IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Real-time Longitudinal ECG Analysis for Prediction of Cardiac Events

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Abstract : Cardiovascular diseases are one of the leading causes of human death globally. Many of these heart diseases such as sudden cardiac arrest, repeated myocardial infarctions, atrial fibrillation, arrhythmia, Left Anterior Fascicular Block (LAFB), ventricular hypertrophy and heart failures can be detected by monitoring the ECG data of the patient thereby potentially saving lives. To mitigate these preventable deaths, this work aims to revolutionize cardiac care through continuous, real-time monitoring and advanced predictive analytics on ECG.

The system integrates primary health sensors such as ECG, temperature, heart rate, and SpO2 monitors providing continuous, real-time transmission of patient's health data to the cloud. With the help of a cloud-based web interface, the doctors or the patient's relatives can track the live patient's health information. Advanced machine learning algorithms are then deployed to analyze this data, identifying patterns and anomalies indicative of potential cardiac events and diseases. This approach facilitates timely and accurate prediction of cardiac issues, offering significant improvements in patient monitoring, early diagnosis, and intervention, ultimately enhancing patient outcomes and reducing healthcare costs.

***IndexTerms* -** cardiovascular disease, ECG, arrhythmia, real- time, health sensors

I.INTRODUCTION

The leading cause of death is resulting from cardiac disease. According to global statistics, one person dies from cardiovas- cular disease every 33 seconds. Particularly in India, 4 people die every minute due to heart attacks. With around 33%, heart diseases form the highest cause of human deaths globally.

To avoid these preventable deaths caused by heart diseases, an efficient analysis of the ECG bio-signal could prove significant in reducing the scary numbers.

Electrocardiogram (ECG) is a non-invasive technique used to diagnose heart conditions. It is a measure of the electrical activity of the heart which is recorded through the body surface potentials. These signals consist of five waves: P, Q, R, S, and T:

- P wave: A small deflection wave representing atrial depolarization
- QRS complex: A key component made up of the Q, R, and S waves that represent ventricular depolarization
- T wave: Represents ventricular repolarization and shows when the lower heart chambers are resetting electrically and preparing for their next muscle contraction.

Other components of an ECG include intervals such as:

- ST segment: The time when the ventricle is contracting but no electricity is flowing through it
- PR interval: The time between the first deflection of the P wave and that of the QRS complex
- QT interval: The time between the onset of ventricular depolarization and the end of ventricular repolarization
- R-R interval: The time interval between 2 QRS complexes QRS-complex is a characteristic oscillation that corresponds to the contraction of the ventricles and expansion of the atria.

The duration and shape of each waveform and the distances between different peaks are used to diagnose the condition of the heart. This technique is used to apply continuous real-time ECG monitoring and analysis to predict the cardiac events of a person [1]. Hence early diagnosis and early medical interventions can be provided.

The goal of this research activity is to develop an efficiently trained machine learning and deep learning models that can predict a variety of heart diseases based on the ECG signal [2] [3]. This research paper outlines the whole process in detail. Firstly, it highlights the benefits and drawbacks of the existing work. Secondly, a detailed overview of the methodology and implementation is provided. Finally, the results and analysis are discussed.

II. BACKGROUND

A. Statistical overview of the problem:

- Cardiovascular diseases: CVDs are the leading cause of death globally. According to the World Health Organization (WHO), around 17.9 million people died from CVDs in 2019, constituting 32% of all global deaths.
- According to the Global Burden of Disease study estimates, nearly a quarter (24.8%) of all deaths in India are attributable to CVD. The age-standardized CVD death rate of 272 per 100000 population in India is higher than the global average of 235 per 100000 population.
- Sudden Cardiac Arrest: Sudden cardiac arrest can often be detected through ECG abnormalities but the survival rate for these events is less than 12% [4].
- Arrhythmias: Conditions such as atrial fibrillation (AFib) increase the risk of stroke and heart failure which can be predicted by ECG analysis [5].
- Impact of Ischemic Heart Disease: Ischemic heart disease is responsible for around 9 million deaths per year globally. Ischemic heart disease (IHD) and stroke constitute the majority (around 83%) of CVD mortality in India.
- Heart Failure: Heart failure affects about 1% of the population annually, which is between 8–10 million people. The risk of developing heart failure increases proportionally with age from less than 1% in people aged 20–39 to more than 20% in people aged 80 and older.

B. Technical Overview

Recent advancements in ECG signal processing and classification have significantly enhanced the detection and prediction of various cardiac conditions [6] [7]. Early works by Pan and Tompkins (1985) laid the foundation for QRS detection using a combination of digital filters and thresholding techniques, which remains a foundation in ECG analysis. Building on this, the development of more refined algorithms, such as those incorporating wavelet transforms and deep learning, has further improved accuracy and robustness. For instance, convolutional neural networks (CNNs) [8] and recurrent neural networks (RNNs) have shown great promise in handling complex temporal patterns and feature extraction from ECG signals [9]. As datasets and computational capabilities grow, recent studies have focused on optimizing model architectures and training techniques to achieve higher accuracy and better generalization across diverse patient populations. This progression underscores the continuous evolution in ECG signal processing, aiming to enhance predictive performance and clinical applicability in diagnosing cardiac diseases. We plan to include the integration of multiple feature extraction methods, such as time-domain, frequency-domain, and morphological features, which collectively contribute to more comprehensive cardiac disease detection models.

III. METHODOLOGY

A. Data Acquisition

Patient data is gathered using various health sensors in real-time. The processing unit used for this is ESP32.

1) ESP32-WROOM-32 is connected to the temperature sensor on the GPIO35 of ESP32. The temperature is measured through the voltage measured from ADC.
2) The pulse oximeter sensor performs finger-based heart rate, SpO2 and blood oxygen saturation measurements and reads PPG signals. The sensor establishes communication with the microcontroller through the standard I2C interface. The measured heart rate and SpO2 data are transferred from the sensor to the ESP32.
3) The AD8232 sensor module provides the output in analogue type. The microcontroller then applies ADC to this input and the ECG is being measured which is periodically transmitted to the Firebase database.

B. Data Transmission

The patient data recordings of sensors from ESP32 to the cloud firebase database through wi-fi connection. Additionally, to enhance the realtime sensing of all health parameters, multi-processing is being implemented in the microcontroller. ESP32-WROOM-32 has dual-core architecture enabling the simultaneous data retrieval from sensors and updation in the database through both the cores in high speed.

C. Real-time ECG Analysis for heart disease prediction

The overall methodology of ECG analysis is shown in Fig. 1 Once a sufficient number of patient's ECG signals are collected from the AD8232 sensor, these signals are ready for predictions. These signals can be uploaded for prediction via CSV files or image files on the website. Upon uploading, the signals are processed by the Machine Learning- Deep Learning model and the predictions are displayed on the webpage.

The ML/DL models are trained to classify 5 types of heart diseases. These heart diseases are the most prevalent ones.

1) Arrhythmia
2) Atrial Fibrillation
3) Ischemia
4) Wolf Parkinsons White Syndrome
5) Cardiac Arrest

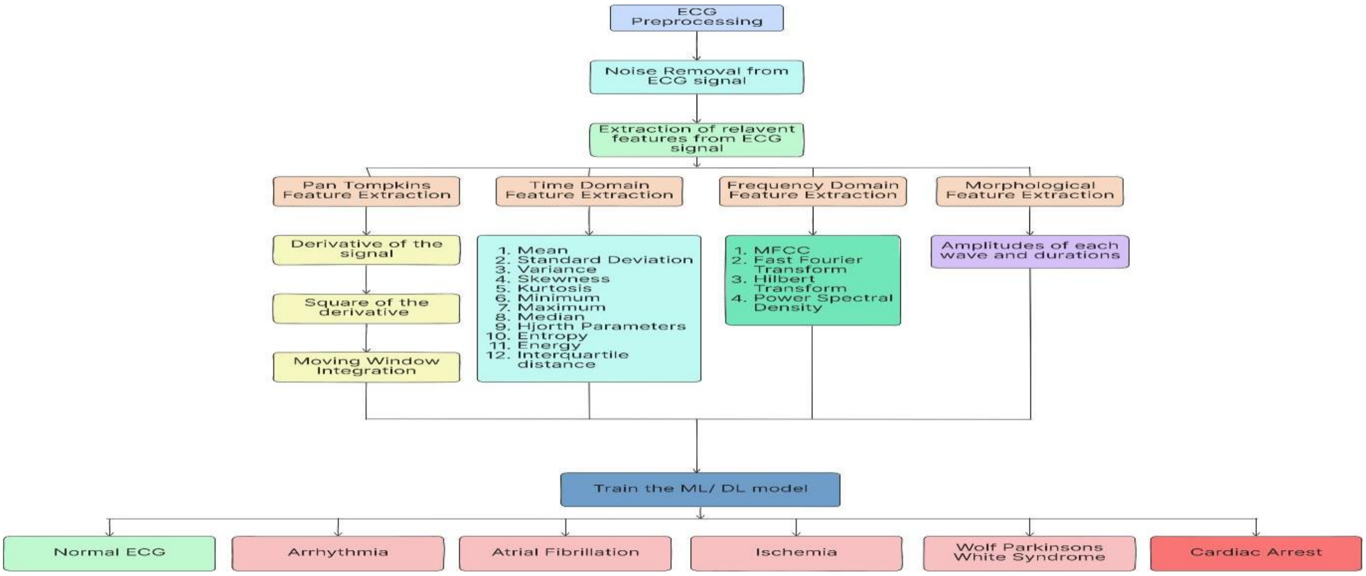
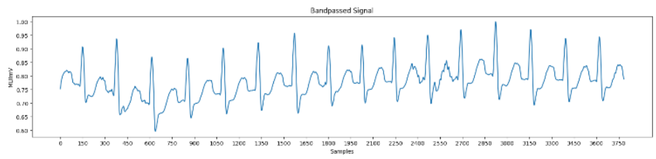


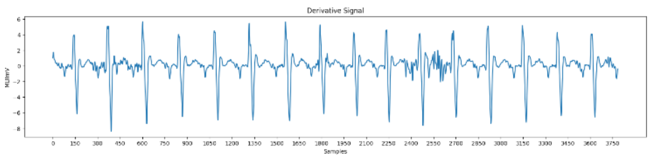
Fig. 1: Outline of ECG Analysis Methodology: The ECG preprocessing is carried out phase by phase as shown in the figure. The first and foremost part of the ECG is the noise removal. Following this, relevant features of the ECG signal are extracted using various methods as depicted. The extracted features are then fed to a model that predicts heart diseases.

The process of ECG analysis includes the following workflow:

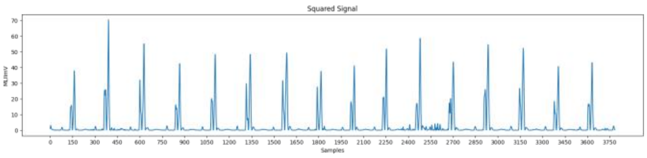
1) *Noise Removal:* The ECG signals collected from sensors are highly prone to noise. Therefore, before these signals are sent for training, they must be filtered so that the noise does not become a factor in giving imperfect predictions. One of the most common methods used to attenuate noise from signals is bandpass filtering. This process performs the collection of signals of the desired range of frequencies. Firstly, a low pass filter with a cutoff frequency of 11Hz is applied, followed by a high pass filter with a cutoff frequency of 5Hz. The resultant signal obtained is a Bandpassed signal ready for feature extraction as shown in Fig. 2a.



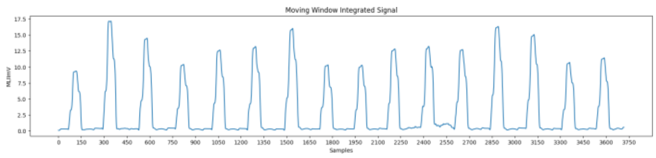
(a) ECG signal after noise removal



(b) Derivative ECG Signal



(c) Squared ECG Signal



(d) Moving Window Integration

Fig. 2: Step by step procedure of Pan Tompkins feature extraction, a highly recommended algorithm for ECG feature extraction.

2) *Feature Extraction of ECG Signals:*

a) Pan Tompkin's Feature Extraction

Detects QRS complexes in an ECG signal. Gives information regarding the slope, width, rate of variance, etc of the QRS complex. as shown in Fig. 2b.

The Pan Tompkins feature extraction entails 4 steps.

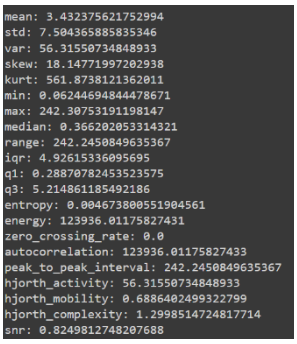
- Noise Removal: This step has been carried out in the first stage of ECG preprocessing.
- Derivative Signal: The band-passed signal's deriva- tive is computed to extract information from the slope of the signal.
- Squared signal: The derivative signal is squared to intensify the slope of the frequency response.
- Moving Window Integration: This step is carried out to capture the important information of the QRS complex like width, slope,etc.

b) Time Domain Feature Extraction:

The main features extracted concerning time domain

- Mean
- Standard deviation
- Median
- Maximum value

- Minimum value
- Range
- Interquartile range
- Interquartile first quarter (Q1)
- Interquartile third quarter (Q3)
- Kurtosis
- Skewness



```
mean: 3.432375621752994
std: 7.504365885835346
var: 56.31550734848933
skew: 18.14771997202938
kurt: 561.8738121362011
min: 0.06244694844478671
max: 242.30753191198147
median: 0.366202053314321
range: 242.2450849635367
iqr: 4.92615336095695
q1: 0.28870782453523575
q3: 5.214861185492186
entropy: 0.004673800551904561
energy: 123936.01175827431
zero_crossing_rate: 0.0
autocorrelation: 123936.01175827433
peak_to_peak_interval: 242.2450849635367
hjorth_activity: 56.31550734848933
hjorth_mobility: 0.6886402499322799
hjorth_complexity: 1.2998514724817714
snr: 0.8249812748207688
```

Fig. 3: Time domain features extracted for each window of a specific ECG Signal.

These features depicted in Fig. 3 help capture various aspects of the ECG signal's behaviour over time and can be useful for detecting anomalies or predicting conditions based on the signal's temporal properties.

c) Frequency Domain Feature Extraction

- Mel frequency cepstral coefficients (MFCC) analysis:

  MFCC is used to convert raw ECG signals into a more manageable form. The initial coefficients computed provide extensive information by focusing on the most significant features regarding the power spectrum which are depicted in Fig. 4.

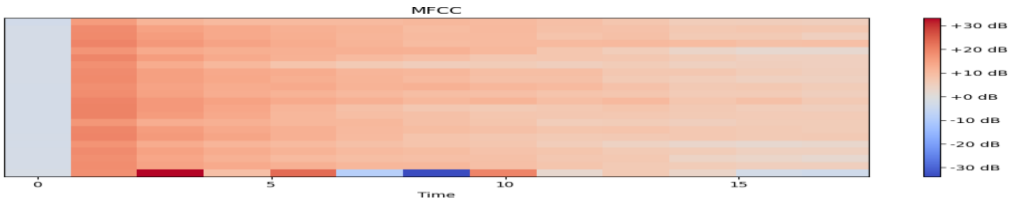


Fig. 4: Mel Frequency Cepstral Coefficients of the ECG Signal are computed to tabulate relevant power spectrum features.

- Fast Fourier Transform:

  Converts values at different time angles as components of different frequencies as shown in Fig. 5.

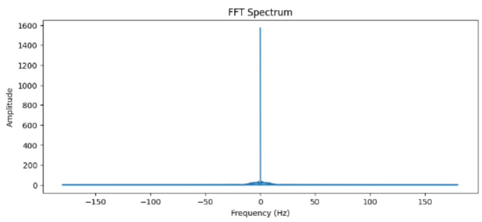


Fig. 5: Fast Fourier Transform Spectrum of the ECG Windows for frequency domain analysis of the ECG signal.

- Wavelet Features:

  Extraction of various wavelet features using continuous wavelet transform that captures numerous traits of an ECG signal in the form of wavelet coefficients at different scales and different orientations as shown in Fig. 6.

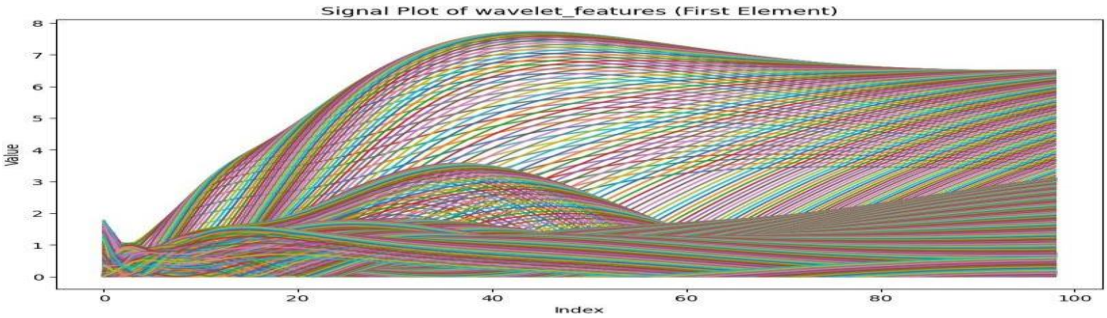


Fig. 6: Wavelet features of the signal. One coefficient for each recording of ECG, forming 1000 coefficients as each window consists of 1000 recordings at 99 different orientations.

- Power Spectral Density

  Describes the distribution of power into frequency components composing a signal signified in Fig. 7.

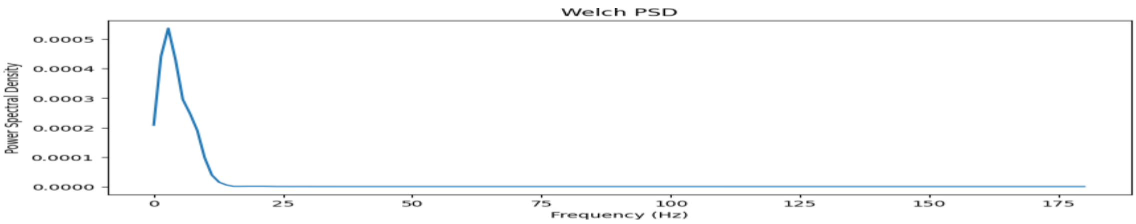


Fig. 7: Welch Power Spectral Density Computation, a highly utilized algorithm to compute power spectral density that forms a predominant part of power and frequency analysis.

d) Morphological Feature Extraction:

ECG signals contain various characteristic waves, including P waves, QRS complexes, and T waves, each with distinct features. The amplitude of these waves represents the electrical activity of the heart, with the P wave corresponding to atrial depolarization, the QRS complex to ventricular depolarization, and the T wave to ventricular repolarization. Time durations between consecutive waves, such as the PR interval (from the start of the P wave to the start of the QRS complex) and the QT interval (from the start of the Q wave to the end of the T wave), provide crucial information about the heart's rhythm and conduction pathways. These features as shown in Fig. 8 are vital for diagnosing various cardiac conditions, such as arrhythmias, ischemia, and heart block.

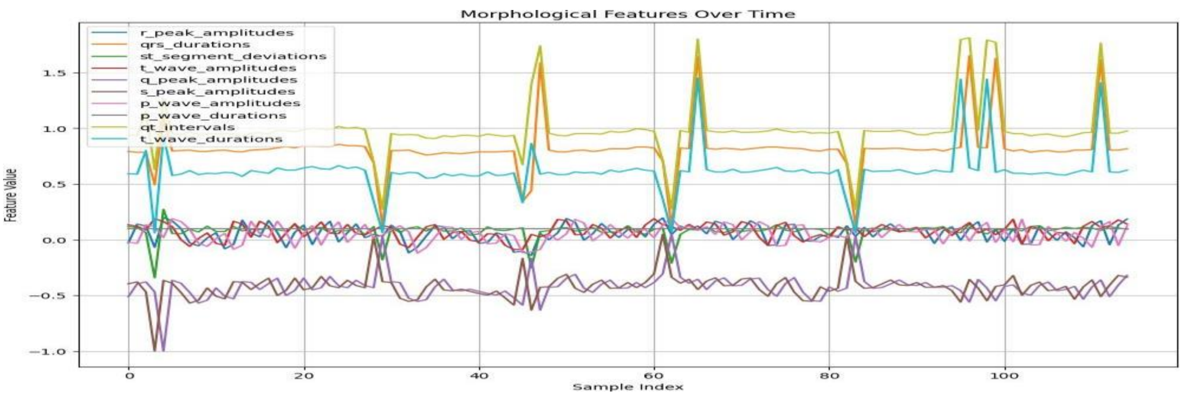


Fig. 8: Morphological Feature Extraction: Extractions of amplitudes and durations of all the waves present in the ECG

3) Training the Machine Learning – Deep Learning Model:

a) Artificial Neural Network:

ANNs consist of layers of interconnected neurons: an input layer where data enters, hidden layers where the network operates and understands from this data, and an output layer where it gives the results. Each neuron calculates a weighted sum of inputs. Following this, we define an activation function that proposes non-linearity. After performing these, the results are compared with the actual outcome. Adjustments of these weights and biases are done by a process called backpropagation, which tweaks them based on errors between predicted and actual outcomes. This adjustment happens iteratively across multiple passes over the data, using techniques like gradient descent to minimize errors. ANNs can be applied to various tasks, from classifying images and detecting diseases across various biological fields.

b) XGBoost:

XGBoost is the full form of eXtreme Gradient Boosting. The hierarchical structure enables the successor to correct the errors of its predecessors. This constitutes gradient boosting, an effective way of improvising the performance. XGBoost also incorporates techniques like regularization to prevent overfitting and improve model accuracy. It's known for its speed and performance.

c) Multi-Layer Perceptron:

Multi-layer perceptron (MLP) is a type of artificial neural network that's designed for solving both classification and regression problems. It consists of at least 3 layers with non-linear activation functions. The process is similar to ANN, where the data is fed as the input and the results propagate through the layers. The predicted outcome is compared to the actual outcome. The network emphasises backpropagation and learns from its mistakes finally getting trained to perform the task effectively. MLPs are versatile and can model intricate relationships in data, making them suitable for a wide range of tasks from image recognition to time series data analysis.

IV. IMPLEMENTATION

This interdisciplinary work involves both hardware and software implementation. The entire structure of the system is demonstrated in Fig. 9

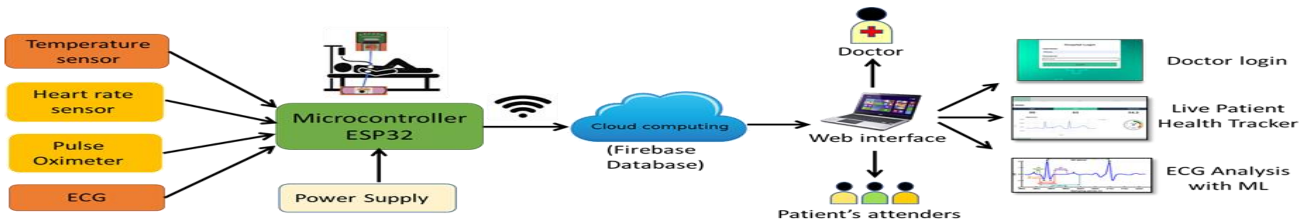


Fig. 9: System architecture of the implementation - The hardware setup includes health sensors interfaced with the microcontroller. The software aspects include the cloud Firebase database and the web interface for live health tracking and ECG analysis.

A. *Hardware*

The system implements the data acquisition and transmission through the microcontroller ESP32 which is interfaced with several health sensors. Heart rate sensor, pulse oximeter, temperature sensor and the ECG sensor are connected to the ESP32 microcontroller which collects health data of the person and sends it to the microcontroller. ESP32 then transmits this real-time health data to the firebase real-time database on the cloud via a wireless wifi connection. The hardware components are explained below:

1) *ESP32 (ESP32-WROOM-32) microcontroller:* ESP32 is a low-power and low-cost system-on-chip microcontroller. It supports many peripherals and interfaces like I2C, SPI, UART, ADC, PWM interfaces. The reason behind using this micro- controller is to get refined and accurate ECG data through its in-built 12-bit ADC. It also has integrated Wi-Fi and Bluetooth capabilities. Our prototype leverages the dual core functionality of ESP32.

2) *LM35 DZ Temperature Sensor:* LM35 is an integrated circuit temperature sensor with a measuring range of -55°C to 150°C. Its output voltage is linearly proportional to temperature. There will be a rise of 10mV (0.01V) for every 1°C rise in temperature.

3) *MAX30102 Pulse Oximeter Sensor:* It is used to measure the heart rate of a person and the level of oxygen (oxygen saturation) in the blood.

4) *AD8232 ECG-sensor:* The AD8232 ECG sensor is used to measure heart's electrical activity. The AD8232 Single Lead Heart Rate Monitor is an operational amplifier that can capture the heart signals of a person.

B. *Software*

The software part of the system includes the microcontroller code behind the ESP32 firmware, the database deployed on cloud, the cloud-based web interface and the ML-DL analysis of ECG to predict cardiac events.

1) *ESP32 Firmware:* The ESP32 microcontroller is coded to handle the data acquisition from sensors, convert the input analog sensor inputs into digital format and upload it to the real-time firebase database through its wifi capability. The data fetched from the sensors is updated in real-time to the Firebase database through the Wi-Fi communications from the ESP32 microcontroller.

2) *Firebase Realtime Database:* It is a NoSQL cloud- hosted database provided by Google which stores the data in JSON format. Firebase real-time database is utilised in this system to store the real-time health data of the patient and sync the data in real-time to every connected client. The patient's body temperature, SpO2, heart-rate and ECG readings are stored in the database as key-value pairs.

Fig. 10: Cloud-based web interface for real-time health tracking - Live patient health data such as body temperature, SpO2, heart rate and ECG can be viewed, tracked and analysed

3) *Web interface:* The health data of the patient can be viewed via a cloud-based web interface as seen in Fig. 10. The patient's real-time body temperature, heart rate, pulse, SpO2 and ECG data will be available on the website. This aids in real-time tracking of the patient's health across a long period to keep an account of the possible health risks and precautionary actions to be taken.

4) *ML and DL models for ECG analysis:* The patient's ECG data can be analysed with the custom developed ML and DL models and any heart disease associated with the ECG can be predicted in advance. Additionally, the patient's family can be notified in prior for early medical intervention increasing the survival rate in patients with heart diseases by early detection. The analysed ECG results can be obtained in the web dashboard as in Fig. 11.

V. RESULTS AND DISCUSSION

The final model resulted in achieving 98.89% accuracy as indicated in Fig. 12, 13 and 14. This type of modelling can be applied to predict many more cardiac diseases.

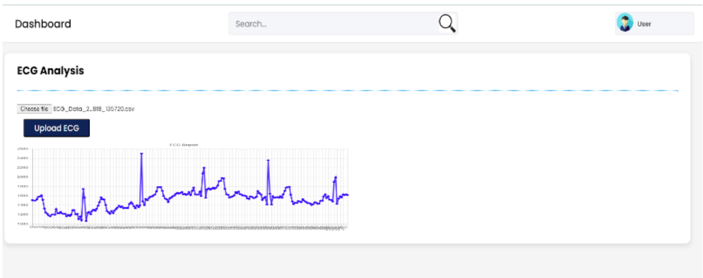


Fig. 11: ECG analysis through the web dashboard - The ML model in the background analyses the ECG data collected and provides the prediction of cardiac diseases such as myocardial infarctions, atrial fibrillation, arrhythmia, and ventricular hy- pertrophy among others.

A. Cardiac events that can be predicted from ECG:

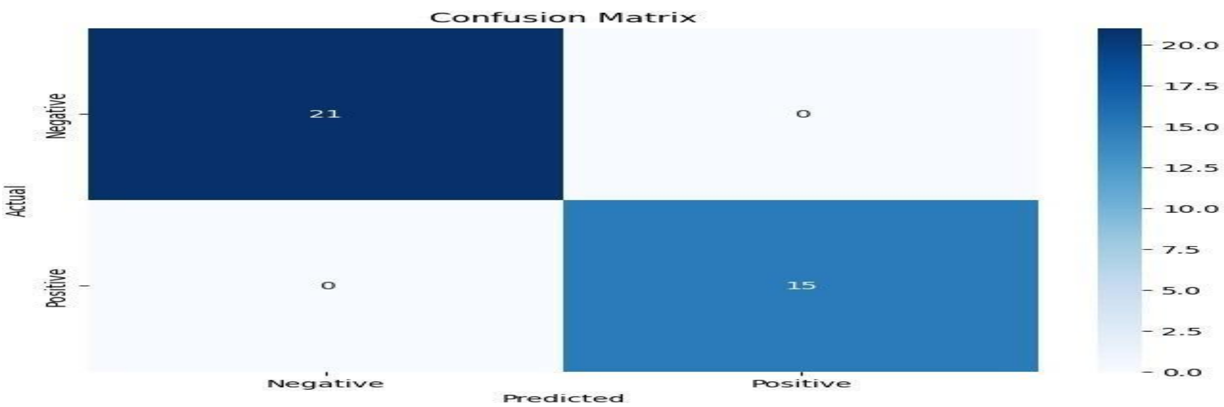


Fig. 12: Confusion Matrix of the final model

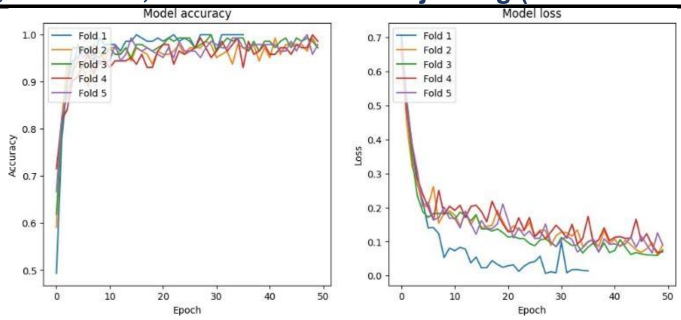


Fig. 13: Model Accuracy and Loss Plots across 5 folds of training and testing

- Amyloidosis – Amyloidosis is a rare disease of misfolded proteins that go astray to form deposits of amyloid in organs, nerves and tissues.
- Low ejection fraction – where the heart is weakened and pumps less blood out to the body
- Arrhythmias – Abnormal heart rhythms
- Hypertrophic cardiomyopathy (HCM) happens when the heart's walls become thicker over time increasing the risk of sudden cardiac death.
- Sudden cardiac arrest

- Atrial fibrillation (AFib)
- Ischemic heart disease
- Heart failure
- Repeated heart attack
- Sleep Apnea Detection

B. Analysis of the models

1) Accuracy of MLP and LSTM is higher.
2) LSTM provides more stability.
3) SVM performs well for training but not during testing as much.
4) Since it is real-time, the stability of models is highly critical.
5) DL models seem to be better as they train on a lot of data as compared to ML models and have good reliability.

C. Applications:

- Deep Learning for Automated ECG Arrhythmia Detection
- Remote Monitoring
- Integration of ECG Data with IoT for Continuous Health Monitoring
- Personalized Medicine through ECG Data Analysis
- ECG-Based Stress Detection and Management System
- ECG Telemetry Systems for Rural Healthcare
- Advanced ECG Visualization Techniques
- ECG Signal Analysis for Sleep Apnea Detection
- Portable ECG Devices for Sports and Fitness Monitoring

VI. FUTURE SCOPE

- In case of emergencies, like temperature spikes or heart- beat spikes, etc. alert is sent to the doctor.
- Incorporation of glucose sensors.
- Development in the electronic devices, by the use of organic electronic devices in sensors.
- Development of flexible sensors for easy handling.
- Incorporating more diseases for ML/DL predictions.
- A more compact way of designing the hardware

VII. CONCLUSION

From the statistics provided, it is a clear indication that portable ECG and health sensor kits are highly needed to predict any ailments at an early stage. This helps in early diagnosis and hence can save millions of lives. Performing analysis of ECG is an add-on significantly enhancing the performance of the system. The models trained with a huge number of datasets show enhanced performance. These form the critical aspects of the health domain. Continuing this on a large scale with seamless deployment can provide higher life time for an individual and hence creating a healthy world.

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