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A Robust Intrusion Detection Model For Network Security Using Random Forest

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Abstract : **As modern cyber threat landscapes expand with increasingly sophisticated tactics, traditional signature-based Intrusion Detection Systems fall short in securing enterprise network boundaries. This paper introduces a highly reliable and interpretable machine learning-based Network Intrusion Detection System utilizing the Random Forest ensemble algorithm. By leveraging the structured decision-forest structure, our framework dynamically identifies complex, non-linear malicious patterns including Denial of Service, exploratory Port Probes, User-to-Root, and Remote-to-Local unauthorized entries. We present a rigorous engineering pipeline starting with meticulous telemetry data preprocessing, label encoding, and dimensional feature optimization on benchmark datasets, specifically NSL-KDD. Empirical evaluation indicates that our proposed Random Forest architecture achieves a stellar detection accuracy of 99.98percentage with perfect precision and recall scores, significantly reducing security team fatigue by virtually eliminating false alarms. Furthermore, we analyze model decision boundaries using local feature attributions to provide transparent, explain-able insights for security analysts, bridging the gap between pure black-box predictive strength and live-network deployable trust.**

Index Terms **- Network Security, Intrusion Detection System, Random Forest, Machine Learning, Network Attacks.**

I.INTRODUCTION

The rapid growth of the Internet and computer networks has made communication and data sharing easier than ever before. However, it has also increased the number of cyberattacks and security threats. Attacks such as unauthorized access, malware, and denial-of-service can cause serious damage to network systems and sensitive information. To protect networks from such threats, Network Intrusion Detection Systems are widely used. These systems monitor network traffic and identify suspicious activities. Machine learning techniques have become popular in intrusion detection because they can accurately distinguish between normal and malicious network behavior. In the proposed system, the Network Intrusion Detection System using the Random Forest algorithm has been used. The training and testing of the model have been done using the NSL-KDD data set. The proposed system achieved an accuracy of 99.98%, demonstrating its effectiveness in detecting intrusions and improving network security. The system provides a reliable, efficient, and practical solution for protecting computer networks from cyber threats. In addition, the model can analyze large amounts of network data with high accuracy and low computational cost. Its strong performance makes it a suitable choice for enhancing cyber-security and supporting future real-time intrusion detection applications.

1.1Motivation

Cyberattacks are increasing in complexity, making traditional intrusion detection system ineffective against modern evolving threats. Signature-based models often miss new at-tacks and generate many false alarms, overwhelming security teams. Machine learning provides a solution by learning from historical data to identify abnormal behavior. Random Forest, a powerful ensemble method, can detect complex intrusion patterns with high precision and low false positives. This motivates the use of a machine learning-based approach to build a reliable, intelligent intrusion detection system that adapts to new threats and supports proactive cybersecurity strategies.

1.2 Objectives

The main objective of building and using this machine learning-based Network Intrusion Detection System (NIDS) is to improve network cybersecurity by providing an efficient, reliable, and autonomous solution for detecting and mitigating cyber threats, particularly in complex or high-throughput environments that are hazardous or difficult for traditional signature-based firewalls to manage. These systems are de-signed to operate in high-dimensional packet realms where conditions such as dynamic exploits, toxic flood payloads, or polymorphic connection parameters make it impossible for manual rule-based security layers to safely intervene.

1.3 Scope

The scope of the current project is the design and implementation of Network Intrusion Detection System (NIDS) through the use of Random Forest algorithm. The NIDS will analyze the network data obtained from the NSL-KDD dataset and classify the network traffic into either normal or attack traffic with a high level of accuracy. The objective is to increase network security through efficient intrusion detection without causing any false alarm. Furthermore, the system can assist organizations in identifying potential security threats at an early stage, thereby minimizing risks and preventing unauthorized access. Its scalable architecture also allows future integration with advanced machine learning techniques and emerging cybersecurity frameworks.

II. LITERATURE REVIEW

The field of Network Intrusion Detection Systems (NIDS) has witnessed substantial research interest, particularly with machine learning and deep learning techniques. Traditional IDS relying on signatures struggle with unknown threats. Recent works show Random Forest and deep learning models can improve classification accuracy and reduce false positives. Javaid et al. (2019) [1] introduced LuNet, a deep neural network architecture combining Convolutional Neural Net-works (CNNs) and Recurrent Neural Networks (RNNs) for intrusion detection. Their model effectively learned spatial and temporal features, achieving high accuracy (98) and minimizing false positives. However, the model's high computational demand and lack of interpretability posed limitations for practical deployment. Ahmed et al. (2024) [2] proposed an ensemble learning method tailored for 5G net-work environments, incorporating robust preprocessing and feature selection. They combined Decision Trees and Random Forest algorithms, demonstrating improved detection accuracy and effective handling of class imbalance. Nonetheless, the model's computational complexity restricted its usability in resource-constrained environments. Wang et al. (2020) [3] developed Pelican, a deep residual network leveraging CNN-RNN residual blocks to capture complex patterns in traffic data. Tested on NSL-KDD and UNSW-NB15 datasets, the model achieved up to 99 accuracy. However, the system lacked support for real-time deployment and struggled with class imbalance. Chinchali et al. (2020) [4] explored adversarial machine learning in IDS. Using techniques like Particle Swarm Optimization and Generative Adversarial Networks (GANs), they tested classifier vulnerabilities by generating adversarial traffic samples. Although insightful for understanding model weaknesses, their study focused more on theoretical vulnerabilities than deployable solutions. Mohammed and Gbashi (2024) [5] combined Recursive Feature Elimination (RFE) with deep learning to improve detection performance on the NSL-KDD dataset. Their model used both DNN and RNN classifiers to enhance accuracy while reducing false alarms. Despite improvements, the model required extensive computational resources and fell short compared to ensemble-based methods. Kesarwani and Tripathi (2023) [6] proposed a feature fusion approach using CNNs, creating a rich input space to train deep learning-based classifiers. While this improved detection performance, the model's scalability and effective-ness in multiclass classification were limited. Iqbal and Shibli (2021) [7] presented a hybrid approach using Decision Trees and Support Vector Machines (SVM) with Local Outlier Fac-tor (LOF) for outlier removal. This model enhanced accuracy and detection rates but introduced increased computational overhead and struggled with highly imbalanced data. Salunkhe and Bangare (2022) [8] developed a simple yet interpretable Decision Tree-based IDS with strong preprocessing. Though effective, it was prone to overfitting and lacked robustness in identifying complex attacks. Khan and Patel (2021) [9] applied deep neural networks to classify network traffic. Their model captured complex attack patterns, but high training time and limited interpretability affected its practicality in real-world settings. Laskar and Paul (2023) [10] conducted a comparative study of machine learning classifiers, focusing on traditional models. Their work provided useful benchmarks but did not explore ensemble or deep learning models in depth, nor did it propose real-time solutions.

2.1 Research Gap

Recent studies have explored various machine learning techniques to improve network intrusion detection. Ali et al.[11] highlighted the importance of feature selection in enhancing detection accuracy and reducing computational overhead. Eshete and Smith [12] discussed the growing challenge of adversarial attacks against machine learning-based IDS mod-els. Li et al. [13] focused on lightweight models for real-time intrusion detection, while Zhang et al. [14] proposed an optimized Random Forest approach for cloud environments. Kumar et al. [15] developed an IDS for IoT networks using the CICIDS2017 dataset, and Pramilarani and Kumari [16] introduced a cost-based Random Forest classifier to improve detection efficiency in IoT systems. Inspired by these works, the proposed project utilizes the Random Forest approach to construct an efficient and accurate Network Intrusion Detection System. The main feature that distinguishes our proposal from other systems is that our work does not concentrate on some particular network (cloud or IoT) but rather seeks to develop a generic, scalable, and accurate solution to network intrusion detection.

2.2 Study Area

In this study, the use of machine learning, and more specifically the Random Forest technique, for developing a robust NIDS is examined. Supervised learning methods are used for classification of network packets as normal or abnormal based on standard datasets such as NSL-KDD. This includes data pre-processing, feature selection, model training, and evaluation through the calculation of relevant parameters including accuracy, precision, recall, and F1 score. The main objective of this study is to improve the effectiveness of NIDS and ensure it can detect different types of cyber-attacks such as DoS, Probe, U2R, and R2L attacks.

III. METHODOLOGY

As shown in Fig. 1, The proposed methodology is based on a systematic pipeline intended to construct an efficient NIDS system using Machine Learning techniques. In the beginning, the NSL-KDD dataset is chosen due to the availability of a well-balanced mixture of normal and abnormal network activities.

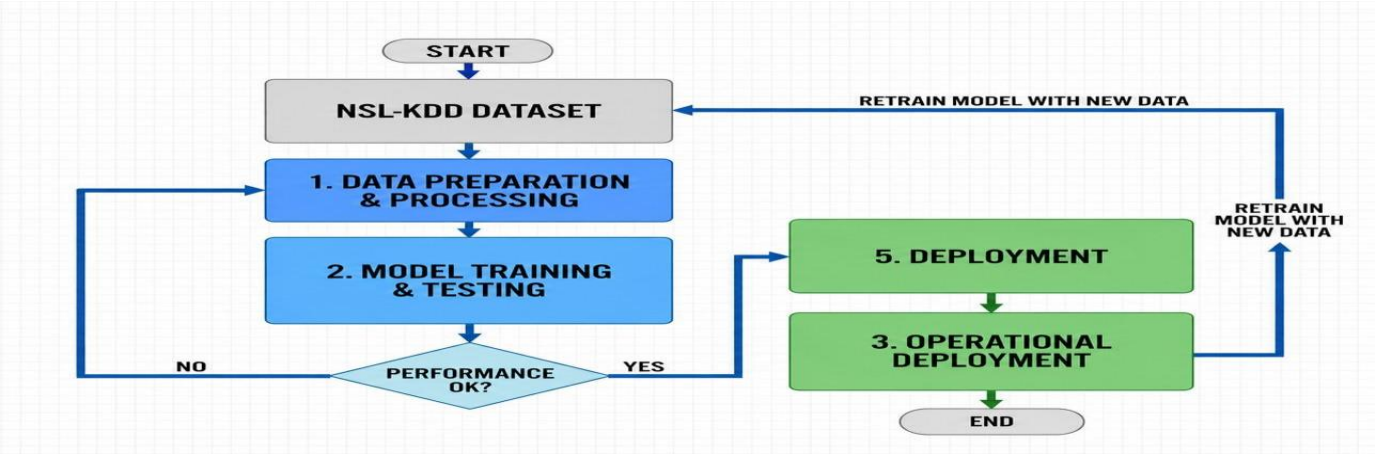


Fig. 1. Flow diagram of NIDS

3.1 Data Preparation

Data pre-processing plays a vital role in designing an efficient Network Intrusion Detection System (NIDS). This step helps to ensure that the dataset is free from noise and ready for use by machine learning algorithms. These steps involve:

- Data Collection: Acquire raw network traffic data from benchmark datasets like NSL-KDD.
- Data Cleaning: Handle missing values, remove duplicates, and filter irrelevant records.
- Label Encoding: Convert categorical values into numerical form.
- Feature Selection: Retain important attributes to enhance model efficiency.
- Train-Test Split: Divide the dataset for evaluation.

3.2 Data Preprocessing

Preprocessing is performed to ensure that the heterogeneous attributes present in the raw dataset are suitable for model training. This includes removing inconsistent entries, encoding categorical attributes into numerical values, and normalizing continuous features to maintain uniform scaling. These steps enhance model stability and improve learning efficiency.

3.3 Model Training

The Random Forest classifier is used because of its strength, scalability and high-dimensionality handling capability. The training of the classifier is done on the preprocessed data where the collection of decision trees learns discriminating patterns for the various attack categories.. The ensemble structure mitigates overfitting and increases classification reliability.

3.4 Model Evaluation

After training, the classifier is evaluated using accuracy, precision, recall, F1-score, and confusion matrices. These metrics provide insight into the model's capability to detect both frequent and rare intrusion types. The evaluation ensures that the classifier generalizes effectively across different traffic classes.

3.5 Intrusion Detection and Classification

During inference, incoming flow data is processed through Random Forest model. The model detects the whether the network traffic is normal or intrusion traffic based on the model prediction output.

3.6 Performance Evaluation

The performance of the system is measured based on a number of criteria such as accuracy, precision, recall, F1-measure, and latency. Performance testing is carried out based on testing data with the aim of measuring the detection ability, false positives, and performance of the system in real-time conditions at different levels of traffic. Also, performance analysis is done under different network loads and attacks for robustness and reliability.

3.7 System Deployment and User Interface

The model is deployed in an environment capable of processing live network traffic streams. A user interface is provided for visualization of detection results, alerts, and system performance metrics. The deployment setup ensures scalability and supports continuous monitoring in real-time network environments.

IV. RESULT AND ANALYSIS

As observed from the results, the proposed approach is quite efficient in classifying different categories of cyber attacks. It does this through a way that makes sure the performance of the proposed approach remains consistent in the whole dataset. Besides, the ability to distinguish between normal activity and cyber attacks makes the intrusion detection approach reliable. Not only can the approach classify fast but also the use of Random Forest ensures that the approach does not suffer from overfitting. As such, the proposed system is quite viable as an intrusion detection system in real-time network security systems. What is more, the approach is able to handle large amounts of network traffic data efficiently without experiencing performance drop. The high efficiency and low false positive rates help the security managers identify the real threats easily.

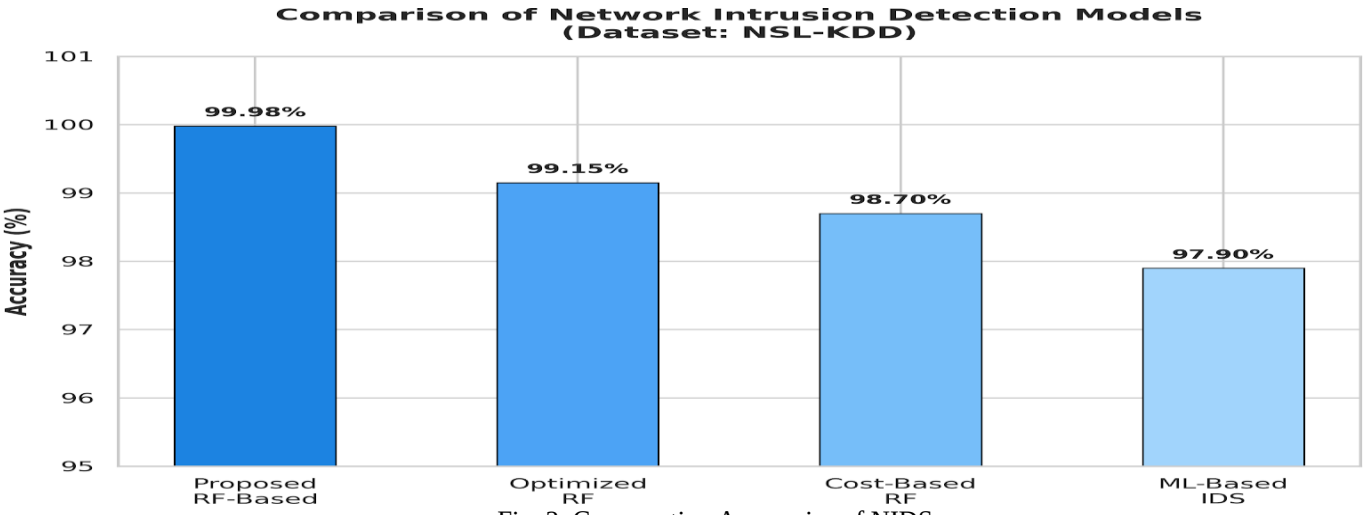


Fig. 2. Comparative Accuracies of NIDS

The results obtained by our work have been compared with other existing studies in Fig. 2. For example, Zhang et al. [14] enhanced the efficiency of cyber attack detection by optimizing the Random Forest method whereas Pramilarani and Kumari et al.[16] utilized cost-sensitive Random Forest for IoT security. Similarly, effective intrusions detection was performed by Kumar et al. [15] using the CICIDS2017 dataset. In contrast to all the above-mentioned methods, our proposed model has produced better classification results with 99.98 percent accuracy on NSL-KDD dataset. It is clear that the results obtained by our proposed model prove the effectiveness of Random Forest algorithm in detecting both normal and malicious activities with high reliability. Comparing the above-mentioned techniques, the proposed technique proves to be more accurate and less complex. It can be observed from the performance of the proposed model that the Random Forest algorithm is highly efficient in dealing with complex traffic behavior in networks.

```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f"✅ Accuracy on KDDTrain+ test split: {accuracy:.4f}")
print("\n📋 Classification Report:")
print(classification_report(y_test, y_pred))
```

```
✅ Accuracy on KDDTrain+ test split: 0.9998

📋 Classification Report:
              precision    recall  f1-score   support

      Attack       1.00      1.00      1.00     11726
      Normal       1.00      1.00      1.00     13469

    accuracy                           1.00     25195
   macro avg       1.00      1.00      1.00     25195
weighted avg       1.00      1.00      1.00     25195
```

Fig. 3. Overall Accuracy of NIDS

The Fig. 3. Represents the overall accuracy of the Network Intrusion Detection System, Additionally, since the model is very accurate and also has low computational cost, it is a feasible method that can be deployed in the real-world environment. In general, it has been shown that the Random Forest algorithm is a useful and feasible solution to network intrusion detection problems.

V. CONCLUSION AND FUTURE WORK

As it is evident from the acquired results, machine learning based approach has shown its effectiveness and the potential to improve the precision and speed of the intrusion detection process. The suggested model provides the required trade-off between the quality of detection and computational costs, thus making it an affordable method of protecting the network. Besides, due to its great classification capabilities, the model provides the ability to eliminate false positives and pay attention only to real threats. Network Intrusion Detection System (NIDS) based on the Random Forest algorithm has proven its efficiency on the NSL-KDD data set, providing 99.98% accuracy with 100% precision, recall, and F1-Score. The system has shown its ability to correctly classify normal and attack traffic. Therefore, it has proven its effectiveness and suitability for real-world implementation due to its

capabilities to deal with high dimensional data and provide clear results. For the future work, the integration of Explainable AI (XAI) methods, such as SHAP and LIME, can be considered.

VI. Acknowledgment

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References

[1] A. Javaid, Q. Niyaz, W. Sun, and M. Alam, "LuNet: A Deep Neural Network for Network Intrusion Detection Using Machine Learning," arXiv preprint arXiv:1909.10031, 2019.

[2] S. Ahmed et al., "Feature Selection and Ensemble Learning for Network Intrusion Detection in 5G Networks," Computer Networks, vol. 238, p.110087, 2024.

[3] X. Wang, Y. Su, and H. Yu, "Pelican: A Deep Residual Network for Network Intrusion Detection," arXiv preprint arXiv:2001.08523, 2020.

[4] Chinchali, Shruti, Harshit Somani, and Aayush Agarwal. "Adversarial Machine Learning in Network Intrusion Detection Systems." arXiv preprint arXiv:2004.11898 (2020).

[5] Mohammed, Bilal, and Ekhlas K. Gbashi. "Intrusion Detection System for NSL-KDD Dataset Based on Deep Learning and Recursive Fea-ture Elimination." Engineering and Technology Journal 39.07 (2024): 1069–1079.

[6] Kesarwani, Swati R., and Rajeev Tripathi. "Network Intrusion Detection Using Feature Fusion and Deep Learning-Based Machine Learning Models." Journal of Big Data 10.1 (2023): 1–23.

[7] Iqbal, Shamsher M., and Muhammad A. Shibli. "A Hybrid Machine Learning Method for Increasing the Performance of Network Intrusion Detection Systems." Journal of Big Data 8.1 (2021): 1–18.

[8] Salunkhe, Rajendra R., and S. A. Bangare. "Design and Implementation of Network Intrusion Detection System Using Machine Learning." Inter-national Journal of Intelligent Systems and Applications in Engineering 10.1 (2022): 258–264.

[9] Khan, Tasneem A., and Nikita Patel. "Network Intrusion Detection System Using Deep Neural Networks and Machine Learning." Journal of Physics: Conference Series 1804.1 (2021): 012138.

[10] Laskar, M. F., and Anupam Paul. "Machine Learning-Based Classification Techniques for Network Intrusion Detection." International Journal of Intelligent Systems and Applications in Engineering 11.2 (2023): 367–373.

[11] Ali, Muhammad Qasim, Amir Anjum, and Irfan Awan. "Supervised Feature Selection Techniques in Network Intrusion Detection Using Machine Learning: A Critical Review." arXiv preprint arXiv:2104.04958 (2021).

[12] Eshete, Birhanu, and Michael R. Smith. "Adversarial Machine Learning in Network Intrusion Detection Domain: A Systematic Review." arXiv preprint arXiv:2112.03315 (2021).

[13] Li, X., et al. "Real-Time Network Intrusion Detection Using Lightweight Machine Learning Models." IEEE Transactions on Network and Service Management 21.1 (2024): 892–904.

[14] Zhang, Y., et al. "An Optimized Random Forest Model for Network Intrusion Detection in Cloud Environments." Future Generation Computer Systems 150 (2024): 245–256.

[15] Kumar, P., et al. "A Machine Learning-Based Intrusion Detection System for IoT Networks Using CICIDS2017 Dataset." Jour-nal of Network and Computer Applications 213 (2023): 103589. https://doi.org/10.1016/j.jnca.2023.103589

[16] Pramilarani, K., and P. V. Kumari. "Cost-Based Random Forest Classifier for Intrusion Detection System in Internet of Things." Applied Soft Computing 151 (2024): 111125.