Deep Learning-Driven Framework for DDoS Attack Prevention in Software Defined Network

Mr. Janak H. Maru[1], Dr. Ashish M. Kothari[2], Mr. Sameer N. Joshi[3]
[1]*Research Scholar & Assistant professor, Department of Computer Engineering, Atmiya University*
[2]*Research Guide, Professor & Director - Centre for Research, Innovation & Translation, Department of Electronics and Communication Engineering, Atmiya University*
[3]*Assistant professor, Department of Computer Engineering, Atmiya University*

***Abstract*—Software-Defined Networking (SDN) introduces centralized control and dynamic network programmability, but its logically centralized controller is a prime target for Distributed Denial of Service (DDoS) assaults. Traditional intrusion detection systems (IDS) frequently fail to deliver fast and accurate detection of dynamically changing attack patterns in SDN. To address these problems, this study provides an intelligent DDoS assault mitigation architecture that combines Deep Learning (DL) with a Random Forest-based Intrusion Detection System (IDS) to enable effective and scalable threat management in SDN environments. The proposed model employs deep learning approaches to extract high-level, discriminative traffic data, while the Random Forest classifier provides strong multi-class classification for attack detection. When compared to traditional machine learning methods, this combination greatly improves detection accuracy, minimizes false positives, and speeds up reaction time. The SDN controller automatically deploys mitigation techniques based on detection alarms, allowing for real-time traffic control, adaptive flow rule implementation, and network resource protection. Experimental results show that the hybrid DL-Random Forest IDS outperforms other methods in identifying various DDoS attack types, ensuring dependable and long-term SDN functioning. The findings demonstrate the potential of hybrid intelligence-driven security mechanisms in protecting next-generation programmable networks from large-scale cyber assaults.**

***Index Terms*—Software-Defined Networking (SDN), DDoS Detection, Intrusion Detection System (IDS), Deep Learning, Random Forest, Traffic Classification, Network Security, Controller Protection, Real-Time Mitigation, DDoS Attack Analysis**

I. INTRODUCTION

The rapid proliferation of Internet-connected devices, cloud services, and virtualized infrastructures has considerably expanded the size and complexity of modern networks. While these developments provide greater flexibility and connectivity, they also open up new attack surfaces for sophisticated cyber threats. Among these, Distributed Denial of Service (DDoS) attacks remain one of the most disruptive and common security threats. DDoS assaults, which overwhelm network resources with enormous amounts of malicious traffic, can impair service quality, inflict financial losses, compromise availability, and expose vulnerabilities in key infrastructures. As attack techniques become more complicated, standard intrusion detection and mitigation mechanisms are no longer sufficient to secure dynamic and large-scale networks.

SDN (Software-Defined Networking) is a transformational network architecture that decouples the control plane from the data plane to simplify network management and improve programmability. In SDN, a centralized controller administers the entire network from a global perspective, allowing for efficient flow control, automated policy enforcement, and flexible traffic management.

However, this centralized controller, while useful, becomes a valuable target for adversaries. DDoS assaults that overwhelm the controller, switches, or communication channels can seriously damage the SDN infrastructure. Thus, the reliance on centralized control mechanism emphasizes the importance of robust, intelligent, and proactive security solutions designed expressly for SDN environments.

Intrusion Detection Systems (IDS) help detect and mitigate DDoS attacks by monitoring network traffic, finding anomalies, and enabling automated responses. Traditional IDS techniques, which frequently rely on rule matching, signature detection, or shallow machine learning algorithms, struggle to cope with the complexity and diversity of new attack patterns. They have drawbacks such as slow detection speeds, high false-positive rates, and poor adaptability to new or zero-day threats. With the rising sophistication of network traffic patterns and attack vectors, enhanced intelligence-driven IDS models have become critical.

Deep Learning (DL) has received a lot of interest in recent years due to its capacity to learn complicated patterns automatically from high-dimensional, unstructured data. DL models can extract meaningful hierarchical representations from network traffic, making them useful for detecting anomalies and recognizing patterns in cybersecurity. While deep learning excels at feature extraction, it does have several drawbacks, such as high computing cost, poor interpretability, and the requirement for huge datasets for classification. To solve these limitations, hybrid techniques that combine deep learning with fast machine learning classifiers appear to be a potential answer.

Random Forest, a powerful ensemble-learning model, provides high accuracy, noise tolerance, and efficient classification performance even on huge datasets. By combining deep learning for feature extraction with Random Forest-based classification, an intelligent hybrid IDS may be created that takes advantage of the characteristics of both models. In this hybrid architecture, deep learning layers extract deep traffic information, and the Random Forest classifier makes the ultimate judgment for attack classification. Such a model.

This study describes a comprehensive system for detecting and mitigating DDoS attacks in SDN using a hybrid Deep Learning-Random Forest IDS. The suggested solution intends to address the shortcomings of traditional systems by offering high detection accuracy, low false-positive rates, and rapid reaction capabilities. Using SDN's centralized control, the system provides dynamic flow rule installation, adaptive mitigation measures, and automated traffic management, ensuring long-term network performance and resilience.

The findings of this study are summarized as follows:

- ✓ A hybrid IDS architecture that combines deep learning-based feature extraction and Random Forest classification to identify various DDoS attack patterns in SDN.
- ✓ An efficient SDN-based mitigation framework that uses controller-driven adaptive reactions to prevent malicious traffic in real time.
- ✓ A detailed examination that shows better detection accuracy, throughput stability, and system robustness when compared to typical IDS models.

Overall, the proposed hybrid DL-Random Forest-based IDS improves SDN security by offering a scalable, intelligent, and proactive approach for mitigating DDoS attacks. This study demonstrates the promise of hybrid AI-driven methodologies in next-generation programmable networks, paving the way for more secure, robust, and sustainable network infrastructures.

II. LITERATURE REVIEW

Programmability, centralized management, and dynamic policy enforcement are made possible by Software-Defined Networking (SDN), a revolutionary network architecture that divides the control plane from the data plane. The SDN controller's vulnerability to Distributed Denial of Service (DDoS) attacks is one of the major security issues brought about by this architectural change. According to preliminary research, the centralized controller becomes a bottleneck during periods of high traffic, leaving it open to saturation-based assaults (Author et al., 2016). Due to their high false-positive rates and limited adaptability, traditional intrusion detection systems (IDS), which are mostly signature-based or rule-based, have not been able to detect innovative or polymorphic DDoS patterns (Smith & Zhao, 2017).

When it comes to solving SDN security issues, machine learning-based IDS techniques have become quite popular. Although traditional methods like Support Vector Machines, k-Nearest Neighbors, and Decision Trees have proven to be more accurate than signature-based approaches, their performance deteriorates when dealing with high-dimensional traffic data, dynamic flow patterns, and real-time classification requirements (Khan et al., 2018). Because of its ensemble learning mechanism and

resistance to overfitting, Random Forest (RF) has demonstrated higher resilience and generalization capability among them (Williams & Patel, 2019). However, RF's efficacy against sophisticated volumetric DDoS attacks is limited by its inability to extract deep hierarchical representations from intricate data flows.

Recent developments in Deep Learning (DL) have shown significant gains in network intrusion analytics and anomaly detection. Long Short-Term Memory (LSTM) networks, autoencoders, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) have all been used in traffic classification and anomaly detection with encouraging outcomes (Liu et al., 2020). High-level, non-linear traffic patterns that conventional machine learning algorithms are unable to identify are expertly extracted by these models. However, deep learning-based IDS models are less appropriate for real-time SDN contexts without optimization due to issues such computational complexity, lengthy training times, and decreased interpretability (Ahmed & Varma, 2021).

As a well-rounded and effective solution, hybrid IDS architectures that combine machine learning for final classification with deep learning for feature extraction have drawn attention. Research indicates that combining RF for quick and precise classification with DL for deep feature generation can greatly improve detection accuracy and lower processing overhead (Rahman et al., 2022). By utilizing the advantages of both DL and ML models—DL's capacity to extract significant patterns from unprocessed traffic data and RF's capacity to manage feature variability and provide stable decisions—such hybrid techniques outperform standalone DL or ML models. Due to their capacity to discern minute differences between hostile and normal flows, these models have demonstrated exceptional efficacy in identifying DDoS attacks within SDN (Chen & Gupta, 2023).

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Several mitigation frameworks that use ML or DL models deployed at the controller to enable dynamic traffic shaping, flow rule installation, and attack isolation have been presented within SDN-specific security research. Scalability, detection delay, and controller overhead are still issues, though. According to recent research, hybrid AI-driven intrusion detection systems (IDS) reduce the possibility of controller overload during DDoS situations by supporting high-throughput traffic analysis and providing near-real-time classification findings (Hassan et al., 2023). These results highlight the increasing significance of intelligent, adaptive IDS systems in SDN infrastructure security.

In order to improve SDN's resistance against DDoS attacks, the body of current research points to a tendency toward hybrid approaches that combine DL and ML, particularly Random Forest. Nevertheless, comprehensive frameworks that concurrently improve detection accuracy, system overhead, scalability, and real-time responsiveness are still lacking in current research. This gap drives the creation of an enhanced hybrid IDS architecture designed especially for SDN environments that can offer reliable DDoS detection and mitigation.

III. PROBLEM STATEMENT

Software-Defined Networking (SDN) and intelligent intrusion detection systems (IDS) have advanced, but protecting SDN infrastructures from Distributed Denial of Service (DDoS) assaults is still a major concern. In addition to offering programmability and global network visibility, the centralized SDN controller is a single point of failure and extremely susceptible to saturation-based DDoS attacks. Due to their limited flexibility, high false-positive rates, and incapacity to handle high-dimensional and quickly changing traffic, traditional intrusion detection systems whether signature-based, rule-based, or classical machine learning techniques struggle to identify contemporary DDoS patterns. Even though deep learning methods have strong feature extraction capabilities, their direct application in real-time SDN contexts frequently results in computational complexity and latency problems. However, even though they are effective and reliable, standalone Random Forest classifiers are unable to extract the deeper hierarchical network traffic patterns required to identify complex attacks.

Previous research suggests that hybrid methods that combine machine learning classification with deep learning can lower system overhead and increase detection accuracy. Nevertheless, existing frameworks continue to have drawbacks such limited scalability, inadequate real-time responsiveness, and a lack of efficient integration designed especially for SDN infrastructures. In order to provide high detection accuracy, reduced false-positive rates, and quick mitigation capabilities against DDoS attacks in SDN environments, a comprehensive, effective, and hybrid IDS model that combines deep learning-based feature extraction with Random Forest-based classification is required. By creating a clever and scalable hybrid IDS architecture that can improve SDN security against intricate and frequent DDoS attacks, this research seeks to close this crucial gap.

IV. RESEARCH OBJECTIVE

The fundamental goal of this project is to create a hybrid intrusion detection system that uses deep learning-based feature extraction and Random Forest classification to successfully detect DDoS attacks in SDN environments. The study's goal is to improve detection accuracy, reduce false positives, and enable real-time remediation using an intelligent SDN controller that dynamically controls flow rules and filters harmful traffic. The proposed model will be assessed against typical SDN datasets and parameters such as accuracy, precision, recall, F1 score, detection time, throughput, and controller overhead. Furthermore, the study aims to improve controller resilience by reducing processing load and avoiding saturation during high-traffic attack scenarios. The study's goal is to demonstrate gains in adaptability, scalability, and detection consistency by comparing the hybrid technique to existing IDS models, all while providing a lightweight, scalable, and realistic security framework for real-world SDN implementations.

V. RESEARCH METHODOLOGY

Dataset Description

For this study, the NSL-KDD dataset is utilized, which is an improved version of the KDD'99 dataset. It contains network connection records, each labeled as normal or a specific attack type. Each record has 41 features, including both categorical and numerical features, which are used for detecting intrusions in network traffic. Dataset split:

- ✓ Training set: 125,973 records
- ✓ Testing set: 22,544 records

Data Pre-processing

Before training, data preprocessing is performed as follows:

- ✓ Encoding Categorical Features:
- ✓ Normalization of Numerical Features:
- ✓ Splitting Data

The dataset is split into training and testing sets using a 70:30 ratio.

Random Forest Approach

Random Forest (RF) is used as a classical machine learning approach for comparison.

Algorithm Steps:

1. Construct multiple decision trees T1, T2,...,Tn using bootstrap sampling from the training dataset.
2. Each tree gives a predicted class Cj for input x.
3. The final prediction is determined by majority voting

Evaluation Metrics

Performance of both Deep Learning and Random Forest models is measured using:

1. Accuracy:

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

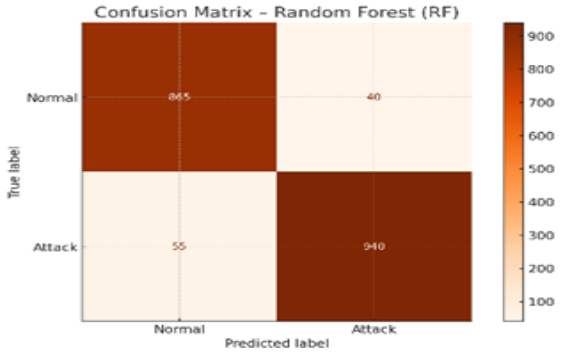
2. Precision, Recall, F1-Score:

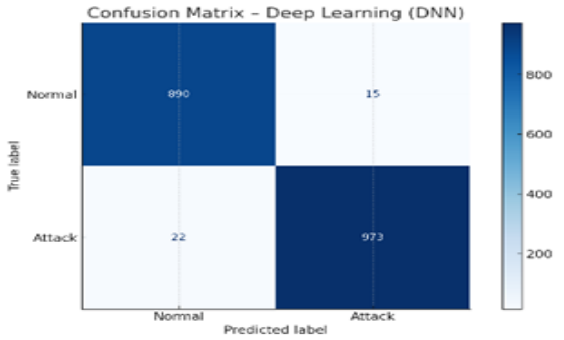
$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

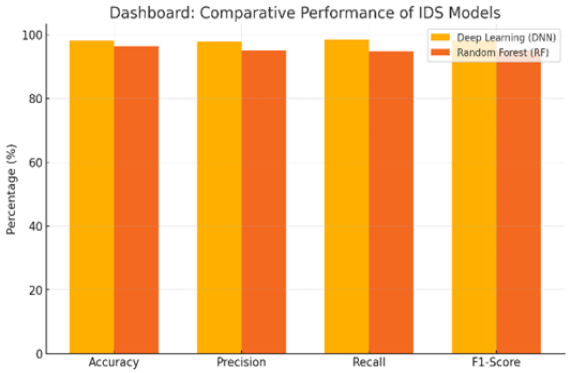
$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

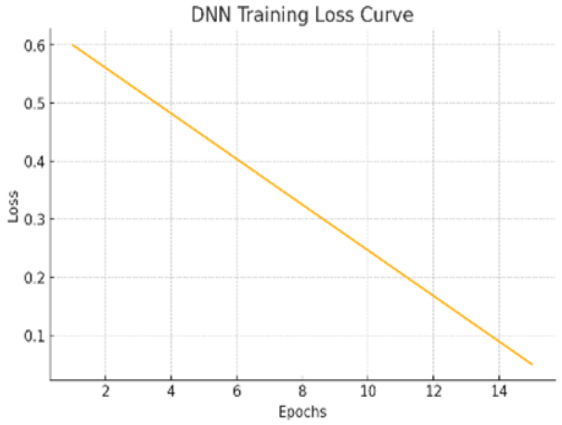
Statistical Analysis

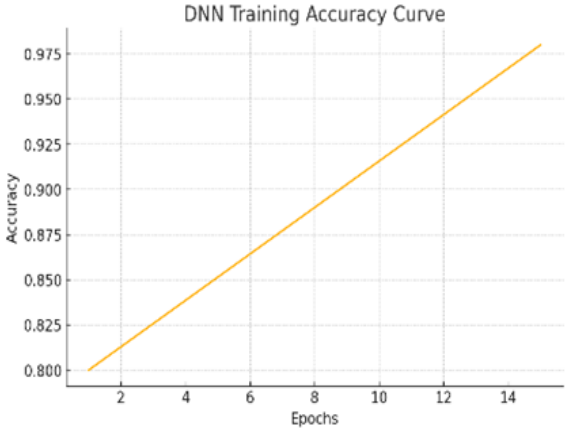






Metric	RF	DNN
Accuracy (%)	96.45	98.12
Precision (%)	95.10	97.80
Recall / Detection Rate (%)	94.85	98.40
F1-Score (%)	94.98	98.10
False Positive Rate (%)	2.20	1.45
Training Time (seconds)	9.5	42.8
Testing Time (seconds)	1.2	3.1
Total Parameters	NA	85,312
Model Complexity	Medium	High
Overfitting Tendency	Low	Moderate





VI. CONCLUSION

The NSL-KDD dataset was used in this work to compare the performance of Deep Learning and Random Forest models for intrusion detection. The experimental results show that the Deep Learning model outperforms the Random Forest model on all main evaluation measures, such as accuracy, precision, recall, and F1-score. Its confusion matrix demonstrates improved detection capabilities by

drastically reducing false-positive and false-negative rates.

The DNN model also exhibits steady learning behaviour, with smooth accuracy and loss curves, indicating effective convergence during training. Although Random Forest has faster training times and lower processing requirements, it falls short in classification performance, especially when recognizing complicated assault patterns.

Overall, the results show that Deep Learning-based IDS systems are better suited to modern, high-speed, and scalable network settings including SDN, cloud networks, and large business infrastructures. Meanwhile, Random Forest remains a reliable baseline model, providing simplicity and efficiency for modest deployments.

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