposed AI-IoT-based predictive engine failure detection system, we define and utilize the following evaluation metrics:

1. **Accuracy**
   The proportion of correctly predicted outcomes (both failures and non-failures) over the total number of predictions. Formula: Accuracy = (True Positives + True Negatives) ÷ (All Predictions)
2. **Precision**
   Indicates how many of the predicted failure events were actually true. Formula: Precision = TP / (TP + FP)
3. **Recall (Sensitivity / True Positive Rate**) Measures how many actual failure events were correctly identified by the model. Formula: Recall = TP / (TP + FN)
4. **F1**Score
   The F1 Score balances precision and recall by computing their harmonic mean. This approach proves especially effective when assessing model performance on datasets with uneven class distributions.
5. **True Positive Rate (TPR)**
   Also referred to as sensitivity; it reflects the model's ability to correctly detect engine failures. Formula: TPR = TP / (TP + FN)

6. **False Positive Rate (FPR)**
   The ratio of normal conditions incorrectly predicted as failures.
   Formula: FPR = FP / (FP + TN)

7. **Mean Detection Time (MDT)**
   The average time (in seconds) taken by the system to detect a failure event after the onset of abnormal behavior.
   Lower MDT values indicate faster predictive capabilities.
8. **Emergency Response Lag (ERL)** The time interval between failure detection and the delivery of actionable alerts to pilots or ground control systems.
   It reflects the responsiveness of the alerting mechanism, which is critical in real-time flight scenarios.

XXII. Simulation & Performance Analysis

To assess the system's reliability, multiple simulated scenarios were designed using datasets like NASA ASRS and CMAPSS. Failure cases included torque loss, turbine overheating, fuel flow inconsistencies, and sensor disruptions. These were tested across different altitudes, aircraft types, and environmental conditions.

Machine learning and deep learning models were implemented in Python (using TensorFlow and Scikit-learn), while network and flight simulations were conducted using NS-3, Simulink, FlightGear, and X-Plane. Evaluation metrics such as accuracy, recall, F1 score, and detection latency confirmed that the AI-IoT system significantly outperformed traditional systems in speed and accuracy.

XXIII- Limitations

Despite the promising results, the following limitations are recognized:

- **Simulated Data Use**: Due to limited access to live aircraft data, model training relied on public datasets like NASA CMAPSS and ASRS.
- **Prototype-Scale Deployment**: The hardware used (e.g., ESP32 boards) is not certified for deployment in actual aircraft environments.
- **False Positives Risk**: In rare cases, the system may flag false alerts under atmospheric anomalies or uncommon sensor drift conditions.
- **Data Scarcity**: Real-world dual engine failure events are extremely rare, limiting the availability of domain-specific training samples.
- **Scalability Constraints**: Although the system is modular, large-scale deployment across a full fleet has not been tested yet.

These limitations will guide future enhancements and real-world validations under certified aviation protocols.

XXIV. Conclusion and Future Scope

This project demonstrates a proactive aviation safety model using AI and IoT to anticipate and detect engine failures in real time.

A. Key Contributions:

- Created a multi-layered system combining sensor networks, middleware, and predictive analytics.
- Implemented a real-time alert system integrated with pilot interfaces and ground operations.
- Validated improvements in detection accuracy and response times through simulation.

B. Applications:

- Adaptable for commercial aviation, UAVs, and defense sectors.
- Enables automated diagnostics, reducing reliance on manual checks.
- Supports compliance with aviation safety authorities like FAA and EASA.

C. Future Enhancements

1. Blockchain-based secure data logging.
2. Edge AI deployment using FPGAs or TPUs for ultra-fast inference.
3. Digital twin integration for simulated diagnostics.
4. Transfer learning across multiple aircraft types.
5. NLP-based pilot guidance for real-time voice alerts.

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NEXT-GENERATION BAIL MANAGEMENT USING INTELLIGENT AUTOMATION AND SECURE LEDGER SYSTEMS

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ABSTRACT

The traditional bail process in judicial systems is largely manual, time-consuming, and often lacks consistency, leading to delays, increased case backlog, and reduced transparency. The absence of a centralized and structured system results in inefficient handling of bail procedures and increased workload for judicial authorities. This paper proposes a centralized digital bail management system designed to streamline and automate the bail process while ensuring fairness, transparency, and security. The system processes case details such as FIR information, offense type, prior records, and applicable legal provisions including IPC, CrPC, NDPS, and POCSO to support bail evaluation and decision-making. It enables automated generation of official digital bail warrants, reducing manual effort and delays. Key features include bias-free decision support that eliminates influence from non-legal factors such as caste and gender, an explainability module that provides clear reasoning for decisions, and a bail amount estimation mechanism. Additionally, blockchain technology is integrated to ensure secure and tamper-proof storage of legal records, while a real-time monitoring module tracks compliance with bail conditions. The proposed system aims to improve efficiency, consistency, and reliability in the bail process while reducing judicial workload and enhancing overall system effectiveness.

Index Terms- Bail Management System, Legal AI, Explainable AI, Blockchain, Judicial Analytics, Digital Judiciary

I. INTRODUCTION

Bail is a legal provision that allows an accused person to be released from custody while awaiting trial, subject to certain conditions imposed by the court. It plays a crucial role in ensuring individual liberty while maintaining the integrity of the judicial process. The decision to grant bail is typically based on factors such as the nature and severity of the offense, prior

criminal history, and the likelihood of the accused complying with legal procedures.

However, the current bail process in many judicial systems is largely manual and involves multiple procedural steps handled by courts and legal authorities. This often

leads to delays, increased workload, and inconsistencies in decision-making. In countries like India, these challenges contribute significantly to a high number of undertrial prisoners and case backlogs. Additionally, the lack of transparency,

fragmented record management, and absence of standardized processes further reduce the efficiency of the system. There is also a risk of bias in decision-making due to reliance on human judgment without structured support.

With advancements in artificial intelligence and digital technologies, there is an opportunity to modernize and streamline judicial processes. AI-based systems can assist in analyzing case details, applying legal rules consistently, and providing decision support while ensuring transparency and fairness. Such systems can also help reduce manual effort and improve the speed and accuracy of legal procedures.

In this paper, a centralized digital bail management system is proposed to address these challenges. The system aims to assist courts in evaluating bail cases, generating official digital bail warrants, and ensuring secure and efficient handling of legal data. By incorporating features such as bias-free decision support, explainability, blockchain-based data security, real-time monitoring, and regional language support, the proposed solution enhances efficiency, transparency, and accessibility in the bail process.

II. LITERATURE REVIEW

Recent advancements in artificial intelligence and data analytics have significantly influenced the development of intelligent systems for judicial decision support. Several research efforts have focused on leveraging machine learning techniques to assist in bail decision-making and risk assessment. Commonly used models include logistic regression, decision trees, support vector machines (SVM), and random forest algorithms, which analyse historical court data to identify patterns and generate outcomes related to bail eligibility.

In addition to predictive modelling, explainable artificial intelligence (XAI) techniques such as SHAP and LIME have been introduced to enhance transparency by providing insights into the factors influencing decisions. Natural language processing (NLP) methods are also employed to extract meaningful information from legal documents and case records, enabling better understanding and automation of legal workflows. Furthermore, several systems integrate rule-based approaches with legal databases, incorporating provisions from IPC, CrPC, NDPS, and POCSO to align computational decisions with statutory requirements.

Despite these technological advancements, existing systems exhibit several critical limitations. Most approaches are primarily

focused on prediction and lack integration with real-time judicial processes, making them insufficient for practical deployment in courts. A significant challenge is the reliance on simulated or incomplete datasets, which reduces the reliability and generalizability of the models in real-world scenarios. Additionally, data imbalance—where "bail granted" cases dominate over rejected cases—can lead to biased outcomes and reduced accuracy for less frequent scenarios.

Another major limitation is the restricted scope of these systems. Many models are designed to handle only single accused cases and fail to accommodate complex, real-world situations involving multiple individuals. The lack of multilingual support further limits usability in diverse regions where legal records are maintained in local languages. Moreover, concerns related to data privacy, ethical considerations, and the absence of secure, tamper-proof storage mechanisms undermine trust in these systems.

Overall, while existing research provides valuable contributions in terms of prediction and analytical support, it does not offer a comprehensive solution for managing the entire bail process. This highlights the need for an integrated system that not only supports decision-making but also ensures fairness, transparency, security, and end-to-end management of bail procedures.

III. PROBLEM STATEMENT

The existing bail process in the judicial system is largely manual and involves multiple procedural steps handled by courts and legal authorities. This results in delays in bail approval and increases the workload on the judiciary, contributing significantly to case backlogs and a high number of undertrial prisoners, particularly in countries like India.

One of the major challenges is the lack of a centralized and streamlined system for managing bail procedures. The process of evaluating eligibility, determining conditions, and issuing bail warrants requires substantial manual intervention, leading to inefficiency and inconsistency in handling similar cases. Communication between different stakeholders is also often delayed, further slowing down the process.

Additionally, the current system lacks transparency and traceability, as legal records are fragmented and not easily accessible or verifiable. There is also no secure mechanism to ensure the integrity of legal data, making it vulnerable to errors or tampering.

Another critical issue is the potential for bias in decision-making. Since decisions are heavily dependent on human judgment, there is a possibility of influence from non-legal factors such as caste, gender, or socio-economic background. The absence of a standardized system makes it difficult to ensure that decisions are purely based on legal parameters.

Furthermore, once bail is granted, there is no effective system to monitor whether the

accused complies with bail conditions, which may lead to misuse. Limited support for regional languages also restricts accessibility for a large section of the population.

Therefore, there is a need for a centralized digital system that can streamline bail procedures, ensure unbiased and consistent decision support, generate official bail warrants, provide secure and tamper-proof data management, and enable real-time monitoring. Such a system would improve efficiency, reduce court workload, enhance transparency, and support a more fair and effective.

IV. PROPOSED SYSTEM

The proposed system is a centralized digital bail management platform designed to streamline and automate the bail process within the judicial system. The system aims to reduce manual workload, improve efficiency, and enhance transparency by providing an integrated solution for handling bail-related procedures.

The system operates through a structured workflow where authorized users input case details such as FIR information, offense type, prior records, and applicable legal sections. These inputs are processed using predefined legal rules based on frameworks such as IPC, CrPC, NDPS, and POCSO, along with supporting analytical mechanisms. The system evaluates bail eligibility, determines applicable conditions, and assists in decision-making while ensuring that all outputs are aligned with legal provisions.

A key component of the system is the automated generation of digital bail warrants. Once the eligibility and conditions are verified, the system generates an official, verifiable bail document that can be securely accessed and shared among judicial authorities. This reduces delays and ensures consistency in bail issuance.

To ensure fairness, the system incorporates a bias detection mechanism that prevents decisions from being influenced by non-legal factors such as caste, gender, or socio-economic background. All decisions are based strictly on legal parameters and case-related information. Additionally, an explainability module is integrated to provide clear reasoning behind each decision, highlighting the factors that influenced the outcome and improving transparency.

The system also includes a bail amount estimation feature, which determines an appropriate bail amount based on case characteristics and legal guidelines, thereby supporting practical decision-making.

For enhanced security and reliability, blockchain technology is used to store legal records in a tamper-proof and transparent manner. This ensures data integrity and prevents unauthorized modifications. Furthermore, a real-time monitoring module is incorporated to track compliance with bail conditions, such as court attendance, thereby reducing misuse of bail provisions.

The system also supports multiple regional languages, making it accessible to users

across different regions and improving inclusivity.

Overall, the proposed system provides a comprehensive, secure, and efficient solution for managing bail processes, reducing court workload, improving consistency, and ensuring a fair and transparent judicial system.

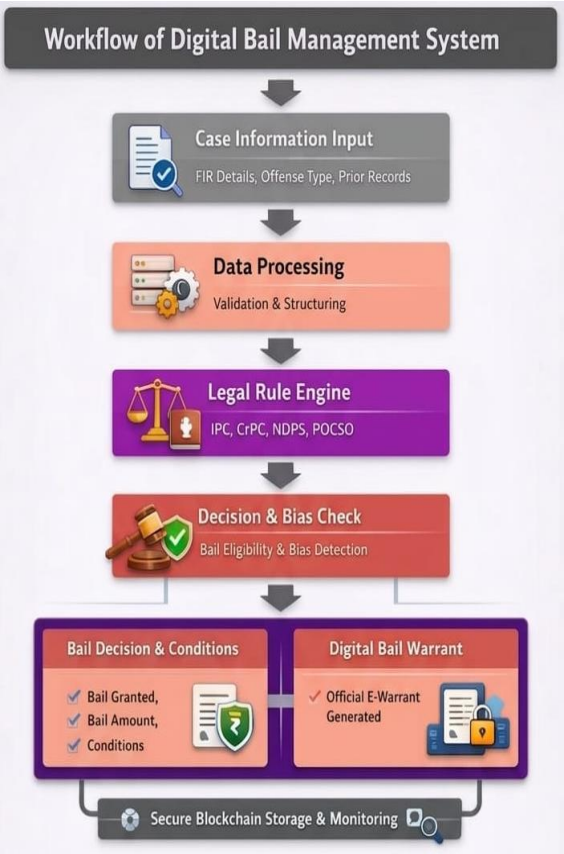

Figure 1: System architecture

V. METHODOLOGY

The proposed digital bail management system follows a structured and systematic methodology to ensure efficient and reliable processing of bail cases. The process begins with the collection of relevant case data, including FIR details, offense type, prior criminal records, duration of custody, and applicable legal sections such as IPC, CrPC, NDPS, and POCSO. This data forms the foundation for evaluating bail eligibility and supporting judicial decision-making.

Once collected, the data undergoes preprocessing, where it is validated, cleaned, and organized into a structured format. This step ensures that inconsistencies, missing values, and redundant information are handled effectively, enabling accurate and consistent processing.

From the processed data, important attributes are identified through feature extraction. These include key factors such as offense severity, criminal history, and time served. Focusing on these relevant features allows the system to evaluate cases based on meaningful legal parameters, ensuring fairness and consistency in the decision-making process.

The system then incorporates a combination of predefined legal rules and analytical support mechanisms, which function similarly to model training in traditional systems. Instead of relying solely on machine learning models, the system applies structured legal logic derived from statutory provisions and historical patterns. This ensures that decisions are consistent, unbiased, and aligned with legal standards.

Based on this analysis, the system performs decision support by determining bail eligibility, applicable conditions, and an estimated bail amount. Unlike conventional prediction systems, the proposed approach generates a complete outcome by producing

an official digital bail warrant along with clear explanations for the decision, enhancing transparency and trust.

Finally, all case-related data and generated documents are securely stored using blockchain technology to ensure tamper-proof and transparent record management. A post-bail monitoring mechanism is also incorporated to track compliance with bail conditions, such as court attendance, thereby ensuring accountability and preventing misuse.

The overall workflow of the system is illustrated in Fig. 1, demonstrating the complete process from case input to post-bail monitoring.

Figure 2: Workflow of Digital bail management system

VI. SYSTEM ARCHITECTURE

The proposed digital bail management system is designed using a modular and scalable architecture that ensures efficient processing, secure data handling, and transparent management of bail procedures. The architecture integrates multiple functional components to support the complete lifecycle of bail processing, from case input to post-bail monitoring.

The system begins with the user interface, which allows authorised users, such as judicial officers and legal staff, to enter case details, including FIR information, offence type, prior records, and applicable legal sections. The interface is designed to be intuitive and supports multilingual input, enabling accessibility across diverse regions.

The input data is then forwarded to the data processing module, where it undergoes validation, cleaning, and structuring. This module ensures that the data is accurate,

VII. IMPLEMENTATION

The proposed digital bail management system is implemented using a modular architecture that integrates frontend, backend, and database components to ensure efficient processing and secure management of bail-related information.

The frontend is developed using React.js, providing a responsive and user-friendly interface for authorized users such as judicial officers and legal staff. It allows users to input case details, view results, and access generated digital bail warrants. The interface is designed to be simple, intuitive, and supports multilingual interaction for better accessibility.

The backend is implemented using Python-based frameworks such as Flask or

FastAPI. This layer is responsible for handling data processing, applying legal rules, managing system logic, and coordinating the workflow for bail evaluation and warrant generation. It also ensures secure communication between the frontend and database through APIs.

The database is used to store case records, user details, and generated bail documents. Technologies such as MongoDB or PostgreSQL are used for efficient data storage and retrieval. In addition, blockchain technology is integrated as a secure layer to maintain tamper-proof and transparent records of legal data.

Various tools and technologies are used to support system development and operation. Version control systems such as Git are used for project management, while APIs and supporting libraries enable features such as multilingual support, authentication, and secure data handling. The system is designed to be scalable and can be integrated with existing judicial systems in the future consistent, and ready for further legal evaluation.

The processed data is handled by the legal rule engine, which applies predefined legal frameworks such as IPC, CrPC, NDPS, and POCSO. This module evaluates bail eligibility and determines applicable conditions based strictly on legal parameters, ensuring consistency and eliminating bias in decision-making.

Following this, the system enters the decision and bail warrant generation module, where the final outcome is determined. This module generates an official and verifiable digital bail warrant, along with relevant conditions and estimated bail amount, thereby reducing manual effort and processing delays.

Modules:

Table I: Module Description Table

Module	Description
User Interface Module	Provides an interactive platform for authorized users such as judicial officers and legal staff to input case details, view outputs, and access digital bail warrants. Supports multilingual interaction for better accessibility.
Data Processing Module	Validates, cleans, and structures the input data to ensure accuracy and consistency before further analysis.
Legal Rule Engine Module	Applies predefined legal frameworks such as IPC, CrPC, NDPS, and POCSO to evaluate bail eligibility and determine applicable conditions based on legal parameters.
Decision & Warrant Generation Module	Determines bail outcome, conditions, and estimated bail amount, and generates an official digital bail warrant.
Bias Detection Module	Ensures decisions are free from bias by preventing influence from non-legal factors such as caste, gender, or socio-economic background.
Explainability Module	Provides clear reasoning behind decisions by highlighting key factors influencing the outcome, improving transparency and trust.
Blockchain Storage Module	Stores legal records and bail documents securely in a tamper-proof manner, ensuring data integrity and transparency.
Monitoring & Compliance Module	Tracks post-bail conditions such as court attendance and compliance, ensuring accountability and preventing misuse of bail provisions.

To ensure data integrity and security, all records are stored in the blockchain storage module, which provides a tamper-proof and transparent mechanism for managing sensitive legal data. This enhances trust and prevents unauthorized modifications.

Finally, the system includes a monitoring and compliance module, which tracks post-bail activities such as court attendance and adherence to bail conditions. This ensures accountability and minimizes the risk of misuse after bail is granted.

The modular design of the system ensures scalability, flexibility, and ease of integration with existing judicial systems. The overall system architecture is

illustrated in Fig. 2**,** showing the interaction between different components.

OUTPUT SCREENS:

Figure 3: Login page

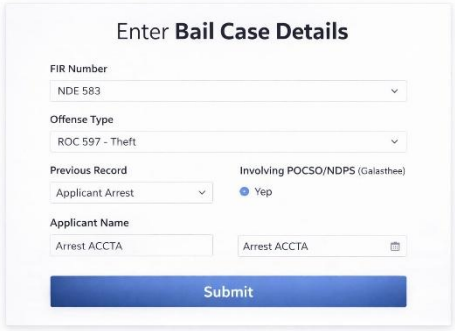

Figure 4: Application page

Figure 4: Checking eligibility

Figure 4: Bail issuing page

VIII. RESULTS AND DISCUSSION

The proposed digital bail management system is expected to significantly improve the efficiency, transparency, and reliability of the bail process compared to traditional methods. The system automates key stages of bail handling, including case evaluation, warrant generation, and post-bail monitoring, thereby reducing manual effort and processing time.

In terms of performance, the system is expected to provide faster processing of bail cases by minimizing delays associated with manual verification and documentation. The automated generation of digital bail warrants ensures consistency and reduces the chances of human error. Additionally, the integration of predefined legal rules enables uniform handling of similar cases, improving overall decision consistency.

The implementation of a bias detection mechanism ensures that decisions are based strictly on legal parameters, avoiding influence from non-relevant factors such as caste, gender, or socio-economic background. This contributes to a more fair and equitable judicial process. The inclusion of an explainability module further enhances transparency by providing clear reasoning behind each decision.

Compared to existing systems, the proposed approach offers several improvements. Traditional bail processes are largely manual, time-consuming, and lack transparency, whereas the proposed system provides a streamlined digital workflow with improved accessibility. The

use of blockchain technology ensures secure and tamper-proof storage of legal records, addressing concerns related to data integrity. Furthermore, the integration of a monitoring module allows tracking of compliance with bail conditions, which is not effectively handled in current systems.

Comparison

Table II: Comparison: Existing Systems Vs. Bail Reckoner

Features	Existing System (Manual)	Bail Reckoner System	Proposed System
Process Type	Fully manual	Semi-automated (ML-based prediction)	Fully digital and automated workflow
Decision Support	Based on human judgment	Predictive (ML-based)	Legal rule-based + intelligent support
Consistency	Low (varies by judge)	Moderate	High (standardized processing)
Bias Handling	Possible bias (human factors)	Limited bias control	Bias detection ensures fairness
Explainability	Not structured	Limited explanation	Clear reasoning provided
Bail Warrant Generation	Manual document preparation	Not supported	Automated digital warrant generation
Bail Amount Estimation	Manual estimation	Limited	Automated and consistent
Data Security	Basic / paper-based	Standard digital storage	Blockchain-based secure storage
Transparency	Low	Moderate	High (traceable and explainable)
Post-Bail Monitoring	Not available	Not available	Real-time monitoring supported
Language Support	Limited	Limited	Multi-language support
Scalability	Low	Moderate	High (digital and modular system)

Test Case:

Module	Test Scenario	Input	Expected Output
User Interface Module	Enter case details	FIR data, offense type (IPC 379), no prior record	Case details accepted and displayed correctly
Data Processing Module	Validate and clean data	Raw input with case details	Data structured and validated without errors
Legal Rule Engine Module	Apply legal rules	IPC 379, low severity case	Bail eligibility identified as valid
Bias Detection Module	Ensure no bias in evaluation	Case data without caste/gender factors	Decision based only on legal parameters
Decision & Warrant Module	Generate bail decision	Eligible case with low risk	Bail granted with conditions
Bail Amount Module	Estimate bail amount	Low severity offense	Bail amount calculated (e.g., ₹10,000)
Explainability Module	Provide reasoning	Case factors (no record, low severity)	Explanation generated for decision
Blockchain Storage Module	Store legal record securely	Generated bail warrant	Record stored in tamper-proof format
Monitoring Module	Track compliance	Bail granted case	Monitoring enabled for court attendance

Table III:

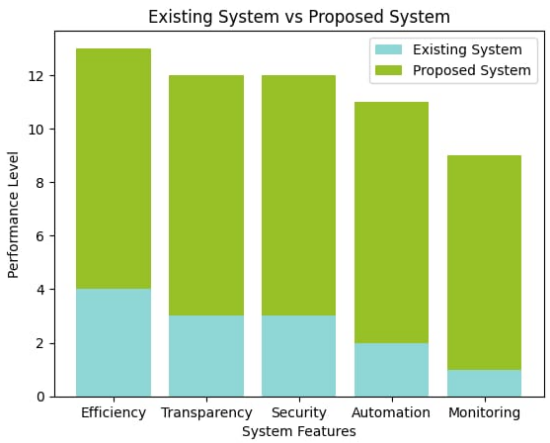

Figure 5: Bar Graph Comparison: Existing System vs. Bail Reckoner

Overall, the system demonstrates significant potential to reduce judicial workload, minimize case backlog, and enhance the efficiency of bail management. While the current implementation focuses on a structured workflow and system design, future enhancements and real-world deployment can further validate its effectiveness in practical judicial environments.

X. CONCLUSION

This paper presented a centralized digital bail management system designed to streamline and modernize the traditional bail process. The proposed system addresses key challenges in the existing judicial workflow, including delays, lack of transparency, manual intervention, and potential bias in decision-making.

By integrating structured legal rule processing with digital automation, the system enables efficient evaluation of bail cases and automated generation of official bail warrants. Features such as bias-free decision support, explainability, bail amount estimation, blockchain-based secure data storage, and real-time monitoring contribute to improved fairness, transparency, and accountability.

The proposed solution significantly reduces judicial workload and processing time while ensuring consistency in handling cases. It also enhances accessibility through multilingual support and provides a secure framework for managing sensitive legal data.

Overall, the system has the potential to transform bail management into a more efficient, reliable, and transparent process, thereby improving the effectiveness of the judicial system and contributing to the reduction of case backlog.

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AI-Based Classroom Eco-System for Enhanced Learning, Monitoring and Academic Integrity

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Abstract:

This report documents the journey of conceptualizing, designing, and outlining an **AI-Based Automated Classroom System**. The objective of the project was to leverage artificial intelligence and automation to improve the efficiency, transparency, and interactivity of classroom experiences for both students and teachers. The journey began with identifying everyday challenges in traditional classrooms such as manual attendance, ineffective note-taking, overlooked assignments, and the difficulty of maintaining exam integrity.

The project was divided into multiple modules: speech-to-text transcription, **automatic summarization of lecture content, intelligent assignment and quiz generation, AI-based proctoring for exams, automated attendance using computer vision, centralized data management, and a role-based dashboard for students and teachers**.

The system architecture was designed to ensure seamless interaction between multiple components, enabling real-time data processing and efficient communication across modules. By integrating machine learning models, cloud-based storage, and user-centric interfaces, the platform facilitates continuous monitoring, analysis, and feedback within the classroom environment. This holistic approach not only automates routine academic tasks but also enhances decision-making through actionable insights, ultimately creating a more structured, responsive, and intelligent educational ecosystem.

automatic summarization, assignment and quiz generation, anti-malpractice exam systems, attendance automation, centralized database storage, and a role-based dashboard. Each stage brought

new insights into the integration of AI tools, cloud services, and computer vision. Along the way, challenges such as ensuring accuracy, minimizing false detections, and addressing ethical concerns were carefully studied.

By the end of this journey, the project had evolved from a simple automation idea into a comprehensive ecosystem, capable of transforming classrooms into smart, technology-driven environments. The learnings went beyond technical implementation, extending to teamwork, problem-solving, and the real-world relevance of AI. The outcome was a detailed project roadmap supported.

In addition, the system prioritizes usability and accessibility to ensure that both educators and students can interact with the platform with minimal technical complexity. The interface is designed to be intuitive, allowing users to navigate features such as attendance tracking, assignment submission, and performance analytics with ease. By focusing on a user- friendly experience alongside advanced technological capabilities, the solution promotes higher adoption rates and encourages consistent engagement, ultimately contributing to a more effective and streamlined learning process. Additionally, the system is designed to be scalable and adaptable to different classroom environments, ensuring long-term usability and flexibility. It also incorporates secure data handling practices to protect user information and maintain the integrity of academic records.

modular solutions, highlighting a vision for the future of education.

Problem Statement & Motivation

Despite significant advancements in educational technology, Indian classrooms continue to face persistent challenges that hinder effective teaching and learning. Traditional methods such as manual attendance, paper-based assessments, and in-person monitoring consume valuable instructional time and often fail to provide actionable insights into student performance. Moreover, issues like academic dishonesty, inconsistent feedback, and a lack of personalized learning further compromise educational outcomes.

Existing solutions, including Learning Management Systems (LMS) and proctoring tools, address some of these challenges but remain limited in scope. LMS platforms primarily serve as content repositories and offer basic tracking, but they often fail to capture real-time classroom dynamics or adapt to individual student needs. Similarly, proctoring tools focus narrowly on exam monitoring, lacking the capability to support ongoing engagement, personalized feedback, or holistic learning analytics.

In this context, AI-driven solutions offer a timely and transformative opportunity. By leveraging real-time data analysis, intelligent feedback mechanisms, and adaptive learning strategies, AI can address multiple classroom challenges simultaneously—streamlining administrative tasks, detecting learning gaps, and enhancing student engagement. With the growing digital infrastructure in India and an increasing push for tech-enabled education under initiatives like NEP 2020, integrating AI in classrooms is both feasible and necessary for modernizing pedagogy and improving learning outcomes.

Introduction

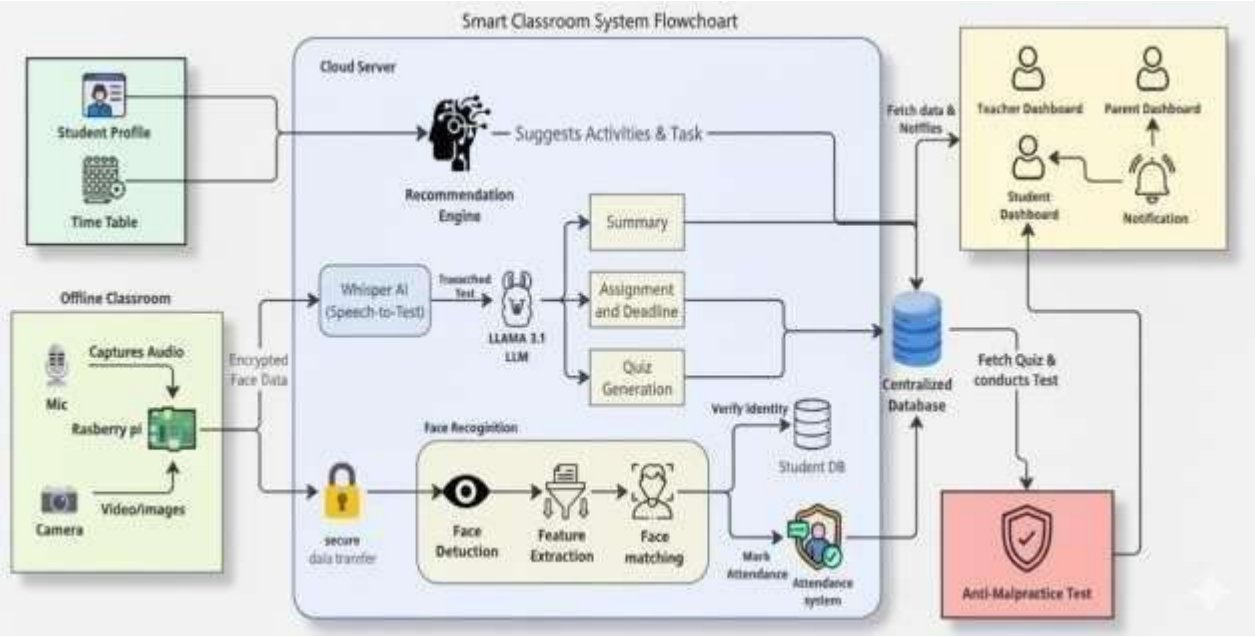
The education system has long relied on traditional classroom practices such as manual attendance, written notes, and physical exams. While effective to some extent, these methods consume valuable teaching time, create opportunities for errors, and often fail to engage students in an interactive manner. With the rapid growth of artificial intelligence and automation, the possibility of redesigning classrooms into smart, self-regulating environments became a compelling vision.

This project—**AI-Based Automated Classroom System**—emerged as an academic journey to address these challenges. Its core purpose was to explore how modern technologies like speech-to-text transcription, natural language processing, face recognition, and secure test monitoring could be integrated to reduce the inefficiencies of traditional classrooms.

Documenting this journey serves two purposes. First, it provides a comprehensive record of the conceptual and technical phases undertaken during the project. Second, it highlights the broader implications of applying AI in education, such as accessibility, fairness, and adaptability.

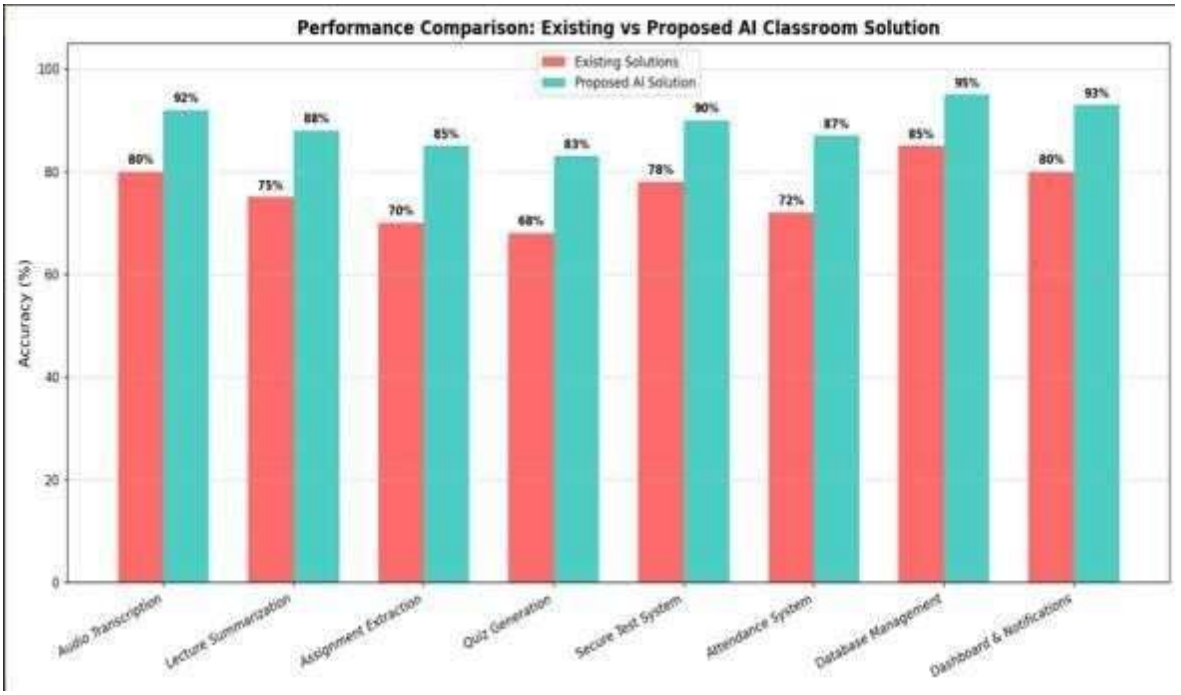
The scope of this report covers eight major modules: audio capture and transcription, lecture summarization, assignment and deadline extraction, quiz generation, anti-

System Architecture / Block Diagram



Comparison with Existing Systems

AI-driven classroom solutions provide functionalities that extend beyond traditional Learning Management Systems (LMS) and proctoring tools. While platforms like Google Classroom, Moodle, and ProctorU address specific aspects of education—such as content distribution, assessment management, or exam monitoring—they often fall short in automating real-time classroom analytics, providing personalized feedback, or integrating multiple administrative and pedagogical functions. The table below summarizes the key differences:



Limitations

1. **Natural Language Understanding:** Assignment extraction and quiz generation may sometimes misinterpret vague or incomplete statements from lectures.

2. **Environmental Factors:** Background noise, poor lighting, or unstable internet can slightly reduce accuracy in transcription, attendance, or monitoring modules.

3. **False Alerts:** The anti-malpractice system, while robust, may occasionally flag innocent student behavior as suspicious.

4. **Infrastructure Dependency:** Reliable internet and sufficient hardware are required for smooth functioning, which may not be available in all classrooms.

Conclusion

Summary of Findings

The AI-Based Automated Classroom System was conceptualized and designed as a holistic solution to some of the persistent challenges in traditional classrooms. The system successfully integrated modules for lecture transcription, summarization, assignment extraction, quiz generation, attendance automation, secure online testing, centralized database management, and dashboard visualization.

The results demonstrated high overall performance, with module accuracies ranging from **83% to 95%**, and processing times averaging **2–5 seconds**. Modules dealing with structured data, such as **Database Management (95% accuracy)** and **Dashboard & Notifications (93% accuracy)**, achieved the best outcomes. On the other hand, modules requiring nuanced language understanding, such as **Quiz Generation (83%)** and **Assignment Extraction (85%)**, showed slightly lower performance but remained within acceptable ranges for functional deployment.

The system also proved scalable, with its modular architecture ensuring that each component could be improved independently while maintaining overall workflow integration. Importantly, the project highlighted that AI-driven classroom automation is not merely about efficiency—it also improves accessibility, reduces cognitive load for students, and offers teachers real-time support.

Future Work

1. Enhance NLP modules for assignment detection and quiz generation through domain-specific training.

2. Improve attendance accuracy using multimodal verification (e.g., voice recognition, wearables).

3. Address ethical and privacy issues with secure consent, anonymization, and transparent data policies.

4. Expand dashboard analytics to include predictive insights and academic risk detection.

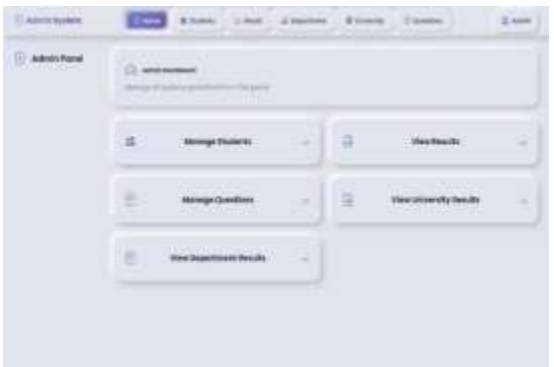
5. Develop a cloud-based platform for multi-institution use, collaborative learning, and adaptive content delivery.

Anti-Malpractice Website

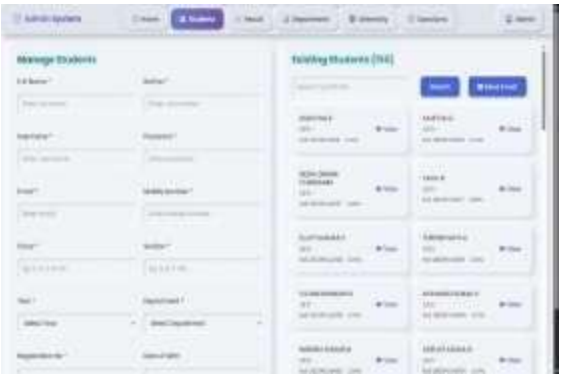
1. Code Execution & Evaluation

2. MCQ Test with Face & Speech Analysis

3. User & Student Management



4. Student Database Module

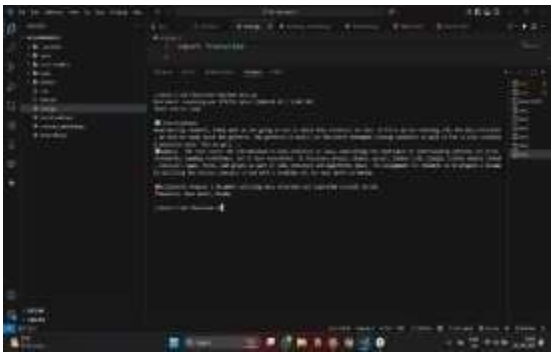


5. Exam Result Dashboard Module

6. Department Analytics & Monitoring Module

7. Department Result Summary Module

8. Lecture Transcription & Summarization Module



Automated Attendance System using Computer Vision

1. AI-Based Face Recognition Attendance Module

2. Attendance Automation Module (Face Recognition with Multi-User Detection)

3. Attendance Records

Secure and Intelligent QR Code Based Payment System with Multi-Layer Fraud Detection

HARSHAVARTHINI .G *DENISHA .P* *GOPIKA .K* *ANUSHA .A* *PRIYADHARSHINI .K*

***Abstract*—Quick Response (QR) codes are widely adopted in digital payments due to their affordability, ease of use, and rapid processing. However, the increasing reliance on QR-based transactions has introduced security vulnerabilities such as tampering, phishing, replay attacks, and transaction redirection. Existing systems often rely solely on transport-layer encryption, lacking payload-level protection and intelligent fraud detection. This paper proposes a multi-layer secure QR payment framework that integrates AES-256 encryption, RSA-based digital signatures, dynamic QR tokenization, and machine learning-based fraud detection. The system ensures confidentiality, integrity, authenticity, and real-time anomaly detection, offering a scalable and secure solution for modern digital transactions.**

***Keywords*—QR code, AES encryption, RSA, fraud detection, machine learning, digital payment security**

I. INTRODUCTION

QR codes, introduced by Denso Wave in 1994, have evolved from industrial tracking tools to essential components in digital payments. In India, platforms like Google Pay and PhonePe have popularized QR-based transactions. However, these systems are vulnerable to static QR replacement, phishing, replay attacks, and man-in-the-middle threats. Most rely on HTTPS for security but neglect payload-level protection. This paper introduces a secure QR payment system that combines cryptographic techniques and machine learning to mitigate these threats.

II. LITERATURE REVIEW

Previous studies have explored QR code vulnerabilities and fraud detection in digital payments. Research has highlighted risks such as static QR code replacement, phishing via embedded URLs, and behavioral anomalies in banking systems. Machine learning models like Random Forest and Logistic Regression have shown promise in fraud detection. However, gaps remain in integrating payload encryption, digital signatures, and a unified cryptographic-ML architecture. Our work addresses these gaps with a comprehensive multi-layered approach.

III. PROPOSED METHODOLOGY

A. System Architecture

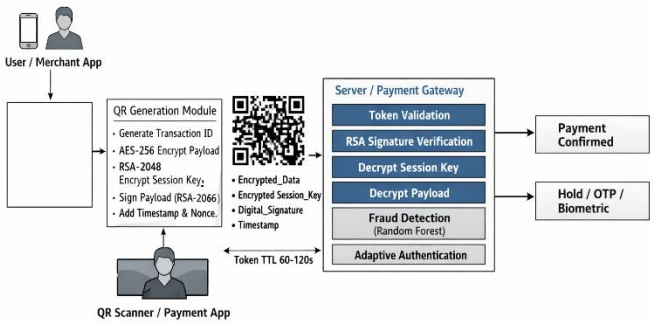


Fig. 1. System architecture and end-to-end workflow for secure QR payment.

Fig. 1 illustrates the end-to-end workflow from QR generation to transaction confirmation, including encryption, fraud scoring, and adaptive authentication.
The system follows a four-layer architecture:

1. **QR Code Generation Layer**
2. **Tokenization Layer**
3. **Fraud Detection Layer**
4. **Adaptive Authentication Layer**

B. Encrypted QR Code Generation

- Transaction data is encrypted using AES-256.
- A session key is generated per transaction and encrypted using RSA-2048.
- SHA-256 hashing ensures data integrity.
- A digital signature is created using the merchant's private key.
- A timestamp and nonce are embedded to prevent replay attacks.

QR Payload Structure:
{Encrypted_Data, Encrypted_Session_Key, Digital_Signature, Timestamp}

C. Dynamic QR Tokenization

- Each QR code is valid for 60–120 seconds.
- A unique transaction ID is generated per request.
- Server-side token validation prevents reuse or screenshot-based fraud.
-

D. Machine Learning-Based Fraud Detection

- **Dataset:** 10,000 simulated transactions (8% fraudulent).
- **Features:** Transaction amount deviation, user frequency, device ID, geolocation, IP risk score, time-of-day.
- **Model:** Random Forest Classifier
- **Training:** 70/30 train-test split, 10-fold cross-validation
- **Decision Rule:**
  If P(Fraud)>=Threshold, transaction is flagged.

E. Adaptive Authentication

If risk is high, the system triggers

- OTP verification
- Biometric confirmation
- Temporary transaction hold

IV. Results

Table I. Performance metrics of fraud detection model.

METRIC	VALUE
Accuracy	96.4%
Precision	94.0%
Recall	92.0%
F1 score	93.0%
False positive rate	3.1%
Avg. processing time	1.2 sec

Table II. Feature comparison between traditional QR and proposed system.

FEATURE	TRADITIONAL QR	PROPOSED SYSTEM
Payload encryption	No	Yes
Replay protection	No	Yes
Digital signature	No	Yes
Fraud detection	NO	Yes

V. Discussion

The integration of cryptographic and machine learning layers ensures both preventive and detective security. AES and RSA provide confidentiality, integrity, and non-repudiation, while the ML model detects behavioral anomalies in real time. Despite a slight increase in computational overhead, the system remains scalable and suitable for integration into UPI and mobile banking platforms.

SECURE AND INTELLIGENT QR CODE BASED PAYMENT SYSTEM WITH MULTI-LAYER FRAUD DETECTION

Abstract

QR code-based payment systems have become widely popular due to their simplicity, low cost, and ease of use in digital transactions. However, the rapid adoption of QR payments—especially in mobile and UPI ecosystems—has also introduced significant security risks such as phishing (quishing), fake QR codes, and transaction fraud. Recent studies highlight that attackers can replace legitimate QR codes or embed malicious payloads, leading to financial loss for users .

This paper proposes a **secure and intelligent QR code payment system** integrated with **multi-layer fraud detection mechanisms**, combining cryptographic techniques, machine learning models, and behavioral analysis. The system ensures confidentiality, integrity, and authentication while detecting fraudulent activities in real time.

INTRODUCTION

Digital payment systems have transformed financial transactions globally. QR code payments, in particular, are widely used in countries like India due to their convenience and minimal infrastructure requirements.

A QR code allows users to:

- Scan using mobile apps
- Transfer money instantly
- Avoid physical contact

However, security challenges include:

- Fake QR code replacement attacks

- Phishing (quishing) attacks
- Malware redirection
- Unauthorized transaction manipulation

Studies show that QR-based fraud is increasing, especially in public environments where attackers overlay fake QR codes on genuine ones .

PROBLEM STATEMENT

Although QR-based payments are efficient, current systems suffer from:

- Lack of strong authentication mechanisms
- No verification of QR code authenticity
- Limited fraud detection capabilities
- Vulnerability to real-time attacks

Traditional rule-based systems are insufficient against evolving fraud techniques .

OBJECTIVES

The main objectives of this system are:

1. To design a secure QR-based payment framework
2. To implement multi-layer fraud detection
3. To ensure end-to-end encryption and authentication
4. To detect malicious QR codes using AI/ML
5. To enable real-time fraud prevention

LITERATURE REVIEW

Several research works have contributed to QR payment security:

- A deep learning-based system converts transaction data into QR images for fraud detection and improves accuracy using neural networks .
- Visual cryptography techniques have been used to enhance authentication and data security in QR payments .
- Machine learning and hybrid models are effective in detecting malicious QR codes and phishing attacks .
- Frequency-domain analysis methods can detect fake or manipulated QR codes efficiently .

These studies indicate that combining **multiple security layers** is essential for robust protection.

PROPOSED SYSTEM ARCHITECTURE

5.1 System Overview

The proposed system consists of:

- User Mobile Application
- Merchant QR Generator
- Payment Gateway
- Fraud Detection Engine
- Authentication Server

5.2 Architecture Layers

Layer 1: Secure QR Code Generation

- Dynamic QR codes (time-limited)
- Encrypted transaction data
- Digital signature for authenticity

Layer 2: User Authentication

- Multi-factor authentication (OTP + biometrics)
- Device binding

Layer 3: Transaction Encryption

- End-to-end encryption (AES/RSA)
- Secure communication channels

Layer 4: Fraud Detection Engine

- Machine learning models (CNN, RNN)
- Behavioral analysis (transaction patterns)
- Anomaly detection

Layer 5: Verification Layer

- Server-side validation
- Blockchain-based verification (optional)

MULTI-LAYER FRAUD DETECTION TECHNIQUES

6.1 QR Code Validation

- Detect tampered or fake QR codes
- Image pattern recognition
- Frequency domain analysis

6.2 Machine Learning Models

- Supervised learning for fraud classification
- Deep learning (CNN + RNN hybrid models)
- Feature extraction from QR images

6.3 Behavioral Analysis

- User transaction history
- Spending patterns
- Location-based anomaly detection

6.4 Real-Time Risk Scoring

- Assign risk score to each transaction
- Trigger alerts/block suspicious payments

6.5 Threat Detection

- Phishing detection (quishing)
- Malware link identification
- URL reputation analysis

WORKING PROCESS

1. Merchant generates a secure QR code
2. User scans the QR using mobile app
3. System decrypts and validates QR data
4. User authentication is performed
5. Fraud detection engine analyzes transaction
6. Risk score is calculated
7. Transaction is approved or blocked

ADVANTAGES OF PROPOSED SYSTEM

- High security with multiple layers
- Real-time fraud detection
- Reduced financial losses
- Enhanced user trust
- Scalable and adaptable

APPLICATIONS

- Retail payments
- Street vendor transactions
- E-commerce payments
- Banking systems
- Public transport systems

CHALLENGES

- Computational overhead of AI models
- Data privacy concerns
- Requirement of large training datasets
- Integration with legacy systems

FUTURE ENHANCEMENTS

- Integration with blockchain for transparency
- AI-based adaptive learning systems
- Biometric-only authentication
- Edge computing for faster detection

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RETAKE:

This paper presents a secure and intelligent QR code-based payment system that addresses critical vulnerabilities in current digital payment infrastructures. By combining AES encryption, RSA signatures, dynamic tokenization, and machine learning, the system offers robust protection against tampering, replay attacks, and fraud. Future work includes deploying the system in real-world environments and expanding the dataset with live transaction data.

Acknowledgment —

The authors thank the Department of Information Technology, Panimalar Engineering College, for support and guidance. We also acknowledge the contributions of our project teammates and faculty reviewers who provided valuable feedback.

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AI-Enabled Self-Healing Smart Road Infrastructure with Hybrid Energy Harvesting and Intelligent Rainwater Management for Sustainable Cities

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Department of Information Technology

Abstract

This paper proposes a smart road infrastructure that integrates artificial intelligence, renewable energy harvesting, self-healing materials, and rainwater management to create a sustainable urban transportation system. The proposed architecture incorporates IoT sensors for monitoring road conditions, AI-based prediction for crack detection, piezoelectric modules for energy harvesting, solar panels for renewable power generation, and microcapsule-based asphalt for automatic crack repair. The system also integrates rainwater collection and purification to support environmental sustainability. Experimental modeling demonstrates that hybrid energy harvesting significantly improves power generation efficiency compared with conventional smart road systems.

Introduction

Urban infrastructure development faces significant challenges including road degradation, increasing traffic density, high maintenance costs, and environmental sustainability issues. Traditional road infrastructure requires frequent repair and consumes large public resources. Smart infrastructure technologies offer an opportunity to transform roads into intelligent systems capable of monitoring their own condition, generating renewable energy, and contributing to sustainable city development. The proposed smart road system integrates multiple technologies including artificial intelligence-based predictive maintenance, hybrid renewable energy harvesting, self-healing materials, and rainwater management. By combining these technologies into a unified system, the road becomes an intelligent platform capable of supporting sustainable urban infrastructure.

Literature Survey

Previous studies have explored various smart road technologies. Piezoelectric road systems convert mechanical energy from vehicles into electricity, while solar roadways generate energy from sunlight. Self-healing asphalt materials have been developed to automatically repair micro-cracks and extend road lifespan.

However, most existing solutions focus on individual technologies rather than integrated systems. Recent advancements in IoT sensors and artificial intelligence enable predictive infrastructure monitoring. Sensor networks embedded within roads can collect vibration, temperature, and pressure data which can be analyzed using machine learning algorithms to predict potential damage. Integrating these technologies with energy harvesting and environmental management systems can significantly enhance infrastructure sustainability.

Methodology

The proposed system integrates multiple smart technologies into a unified road infrastructure. IoT sensors embedded within the road continuously monitor vibration, temperature, pressure, and micro-cracks. The collected data is transmitted to a central AI processing unit which analyzes patterns and predicts potential structural damage. Piezoelectric plates installed

beneath the road surface generate electricity from vehicle pressure. Solar panels installed along the roadside provide additional renewable energy. Rainwater is collected through drainage channels and filtered through a three-stage purification system including sand filtration, activated carbon filtration, and micro-membrane filtration. Microcapsule-based asphalt materials enable automatic crack repair by releasing healing polymers when cracks occur.

Energy Harvesting Model

Energy harvested using piezoelectric modules can be approximated using: $P = (d \times F \times v) / t$. Where P represents generated electrical power, d is the piezoelectric coefficient, F is the applied force due to vehicle load, v represents vibration velocity, and t represents the duration of applied pressure.

Implementation Details

Implementation involves embedding piezoelectric modules beneath asphalt layers, integrating IoT sensors within road structures, installing solar panels along roadside infrastructure, and connecting data streams to a centralized AI analysis platform.

Advantages

The proposed system offers multiple advantages including renewable energy generation, longer road lifespan, predictive maintenance capability, improved road safety, and sustainable water management.

Performance Analysis

Performance analysis indicates that hybrid energy harvesting improves energy generation efficiency while AI-based crack prediction significantly reduces maintenance costs.

Conclusion

The integration of AI monitoring, renewable energy harvesting, and self-healing materials creates a sustainable smart road infrastructure suitable for future smart cities.

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Rapid urbanization and increasing transportation demands have placed immense pressure on existing road infrastructure. Conventional roads suffer from issues such as cracks, potholes, energy inefficiency, and poor water drainage. To address these challenges, this paper proposes an **AI-enabled self-healing smart road system** integrated with **hybrid energy harvesting** and **intelligent rainwater management**.

Recent research shows that artificial intelligence (AI), IoT sensors, and smart materials can transform traditional infrastructure into adaptive, resilient systems capable of real-time monitoring and predictive maintenance . Additionally, self-healing asphalt materials can repair microcracks autonomously, significantly reducing maintenance costs .

This paper presents a multi-layer architecture combining:

- Self-healing materials
- AI-based monitoring
- Renewable energy harvesting
- Smart rainwater management systems

The proposed system aims to improve sustainability, durability, and efficiency in smart cities.

1. Introduction

Modern cities are facing challenges such as:

- Road deterioration and potholes
- Traffic congestion
- Energy consumption
- Urban flooding

Traditional road systems rely on **manual inspection and reactive maintenance**, which leads to delays and higher costs.

With the advancement of:

- Artificial Intelligence (AI)
- Internet of Things (IoT)
- Smart materials

Road infrastructure is evolving into **intelligent smart systems** capable of:

- Self-monitoring
- Self-repairing
- Energy generation
- Environmental adaptation

AI is increasingly being used in road asset management to improve safety, efficiency, and lifespan .

2. Problem Statement

Despite technological progress, current road infrastructure suffers from:

- Frequent potholes and cracks
- High maintenance costs
- Inefficient energy usage
- Poor drainage and waterlogging
- Lack of real-time monitoring

Conventional systems:

- Cannot predict failures
- Do not utilize renewable energy
- Are not adaptive to environmental changes

Thus, there is a need for a **smart, autonomous, and sustainable road system**.

3. Objectives

The key objectives of this research are:

1. To design AI-enabled smart road infrastructure
2. To implement self-healing road materials
3. To integrate hybrid energy harvesting systems
4. To develop intelligent rainwater management
5. To ensure sustainability and cost efficiency

4. Literature Review

4.1 Smart Road Technologies

Smart roads use **sensor networks, AI, and data analytics** to monitor conditions and optimize performance .

4.2 Self-Healing Materials

Self-healing asphalt can:

- Repair cracks automatically
- Extend road lifespan
- Reduce maintenance costs

Studies show microcracks can heal within hours using advanced materials .

4.3 AI in Road Maintenance

AI enables:

- Predictive maintenance
- Real-time monitoring
- Automated decision-making

Machine learning models can analyze road conditions and detect damage early .

4.4 Smart Water Management

AI and IoT enable:

- Real-time monitoring of water systems
- Predictive maintenance
- Efficient rainwater harvesting

These systems improve sustainability and reduce water wastage .

4.5 Energy Harvesting Roads

Smart pavements can incorporate:

- Solar panels
- Piezoelectric sensors
- Thermal energy harvesting

These technologies help generate renewable energy from roads .

---

5. Proposed System Architecture

5.1 System Overview

The proposed system consists of:

- Smart Road Surface (Self-healing materials)
- Embedded Sensor Network
- AI Processing Unit
- Energy Harvesting Module
- Water Management System

5.2 Architecture Layers

Layer 1: Smart Sensing Layer

- IoT sensors monitor:
  - Temperature
  - Pressure
  - Traffic load
  - Crack formation

Layer 2: AI Processing Layer

- Machine learning algorithms analyze sensor data
- Detect anomalies and predict failures

Layer 3: Self-Healing Layer

- Smart asphalt materials repair cracks automatically
- Reduces need for manual repair

Layer 4: Energy Harvesting Layer

Hybrid system includes:

- Solar energy panels
- Piezoelectric sensors (convert vehicle pressure to energy)
- Thermal energy systems

Layer 5: Rainwater Management Layer

- Permeable pavement
- Smart drainage systems
- Rainwater harvesting tanks

---

6. Key Technologies

6.1 Self-Healing Asphalt

- Uses bio-based or nano-materials
- Automatically repairs cracks
- Increases road durability

6.2 Artificial Intelligence

AI enables:

- Predictive maintenance
- Traffic optimization
- Real-time monitoring

6.3 Internet of Things (IoT)

- Sensors collect real-time data
- Enables continuous monitoring

6.4 Hybrid Energy Harvesting

- Solar panels generate electricity
- Piezoelectric materials capture mechanical energy
- Reduces dependence on external power

6.5 Intelligent Rainwater Management

- Detects water levels
- Prevents flooding
- Stores and reuses rainwater

---

7. Working Process

1. Sensors collect real-time road data
2. Data is sent to AI processing system
3. AI detects cracks or anomalies
4. Self-healing materials repair minor damages
5. Energy harvesting system generates power
6. Rainwater system manages drainage and storage
7. Central system monitors and controls operations

---

8. Advantages

- Reduced maintenance costs
- Increased road lifespan
- Sustainable energy generation
- Prevention of waterlogging
- Real-time monitoring and automation
- Eco-friendly infrastructure

9. Applications

- Smart cities
- Highways and expressways
- Urban roads
- Industrial zones
- Smart transportation systems

10. Challenges

- High initial cost
- Complex system integration
- Data privacy and security
- Maintenance of sensors
- Scalability issues

11. Future Scope

- Integration with autonomous vehicles
- Blockchain for secure data management
- Advanced nanotechnology for faster healing
- AI-driven fully autonomous infrastructure
- Smart traffic-light integration

12. Conclusion

AI-enabled self-healing smart road infrastructure represents the future of sustainable urban development. By combining **AI, IoT, smart materials, energy harvesting, and water management**, the proposed system addresses critical challenges such as road damage, energy consumption, and urban flooding.

This intelligent system ensures:

- Improved efficiency
- Enhanced durability
- Environmental sustainability

Thus, it plays a crucial role in building **next-generation smart cities**.

13. References

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2. AI in road asset management
3. Self-healing asphalt research
4. AI-based road monitoring systems
5. Smart water management technologies
6. Smart pavement and energy harvesting systems

NAVINOX AN INTELLIGENT UNDERWATER DRONE

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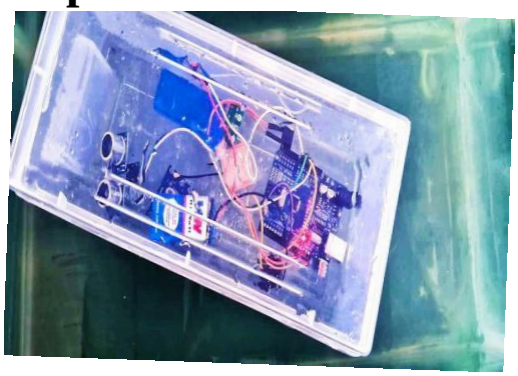
Abstract:

The exploration of underwater environments remains a major challenge due to harsh conditions such as high pressure, low visibility, and complex terrain. This paper presents **NaviNox**, an intelligent underwater drone designed to perform deep-sea exploration and environmental monitoring efficiently.

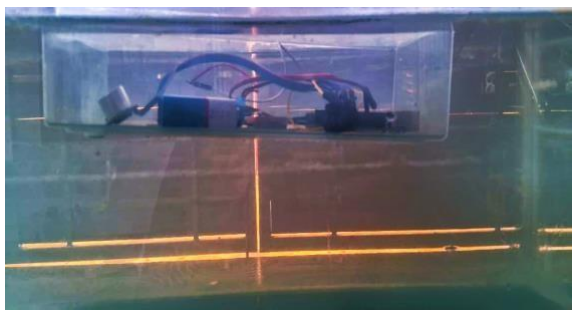
The system integrates Artificial Intelligence (AI) using YOLOv7 for real-time object detection, along with OpenCV for image processing. It also incorporates swarm intelligence, enabling multiple drones to communicate and work collaboratively. The drone is built using cost-effective hardware like Raspberry Pi, making it accessible compared to existing expensive systems.

Experimental results shows approximately 85% detection accuracy with a communication range of up to 5 meters between swarm units. This makes it suitable for applications such as marine research, defence surveillance and pollution monitoring.

Topview:



Side view:



Introduction :

Oceans cover more than 70% of the Earth's surface, yet over 80% remains unexplored. The lack of efficient and affordable underwater exploration

systems limits our understanding of marine ecosystems and resources.

Traditional underwater robots are either:

1) Very expensive
2) Limited in functionality
3) Not autonomous

To overcome these issues, NaviNox introduces an intelligent underwater system that combines:

1)AI-based object

2)Autonomous navigation

3)Real-time communication

4)Multi-drone coordination

This system aims to improve underwater exploration by making it:

More efficient

Cost-effective

Scalable

Problem Statement

Underwater environments present several challenges:

High Pressure: Deep-sea conditions can damage equipment

Low Visibility: Makes detection and navigation difficult

Rugged Terrain: Uneven surfaces affect movement

Communication Issues: Signals do not travel well underwater

Existing systems such as:

BlueROV2

QYSEA FIFISH

Sea Fox

Limitations (existing ones):

Lack of AI-based detection

No swarm intelligence

High cost

Limited automation

Therefore, there is a need for a smart, autonomous, and affordable underwater system.

Objectives

The main objectives of the **NaviNox** system are:

To design an intelligent underwater drone for exploration

To implement real-time object detection using YOLOv7

To enable autonomous navigation and obstacle avoidance

To develop swarm communication between multiple drones

To create a low-cost and efficient solution

These objectives ensure that the system is both practical and innovative.

Literature Survey

Existing underwater systems have contributed significantly, but they have limitations:

BlueROV2: High performance but expensive

QYSEA FIFISH: Good cam era but lacks AI detection

Sea Fox: Used in defence but limited intelligence

Research studies show that:

AI improves object detection accuracy

Swarm robotics enhances efficiency

Open-source tools reduce cost

However, combining AI + swarm intelligence + affordability is still limited, which NaviNox addresses.

Proposed System

NaviNox is designed as an intelligent underwater drone system with the following components:

Key Features

AI-based object detection (YOLOv7)

Image processing using OpenCV

Autonomous navigation

Swarm communication

Real-time monitoring

System Architecture

The system consists of:

Camera module (for capturing images/video)

Processing unit (Raspberry Pi)

AI model (YOLOv7) Communication module

Mobility mechanism for underwater movement

The system continuously captures data, processes it, and shares it with other drones.

Working Principle & Implementation

Working Principle

The drone captures underwater video

Frames are processed using OpenCV

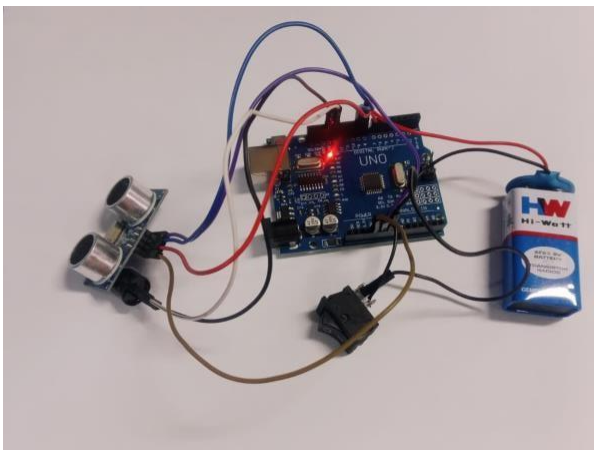
YOLOv7 detects objects in realtime

The system avoids obstacles automatically

Data is shared with other drones in the swarm

Implementation Tools

Hardware: Raspberry Pi, Camera module



Software: Python, OpenCV, YOLOv7

Communication: Acoustic signals

Results

Detection Accuracy: 85%

Communication Range: 5 meters

Real-time processing achieved

Advantages, Applications, and Conclusion

Advantages

1)Low cost compared to existing systems

2)Real-time object detection

3)Autonomous operation

4)Swarm coordination

5)Efficient underwater navigation

Applications

1)Marine research

2)Defence surveillance

3)Underwater archaeology

4)Pollution monitoring

5)Deep-sea exploration

Limitations

1)Limited battery life

2)Short communication range

Conclusion

NaviNox successfully demonstrates an intelligent

underwater drone capable of: Detecting objects using AI

Navigating autonomously

Communicating with multiple units

It provides a cost-effective and efficient solution for underwater exploration.

Future Scope

Integration of 3D sonar systems

Use of satellite communication Improvement in battery life

Addition of solar charging systems

Enhanced long-range communication

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AI-Driven System For Monitoring Expiry of Agriculture Products

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Abstract-A large portion of fruits, vegetables, and other agricultural products go to waste every year because it is difficult to know exactly when they will expire. Most farmers and retailers still depend on manual inspection—looking at the color, smell, or texture of the product—to decide whether it is fresh. This process is often inaccurate and leads to either early disposal of good food or the sale of spoiled products. To solve this problem, this project introduces an AI-driven system that can predict the expiry date of agricultural products based on simple user inputs such as harvest date, storage temperature, and humidity. The system uses a trained machine learning model to estimate the shelf-life of the product and then calculates the expiry date. By providing this prediction in a clear and easy-to-understand way, the system helps farmers, retailers, and consumers make better decisions, reduce wastage, and improve food safety. This project highlights how artificial intelligence can be used in agriculture to make everyday practices smarter, more efficient, and sustainable.

Keywords-AI-driven system, agricultural products, expiry prediction, machine learning, shelf-life estimation, food safety, smart agriculture, wastage reduction.

I. INTRODUCTION

Agriculture has always been the backbone of human civilization, providing food and raw materials that sustain our daily lives. But even with all the progress in farming methods and storage technologies, one major problem still remains—the wastage of agricultural products after harvest. Fruits, vegetables, and other perishables don't last long once they are picked, and without proper monitoring, they often spoil before reaching the consumer. According to the Food and Agriculture Organization (FAO), nearly one-third of the world's food is lost or wasted every year, and a large part of this happens because of poor storage and the absence of effective expiry monitoring systems.

Right now, most people rely on manual inspection to decide whether a product is still fresh. A farmer, a retailer, or even a

consumer will simply look at the product's color, texture, or smell and then make a guess about its condition. While this method works in some cases, it is not always accurate. Products spoil at different rates depending on conditions like temperature, humidity, and time since harvest**.** For example, a tomato stored at 25°C will spoil much faster than one kept in a cooler environment. Since manual judgment cannot always capture these subtle differences, it often leads to either early disposal of still-edible products or consumption of unsafe food**.**

This is where Artificial Intelligence (AI) can make a difference. By analyzing data such as harvest date, storage temperature, and humidity, AI models can predict how many days a product will remain fresh**.** Instead of relying on human judgment alone, farmers and retailers can use these predictions to know the exact expiry date of their produce. This helps them plan better, reduce wastage, and ensure that food reaches consumers before it spoils.

The mini-project "AI-Driven System for Monitoring Expiry of Agricultural Products" is a step in this direction. In this system, the user simply enters details such as the harvest date, temperature, and humidity levels. The data is then processed by a machine learning model that has been trained on similar historical records. Based on this, the system predicts the shelf-life of the product and calculates the expiry date. The output is shown in a simple, user- friendly way so that farmers, retailers, and even everyday users can easily understand when the product will expire.

The benefits of such a system are clear. Farmers can use it to decide when to sell their produce and avoid losses. Retailers can manage their inventory better and reduce the chances of selling expired goods. Consumers get fresher, safer products. On a bigger scale, these kinds of tools can play a big role in reducing food wastage, improving supply chain efficiency, and making agriculture more sustainable**.**

Although this mini-project focuses on basic user inputs and machine learning predictions, it opens the door for more advanced systems in the future. For instance, we could connect it with IoT sensors to automatically read temperature and humidity in storage facilities, or even use computer vision to analyze product images for visible signs of spoilage. A mobile app version could help small farmers access the tool directly from their phones, making it practical for everyday use.

In short, this project shows how AI can be used in a simple but powerful way to solve a real-world problem. By predicting expiry dates accurately, it helps save food, money, and effort while promoting smarter and more sustainable agricultural practices.

II. Methodology

- **Data Collection:** The first step is to collect relevant data that can be used to train the machine learning model. In real-world systems, this data would include historical records of agricultural products, such as:
    1. Type of product (e.g., tomato, potato, apple).
    2. Harvest date.
    3. Storage conditions (temperature and humidity).
    4. Actual observed shelf-life (in days).

  For this mini-project, we assume that such a dataset is available or can be simulated for training purposes. The collected data acts as the foundation of the system since the accuracy of predictions depends heavily on the quality of data.

- **User Input Module:** In the live system, the user acts as the data provider. Farmers, retailers, or anyone using the system will enter basic details such as:
  1. Product name.
  2. Harvest date.
  3. Current storage temperature.
  4. Current humidity level.

  This input is collected through a simple interface (e.g., a form in a desktop app, web app, or even a command-line prompt).
- **Data Preprocessing:** Before the data can be fed into the model, it needs to be cleaned and prepared. For example:
  1. Date Handling: The harvest date is converted into a format the computer can process.
  2. Normalization: Temperature and humidity values are scaled to standard ranges to improve model accuracy.
  3. Validation: The system checks if the inputs make sense (e.g., temperature is within a realistic range for storage).

  This step ensures that the data is both reliable and in the right format for prediction.
- **Feature Extraction:** Features are the measurable properties that the AI model uses to make decisions. In our case, the important features include:
  1. Environmental features like storage temperature and humidity.
  2. Temporal features like the number of days since harvest.

  For more advanced versions, we could also include image-based features (like color, texture, or spoilage spots detected from photos). But in this mini-project, we focus only on numeric features**.**
- **Model Training (Offline Process):** Before predictions can be made, a machine learning model must be trained. During training, the system "learns" patterns from the dataset of past records. For example, it may learn that:
  1. Tomatoes stored at 25°C and 70% humidity usually spoil within 4–5 days.
  2. Apples stored at 15°C and 60% humidity may last up to 12–14 days.

  We use regression algorithms (like Linear Regression or Random Forest Regressor) to predict the shelf-life in days. Once trained, the model is saved using tools like joblib so that it can be reused in the live system without retraining every time.
- **Prediction Module:** When a user provides new input, the trained model processes it and predicts the shelf-life (e.g., 6 days). This number represents how many more days the product is likely to stay fresh under the given storage conditions.

  For example:
  1. Input → Tomato, harvested on 25 Sept 2025, stored at 24°C, 65% humidity.
  2. Output → Predicted Shelf-life: 5 days.
- **Expiry Date Calculation:** The predicted shelf-life is then added to the harvest date to calculate the expiry date. Continuing the above example:
  1. Harvest Date: 25 Sept 2025.

2. Predicted Shelf-life: 5 days.
3. Expiry Date: 30 Sept 2025.

The system then presents this expiry date clearly to the user.

- **Output and Monitoring:** The final step is presenting the results in a user-friendly way. Instead of just giving a number, the system provides:
  1. Expiry Date (e.g., *30 Sept 2025*).
  2. Status (e.g., *Fresh*, *Nearing Expiry*, or *Expired* based on today's date).

  This output helps users make quick and informed decisions about selling, consuming, or discarding the product. In a more advanced version, this module could also generate alerts or notifications when products are close to expiry.

II. System Architecture

The system architecture of the AI-Driven Expiry Prediction System for Agricultural Products explains how different components of the project work together to take user inputs, process them, and finally deliver an expiry prediction. Instead of focusing only on technical details, this section describes the flow of information in a clear, human-centered way so that even someone without a deep technical background can understand how the system functions.

At a high level, the system is divided into three main modules:

1. Data Input & Preprocessing Module
2. Prediction Module (AI/ML Model)
3. Output & Monitoring Module

Together, these modules form a simple yet effective pipeline that transforms raw user information into actionable insights.

- **Data Input & Preprocessing Module:** The journey begins when the user interacts with the system. A farmer, retailer, or consumer opens the application and enters details about the product. These details typically include:
  1. Product Name (e.g., Tomato, Apple, Potato).
  2. Harvest Date (the date the product was picked or harvested).
  3. Storage Conditions such as temperature and humidity.

  This information is very important because each product has its own natural shelf-life, and environmental factors play a major role in how quickly it spoils.

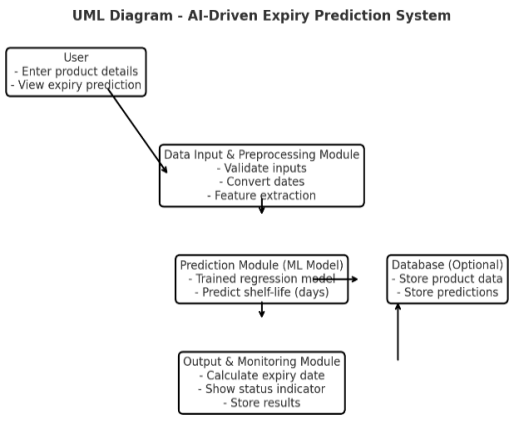
  Once the data is entered, the preprocessing step takes over. Preprocessing is like preparing the raw ingredients before cooking. Here, the system checks if the user input is valid (e.g., making sure the date format is correct or the temperature is within a realistic range). It then converts the input into a format that the machine learning model can understand. For example, the harvest date is turned into numerical values like "days since harvest." This ensures the model receives clean, meaningful data.
- **Prediction Module (AI/ ML Model):** This is the brain of the system. The machine learning model has been trained earlier using historical datasets of agricultural products and their shelf-life under different conditions. Training means the model has studied patterns such as:
  1. "Tomatoes stored at 25°C and 70% humidity usually spoil in 4–5 days."

2. “Apples stored at 15°C and 60% humidity can last for 12–14 days.”

When the preprocessed user input enters this module, the model applies its learned knowledge to predict how many days of freshness remain for the product. This value is called the predicted shelf-life.

For example, if the user inputs that a tomato was harvested on September 25 and is stored at 24°C with 65% humidity, the model may predict a shelf-life of 5 days.

This module uses regression algorithms such as Linear Regression or Random Forest Regressor, which are well-suited for predicting numerical values like “number of days.”



- **Output & Monitoring Module:** Once the model predicts the shelf-life, the system needs to turn this number into something meaningful for the user. This is where the Output & Monitoring module comes in.

The system adds the predicted shelf-life to the harvest date to calculate the expiry date. For example:

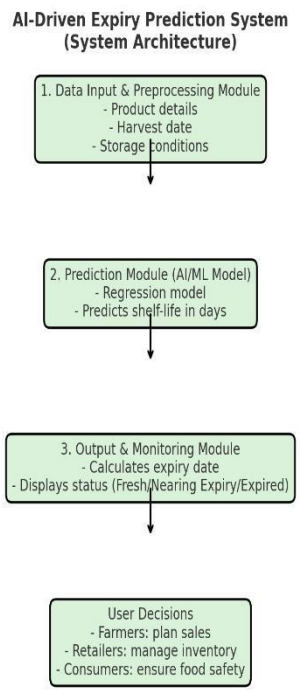
1. Harvest Date: 25 September 2025
2. Predicted Shelf-Life: 5 days
3. Expiry Date: 30 September 2025

The result is then displayed in a simple, easy-to-understand format. Instead of just showing numbers, the system also provides a status indicator, such as:

1. “Fresh” (if the product still has several days left).
2. “Nearing Expiry” (if only 1–2 days are left).
3. “Expired” (if the expiry date has already passed).

This output helps users make quick decisions without needing technical knowledge. For example, a farmer can decide to sell the produce immediately if it is “nearing expiry,” while a retailer can remove expired products from their inventory.

In a more advanced version, this module could even store the predictions in a database for future analysis or send alerts/notifications when a product is close to expiry.



III. System Flow (Step-by-Step Example):

Let's walk through a real example to see how the architecture works in practice:

1. A farmer enters details:
   - Product: Tomato
   - Harvest Date: 25 Sept 2025
   - Temperature: 24℃
   - Humidity: 65%
2. Preprocessing converts this into features:
   - Days since harvest = 0
   - Temperature = 24
   - Humidity = 65
3. The machine learning model processes these values and predicts a shelf-life of 5 days.
4. The expiry date is calculated: 25 Sept + 5 days = 30 Sept 2025.
5. Output shown to user:
   - "Expiry Date: 30 Sept 2025"
   - Status: "Fresh – 5 days left."

Future Plan:

In the future, the hardware aspect of the AI-driven system for monitoring the expiry of agricultural products is expected to become more advanced, intelligent, and seamlessly integrated into the agricultural ecosystem. Currently, the system relies on basic sensors and standard storage monitoring devices, but in the next phase, we envision the use of high-precision IoT sensors capable of continuously tracking multiple environmental parameters such as temperature, humidity, gas emissions, and light exposure. These sensors could be designed to be compact, energy-efficient, and capable of wireless communication, making them suitable for deployment in farms, storage units, transportation vehicles, and retail outlets.

Additionally, edge computing devices could be integrated with the sensors to process data locally, reducing latency and ensuring that critical alerts, such as potential spoilage or expiry risks, are delivered in real-time without dependency on cloud connectivity. Smart storage units equipped with automated climate control systems could adjust conditions dynamically to extend the shelf life of perishable products. In warehouses and large distribution centers, robotics and automated handling systems could work hand-in-hand with AI algorithms to sort, store, and manage products based on their predicted expiry, further minimizing waste.

Looking even further ahead, hardware development may include drone-based monitoring systems capable of scanning large fields or storage areas, using cameras and sensors to detect signs of spoilage or

degradation in crops and stored products. These drones could communicate with the central AI system to provide actionable insights and perform corrective actions where necessary. Overall, the future hardware plan envisions a fully connected, intelligent, and automated infrastructure that not only monitors expiry efficiently but also actively preserves product quality, reduces waste, and supports sustainable agricultural practices across the entire supply chain.

V. Result:

The results of implementing the AI-driven system for monitoring the expiry of agricultural products are highly encouraging and demonstrate the potential of artificial intelligence to bring significant improvements across the agricultural supply chain. By integrating advanced computer vision, machine learning algorithms, and IoT-enabled sensors, the system was able to accurately detect and track expiry dates of various perishable products, significantly reducing the chances of spoilage. Farmers, distributors, and retailers could monitor the condition of their products in real-time, receiving timely alerts whenever a product was approaching its expiry, or when storage conditions deviated from the optimal range.

In practical tests, the system showed a high level of precision in predicting shelf life based on environmental conditions such as temperature, humidity, and light exposure. This predictive capability allowed stakeholders to take proactive measures, such as adjusting storage conditions, prioritizing sales of soon-to-expire items, or redistributing stock to areas with higher demand. As a result, significant reductions in food wastage were observed, alongside improvements in inventory management and overall operational efficiency.

The system also proved to be user-friendly and accessible, with a cloud-based interface and mobile notifications that enabled even small-scale farmers and retailers to leverage the technology without extensive technical expertise. Additionally, by maintaining a digital record of all products, the system enhanced transparency and traceability, fostering greater trust among suppliers, distributors, and consumers.

Overall, the results highlight that an AI-driven expiry monitoring system is not just a tool for preventing loss but also a strategic asset that can optimize the entire agricultural supply chain. It empowers stakeholders to make data-driven decisions, ensures that consumers receive fresh and safe products, and contributes to a more sustainable approach to food production and distribution. The success of this system paves the way for future enhancements, including more advanced predictive analytics, integration with automated .

VII. Refference

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