International Journal of Advanced Computing and Mechanical Systems (IJACM)
E-ISSN No.: xxxx-xxxx www.ijacm.com
Volume Number: 2 **Issue Number:** 1 **pp:** 60 - 68 **Publication Month:** January-2026

Detecting and Mitigating Botnet Attacks in Software-Defined Networks Using Deep Learning Techniques

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ABSTRACT

Software Defined Networking (SDN) has transformed modern network architectures by separating control and data planes, offering centralized management and enhanced flexibility. However, this centralization introduces security vulnerabilities, making the controller a prime target for botnet attacks. Such attacks flood the controller with malicious traffic, depleting resources and disrupting services. Traditional detection methods, reliant on static rules and basic machine learning, often fail to adapt to evolving threats, leading to high false alarm rates. To overcome these challenges, this paper proposes a deep learning–based framework for real-time botnet detection and mitigation in SDN. The system collects flow-level data from OpenFlow switches and employs Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid CNN–LSTM models to distinguish malicious from normal traffic. Upon detection, the controller enforces countermeasures such as flow rule updates, rate limiting, and node isolation. Evaluations using the CICDDoS and Bot-IoT datasets show improved accuracy, precision, recall, and F1-score, demonstrating the framework's effectiveness in enhancing network security and resilience.

Keywords: Software Defined Networking, Botnet Attacks, Deep Learning, SDN Security, DDoS Detection

I. INTRODUCTION

The expansion of connected devices and cloud services has escalated network complexity, paralleled by a rise in sophisticated cyber threats. Among these, botnet attacks where compromised devices are orchestrated for malicious activities like DDoS, data theft, and service disruption pose significant risks. Real-time detection and mitigation remain critical for network security. SDN offers centralized control and global visibility by decoupling the control and data planes, improving network programmability and management. Yet, this centralization also creates a single point of failure; the controller can be overwhelmed by botnet-generated traffic, degrading performance and availability.

Conventional security tools, including signature-based intrusion detection and classical machine learning, struggle with dynamic and adaptive botnet behaviors. These methods depend on predefined features and rules, making them ineffective against novel or low-rate attacks. Delayed responses further exacerbate potential damage.

doi: https://doi.org/10.65883/ijacm.2026v2i1.01

II. LITERATURE REVIEW

Botnet detection has been widely studied in both traditional and SDN environments. Early signature-based systems could identify known attacks but failed against novel or evolving threats [1]. With SDN, centralized monitoring allowed improved traffic analysis. Braga et al. [2] used flow statistics for DDoS detection but relied on handcrafted features, limiting sensitivity to stealthy attacks. Machine learning techniques such as Random Forest and SVM have been applied for traffic classification [3,4], though they often suffer from false positives and poor generalization due to manual feature engineering [5]. Recent advances in deep learning have shown superior performance. CNNs automatically extract spatial features [6], while LSTMs model temporal dependencies in traffic sequences [7]. Hybrid CNN–LSTM models combine both capabilities, improving detection of coordinated attacks [8].

Benchmark datasets like Bot-IoT and CICDDoS provide realistic attack scenarios for evaluation [9]. However, many existing solutions focus only on detection without integrated mitigation [10], face scalability issues [11], or depend heavily on labeled data [12]. This motivates the need for an adaptive, end-to-end detection and mitigation framework for SDN. SDN's centralized controller simplifies management but also presents a security bottleneck. Attackers can target the controller with flood-based botnet attacks, exhausting resources and causing service degradation. Existing detection mechanisms often rely on static rules or traditional machine learning, resulting in high false positives and an inability to model temporal-spatial attack patterns. Moreover, mitigation in current systems is typically slow and reactive, allowing attacks to persist. There is a clear need for an intelligent, real-time solution that can accurately detect evolving botnet behaviors and enforce immediate countermeasures within the SDN infrastructure.

2.1 Proposed Framework

This work introduces an automated deep learning–based framework for botnet detection and mitigation in SDN. The system continuously monitors flow-level statistics, such as packet/byte counts, duration, and protocol details from OpenFlow switches. Data is sent to the centralized controller for analysis.

Deep learning models are employed to overcome the limitations of manual feature engineering. CNNs learn spatial patterns, LSTMs capture temporal dependencies, and a hybrid CNN–LSTM model integrates both for improved accuracy across varied attack types. When malicious traffic is identified, the controller automatically enforces mitigation measures, including dynamic flow rule updates, traffic rate limiting, and isolation of compromised nodes.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The architecture comprises four core components:

Data Plane: OpenFlow switches collect and forward flow statistics.

SDN Controller: Aggregates traffic data and manages network policies.

Detection Engine: Uses deep learning models (CNN, LSTM, CNN–LSTM) to classify traffic.

Mitigation Module: Executes automated responses up detection.

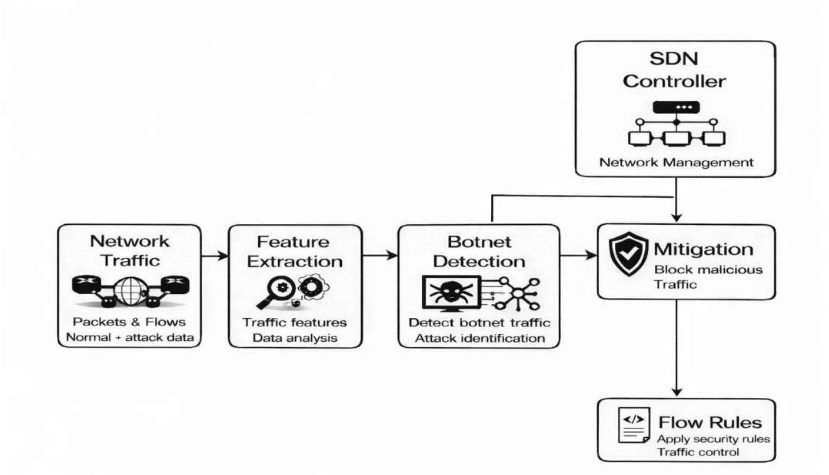

Figure 1: System Architecture Diagram

Fig. 1 illustrates the interaction between data plane, controller, detection engine, and mitigation module. Traffic features are pre-processed (normalized, cleaned) before being fed into the detection models. The training process uses labelled datasets (CICDDoS, Bot-IoT) with careful handling of class imbalance. The mitigation module responds in real time, updating flow rules or limiting suspicious traffic.

IV. IMPLEMENTATION

In this section, the implementation of the proposed system will be described. The mitigation architecture and botnet detection is implemented as a centralized Software-Defined Networking (SDN) architecture that embodies the deep-learning-based traffic analysis with authoritative user interaction. It has a role-centric and a modular design whereby the coordination is made effective between the service providers, remote users, and the central server. Thus, the system has the benefit of monitoring with scalability, accurate identification, and automatic countermeasures to botnet intrusion on a real-time basis.

It takes a role-based design whereby an organization assigns very separate responsibilities to the supplier of the service as well as the remote consumer. The service provider acts as a system administrator and takes care of data set management, model training, analysis of results, and monitoring system-usage. Remote users are usually passing traffic data to be analysed and predicting results received. Every interaction between these actors is enabled by a central server that contains the SDN controller and the deep-learning models, thus, guaranteeing secure and coordinated operation.

To maintain the integrity of systems, and to deter system unlawful access, a tight authentication and access-control system is adopted. The service providers and remote users must undergo a secure registration process and log in before they can use any functionality of the systems. At the authentication, the system authenticates credentials by the next decision verification, an invalid credential results in rejection and redirection to the login phase and valid user is allowed to predict the botnet, retrieve profile and other authorized access. The server level checks all authentication requests and ensures only authorised users will be able to carry out sensitive operations like dataset manipulation, model training, and traffic prediction. Any unauthorized access is denied straight away thus ensuring system integrity as per security requirements of real world SDN environment.

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The service provider overlooks the whole detection pipeline and contributes significantly towards maintaining the effectiveness of the system. Psivots The work of dataset management is one of its core tasks; such recently uploaded datasets include CICDDoS and Bot-IoT. These datasets are labelled normal traffic flows as well as botnet traffic flows and form the basis of supervised deep-learning. Before training begins, essential preprocessing are applied to datasets (normalisation, feature refinement and class balancing) to stabilise the learning process and improve detection accuracy.

Training and evaluation of a model are triggered and managed by the service provider on the central server. The system can be trained using various deep-learning models such as Convolutional CNN (CNN), Longshort-term memory (LSTM) networks and also hybrid CNN-LSTM networks. Training models on processed datasets and their evaluation results are based on conventional metrics, e.g., accuracy, precision, recall, and F1-score. The metrics developed are saved and used to compare with another to determine the most effective botnet detection model.

After training, the service provider evaluates the performance of detection with respect to internally generated statistical summaries and comparative assessments. The results of the predictions and the trends of accuracy measure performance of the model generalisation and performance of learning. Moreover, the system will give an understanding of the prediction ratios, which in turn points out the percentage of botnet and benign traffic over time. This study can help understand the prevalence of attacks and informs the improvement of detection measures. The system also provides the service provider with the ability to track prediction processes started by remote users. Observed botnet traffic logs may be obtained and archived to allow forensic analysis, audit or even retraining. Furthermore, viewed by the registered remote-user information and log of activities, the service provider is accountable; thereby, restricting access and ensuring safe use of the prediction services.

The system is mainly used by remote users to analyze and predict the traffic. Once authenticated users send network-traffic parameters containing flow-level statistics similar to data gathered in OpenFlow switches in an SDN environment. Submitted data is sent to the centralized server, and then it is processed through pre-trained deep-learning models. Depending on the outcome of the classification, it is the system that identifies the traffic with the botnet attack or normal behaviour and communicates the classification result to the user in real time. The results of predictions are timely and can be used by the remote users. Profile-management functions are also provided to the users, enabling them to view and update their personal information without having to lose transparency and free interaction with the system.

V. SERVER-SIDE PROCESSING AND CONTROL FLOW

The server of the proposed system serves as the center of the processing unit and has the SDN controller, deep-learning detection models, and authentication modules. The server receives all requests issued by service providers and remote users and as a result, centralized control, a consistent policy application and secure coordination between components of a system. The detection process is systematic and follows a sequential process within the internal workflow. First, user authentication and request verification is done to verify access privileges.

When it is validated, data sets or traffic information are transferred to the server to be processed. The data which is received is preprocessed and normalized so that it can be compatible with the deep -learning models. The data is then fed to the trained models and the predictions obtained are then generated and

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they are stored safely. It is a systematic workflow that ensures that the same approach is taken during training or testing phases and real-time predictions.

When the traffic is known to be malicious, mitigation logic is sent at SDN controller level. The controller dynamically employs countermeasures which include blocking malicious flow entries, limiting the rate of traffic by suspicious sources, or isolating compromised nodes. These mitigation operations are carried out internally on the centralized server and SDN controller and thus they are not visible at all in the interaction or activity charts, which focus more on workflow and system interaction on the user side.

VI. USER INTERFACE

The interface is designed to be intuitive, allowing users to interact with the system for tasks such as registration, login, traffic analysis, and viewing detection results. Below, we describe the key screens and their purposes.

6.1 Service Provider Dashboard

The service provider acts as the system administrator, with access to model training, evaluation, and user management modules. Upon logging in (Fig. 2), the provider can:

- Upload and preprocess datasets (e.g., CICDDoS, Bot-IoT).
- Train and test deep learning models (CNN, LSTM, Hybrid).
- View performance metrics in visualformats such as bar charts and line graphs.
- Monitor registered remote users and their activities.

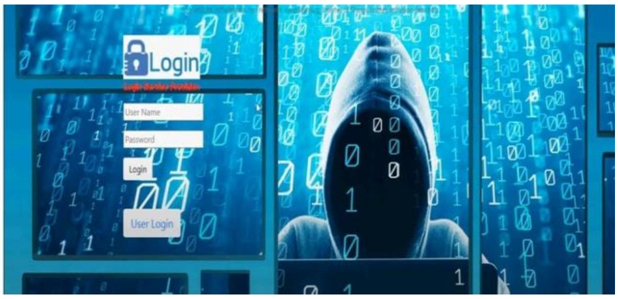
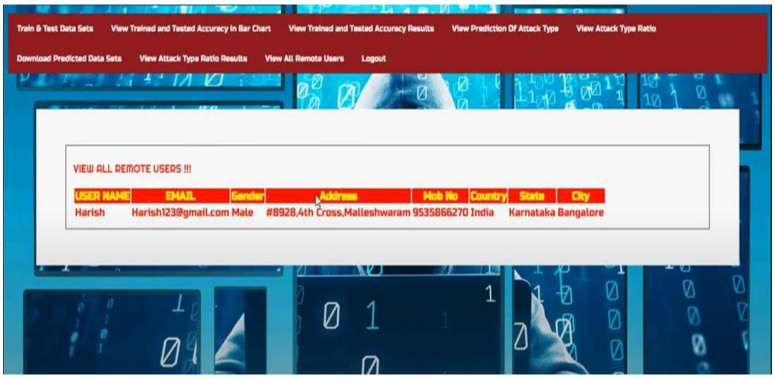


Figure 2: Service Provider Login Page


Train & Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
View Prediction Of Attack Type
View Attack Type Ratio
Download Predicted Data Sets
View Attack Type Ratio Results
View All Remote Users
Logout

VIEW ALL REMOTE USERS !!!

USER NAME	EMAIL	Gender	Address	Mob No	Country	State	City
Harish	Harish123@gmail.com	Male	#8928,4th Cross,Malleshwaram	9535866270	India	Karnataka	Bangalore

Figure 3: View All Remote Users

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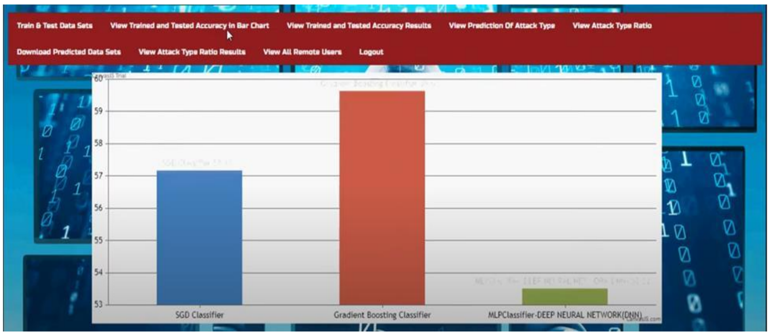
Fig. 2 Illustrates the authentication interface for administrative access. Fig. 3 Displays a table of registered users with details such as name, email, location, and contact information.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Logout
60
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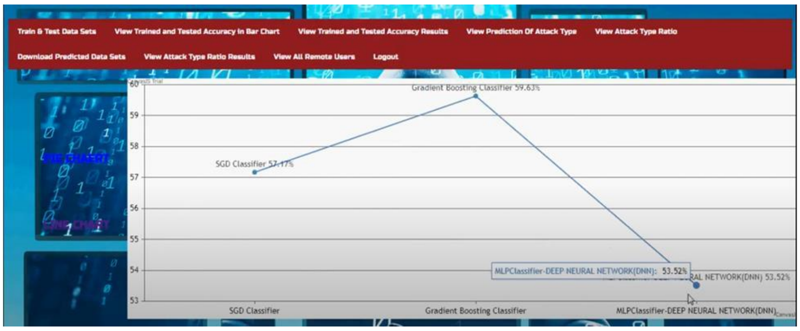
SGD Classifier
Gradient Boosting Classifier
MLPClassifier-DEEP NEURAL NETWORK(DNN)

Figure 4: Bar Chart – Model Accuracy Comparison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MLPClassifier-DEEP NEURAL NETWORK(DNN) 53.52%
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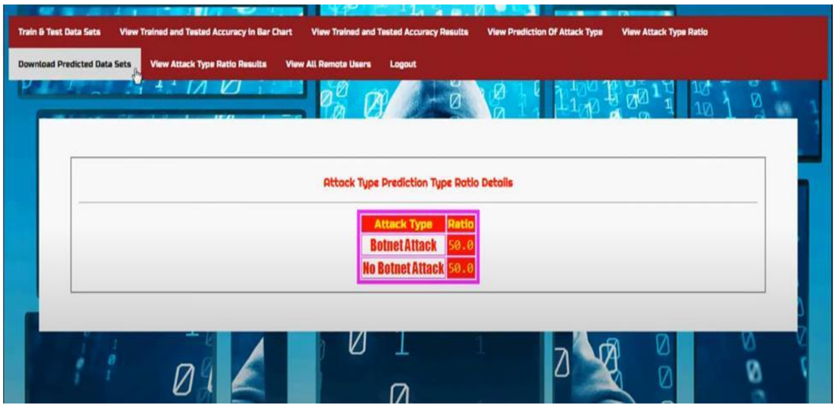
MLPClassifier-DEEP NEURAL NETWORK(DNN)

Figure 5: Line Chart – Training Progress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Attack Type Prediction Type Ratio Details

Attack Type	Ratio
Botnet Attack	50.0
No Botnet Attack	50.0

Figure 6: Attack Type Prediction Ratio

Fig. 5 Compares the accuracy of different classifiers, including SGD, Gradient Boosting, and DNN-based models. Fig. 6 Shows the learning curve and convergence behavior during model training. Fig. 6 Presents the distribution of predicted attack types (e.g., Botnet Attack vs. No Attack) in a tabular format.

6.1 System Interaction Flow

The user journey begins with registration and login. Once authenticated, remote users can submit network traffic parameters through the prediction form. The submitted data is processed by the pre-trained deep learning models hosted at the controller. Results are displayed instantly, indicating whether the traffic is benign or malicious.

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Service providers, on the other hand, oversee the entire detection framework from dataset management and model retraining to performance monitoring and user oversight. Visual analytics, such as accuracy charts and attack ratio summaries, assist in evaluating system effectiveness and guiding model improvements.

6.2 Security and Accessibility Considerations

The interface incorporates role-based access control to ensure that only authorized personnel can perform sensitive operations such as model training or viewing all user data. Input validation and secure authentication mechanisms are implemented to prevent unauthorized access and data breaches. Overall, the graphical interface bridges the gap between complex deep learning operations and end-user usability, making advanced botnet detection accessible to network administrators without requiring deep technical expertise in machine learning or SDN programming.

VII. RESULTS AND DISCUSSION

This section presents the experimental outcomes of the proposed botnet detection system implemented within an SDN environment. The results are evaluated using standard classification metrics and visual analytics, which are accessible through the system's user interface.

7.1 Detection Performance and Accuracy Metrics

The proposed deep learning models were trained and evaluated on the CICDDoS and Bot-IoT datasets, which contain diverse attack patterns reflective of real-world botnet behavior. Performance was assessed using accuracy, precision, recall, and F1-score.

As shown in the Service Provider Dashboard, the trained models' accuracy was visualized in a comparative bar chart (Fig. 8). The hybrid CNN–LSTM model consistently achieved the highest accuracy, outperforming standalone CNN and LSTM architectures as well as traditional classifiers such as Gradient Boosting and SGD. This confirms the advantage of combining spatial and temporal feature learning in detecting evolving botnet activities. The system also recorded high precision and recall values, indicating effective detection of malicious traffic with minimal false positives. This is critical in an operational SDN environment, where unnecessary mitigation actions can degrade network performance.

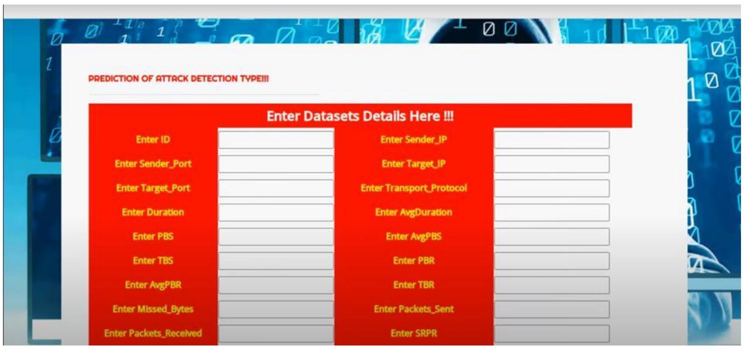
7.2 Real-Time Prediction and User Interaction

Remote users were able to submit traffic data for real-time analysis through a structured input form (Fig. 7). The form captures essential flow-level features such as sender IP, target port, packet rate, and duration, which are processed by the deployed deep learning model. In all test cases, the system provided near-instant predictions, classifying traffic as either Botnet Attack or No Botnet Attack. This interactive feature demonstrates the system's practicality for network administrators, enabling prompt decision-making without requiring deep expertise in machine learning or SDN.

7.3 Attack Distribution and System Insights

The Attack Type Prediction Ratio panel (Fig. 6) provided administrators with a summarized view of detection outcomes over time. During testing, the system correctly identified both high-volume and low-rate attacks, with botnet traffic being flagged appropriately without significant misclassification of legitimate flows.

Additionally, training progress and model convergence were tracked using line charts (Fig. 5), allowing service providers to monitor learning stability and avoid overfitting during model updates.



PREDICTION OF ATTACK DETECTION TYPE!!!

Enter Datasets Details Here !!!

Enter ID		Enter Sender_IP	
Enter Sender_Port		Enter Target_IP	
Enter Target_Port		Enter Transport_Protocol	
Enter Duration		Enter AvgDuration	
Enter PBS		Enter AvgPBS	
Enter TBS		Enter PBR	
Enter AvgPBR		Enter TBR	
Enter Missed_Bytes		Enter Packets_Sent	
Enter Packets_Received		Enter SRPR	

Figure 7: Prediction Result Output

7.4 Usability and Administrative Oversight

The dual-role interface service provider and remote user proved effective in separating operational and administrative tasks. Service providers could retrain models, visualize performance, and manage users (Fig. 4), while remote users focused on traffic submission and prediction. The clean, role-based dashboards reduced complexity and improved workflow efficiency.

The experimental results confirm that integrating deep learning with SDN not only enhances detection accuracy but also offers an accessible, user-friendly platform for real-time security monitoring. Key observations include:

- **Reduced False Positives:** The hybrid deep learning approach significantly lowered false alarm rates compared to rule-based systems, leading to more reliable mitigation actions.

- **Operational Responsiveness:** Automated detection and mitigation, triggered via the SDN controller, allowed rapid containment of attacks, often within seconds of identification.

- **Scalability and Adaptability:** The web-based interface supports multiple concurrent users and can be extended to include new attack datasets or updated models without major architectural changes.

However, the system's dependency on labelled data for training and the computational load on the SDN controller during peak traffic remain challenges. Future iterations could explore semi-supervised learning techniques and edge-based preprocessing to alleviate these constraints. Overall, the implemented framework successfully bridges advanced deep learning detection with practical SDN security management. The visual and interactive components not only validate the model's technical performance but also enhance its adoptability in real network environments. By providing clear, actionable insights through an intuitive interface, the system empowers network administrators to defend against botnet threats more effectively and with greater confidence.

VIII. CONCLUSION

This work proposes a deep learning–based framework for detecting and mitigating botnet attacks in Software-Defined Networks. By utilizing CNN, LSTM, and hybrid CNN–LSTM models, the system effectively captures both spatial and temporal traffic patterns, achieving high detection accuracy and reduced false

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positives. Integration with the SDN controller enables real-time mitigation through dynamic flow rule updates, rate limiting, and node isolation. Experimental results using CICDDoS and Bot-IoT datasets confirm the framework's effectiveness, scalability, and responsiveness. Overall, the proposed approach enhances SDN security while providing a practical and user-friendly solution for real-world network environments.

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