Enhanced DDoS Attack Detection with a Hybrid Machine Learning Model

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***Abstract*—In the digital age, the proliferation of networked systems has made cybersecurity a critical concern, particularly with the increasing frequency and sophistication of Distributed Denial of Service (DDoS) attacks. These attacks try to make services unavailable by flooding the target with a huge amount of traffic, often making it look like normal activity to avoid being detected. Traditional DDoS detection methods which rely on signature-based and rule-based approaches, are unable to keeping up with the changing strategies of attackers.This study contributes to the advancement of DDoS detection techniques by leveraging recent datasets and effective hybrid modeling approaches. This paper proposes a hybrid machine learning model leveraging LSTM networks integrated with XGBoost to enhance DDoS detection capabilities. The CICDDoS2019 dataset, consisting of various DDoS attack types, is used to evaluate the proposed model performance, which includes a broader range of DDoS attack types. The results from our study reveal that the LSTM with XGBoost combination outperforms other models, offering significant improvements in detection accuracy and robustness. Our findings indicate that the hybrid model outperforms individual models in both accuracy and reliability when detecting DDoS attacks. Specifically, the hybrid approach yielded an accuracy of 95%, significantly outperforming an end-to-end LSTM model which achieved 90.3%. The findings underscore the potential of combining deep learning and machine learning techniques to create more resilient cybersecurity defenses.**

***Index Terms*—Cybersecurity, DDoS Attacks, Machine Learning, LSTM, XGBoost**

I. Introduction

In today's digital age, our dependence on networked systems has grown exponentially, supporting essential infrastructures like finance, healthcare, and communication. As a result, securing these systems has become crucial, with DDoS attacks being one of the most prominent threats. A DDoS attack seeks to interrupt the normal operation of a targeted server, service, or network by bombarding it with excessive internet traffic. The simplicity of launching such attacks, coupled with their potential to cause substantial disruption and financial loss, underscores the urgent need for effective detection and mitigation strategies.

Traditional approaches to DDoS detection often rely on predefined rules and signature-based methods, which, although effective against known attack patterns, fall short when challenged with novel or evolving threats. These methods struggle to adapt to the rapidly changing landscape of cyber attacks, where adversaries continually develop sophisticated techniques to bypass existing defenses. Consequently, there is an increasing interest in utilizing machine learning (ML) and deep learning (DL) technologies to enhance the detection capabilities against DDoS attacks.

Machine learning offers a promising avenue for DDoS detection by enabling systems to learn from historical data and identify patterns indicative of an attack. Techniques such as Support Vector Machines (SVM), Decision Trees, and Random Forests have shown potential in classifying network traffic and detecting anomalies. However, these traditional ML approaches often face challenges related to the high dimensionality and dynamic nature of network traffic data. Furthermore, the performance of these models can be hindered by the quality and quantity of labeled data available for training.

Deep learning, a subset of machine learning, has gained popularity due to its capability to automatically extract significant features from raw data, minimizing the requirement for manual feature extraction. Recurrent Neural Networks (RNNs) with its extensions, like LSTM networks, have proven especially proficient at identifying temporal patterns in sequential data, making them well-suited for examining network traffic over time. Convolutional Neural Networks (CNNs), known for their proficiency in image and pattern recognition, have also been adapted to the cybersecurity domain, demonstrating strong performance in identifying complex attack signatures within traffic data.

Despite these advancements, the application of deep learning models to DDoS detection is not without its challenges. Deep learning models require intensive computation and significant amounts of labeled training data, that may not always be feasible in practical scenarios. Additionally, these models can often function as 'black boxes,' making it challenging to interpret their decisions and understand the factors driving their predictions

In response to these challenges, recent research has explored hybrid approaches that combine the strengths of multiple machine learning and deep learning techniques. Hybrid models aim to leverage the complementary benefits of different algorithms to enhance detection accuracy and robustness. For instance, combining the feature extraction capabilities of

CNNs with the temporal analysis strengths of LSTMs has shown promise in improving detection performance.

We propose a hybrid model with experimentation on new benchmark dataset in this study that integrates LSTM and XGBoost for DDoS detection. LSTM networks are employed to capture the temporal dependencies in network traffic, while XGBoost, a powerful gradient boosting framework, is utilized for its best classification performance. By combining these two models, we aim to address the limitations of individual approaches and provide a robust and efficient solution for detecting DDoS attacks. Our contributions are as follows:

- Developed a hybrid LSTM-XGBoost model combining deep learning and machine learning for improved DDoS detection.
- number of experiments are conducted on most recent datasets, demonstrating the model's effectiveness in accurately detecting DDoS attacks.
- Analyzed the model's interpretability, highlighting key features and temporal patterns influencing its decisions.
- Performed a comparative analysis of different hybrid models to showcase our model's superior performance.

The remainder of this paper is structured as follows: Section 2 reviews related work in the domain of DDoS detection using machine learning and deep learning approaches. Section 3 describes the architecture and methodology of our proposed hybrid model. Section 4 presents the experimental setup and results, followed by a discussion. Finally, Section 5 concludes the paper and outlines potential directions for future research.

II. Related Work

The detection and mitigation of DDoS attacks have been extensively explored, with numerous methodologies proposed to enhance the security and robustness of network systems. This section reviews significant works in this domain, particularly focusing on the use of machine learning techniques for DDoS detection.

Numerous studies have utilized traditional machine learning algorithms to identify DDoS attacks. Mirkovic and Reiher [1] provided a comprehensive taxonomy of DDoS attack and defense mechanisms, emphasizing the effectiveness of classifiers like Support Vector Machines (SVM) and Decision Trees in distinguishing between benign and malicious traffic. Modi et al. [2] reviewed various intrusion detection techniques, highlighting the potential of machine learning methods such as Naive Bayes and Random Forest in enhancing detection accuracy. Anomaly detection, another widely used method, involves training machine learning models on normal traffic patterns to identify deviations indicative of an attack. Zhang et al. [3] proposed an anomaly detection method using PCA and k-means clustering to identify DDoS attacks, demonstrating the effectiveness of clustering techniques in isolating abnormal traffic behavior.

Deep learning techniques, particularly Recurrent Neural Networks (RNNs) and their variants, have shown significant promise in DDoS detection. RNNs, known for capturing temporal dependencies, are well-suited for analyzing network traffic data. Yin et al. [4] utilized a LSTM network to detect DDoS attacks, achieving high detection accuracy by leveraging temporal patterns in network traffic. Convolutional Neural Networks (CNNs) have also been explored for DDoS detection, with their ability to extract hierarchical features from network traffic data. Doshi et al. [5] employed CNNs to detect DDoS attacks, demonstrating the high accuracy of CNNs in classifying traffic patterns.

Recent research has increasingly focused on combining different machine learning models to leverage their respective strengths. Hybrid models aim to improve detection performance by integrating various algorithms. For instance, Tang et al. [6] proposed a hybrid model combining CNN and LSTM for DDoS detection. TTheir methodology employed Convolutional Neural Networks (CNNs) to extract spatial characteristics from traffic data, while Long Short-Term Memory (LSTM) networks were used to capture temporal patterns, leading to improved detection accuracy. Jasem and Jawhar [15] developed an Intrusion Detection System (IDS) that integrates LSTM and CNN algorithms to capture both spatial features along with temporal features from network traffic. This hybrid approach was tested on various datasets, including CIC-IDS2017, UNSW-NB15, and WSN-D, showing impressive accuracy in binary and multiclass classification tasks. Oleiwi et al. [17] designed a deep learning system for network intrusion detection by analyzing both spatial and temporal aspects of network traffic. Their hybrid model, combining LSTM and CNN algorithms with a category weight optimization technique, was evaluated using the CICIDS2017 dataset and demonstrated high performance. Other researchers introduced various ensemble-based deep learning methods and network intrusion detection systems leveraging different combinations of algorithms and techniques, such as K-means clustering, transfer learning, Random Forest feature selection, and bio-inspired algorithms, all achieving high accuracy and performance across multiple datasets [18-24]. Manickam et al. [25] created an ICMPv6-DDoS attack dataset using a GNS3 network simulation tool to simulate normal and abnormal ICMPv6 traffic, achieving high detection accuracy and low false positives, making it valuable for future research. Other researchers explored the role of blockchain and artificial intelligence in enhancing cybersecurity for the Internet of Medical Devices. These works examined the effectiveness of machine learning-based IDSs in differentiating between malicious and normal traffic, proposed methods for detecting ICMPv6 DDoS attacks on IPv6 networks using modified algorithms for feature selection, and investigated the integration of machine learning with blockchain technology to secure IoT devices [26-29]. Kim et al. [30] developed a hybrid deep learning model combining GRU and CNN for real-time detection of network intrusions. Tested on the UNSW-NB15 and CICIDS2017 datasets, their model demonstrated superior performance in identifying various types of network attacks. Lee and Park [31] introduced an advanced IDS using reinforcement learning and deep neural networks to adaptively respond to evolving cyber threats. Their system, evaluated on multiple datasets

including NSL-KDD and CIC-IDS2017, showed significant improvements in detection accuracy and response times.

These studies highlight the rapid advancements in the field of cybersecurity, particularly in developing robust and adaptive intrusion detection systems leveraging deep learning, machine learning, and blockchain technologies.

While existing methods have demonstrated substantial efficacy in DDoS detection, several limitations persist. Traditional machine learning approaches often struggle with the high dimensionality and dynamic nature of network traffic data. Deep learning models, despite their accuracy, can be computationally intensive and require significant training data. Moreover, many studies have focused on specific types of DDoS attacks, limiting their generalizability across different attack vectors.

Building on these existing works, our study proposes a hybrid model that combines the temporal feature extraction capabilities of LSTM with the powerful classification performance of XGBoost. This approach aims to address the limitations of individual models by utilizing their combined strengths, resulting in a robust and efficient solution for DDoS attack detection.

III. Proposed Hybrid Model Architecture

The hybrid model architecture proposed in this study leverages the strengths of both LSTM networks integrated with XGBoost for the classification of DDoS attacks. This section details the design and implementation of the hybrid model, including data preprocessing, feature extraction, and model training. The first approach in analyzing the "DDoS Attack 2019" dataset involves a combination of LSTM networks integrated with XGBoost, aiming to leverage the strengths of both deep learning and gradient boosting for the classification task.

A. LSTM for Feature Extraction

The LSTM model starts with an LSTM layer of 128 units, followed by dropout layers to prevent over-fitting. It then includes additional LSTM layers with progressively fewer units (64 and 32 units), reflecting a tiered approach to feature extraction. The final part of the LSTM model uses RepeatVector and TimeDistributed layers. The RepeatVector layer repeats the input to match the desired output length of the sequence, and TimeDistributed layers apply a dense layer to every temporal slice of an input. LSTM networks are well-suited for sequential data and can capture long-term dependencies in the dataset. The architecture of the LSTM model used in this study is as follows:

Input Layer: The input layer receives sequences of network traffic data.

LSTM Layer 1: This layer consists of 128 units and is configured with 'return_sequences=True' to output the full sequence to the next layer.

Dropout Layer 1: A dropout rate of 0.2 is applied to prevent over-fitting.

LSTM Layer 2: This layer has 64 units, with 'return_sequences=False' to output only the final state.

Dropout Layer 2: Another dropout layer with a rate of 0.2.

Dense Layer 1: A dense layer with 32 units and ReLU activation.

Dropout Layer 3: A dropout rate of 0.2 is applied.

Dense Layer 2: Another dense layer with 32 units and ReLU activation.

Output Layer: The final dense layer has 12 units, corresponding to the number of classes, with a softmax activation function for classification.

The LSTM model is trained using the Adam optimizer and sparse categorical cross-entropy loss. Early stopping is employed to halt training if the validation loss does not improve after a specified number of epochs, thereby preventing over-fitting.

B. XGBoost for Classification

The features extracted by the LSTM model are used as input for an XGBoost classifier. The XGBoost model is configured with specific hyperparameters such as colsample_bytree, learning_rate, and max_depth. The objective is set to multi:softprob for multiclass classification, producing predicted probabilities of each data point belonging to each class. XGBoost is a powerful gradient boosting algorithm that excels at classification tasks. In the hybrid model, the features extracted by the LSTM network are fed into an XGBoost classifier. The steps involved are:

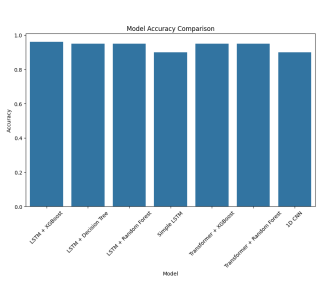
1) **Feature Preparation**: The output from the LSTM model is reshaped to fit the input requirements of XGBoost.
2) **XGBoost Configuration**: Key hyperparameters include 'colsample_bytree', which specifies the fraction of features to be used per tree, 'learning_rate' for controlling the step size during updates to prevent overfitting, and 'max_depth' for the maximum depth of a tree. The objective function is set to 'multi:softprob', suitable for multiclass classification, and 'num_class' is set to the number of classes.
3) **Model Training**: The XGBoost model is trained using the features extracted by the LSTM network and the original class labels from the dataset.
4) **Evaluation**: The model's performance is evaluated on a separate test set, with metrics such as accuracy, precision, recall, and F1-score providing insights into its effectiveness in identifying different types of DDoS attacks.

C. Dataset overview

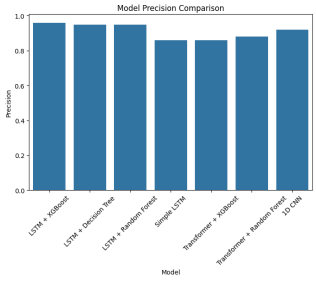
The dataset utilized in this paper comprises multiple CSV files, each representing different types of DDoS attacks, derived from network traffic logs. Each file is extensive, typically around 2 GB in total, but for computational efficiency, only a subset of 15,000 rows per file is used. The goal of this work is to create a hybrid machine learning model that effectively identifies and classifies DDoS activities within

Model	Input Layer	Feature Extraction	Batch Norm.	Dropout	Classifier	Accuracy	Precision	Recall	F1-Score
LSTM coupled with XGBoost	Standard Input	LSTM: 128, 64, 32	After each LSTM	After each LSTM	XGBoost	0.96	0.96	0.96	0.96
LSTM + Decision Tree	Standard Input	LSTM: 128, 64, 32	After each LSTM	After each LSTM	Decision Tree	0.95	0.95	0.95	0.95
LSTM + Random Forest	Standard Input	LSTM: 128, 64, 32	After each LSTM	After each LSTM	Random Forest	0.95	0.95	0.95	0.95
Simple LSTM	Standard Input	LSTM: 128, 64, 32 Dense: 64, ReLU	After each LSTM	50% after each LSTM	Dense + Softmax	0.90	0.86	0.90	0.88
Transformer + XGBoost	Input Layer Reshaping	Transformer Block Flatten Layer	Layer Norm.	Dropout in Transformer block	XGBoost	0.95	0.94	0.94	0.93
Transformer + Random Forest	Input Layer Reshaping	Transformer Block Flatten Layer	Layer Norm.	Dropout in Transformer block	Random Forest	0.95	0.94	0.94	0.94
1D CNN	Input Layer	Conv Layer: Kernel 7 Residual Blocks Dense: 64	After each Conv	In Dense Layers	Dense + Softmax	0.90	0.92	0.90	0.88

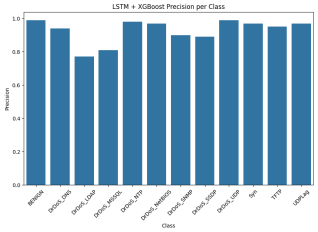
TABLE I: Model Architecture and Performance Comparison



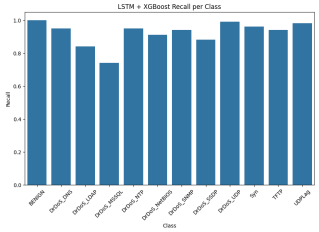
(a) Model Accuracy Comparison



(b) Model Precision Comparison



(c) LSTM coupled with XGBoost Precision per Class



(d) LSTM coupled with XGBoost Recall per Class

Fig. 1: Comparison of Model Metrics

network traffic, leveraging the strengths of both XGBoost and LSTM networks and algorithms. The CICDDoS2019 dataset is central to our study on DDoS attack classification. It is sourced from the Canadian Institute for Cybersecurity (CIC). The CICDDoS2019 dataset is publicly available through the Canadian Institute for Cybersecurity's dedicated datasets page. CICDDoS2019 encompasses a wide array of reflective and exploitation-based DDoS attacks, including but not limited to SYN, UDP, UDP-Lag, NTP, DNS, and MSSQL. These attacks were executed over two days, with detailed logs and traffic patterns recorded. The dataset used is the CICDDoS2019 dataset, which includes multiple types of DDoS attacks. Each type of attack is stored in a separate CSV file. The preprocessing steps are critical to ensure that the data is in a suitable format for the machine learning models.

IV. Results and Discussion

The methodologies were evaluated based on their classification accuracy and the detailed metrics provided by the classification report. The Table 1 presents a detailed comparison of various hybrid and standalone models in terms of their architecture and performance metrics. The LSTM coupled with XGBoost model stands out with the highest accuracy, precision, recall, and F1-score of 0.96, indicating its strong capability in capturing temporal patterns and providing robust predictions. The Transformer-based models, both with XGBoost and Random Forest classifiers, also demonstrate high accuracy of 0.95, showcasing the effective feature extraction capabilities of the Transformer architecture. The simpler models, such as the Simple LSTM and 1D CNN, while still performing well, have lower accuracy (0.90) and exhibit variations in precision and recall, highlighting their potential limitations in handling complex, high-dimensional data. Overall, the hybrid models, especially those combining LSTM or Transformer with ensemble classifiers, show superior performance, making them suitable for complex classification tasks in time-series data.

The following figures illustrate the performance of different models in terms of accuracy, precision, and per-class metrics for the LSTM coupled with XGBoost hybrid model. The comparison of different models through these plots highlights the superior performance of the LSTM coupled with XGBoost hybrid model. The combination of LSTM's temporal pattern recognition capabilities with XGBoost's powerful classification performance proves to be highly effective for DDoS attack detection.

Figure 1a shows the overall accuracy of different models. The LSTM coupled with XGBoost hybrid model achieves the highest accuracy of 96%, outperforming the other models. This indicates that combining LSTM for feature extraction with XGBoost for classification leverages the strengths of both methods, resulting in superior performance.

Figure 1b presents the precision of each model. Similar to the accuracy results, the LSTM coupled with XGBoost model exhibits the highest precision, demonstrating its capability to correctly identify positive instances across various DDoS attack types. The precision of this hybrid model underscores its robustness in handling imbalanced datasets and reducing false positives.

Figure 1c provides a detailed view of the precision for each class using the LSTM coupled with XGBoost model. The model shows particularly high precision for the BENIGN and DrDoS_UDP classes, indicating that it can effectively distinguish between benign traffic and specific types of DDoS attacks. However, there is a noticeable drop in precision for the DrDoS_MSSQL and DrDoS_LDAP classes, suggesting areas where further tuning may be beneficial.

Figure 1d depicts the recall for each class with the LSTM coupled with XGBoost model. The recall rates are high for most classes, indicating the model's ability to correctly identify a large proportion of true positives. Notably, the recall for the DrDoS_MSSQL class is lower compared to others, which aligns with the precision results and highlights a potential area for improvement.

The hybrid model achieved a remarkable overall accuracy of 95%. The classification report indicated high precision and recall across most categories. The hybrid model combining LSTM networks with XGBoost demonstrated impressive performance with an overall accuracy of 95%. This model utilizes the sequential learning capability of LSTM to capture temporal dependencies and patterns in network traffic, which are then used by the XGBoost classifier to make accurate predictions. The classification report for this model is detailed in Table II. The results indicate that the model performs exceptionally well across most classes. For instance, the model achieved a perfect precision and recall of 1.00 for the BENIGN class, demonstrating its high capability in identifying normal traffic accurately. Similarly, it achieved near-perfect scores for DrDoS_UDP, with a precision and recall of 0.99, reflecting its effectiveness in detecting UDP-based distributed denial-of-service (DDoS) attacks.

The model also performed well in identifying various DrDoS attack types, with F1-scores ranging from 0.77 to 0.96. Notably, DrDoS_LDAP and DrDoS_MSSQL had lower scores compared to other classes, which could be attributed to the less distinctive features of these attacks or potential imbalances in the dataset. However, the overall performance is commendable, as the model maintains high precision and recall for most classes, including DrDoS_NTP and DrDoS_NetBIOS, with F1-scores of 0.96 and 0.94, respectively.

In summary, the hybrid LSTM coupled with XGBoost model proves to be a robust tool for classifying and detecting various network traffic patterns, particularly in identifying benign and malicious activities. While there is room for improvement in the detection of certain types of DDoS attacks, the model's overall performance highlights its effectiveness and reliability in practical applications.

TABLE II: Classification Report of Hybrid Model

Class	Precision	Recall	F1-Score	Support
BENIGN	0.99	1.00	1.00	3000
DrDoS_DNS	0.94	0.95	0.95	3000
DrDoS_LDAP	0.77	0.84	0.80	3000
DrDoS_MSSQL	0.81	0.74	0.77	3000
DrDoS_NTP	0.98	0.95	0.96	3000
DrDoS_NetBIOS	0.97	0.91	0.94	3000
DrDoS_SNMP	0.90	0.94	0.92	3000
DrDoS_SSDP	0.89	0.88	0.88	3000
DrDoS_UDP	0.99	0.99	0.99	3000
Syn	0.97	0.96	0.97	3000
TFTP	0.95	0.94	0.94	3000
UDPLag	0.97	0.98	0.98	3000

V. Conclusion

The findings from this study underscore the efficacy of the hybrid model combining LSTM networks with XGBoost for DDoS attack detection. Our experiments demonstrate that this hybrid approach significantly outperforms the standalone LSTM model in terms of classification accuracy and other key performance metrics. By leveraging LSTM's ability to capture complex temporal dependencies and XGBoost's strength in classification through gradient boosting, this model successfully integrates the strengths of both techniques, leading to improved detection and classification of various DDoS attack types. Future research could explore additional hybrid combinations and further tuning to address the lower precision and recall for certain attack types, thereby enhancing the overall robustness of the model

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