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Network Intrusion Detection System

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Abstract: In the modern digital era, organizations increasingly rely on computer networks to store, exchange, and manage sensitive information, which has significantly expanded the landscape of cyber threats. Traditional security mechanisms such as firewalls and signature-based systems are limited in detecting unknown or zero-day attacks. To address these challenges, Intrusion Detection Systems (IDS), particularly Network Intrusion Detection Systems (NIDS), are employed to monitor network traffic and identify malicious activities. In this work, a Network Intrusion Detection System is developed using a hybrid approach that integrates ensemble learning models, namely Random Forest and XGBoost, with a Deep Neural Network (DNN) to enhance detection performance. The system is trained and evaluated using the NSL-KDD dataset, a widely used benchmark in intrusion detection research. Experimental results demonstrate that the proposed system achieves high detection accuracy, with the DNN model attaining approximately 96%, outperforming the other models. The results indicate that combining machine learning and deep learning techniques improves detection accuracy and robustness, making the proposed system suitable for real-world cybersecurity applications.

Key Words: Machine Learning, Deep Learning, Deep Neural Network, Random Forest, XGBoost, Anomaly Detection, NSL-KDD

1. Introduction

Organizations today heavily depend on IP-based networks to store, process, and transmit mission-critical information, thereby increasing the potential impact of security breaches. As the volume and sophistication of cyberattacks continue to grow, relying solely on traditional perimeter defense mechanisms such as firewalls and antivirus systems is no longer sufficient. Signature-based detection techniques, in particular, struggle to identify previously unseen or rapidly evolving threats. To overcome these limitations, both academia and industry have increasingly adopted data-driven intrusion detection approaches that model normal and malicious behaviors directly from network traffic. The growing trend of hyper-connectivity—linking users, devices, services, and data—has further expanded the attack surface, providing adversaries with new opportunities to exploit system vulnerabilities [1]. The Internet of Everything (IoE) has significantly enhanced connectivity and operational efficiency; however, it has also introduced critical security challenges. Advanced attack strategies such as Advanced Persistent Threats (APTs) enable attackers to infiltrate systems, disrupt services, and compromise sensitive data. Consequently, intrusion detection, particularly using Deep Learning (DL), has emerged as a key area of research in cybersecurity. Intrusion Detection Systems (IDS) are designed to automatically detect malicious activities, yet their limitations can lead to severe consequences if not addressed effectively. A notable example is the Colonial Pipeline ransomware attack in 2021, which disrupted nearly 45\% of fuel supply on the U.S. East Coast [2]. Modern networked systems often consist of interconnected and time-sensitive components requiring reliable communication. Technologies such as IEEE 802.1 Time-Sensitive Networking (TSN) provide low-latency and fault-tolerant communication but also introduce new security vulnerabilities. Therefore, the timely and accurate detection of intrusions is critical, especially in safety-critical environments.

A. Motivation

The motivation for this work arises from the increasing complexity and sophistication of cyber threats, which traditional security mechanisms fail to detect effectively. As network environments become more dynamic and data-driven, there is a

growing need for intelligent systems capable of automatically analyzing traffic and identifying anomalous behavior. Machine Learning (ML) and Deep Learning (DL) techniques enable intrusion detection systems to learn complex traffic patterns, improving detection accuracy and adaptability Hence, developing an AI-based Network Intrusion Detection System (NIDS) is essential for achieving proactive and real-time network security.

B. Research Contributions

This paper proposes a hybrid AI-based Network Intrusion Detection System that integrates ensemble learning techniques with deep learning models to enhance detection performance. The main contributions of this work are summarized as follows:

- Design and development of a real-time NIDS capable of capturing and analyzing live network traffic and classifying it as normal or intrusive.
- Proposal of a hybrid detection framework combining ensemble models (Random Forest and XGBoost) with a Deep Neural Network (DNN) to improve generalization and detection accuracy.
- Implementation of an interactive user interface using Streamlit for real-time monitoring, manual prediction, batch processing, and visualization of intrusion reports.
- Comprehensive evaluation of the proposed models using the NSL-KDD dataset, demonstrating that the DNN achieves the highest accuracy of 96\%, outperforming RF and XGBoost.
- Development of a reporting module that provides detailed insights, including classification reports, intrusion timelines, and attack source identification.

C. Paper Organization

The remainder of this paper is organized as follows. Section II presents the literature survey and reviews existing intrusion detection approaches. Section III discusses the research gap and limitations of current IDS techniques. Section IV describes the dataset used in this study. Section V explains the proposed methodology and system architecture. Section VI presents the model evaluation and performance analysis. Section VII discusses the experimental results, and Section VIII concludes the paper with future research directions.

2. Literature Survey

Recent advancements in intrusion detection systems (IDS) have explored a wide range of machine learning and deep learning techniques to improve detection accuracy and adaptability. Ajmeer Kiran et al. (2023) [3] proposed an Internal Intrusion Detection and Protection System (IIDPS) that monitors abnormal behavior through system call analysis. Their approach integrates administrative and user-level interfaces, enhancing practicality for real-world deployment. However, such host-based methods may face limitations in detecting large-scale network-level attacks. Chen et al. (2022) [4] focused on securing critical infrastructure systems, particularly power monitoring networks, using multidimensional data mining techniques. Their framework improved resilience against cyberattacks, but its applicability to general-purpose network environments remains limited. Ahmed and Hamad (2021) [5] presented a comprehensive survey of machine learning-based IDS approaches, categorizing them into classification, clustering, hybrid, and deep learning methods. Their study highlighted that hybrid and deep learning approaches offer improved adaptability and detection performance, encouraging further research in scalable AI-based intrusion detection. Kumar and Singh (2020) [6] developed a distributed IDS framework utilizing blockchain and cloud technologies to enhance scalability and trust. While effective in distributed environments, the approach introduces additional computational overhead and latency challenges. Zhang et al. (2019) [7] proposed a CNN-based IDS to address class imbalance in network datasets through oversampling and noise reduction techniques. Their work demonstrated improved detection of minority attack classes; however, deep learning models often require significant computational resources. In an earlier study, Zhang et al. (2018) [8] integrated Snort with a MySQL backend and visualization tools to develop a deployable IDS. Although effective, the system suffered from high false alarm rates, limiting its reliability in enterprise environments. Samrin and Vasumathi (2017) [9] explored a hybrid approach combining KNN and SVM algorithms to improve anomaly detection accuracy. Their findings emphasized the trade-off between detection efficiency and false positives, indicating the need for more balanced models. Deng and Qiao (2016) [10] introduced an intrusion detection framework based on incremental convolutional neural networks, enabling real-time traffic monitoring and adaptive learning. While promising, the model complexity may affect scalability in real-time deployments. Overall, existing studies demonstrate that while machine learning and deep learning approaches significantly improve intrusion detection performance, challenges such as class imbalance, computational complexity, false positives, and lack of generalization across different datasets remain unresolved. These limitations highlight the need for hybrid models that combine the strengths of multiple algorithms to achieve improved accuracy and robustness.

3. Research Gap

Network Intrusion Detection Systems (NIDS) are essential for monitoring network traffic and detecting malicious activities; however, existing approaches still face significant limitations. Traditional signature-based methods are ineffective against unknown or zero-day attacks, while recent machine learning and deep learning models, although improving detection accuracy, often suffer from high false positive rates, limited generalization across different datasets, and increased computational complexity. Additionally, many existing studies rely on single-model approaches, which restrict their ability to capture diverse and complex patterns in network traffic. Furthermore, commonly used benchmark datasets such as NSL-KDD, while useful for evaluation, do not fully represent modern network environments, posing challenges for real-world applicability. These limitations highlight the need for a hybrid intrusion detection framework that integrates multiple machine learning and

deep learning techniques to enhance detection accuracy, robustness, and generalization capability, which forms the basis of the proposed work.

4. Dataset

The proposed Network Intrusion Detection System is developed and evaluated using the NSL-KDD (Network Security Knowledge Discovery in Databases) dataset, a widely recognized benchmark dataset for intrusion detection research. NSL-KDD is an improved version of the original KDD'99 dataset and is maintained by the University of New Brunswick (UNB), Canada, as part of the Canadian Institute for Cybersecurity (CIC) repository. It was specifically designed to eliminate the redundant records and sampling issues present in KDD'99, making it significantly more suitable for machine learning–based and deep learning–based intrusion detection studies by preventing classification models from becoming biased toward frequent records.

The structural architecture of the dataset consists of 41 distinct input features and 1 final class label, capturing a broad spectrum of network activities. These inputs cover both normal network traffic and four major operational categories of cyberattacks: Denial of Service (DoS), Probe, User-to-Root (U2R), and Remote-to-Local (R2L). For rigorous training and evaluation phases, the NSL-KDD dataset includes two main predefined subsets: the **KDDTrain+** partition, which contains approximately 125,973 records, and the **KDDTest+** partition, which contains 22,544 independent records reserved for final model verification.

One of the most critical characteristics of this dataset is that it is highly imbalanced across its target classes. As outlined in the statistical distribution data, certain minority attack categories, such as U2R (52 samples) and R2L (995 samples), appear far less frequently compared to majority classes like DoS (45,927 samples) or baseline Normal traffic (67,343 samples). This stark statistical imbalance poses severe challenges for standard classification algorithms, as minority threat types are inherently harder to isolate, which often leads to biased machine learning boundaries. To ensure robust performance, data preprocessing steps—such as categorical feature encoding, Min-Max normalization, and algorithmic class balancing techniques—are systematically applied to the pipeline before feeding the matrices into the core classifiers.

5. Methodology

The proposed Network Intrusion Detection System (NIDS) follows a structured pipeline consisting of data acquisition, preprocessing, feature engineering, model training, classification, and result visualization. The overall architecture of the proposed system is illustrated in Fig. 1.

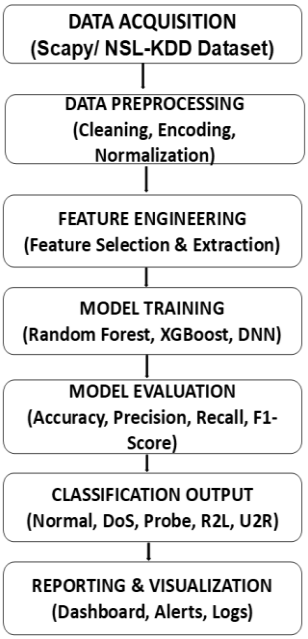

Fig 1: Proposed Network Intrusion Detection System Architecture

A. Data Acquisition

In this initial stage, raw network traffic parameters are systematically collected either from live, operational packet capture frameworks or from established benchmark repositories. Real-time traffic strings are actively acquired utilizing specialized packet sniffing engines such as Scapy, Wireshark, or tcp dump utilities. Alternatively, static benchmark datasets such as the NSL-KDD corpus supply pre-structured historical communication records for training operations. The ingested data vectors encapsulate core protocol layer parameters, packet metadata, transmission service classifications, and connection-level statistics. (10)

B. Preprocessing

The raw data streams must undergo rigorous preprocessing to ensure compatibility with numerical machine learning mathematical structures. This defensive processing phase removes redundant records, drops corrupted or incomplete packet headers, and imputes missing data tokens. Categorical string variables within the network data—specifically protocol types, service domains, and handshake flags—are mathematically transformed using One-Hot Encoding matrices. Concurrently, numeric variables are standardly scaled using Min-Max Normalization techniques to bounding ranges between 0 and 1, neutralizing mathematical dominance from high-magnitude features.

C. Feature Engineering

Feature engineering elevates the underlying descriptive quality of the network dataset by deriving high-influence representations from raw traffic vectors. Redundant or noise-inducing columns are systematically dropped by applying Pearson Correlation matrices alongside model-driven feature importances. Supplemental derived attributes, such as active connection durations, rolling packet exchange rates, and inter-arrival time statistical metrics, are dynamically engineered. This compression reduces dimensionality, shortens computational training epochs, and maximizes structural classification performance.

D. Model Training

Three separate algorithmic paradigms are established and trained upon the processed feature arrays: Random Forest (RF), Extreme Gradient Boosting (XGBoost), and a customized Deep Neural Network (DNN). The RF model acts as a robust bagging baseline classifier, aggregating predictions across uncorrelated decision trees via majority voting to mitigate overfitting. The XGBoost architecture utilizes regularized gradient boosting steps to explicitly counter the severe minority class distribution problems inherent to network logs. Lastly, the DNN architecture is constructed using fully connected multi-layer perceptron dense blocks equipped with Rectified Linear Unit (ReLU) activations, dropout layers to enforce regularization, and a Softmax output layer for multi-class probability scoring. The models are trained on the **KDDTrain+** dataset and validated across the **KDDTest+** set.

E. Classification

During active classification, the trained parameter weights map unknown incoming network connections into five discrete structural labels: Normal, DoS, Probe, U2R, and R2L. In a live configuration, each intercepted network data frame is instantly piped through the identical preprocessing transformation before being fed into the selected classifier to resolve a definitive threat label and corresponding probability distribution matrix.

F. Reporting Dashboard

The final architectural tier involves projecting the system classifications onto an interactive administrative interface built using the Streamlit framework. This dashboard provides human operators with real-time visualization streams of system metrics, predictive logs, and instant warning notifications during active anomalies. By hosting interactive confusion matrices, precision curves, and threat timelines, the platform bridges the gap between deep learning outputs and real-time security infrastructure monitoring.

6. Model Evaluation

The performance of the proposed Network Intrusion Detection System (NIDS) is evaluated using a comprehensive set of quantitative metrics and visualization-based analyses. Each model—Random Forest (RF), XGBoost (XGB), and Deep Neural Network (DNN)—is trained on the KDDTrain+ dataset and evaluated on the independent KDDTest+ dataset to ensure unbiased generalization. The evaluation focuses on measuring the ability of each model to accurately classify both normal and malicious traffic across multiple attack categories.

A. Evaluation Metrics

To obtain a detailed understanding of model performance, multiple evaluation metrics are employed rather than relying solely on accuracy. These metrics are computed using True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Accuracy: Accuracy represents the overall correctness of the classifier.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

Precision:

Precision measures the proportion of correctly predicted attack instances among all predicted attacks.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

F1-Score:

F1-Score is the harmonic mean of Precision and Recall, providing a balance between false positives and false negatives.

$$F1\ Score = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Macro-F1:
For multiclass classification (Normal, DoS, Probe, U2R, R2L), Macro-F1 is computed to treat all classes equally.

$$Macro - F1 = 1/N \sum_{i=1}^{N} F1i$$

where N represents the number of classes.

B. Discussion

The evaluation results indicate that all three models demonstrate strong intrusion detection capabilities; however, the DNN consistently achieves superior performance due to its ability to capture complex nonlinear patterns in network traffic data. Ensemble models such as RF and XGBoost provide competitive results with better interpretability and lower computational complexity.

Despite achieving high overall accuracy, the models exhibit reduced performance on minority attack classes such as U2R and R2L, primarily due to dataset imbalance. This limitation highlights the need for advanced techniques such as synthetic data generation, resampling strategies, or hybrid anomaly detection methods to further improve detection of rare attack types. Overall, the results confirm that the proposed hybrid approach enhances detection performance while maintaining robustness across different attack categories.

7. Result and Discussion

A. Accuracy Comparison

Algorithm	Accuracy %
Random Forest	93
XGBoost	95
Deep Neual Network	96

Table no 1: Model Accuracy on NSL-KDD Dataset

Table I presents the overall classification accuracy achieved by the three models on the NSL-KDD dataset. The Deep Neural Network (DNN) achieves the highest accuracy of 96\%, indicating its superior ability to capture complex and nonlinear patterns in network traffic data. XGBoost achieves 95\%, demonstrating strong performance with efficient gradient boosting techniques, while Random Forest achieves 93\%, providing a reliable and interpretable baseline.

B. Performance Comparison

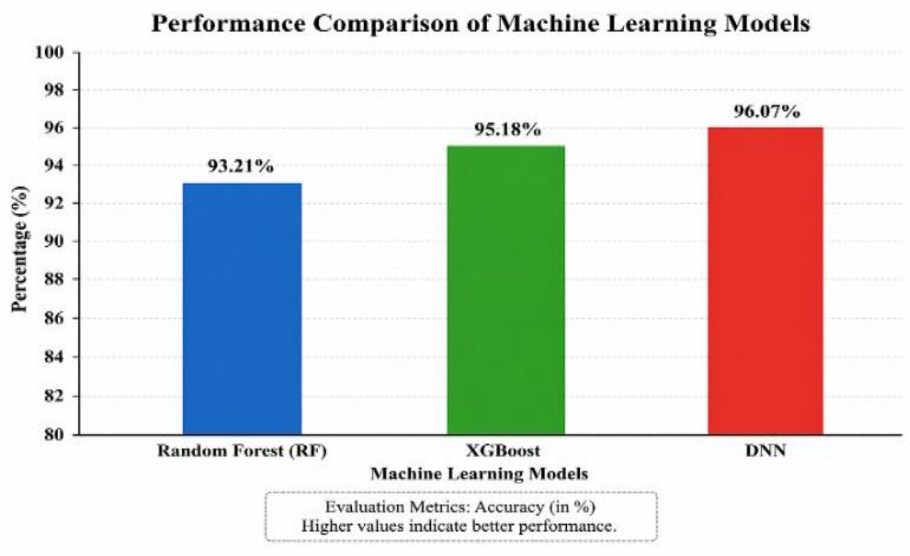

Fig. 2: Comparison of Model Performance on NSL-KDD Dataset

Fig 2. illustrates the comparative performance of the models. It is evident that the DNN outperforms both Random Forest and XGBoost in terms of accuracy. This improvement can be attributed to the ability of deeplearning models to learn hierarchical feature representations and capture complex relationships within network traffic data. Although the performance difference is relatively small, the consistent improvement demonstrates the effectiveness of the proposed hybrid framework.

C. Confusion Matrix Analysis

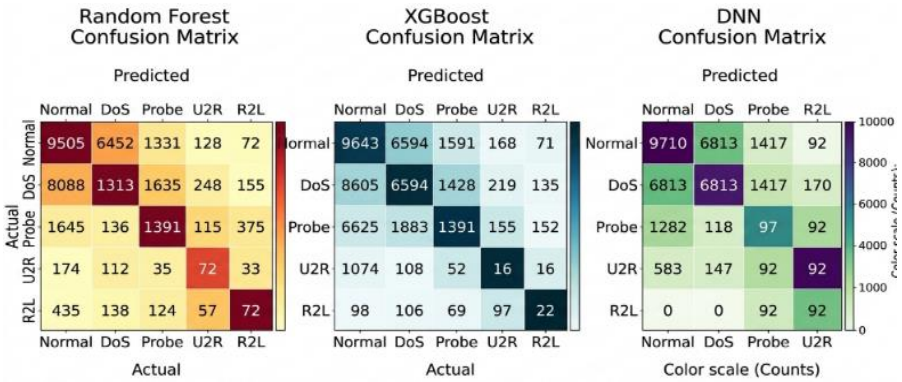

Fig. 3: Multi-Class Confusion Matrix Mapping for RF, XGBoost, and DNN Models

The confusion matrix shown in Fig. 3 provides a detailed view of classification performance across different attack categories. The DNN model demonstrates strong performance in identifying major classes such as Normal, DoS, and Probe. However, misclassifications are observed in minority classes such as U2R and R2L, which can be attributed to the inherent class imbalance in the NSL-KDD dataset.

D. Discussion

The experimental results demonstrate that both ensemble learning and deep learning approaches significantly enhance intrusion detection performance. The integration of Random Forest, XGBoost, and Deep Neural Networks within the proposed framework ensures improved robustness and reliability.

While the DNN achieves the highest overall accuracy, ensemble models provide advantages in terms of interpretability and computational efficiency. Despite the high accuracy values, detecting rare attack types remains a challenge due to limited training samples. This highlights the need for advanced techniques such as data balancing, synthetic sample generation, or anomaly-based detection methods.

Overall, the proposed intrusion detection system achieves competitive performance and demonstrates its effectiveness in accurately classifying network traffic, making it suitable for real-world cybersecurity applications.

8. Conclusion and Future Work

This paper presents a hybrid Network Intrusion Detection System (NIDS) that integrates ensemble learning techniques (Random Forest and XGBoost) with a Deep Neural Network (DNN) to enhance intrusion detection performance. The proposed framework effectively classifies normal and malicious network traffic by leveraging the strengths of both ensemble and deep learning models. Experimental evaluation on the NSL-KDD dataset demonstrates that the DNN achieves the highest accuracy of 96\%, while ensemble models provide stable and interpretable performance.

The system supports real-time monitoring and structured reporting of network activities, making it suitable for practical deployment in modern cybersecurity environments. The results indicate that combining multiple learning approaches improves overall detection capability and robustness compared to single-model systems.

Despite achieving high accuracy, the proposed system faces challenges in detecting minority attack classes such as U2R and R2L due to dataset imbalance. Additionally, the use of benchmark datasets may limit real-world generalization.

Future work will focus on incorporating advanced deep learning architectures such as Long Short-Term Memory (LSTM) networks to capture temporal dependencies in network traffic. Further improvements include evaluating the model on more recent and realistic datasets, enhancing zero-day attack detection capabilities, and integrating automated response mechanisms for real-time threat mitigation.

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