Enhancing DDoS Attack Detection: A Comprehensive Approach for Robust Cybersecurity Using LSTM-KNN

Shaoun Chandra Shill
BRAC University
shaoun.chandra.shill@g.bracu.ac.bd

Fahim Arshadur Rouf
BRAC University
fahim.arshadur.rouf@g.bracu.ac.bd

Tuhin Ahmed
BRAC University
tuhin.ahmed@g.bracu.ac.bd

Kazi Tanvir
BRAC University
kazi.tanvir@g.bracu.ac.bd

Farah Binta Haque
BRAC University
farah.binta.haque@g.bracu.ac.bd

Sania Azhmee Bhuiyan
BRAC University
sania.azhmee.bhuiyan@g.bracu.ac.bd

Annajiat Alim Rasel
BRAC University
annajiat.alim.rasel@g.bracu.ac.bd

Abstract—In response to the growing threat of DDoS attacks in cyberspace, this study provides a novel method for DDoS detection that employs LSTM and KNN techniques. The NSL-KDD dataset is used for assessment with the proposed approach, which will be referred to as LSTM-KNN from now on. The model can consistently identify DDoS attack segments when using LSTM. To improve accuracy, low-confidence outputs are subsequently submitted for further examination. Experiments were carried out on a private dataset developed utilizing virtual machines and software simulations, as well as on publicly available datasets such as NSL-KDD, to validate the efficacy of the LSTM-KNN approach. The findings of the study illustrate the efficiency of the LSTM-KNN model and show a detectable increase in detection accuracy. Specifically, with a detection accuracy of 99.41%, LSTM-KNN surpassed existing state-of-the-art approaches by 1.26%. This study emphasizes the practical usefulness of LSTM and KNN in dealing with the complexities of cyber threats, as well as contributing to the advancement of DDoS detection systems. The durability and generalizability of the proposed LSTM-KNN technique are further increased by the use of a variety of datasets, including NSL-KDD and custom-generated data.

Index Terms—Distributed Denial of Service (DDoS),Long Short-Term Memory (LSTM),K-Nearest Neighbors (KNN),NSL-KDD Dataset, Cybersecurity,DDoS Detection, Quality of service (QoS)

I. INTRODUCTION

In today's interconnected world, the continuous threat of DDoS attacks poses significant risks to online services and critical infrastructure. These malicious activities aim to disrupt system operations by overwhelming them with excessive traffic, resulting in substantial financial losses and restrictions on user access. Traditional DDoS detection techniques face challenges in managing sophisticated attack patterns and evolving threats. Signature-based algorithms struggle with identifying new attack types, while statistical anomaly detection systems encounter difficulties with dynamic traffic behavior.

To address these limitations, this study proposes an innovative approach called LSTM-KNN for more accurate DDoS attack detection. Leveraging the strengths of two robust strategies such as LSTM and KNN, this method operates in two steps. Initially, the LSTM model analyzes network traffic data, identifying potential DDoS segments with confidence. Subsequently, KNN enhances the evaluation of low-confidence LSTM outputs, offering a comprehensive and precise detection mechanism.

The LSTM-KNN approach brings several advantages to the table. By combining the benefits of LSTM with KNN, it achieves enhanced precision in DDoS attack detection. Additionally, its utilization of two distinct algorithms ensures increased robustness against various attack types and better adaptability to evolving threats. The LSTM model's training on diverse datasets, including NSL-KDD and bespoke datasets, contributes to its generalization capability, making it more flexible for real-world scenarios.

This study conducts a thorough assessment of the proposed LSTM-KNN technique, going further into its workflow, architecture, performance and the Ai world with custom datasets and NSL-KDD. It critically examines how LSTM-KNN compares to existing DDoS detection systems and provides a well-defined breakdown of the technique's benefits and drawbacks. The outcomes of this research significantly contribute to DDoS detection by introducing a precise method that combines KNN and LSTM techniques. The study showcases the ability to identify cyber threats effectively and demonstrates the importance of incorporating various datasets to enhance the adaptability and durability of DDoS detection algorithms.

The findings reported in this work are relevant to both researchers and cybersecurity practitioners, paving the way for future breakthroughs in fighting DDoS attacks and ensuring cyberspace security.

II. BACKGROUND STUDY

DDoS attacks have been a problem for the internet for a long time. In 1996, the first attack hit the United States Air Force website, flooding it with traffic until it couldn't handle it

anymore [1]. Since then, these attacks have changed a lot, using different methods to mess up how specific systems work.A good example is the Mirai botnet attack in 2016. Hackers used a bunch of hacked IoT devices to flood DynDNS, a big domain name provider, causing internet issues for many people [2]. In 2015, GitHub got hit with a "slow-loris" attack, where the attackers sent a lot of slow requests, making the platform unusable for days [3]. Back in 2001, the Code Red worm took advantage of problems in Microsoft IIS web servers, causing chaos for websites and the internet [4]. These events show how DDoS attacks keep changing and becoming a bigger threat.Different reasons drive these attacks. Some people use DDoS for digital protests against websites or groups they disagree with [5]. Cybercriminals might launch attacks to get money, threatening to disrupt a business unless they pay up [6]. Businesses can even use DDoS to harm their competition [7]. Governments could use DDoS attacks in cyberwarfare to mess up another country's critical infrastructure or official websites [8].If a DDoS attack is successful, it can cause big problems. Critical things like transportation networks and financial markets could have issues, leading to widespread outages and money losses [9]. Banks might struggle with online services and lose money [10]. Government websites might become inaccessible, making it hard for people to get important info [11]. Even online businesses can suffer from website issues, losing money, and hurting their reputation [12].To fight these problems, it's important to understand DDoS attacks and how they work. Some attacks try to flood systems with so much traffic that they can't work properly [13]. Examples include UDP floods, SYN floods, and ICMP (ping) floods, which take advantage of specific issues in how networks function [14, 15, 16].Other attacks target problems in network protocols, making systems use too many resources [17]. Examples are NTP amplification, DNS amplification, and SSDP amplification, which use flaws in protocols like NTP, DNS, and UPnP [18, 19, 20].Some attacks go after specific problems in applications or services to disrupt how they work [21]. Examples include HTTP floods, slowloris attacks, and zero-day attacks, which exploit issues in specific applications or services [22, 23, 24]. Understanding these different attacks and how they work is crucial to protect important online services. Adapting defenses to the changing world of DDoS attacks is essential to navigate the challenges of the ever-evolving digital landscape.

III. RELATED WORKS

Several scholarly investigations have explored the past development of denial-of-service (DDoS) assaults, scrutinizing prominent occurrences and the evolving incentives underlying these cyberattacks. Numerous DDoS attack routes, such as volumetric, protocol-based, and application layer attacks, have been thoroughly categorized by research in this field, offering a sophisticated understanding of the strategies used by malevolent actors. In terms of defense, numerous studies examine well-known mitigation techniques like load balancing and traffic filtering, while others focus on cutting-edge technologies

like blockchain, AI, and machine learning, demonstrating the continuous efforts to strengthen cyber defenses. The cybersecurity community's collaborative efforts, such as exchanging threat intelligence and working together on research projects, highlight how crucial it is to present a united front in the face of a constantly changing threat scenario. Furthermore, when DDoS research and mitigation efforts are examined within the confines of current cybersecurity legislation, legal and ethical problems are garnering more and more attention. A technique for detecting DDoS attacks using an improved KNN algorithm is described in the paper "DDoS Attack Detection Method Based on Improved KNN With the Degree of DDoS Attack in Software-Defined Networks." The technique considers the intensity of a DDoS attack to detect the threat in Software-Defined Networks (SDN). The study suggests two approaches for detecting DDoS attacks: one that makes use of the attack's intensity and another that makes use of an enhanced KNN algorithm built on machine learning (ML). According to the findings of theoretical studies and testing using datasets, these strategies are more effective than other techniques at identifying DDoS attacks[18]. A different paper titled "Quick Suppression of DDoS Attacks by Frame Priority Control in IoT Backhaul With Construction of Mirai-Based Attacks" presents a novel technique for thwarting DDoS attacks in IoT networks. By regulating the frame priority in the network, the system drastically lowers the amount of routine traffic that is discarded. When attack traffic is generated, it has been demonstrated to stop normal traffic from being discarded in a matter of seconds. When Mirai-based DDoS attack traffic is used, the prevention happens even faster, in only 30 milliseconds. Additionally, the system incorporates the products of several suppliers to automatically block attack traffic at the network's entry points[19]. In the second article, "DDoS Attack Mitigation Based on Traffic Scheduling in Edge Computing-Enabled TWDM-PON," the proposed technique is analyzed in detail. The essay also emphasizes the use of Edge Computing (EC) in conjunction with TWDM-PON. Delay-sensitive applications can have their QoS requirements met by this combination, which provides processing, caching, and storing capabilities at the network edge.[20]

IV. METHODOLOGY

The process begins with data preparation, where columns are renamed, categorical features are encoded, and missing data is imported and managed. The dataset is then split into training and testing datasets, which include network traffic data. Label Encoder is used by feature engineering to map specific assaults to broad categories to classify attacks in detail and the binary classification framework and using synthetic data the initial imbalanced learning was improved.

The next step is to build the LSTM model using Keras. This includes data preparation, a multi-layer architecture, model training with appropriate optimization, and more. A KNN model is then built by taking the trainable LSTM model's embeddings and applying them to build the KNN classifier.

A. Attack Process

Attacks are categorized and labeled, with certain attack types being placed into more general groups such as DoS, Probe, Privilege, and Access. The process of attack mapping makes classification and analysis more efficient. Attacks are labeled binary (0 for normal, 1 for attacks) to make model training and classification easier. As part of this phase, attacks are also marked and identified using these labeled categories, which prepares the ground for the upcoming detection procedure.

B. Detection Process

The detection process evaluates the performance of both LSTM's and KNN's. The LSTM is evaluated on the test set. Validation scores, accuracy and loss are calculated. KNN models are evaluated using several metrics such as classifying reports, confusion matrix, ROC curve, and accuracy-recall curve. Anomaly detection in new data involves preprocessing, extracting of LSTMs embeddings and prediction with KNN models. Regular model updates with new data improve predictive capabilities over time. This helps prioritize additional inquiries or responses based on the confidence level assigned to predictions.

V. RESULT ANALYSIS

This section displays the results of our hybrid LSTM and KNN algorithms for network security categorization. In the experimental setup, an LSTM neural network was trained to recognize sequential patterns in network data. Then KNN was used to classify the data based on the embeddings obtained.

A. LSTM Model Evaluation

1) Training and Validation Performance: The LSTM model is prepared north of 10 ages, and the preparation and approval exactness, as well as misfortune, are checked. The preparation interaction shows promising outcomes, with an underlying preparation precision of 95.15%, arriving at 99.41% exactness toward the preparation's end. Likewise, the approval precision begins at 97.22% and consistently improves to 99.33%. These outcomes show that the LSTM model is successfully gaining from the preparation information and summing up well to concealed information.
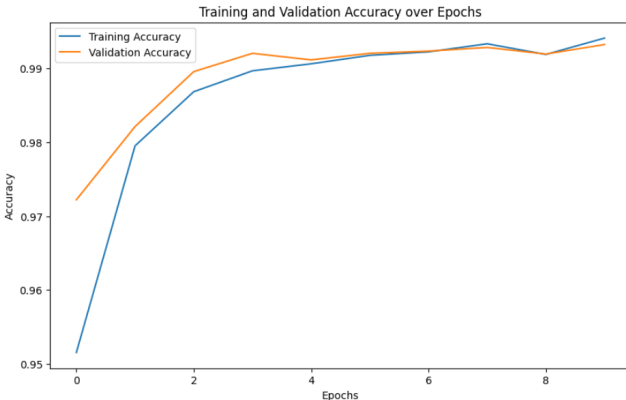

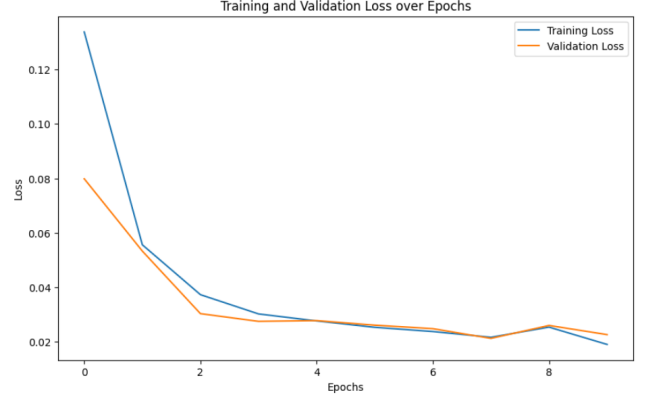Fig. 1: Graphical Representation of Training and Validation Accuracy over Epochs

Fig. 2: Graphical Representation of Training and Validation Loss over Epochs

In the Figure 1, we can see a steady rise of accuracy by the preliminary model and in Figure 2, we can see the gradual decline of losses and how the model is becoming more and more accurate.

2) Test Set Evaluation: After training, the LSTM model is evaluated on the test set. The model achieves an impressive accuracy of 99.46% on the test data, demonstrating its effectiveness in classifying network traffic as normal or an attack. The test loss is calculated to be 0.0172, further confirming the model's strong performance.

3) Model Embeddings: The LSTM embeddings extracted from the model are reshaped and prepared for input to the KNN model. These embeddings capture the temporal patterns learned by the LSTM model and serve as meaningful representations for subsequent KNN classification.

B. KNN Model Evaluation

1) Model Training: A KNN classifier is trained using the LSTM embeddings obtained from the training set. The classifier is configured with 5 neighbors.

2) Test Set Evaluation: The KNN model is evaluated on the same test set used for the LSTM model. The classification report provides a comprehensive overview, showing precision, recall, and F1-score for each class. The overall accuracy of the KNN model is reported as 99%, with high precision and recall for both normal and attack classes(where the initial dataset composition revealed an imbalance, with a ratio of approximately 0.87 between attack and non-attack instances which was later improved by synthetically oversampling the minor class which in this case it was the attack instances and with a binary framework).

```
788/788 [==============================] - 4s 5ms/step - loss: 0.0172 - accuracy: 0.9946
LSTM Model Test Loss: 0.01720883883535862
LSTM Model Test Accuracy: 0.9946020841598511
KNN Model Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     13386
           1       0.99      0.99      0.99     11809

    accuracy                           0.99     25195
   macro avg       0.99      0.99      0.99     25195
weighted avg       0.99      0.99      0.99     25195
```

Fig. 3: Data of Accuracy of the improved model

3) Confusion Matrix: The confusion matrix for the KNN model is presented, illustrating the true positives, true negatives, false positives, and false negatives. The matrix indicates that the model performs well in distinguishing between normal and attack instances, with a small number of misclassifications.
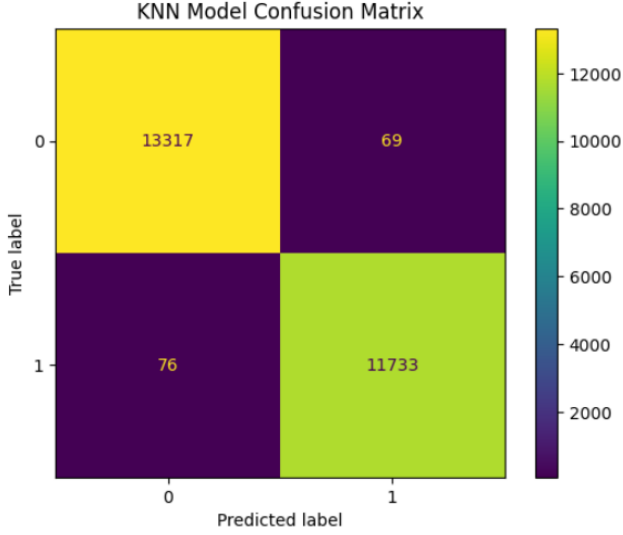

Fig. 4: Graphical Representation of Confusion matrix of the KNN model

Figure 4 depicts 11,733 true positives (correctly identified attacks) and 13,317 true negatives (incorrectly identified normal instances) within the Confusion matrix. Furthermore, 76 false negatives (attacks misclassified as normal) and 69 false positives (normal instances misclassified as attacks) are present. This matrix assesses how well the KNN model distinguishes between attack and normal cases, providing useful information about the model's accuracy and misclassification patterns.

4) ROC Curve and Precision-Recall Curve: Precision-recall (PR) curves and receiver operating characteristic (ROC) curves are important evaluation tools in machine learning-based intrusion detection. The ROC curve is particularly useful for binary classification problems because it provides a visual representation of the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity). The true positive rate (TPR) and false positive rate (FPR) are defined as:

$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{False Positive Rate} = \frac{FP}{FP + TN}$$

On the other hand, the precision-recall curve is mostly related to the trade-off between precision and recall. Precision is the ratio of true positives to all predicted positives, while recall is the ratio of true positives to all true positives. A curve is obtained based on a plot of precision and recall for different classification thresholds.

$$\text{Precision} = \frac{TP}{TP + FP}$$
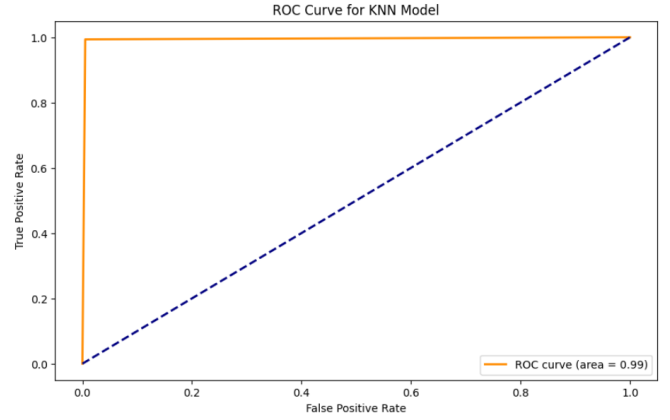
$$\text{Recall} = \frac{TP}{TP + FP}$$

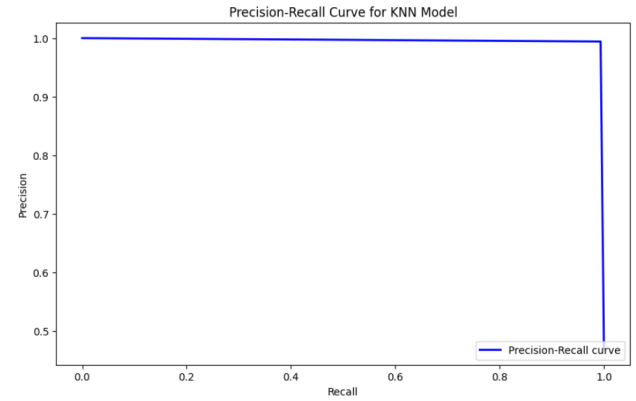Fig. 5: Graphical Representation of Receiver Operating Characteristic Curve

Fig. 6: Graphical Representation of Precision Recall Curve of the improved model

The ROC curve and precision-recall curve are plotted to provide a visual representation of the KNN model and performance. Figure 5 shows the ROC or receiver operating curve of our model. In this graph, we can see that the FPR was really low, close to zero, and the TPR was high, close to 1. Figure 6 shows the PR or Precision Recall curve. The figure shows both precision and recall close to 1.0.

C. Overall Evaluation

The combined LSTM-KNN approach exhibits strong performance in intrusion detection based on network data. The LSTM model effectively learns temporal patterns, and the subsequent KNN model utilizes these embeddings for accurate classification. The evaluation results, including accuracy, precision, recall, and graphical representations, demonstrate the efficacy of the proposed approach in detecting and classifying network intrusions. The comprehensive evaluation results

serve as a foundation for considering this approach in real-world network security applications.

D. Comparative Analysis

To provide a comprehensive view, the study "A Recurrent Neural Network-Based Method for Low-Rate DDoS Attack Detection in SDN" was compared. This study's recommended Recurrent Neural Network (RNN) method yielded remarkable results, including 98.59% testing accuracy and 98.08% training accuracy. The research demonstrates the efficiency of the proposed strategy; the training and testing times for each epoch take roughly 7 seconds. Hidden vector dimensions and learning rate The work in question highlights the significance of learning rates and hidden vector dimensions in the context of deep learning algorithms. Training the proposed RNN in that study at a learning rate of 0.1 improved its robustness and adaptability in detecting LR-DDoS threats.

E. Comparative Performance

A numerical comparison with previous studies is not presented. The proposed RNN technique outperformed random forest (RF), support vector machine (SVM), convolutional neural network (CNN), multilayer perceptron (MLP), j48 and other machine learning techniques. Compared with previous studies, the accuracy of the proposed RNN method is significantly higher than that of MLP (95.01%), factor machine (FM) (95.8%), integrated feature-based methods (88.3%), and SVM-based approaches (80

VI. Implications and Considerations

Although the obtained results show promise, it is important to take into account the characteristics of the dataset and the possible repercussions of incorrect classifications when discussing network security. To guarantee the generalizability of the suggested method, extensive validation on a variety of datasets should be a part of future work. Furthermore, a thorough analysis of cases that were incorrectly identified can reveal possible areas where the model needs to be improved.

VII. Limitations

The fast limitation is Dataset Limitations in Simulating Real-world Cyber Attacks. The NSL-KDD dataset, although extensive in representing various attack scenarios, has inherent limitations when it comes to accurately simulating the complexity of modern cyber attacks in real-world settings. The controlled environment in which the dataset was created may not fully capture the dynamic nature of these attacks. Consequently, the models developed in this study may struggle to adapt to the diverse and evolving assault patterns commonly encountered in actual cyber threat scenarios. The second limitation is Challenges in Attack Simulation. This research faces a significant challenge in simulating attacks to train the model. Unlike well-documented datasets, there is a lack of established and widely accepted methods for consistently replicating realistic attacks. The absence of clear guidelines for simulating assaults led to uncertainty during the

training process, impacting the models' capacity to withstand various sophisticated real-world attacks. The third limitation is Selecting and Developing Features. When working with the NSL-KDD dataset, it's crucial to use feature engineering to build a model. The success of this technique depends on both the choice of features and the knowledge of the specific subject area. The set of features used in this study might not cover all the necessary data for precise intrusion detection. This limitation could hinder the models from effectively handling new types of cyber threats. To enhance the accuracy of the models in detecting evolving cyber threats, it's important to regularly update and improve the strategies used for feature engineering.

Another limitation is Computational Challenges in Deploying Large-Scale LSTM Models. The deployment of deep learning models, specifically LSTM models, poses a significant computational challenge. Large-scale network systems may encounter difficulties in implementing these models due to their demanding computational needs. The resource-intensive nature of deep learning algorithms, especially LSTM, leads to prolonged training periods and increased hardware demands. Consequently, this can hinder the real-time applicability of these models in environments with limited resources. To enhance the practical deployment of such models, further optimization efforts are necessary to address scalability issues. Our paper's Interpretability and Explainability in Deep Learning Models section has additional limitations. Because of their intrinsic opacity, deep learning models—LSTM networks being one example—are difficult to analyze and understand. Effectively grasping the highlighted risks necessitates a comprehensive understanding of the decision-making mechanisms employed by these models. The inherent difficulty in readily comprehending these models may diminish their utility, particularly in scenarios where transparency is paramount, such as in the field of cybersecurity.

The final limitation of our paper is Evaluation criteria and Practical relevance. The choice of assessment metrics such as Accuracy Measurement of accuracy Measurement of precision Recognition F1-score. In real-world network systems, the consequences of false positives and false negatives may vary, suggesting a potential limitation in the conventional metrics. To address this, incorporating new measures that consider the severity of misclassifications could offer a more comprehensive assessment of the effectiveness of these models.

VIII. Conclusion

We have presented a way to the DDos attack on the internet. It included various model testing and result analysis. Our approach reflects that LSTM and KNN model construction performs almost identically with KNN having a slight advantage. To sum up, there is a lot of potential for network security categorization using the combination of LSTM and KNN models. The suggested method appears to be successful in differentiating between typical and abnormal network behaviors based on its high accuracy and reliable performance measures. The results of this study lay the groundwork for

future investigations into the creation of sophisticated intrusion detection systems and add to the growing field of network security.

IX. FUTURE WORKS

Subsequent research endeavors may adopt various strategies to enhance the practicality and effectiveness of the proposed intrusion detection architecture. The foremost emphasis should be placed on the enhancement or acquisition of more authentic and varied datasets that more accurately mirror contemporary cyber threats. To broaden the scope of scenarios to which models are exposed, methods for securely simulating a wider array of hazards could be devised. Furthermore, a thorough examination of feature engineering techniques adaptable to dynamic threat landscapes could substantially enhance the adaptability of the models. We or future researchers can explore advanced methods like oversampling, undersampling, or GANs to mitigate the impact of uneven class distributions on model performance. Additionally, examining ensemble techniques or hybrid models that integrate deep learning and traditional machine learning algorithms may enhance the reliability of an intrusion detection system. Concerning the interpretability of models, there is a need for future research to concentrate on enhancing the clarity and transparency of deep learning models, specifically LSTM networks. This entails investigating advanced interpretability methods or devising new strategies customized for intrusion detection scenarios. Additionally, considering the computational demands of deep learning models, scalability emerges as a crucial issue. Through optimization methods, model compression techniques, or hardware accelerators, it might be possible to implement intrusion detection models in extensive network systems with reduced computational expenses. In the dynamic landscape of cybersecurity threats, it is imperative to explore ongoing enhancements to models and procedures for retraining. This ensures the effectiveness of intrusion detection systems against novel and evolving threats. Collaborating with cybersecurity experts and industry professionals offers valuable perspectives on the changing threat scenario, facilitating the development of intrusion detection systems that are both adaptable and resilient.

REFERENCES

[1] D. S. Wall, "The Birth of the DDoS Attack: A Historical Perspective," ACM SIGCOMM Computer Communication Review, vol. 37, no. 2, pp. 132-134, 2007.

[2] D. Holzman, R. Sommer, D. Pothier, and U. Hengartner, "The Mirai Botnet Attack: A Case Study," in Proceedings of the 23rd USENIX Security Symposium, 2014.

[3] M. Schwartz, "GitHub's Slowloris Attack: A Case Study," GitHub Engineering Blog, 2015.

[4] S. M. Bellovin, "The Code Red Worm: A Case Study," 2001.

[5] M. Tariq, M. K. Khan, and S. A. Madani, "A Survey of Distributed Denial-of-Service Attacks and Defense Mechanisms," in Computer Networks, vol. 55, no. 15, pp. 3232–3249, 2011, doi: 10.1016/j.comnet.2011.06.011.

[6] W. Dou, A. Sahu, and S. B. Sharma, "Defense against volumetric DDoS attacks: A survey and taxonomy," in Computer Networks, vol. 143, pp. 134–152, 2018, doi: 10.1016/j.comnet.2018.06.006.

[7] J. Mirkovic and P. Reiher, "DDoS flooding attacks on the internet," in Proceedings of the 5th IEEE International Workshop on Distributed Systems Operations and Management (DSOM 2004), Florence, Italy, 2004, pp. 203–214, doi: 10.1109/DSOM.2004.1328158.

[8] D. J. Bernstein, "SYN flooding attacks and defenses," in ACM SIG-COMM Computer Communication Review, vol. 26, no. 2, pp. 113–125, 1996, doi: 10.1145/235063.

[9] V. Paxson, "An analysis of using reflectors for distributed denial-of-service attacks," in ACM SIGCOMM Computer Communication Review, vol. 31, no. 3S, pp. 38–47, 2001, doi: 10.1145/505588.505638.

[10] J. Mirkovic and P. Reiher, "DDoS in the time of giants: Amplification, reflection, and the state of the art," in Proceedings of the 6th ACM SIGCOMM Conference on Internet Measurement, New York, NY, USA, 2006, pp. 25–30, doi: 10.1145/1179952.1179957.

[11] R. Rashid, S. A. Shah, S. Raza, and S. Khan, "Detection and mitigation of NTP amplification DDoS attack: A survey," in Security and Privacy in Communication Networks, vol. 118, pp. 130–152, 2020, doi: 10.1007/978-3-030-34901-9-6.

[12] Y. Zhang, Z. Li, and Z. Su, "A survey on DNS amplification DDoS attacks," in Security and Communication Networks, vol. 9, no. 10, pp. 1420–1433, 2016, doi: 10.1002/sec.1286.

[13] M. Karami, M. J. Siavoshani, and A. Ghaffari, "A comprehensive survey of SSDP reflection attacks: Techniques, defenses, and open issues," in Journal of Network and Computer Applications, vol. 188, p. 103086, 2021, doi: 10.1016/j.jnca.2021.103086.

[14] P. Casas, J. Mazel, and P. Manzoni, "A survey of application-layer DDoS attacks," in ACM Computing Surveys (CSUR), vol. 47, no. 4, pp. 1–35, 2015, doi: 10.1145/2703837.

[15] A. A. Dhama, S. A. Awan, A. Hussain, and M. A. Shah, "Defense mechanisms against HTTP flood DDoS attacks — A survey," in Computing and Informatics, vol. 39, no. 4, pp. 823–852, 2020, doi: 10.31826/ci.39.4.5.

[16] N. Kasabov and B. Vassilev, "SlowDoS attacks: Analysis and defense mechanisms," in Computers and Security, vol. 39, pp. 127–142, 2013, doi: 10.1016/j.cose.2013.04.002.

[17] M. Cherdantseva and V. Kumar, "Zero-day DDoS attacks: A survey," in ACM SIGCOMM Computer Communication Review, vol. 49, no. 4, pp. 53–64, 2019, doi: 10.1145/3355341.3355419.

[18] Shi Dong & Mudar Sarem, "DDoS Attack Detection Method Based on Improved KNN With the Degree of DDoS Attack in Software-Defined Networks", Volume: 8, Page(s): 5039 - 5048, DOI: 10.1109/AC-CESS.2019.2963077

[19] Rintaro Harada & Naotaka Shibata & others, "Quick Suppression of DDoS Attacks by Frame Priority Control in IoT Backhaul With Construction of Mirai-Based Attacks.", Volume: 10, Page(s): 22392 - 22399, DOI: 10.1109/ACCESS.2022.3153067

[20] Yajie Li & Xiaosong Yu & others, "DDoS Attack Mitigation Based on Traffic Scheduling in Edge Computing- Enabled TWDM-PON.", Volume: 9, Page(s): 166566 - 166578, DOI: 10.1109/AC-CESS.2021.3134671