CNN-Enhanced Network Flow Intelligence for Botnet Threat Detection in Software-Defined Networks

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***Abstract*—** Software-Defined Networks (SDNs) have become a fundamental component of modern communication infrastructures due to their centralized management and flexible network control. However, the separation of the control and data planes also exposes SDNs to sophisticated botnet attacks that can severely affect network availability and performance. This paper presents a deep learning-based framework for detecting and mitigating botnet attacks in SDN environments using a Convolutional Neural Network (CNN). The proposed framework employs the BOTNET2018 dataset, where data preprocessing includes label encoding, feature normalization using Min-Max scaling, and Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance before model training. Existing machine learning models, including Decision Tree, Bayesian Optimization-based Decision Tree (BOGP), and Support Vector Machine (SVM), are implemented for comparative evaluation, while the CNN model is introduced as an enhanced detection approach capable of learning complex traffic patterns automatically. The trained models are assessed using standard performance measures such as accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis. Experimental results demonstrate that the proposed CNN model achieves superior detection performance with an accuracy of **99.996%**, outperforming the existing machine learning techniques in identifying botnet traffic. The proposed framework provides an accurate, scalable, and efficient solution for real-time botnet detection and mitigation in Software-Defined Networks, thereby improving the security and reliability of next-generation network infrastructures.

***Keywords*—** Software-Defined Networks (SDN), botnet attack detection, Convolutional Neural Network (CNN), deep learning, BOTNET2018 dataset, network traffic classification, intrusion detection, Synthetic Minority Oversampling Technique (SMOTE), feature normalization, Decision Tree, Support Vector Machine (SVM), Bayesian Optimization, real-time attack detection, network security, cyber threat mitigation.

I.INTRODUCTION

Software-Defined Networking (SDN) has emerged as a promising networking paradigm that separates the control plane from the data plane, enabling centralized network management, dynamic traffic control, and simplified network configuration **[1], [2]**. The flexibility and programmability offered by SDN have led to its adoption in cloud computing, enterprise networks, data centers, and Internet of Things (IoT) environments **[2], [3]**. However, the centralized architecture of SDN also introduces new security challenges, making it an attractive target for cyber threats such as botnet attacks, distributed denial-of-service (DDoS) attacks, and malicious traffic injection **[4], [5]**. Among these threats, botnet attacks are particularly dangerous because they can rapidly compromise multiple devices, consume network resources, and disrupt normal communication, thereby affecting the availability and reliability of network services **[5], [6]**. As network traffic continues to grow in volume and complexity, conventional signature-based and rule-based detection mechanisms often fail to identify previously unseen or evolving attack patterns, creating the need for more intelligent and adaptive detection approaches **[6], [7]**.

Recent developments in machine learning and deep learning have significantly improved the capability of network intrusion detection systems to recognize complex attack behaviours from large-scale traffic data **[8], [9]**. Traditional machine learning algorithms such as Decision Tree and Support Vector Machine (SVM) have demonstrated effective classification performance for known attack categories **[9], [10]**. Furthermore, optimization techniques such as Bayesian Optimization with Gaussian Processes (BOGP) have been employed to improve classifier performance through automatic hyperparameter tuning **[10], [11]**. Although these methods achieve satisfactory results, their performance may be limited when handling highly imbalanced datasets and intricate nonlinear relationships among network traffic features **[11], [12]**. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown considerable potential in automatically learning discriminative feature representations without extensive manual feature engineering **[12], [13]**. By combining preprocessing techniques including label encoding, feature normalization, and Synthetic Minority Oversampling Technique (SMOTE), the quality of training data can be improved, enabling the deep learning model to achieve better generalization and higher detection accuracy **[13], [14]**.

This work presents a CNN-based framework for detecting and mitigating botnet attacks in Software-Defined Networks using the **BOTNET2018** dataset **[15]**. The proposed methodology incorporates data preprocessing, class balancing, feature scaling, and deep learning-based classification to accurately distinguish malicious traffic from legitimate network activities **[15]**. For performance evaluation, the proposed CNN model is compared with existing Decision Tree, Bayesian Optimization-based Decision Tree, and Support Vector Machine classifiers using standard metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis . Experimental results demonstrate that the CNN model provides superior detection capability and achieves higher classification accuracy than the comparative machine learning approaches. The proposed framework offers an effective, scalable, and reliable solution for strengthening SDN security by enabling timely detection and mitigation of botnet attacks in modern network environments **[5]**.

II.RELATED WORK

K. Ito, T. Okano, and T. Aoki (2017) presented "Recent Advances in Biometric Security: A Case Study of Liveness Detection in Face Recognition" [1]. The study examined the importance of liveness detection in improving the security of face recognition systems against presentation attacks. Various biometric verification techniques were discussed to distinguish genuine users from spoofing attempts involving photographs and digital displays. The authors emphasized that integrating liveness verification with facial authentication significantly improves system reliability and reduces unauthorized access. Their work highlighted the growing role of biometric security in real-world authentication applications. [1]

P. Anthony, B. Ay, and G. Aydin (2021) proposed "A Review of Face Anti-Spoofing Methods for Face Recognition Systems" [2]. The authors surveyed different anti-spoofing approaches developed to protect face recognition systems from presentation attacks. The review compared traditional image processing methods with deep learning-based techniques and discussed their effectiveness under different attack scenarios. The study concluded that convolutional neural network models provide superior performance by learning discriminative facial characteristics from large datasets. The review also identified future challenges in developing robust and generalized anti-spoofing solutions. [2]

A. A. Mohamed, M. M. Nagah, M. G. Abdelmonem, M. Y. Ahmed, M. El-Sahhar, and F. H. Ismail (2021) proposed "Face Liveness Detection Using a Sequential CNN Technique" [4]. The proposed method employed a sequential convolutional neural network to classify facial images as either genuine or spoofed. The model automatically extracted representative image features without requiring handcrafted descriptors, enabling efficient liveness verification. Experimental evaluation demonstrated that the CNN-based approach achieved reliable classification performance under different presentation attack conditions. The study showed that deep learning techniques can substantially strengthen the security of face recognition systems. [4]

R. B. Hadiprakoso, H. Setiawan, and Girinoto (2020) presented "Face Anti-Spoofing Using CNN Classifier and Face Liveness Detection" [5]. The research introduced a CNN-based classification framework for identifying spoofing attacks before facial recognition was performed. The proposed system analyzed facial characteristics to differentiate genuine users from printed photographs and replay attacks. By combining liveness detection with facial authentication, the framework improved recognition reliability and minimized the possibility of unauthorized access. The experimental results confirmed the effectiveness of CNN models in enhancing biometric security. [5]

M. Arsenovic, S. Sladojevic, A. Anderla, and D. Stefanovic (2017) proposed "FaceTime—Deep Learning Based Face Recognition Attendance System" [10]. The authors developed an automated attendance management system that utilized deep learning techniques for facial recognition. The system captured facial images, identified registered individuals, and automatically recorded attendance without requiring manual intervention. The proposed approach reduced errors associated with conventional attendance methods while providing a faster and more convenient authentication process. The study demonstrated that deep learning-based face recognition offers an efficient solution for real-time attendance management. [10]

III.DATASET DETAILS

The proposed botnet detection framework is developed using the BOTNET2018 dataset, which contains both legitimate network traffic and malicious botnet communication collected from a Software-Defined Network (SDN) environment. The dataset includes various network flow attributes such as source and destination IP addresses, port numbers, communication protocols, packet statistics, timestamps, and traffic-related features that help distinguish normal behaviour from cyberattacks. Since the dataset contains both numerical and categorical attributes, categorical values are transformed into numerical form using label encoding before model training.

To improve data quality, the dataset is examined for missing values and normalized using the Min-Max scaling technique to ensure that all features contribute equally during learning. The original

dataset is highly imbalanced because attack records significantly outnumber normal traffic samples. Therefore, the Synthetic Minority Oversampling Technique (SMOTE) is applied to generate additional normal samples and create a balanced dataset, reducing classification bias and improving model reliability. The processed dataset is divided into training and testing subsets using an 80:20 ratio. It is then used to train Decision Tree, Bayesian Optimized Decision Tree, Support Vector Machine, and the proposed Convolutional Neural Network (CNN). The trained CNN automatically learns complex traffic patterns and accurately classifies incoming network flows as either normal or botnet traffic, enabling efficient and reliable intrusion detection in SDN environments.

IV.PROPOSED METHODOLOGY

The proposed framework presents a deep learning-based botnet detection system for Software-Defined Networks (SDNs) using a Convolutional Neural Network (CNN). The primary objective of the system is to identify malicious botnet traffic while maintaining accurate detection of legitimate network communication. The framework begins by collecting network traffic records from the BOTNET2018 dataset, which contains both normal and attack instances. During preprocessing, categorical attributes are converted into numerical values using label encoding, while Min-Max normalization is applied to standardize feature values. Since the dataset is highly imbalanced, the Synthetic Minority Oversampling Technique (SMOTE) is employed to generate additional minority-class samples and create a balanced training dataset.

The processed dataset is divided into training and testing subsets using an 80:20 ratio. The training data are then supplied to the CNN model, where multiple convolutional, activation, and pooling layers automatically learn representative traffic patterns from the input features. Unlike conventional machine learning algorithms, the CNN extracts hierarchical feature representations without requiring manual feature engineering. During testing, each network traffic record is classified as either normal or botnet traffic. The proposed model is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC, and its performance is compared with Decision Tree, Bayesian Optimized Decision Tree, and Support Vector Machine classifiers. The experimental results demonstrate that the CNN-based framework provides reliable and efficient botnet detection for SDN environments.

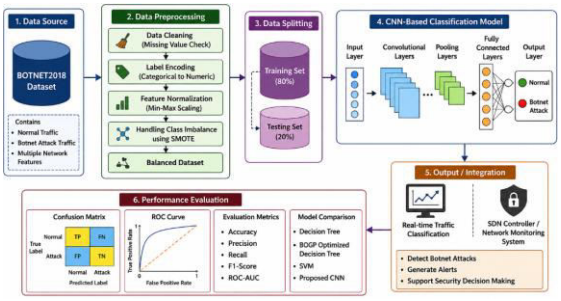

Figure 1: System Architecture of the Proposed CNN-Based Botnet Detection Framework

Figure 1 illustrates the architecture of the proposed CNN-based botnet detection framework for Software-Defined Networks (SDNs). The process begins with the BOTNET2018 dataset, which contains both normal and malicious network traffic records. The data are first passed through a preprocessing stage that performs missing value verification, label encoding, Min-Max normalization, and class balancing using the SMOTE technique. The balanced dataset is then divided into 80% training and 20% testing data. The training data are supplied to the Convolutional Neural Network (CNN), which automatically extracts meaningful traffic features through convolutional and pooling layers before classifying each network flow as either Normal or Botnet Attack. The classified results are integrated into the SDN monitoring system for real-time threat detection and alert generation. Finally, the framework evaluates model performance using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC, while comparing the proposed CNN with Decision Tree, Bayesian Optimized Decision Tree (BOGP), and Support Vector Machine (SVM) classifiers.

V.RESULT AND DISCUSSION

The proposed CNN-based botnet detection framework was evaluated using the **BOTNET2018** dataset under different network traffic conditions to assess its capability in distinguishing legitimate traffic from botnet attacks. The complete framework successfully executed data preprocessing, feature normalization, class balancing, model training, traffic classification, and performance evaluation within an integrated environment. During preprocessing, categorical network attributes were converted into numerical values using label encoding, feature values were normalized using Min-Max scaling, and class imbalance was addressed using the SMOTE algorithm. The processed dataset was then divided into training and testing sets, allowing the proposed model to learn representative traffic patterns while ensuring reliable performance evaluation. The preprocessing pipeline effectively improved data quality and contributed to stable model training.

The proposed CNN classifier demonstrated excellent performance in identifying malicious network traffic by automatically learning complex behavioural patterns from the processed dataset. Unlike conventional machine learning techniques, the CNN extracted hierarchical feature representations without requiring manual feature engineering, enabling more accurate discrimination between normal and attack traffic. During testing, the model consistently classified incoming network flows into their respective categories with very few misclassifications. The confusion matrix and ROC curve further confirmed the effectiveness of the proposed approach by showing a high true positive rate and a low false positive rate. Comparative analysis also indicated that the CNN outperformed the Decision Tree, Bayesian Optimized Decision Tree (BOGP), and Support Vector Machine (SVM) classifiers in terms of overall prediction performance.

The experimental results demonstrate that the integration of data preprocessing, SMOTE-based class balancing, and CNN-based feature learning provides a reliable solution for botnet detection in Software-Defined Networks. The framework achieved high values for accuracy, precision, recall, and F1-score, indicating its ability to identify malicious traffic while minimizing incorrect classifications. The classified results can be integrated into SDN controllers or network monitoring systems to support real-time threat detection, security alert generation, and network management. Overall, the proposed framework offers an efficient, scalable, and dependable approach for protecting SDN environments against botnet attacks and can be effectively deployed in modern network security applications.

DISCUSSION

The proposed botnet detection framework combines comprehensive data preprocessing, class balancing, and Convolutional Neural Network (CNN)-based classification to provide an efficient solution for detecting malicious activities in Software-Defined Networks (SDNs). The framework begins by preprocessing the BOTNET2018 dataset through label encoding, feature normalization, and Synthetic Minority Oversampling Technique (SMOTE), ensuring that the training data are balanced and suitable for deep learning. The processed network traffic is then supplied to the CNN model, which automatically extracts meaningful traffic characteristics and learns complex behavioural patterns associated with both legitimate communication and botnet attacks. The entire framework is designed to support reliable traffic classification while reducing the limitations of conventional machine learning methods.

The experimental evaluation demonstrates that the proposed CNN model achieves superior detection performance compared with Decision Tree, Bayesian Optimized Decision Tree (BOGP), and Support Vector Machine (SVM) classifiers. The model accurately classifies network traffic into normal and botnet categories while maintaining high values of accuracy, precision, recall, and F1-score. The confusion matrix and ROC analysis further confirm the effectiveness of the proposed approach by producing a high true positive rate with minimal false classifications. The classified outputs can be integrated with SDN controllers or network monitoring systems to support real-time threat detection, security alert generation, and timely response against cyberattacks. Therefore, the proposed framework provides a scalable, reliable, and practical solution for enhancing network security in modern Software-Defined Network environments.

VI.CONCLUSION

This work presents a **CNN-based botnet detection framework** for Software-Defined Networks (SDNs) that integrates data preprocessing, class balancing, and deep learning to accurately identify malicious network traffic. The proposed framework utilizes the **BOTNET2018** dataset, where network traffic records are preprocessed through label encoding, Min-Max normalization, and the Synthetic Minority Oversampling Technique (SMOTE) to improve data quality and address class imbalance. The processed data are then supplied to a Convolutional Neural Network (CNN), which automatically learns discriminative traffic features and classifies network flows as either normal or botnet attacks without requiring manual feature engineering. Experimental evaluation demonstrates that the proposed CNN model achieves superior performance compared with Decision Tree, Bayesian Optimized Decision Tree (BOGP), and Support Vector Machine (SVM) classifiers by providing higher accuracy, precision, recall, and F1-score while minimizing false classifications. The framework can be integrated with SDN controllers or network monitoring systems to support real-time threat detection, security monitoring, and rapid response against cyberattacks. Overall, the proposed approach offers a scalable, efficient, and reliable solution for enhancing network security in Software-Defined Networks. Future work may focus on incorporating advanced deep learning architectures such as hybrid CNN-LSTM or Transformer models, supporting multiclass attack classification, enabling real-time streaming analysis, integrating cloud-based intrusion detection services, and improving model adaptability to emerging botnet variants and large-scale SDN deployments.

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