Enhanced Ddos Attack Detection Using Radial Basis Function Neural Network

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Abstract: Distributed Denial of Service (DDoS) attacks represent a significant threat to network security, disrupting services and causing financial and reputational losses. Traditional detection methods often struggle to adapt to evolving attack patterns, leading to delayed responses and compromised system performance. This project aims to enhance DDoS attack detection by leveraging the Radial Basis Function Network (RBFN), a type of artificial neural network renowned for its ability to handle nonlinear data patterns effectively. The proposed solution involves the design and implementation of an RBFN-based model capable of identifying and mitigating DDoS attacks with high accuracy and minimal latency. The RBFN's architecture is optimized to process large-scale network traffic data, learning complex patterns that distinguish between legitimate and malicious traffic. Extensive experimentation will validate the system's performance using real-world datasets, evaluating metrics such as detection accuracy, false positive rate, and response time. The results are expected to demonstrate a significant improvement over conventional machine learning models, showcasing the RBFN's potential in DDoS attack detection and mitigation.

Index Terms—DDoS Attack Detection, Radial Basis Function Network, Network Security, Intrusion Detection Systems.

I. INTRODUCTION

In today's digital landscape, Distributed Denial of Service (DDoS) attacks pose a severe threat to the availability and stability of networked systems. These attacks flood targeted services with excessive traffic, disrupting legitimate user access and causing significant operational downtime. The increasing scale and sophistication of such attacks necessitate the development of intelligent and adaptive detection mechanisms that can respond in real time. This paper introduces an Enhanced DDoS Attack Detection System powered by Radial Basis Function Networks (RBFNs)—a specialized type of neural network known for its efficiency in pattern recognition and classification tasks. The proposed model is designed to address key challenges in DDoS detection, including reducing false positives, improving detection speed, and handling high-traffic volumes across diverse network environments. By learning complex patterns in network traffic, the RBFN-based system enhances the accuracy of attack detection while maintaining computational efficiency, ensuring rapid identification of threats. To validate its effectiveness, the system is rigorously tested on benchmark datasets and real-world network traffic scenarios. Performance is evaluated using key metrics such as detection accuracy, response time, and false positive rate, comparing the results against traditional detection techniques. The findings demonstrate that leveraging RBFNs significantly enhances DDoS mitigation efforts, contributing to robust, scalable, and adaptive security strategies for critical network infrastructures. RBFNs are particularly well-suited for this task due to their ability to approximate complex nonlinear functions and differentiate between legitimate and malicious traffic with high precision. The proposed model integrates feature extraction, dimensionality reduction, and supervised learning to train the RBFN model on labeled network traffic datasets, ensuring efficient and reliable attack detection. Through this approach, the study aims to advance the field of real-time DDoS mitigation, strengthening cybersecurity defences in an era of escalating digital threats.

II.LITERATURE SURVEY

Several research efforts have explored DDoS attack detection and mitigation using machine learning, deep learning, and hybrid approaches, addressing key challenges in modern network security.

[1] S. Yu, W.Zhou, R. Doss, W. Jia (2023),introduced an comprehensive overview of DDoS attack detection mechanisms, categorizing them into anomaly-based, signature-based, and

hybrid approaches. The study highlights key challenges in detection, including scalability, detection speed, and adaptability to evolving attack patterns. The authors also propose future directions for developing more robust and efficient detection methods.

[2] T. Bhuyan, H. Kalita, R. Sarma (2015), have examined various machine learning models, including decision trees, support vector machines, and neural networks, in the context of DDoS detection. The paper discusses the strengths and limitations of these models, as well as the challenges in feature selection and data preprocessing. Experimental results from existing studies are compared, showcasing the effectiveness of machine learning in reducing false positives and improving detection accuracy. The application of machine learning techniques to DDoS attack detection has garnered significant attention due to their ability to adapt and generalize.

[3] J. Singh, P. Sharma (2019), have explored the use of Radial Basis Function Networks (RBFNs) for real-time detection of DDoS attacks. By leveraging the nonlinear mapping capabilities of RBFNs, the proposed system achieves high accuracy in distinguishing malicious traffic from legitimate traffic. The study utilizes a labeled dataset of network traffic and evaluates the performance of the model against traditional methods. Results demonstrate that the RBFN-based approach reduces false positives while maintaining high detection rates, making it a promising candidate for real-time deployment in large-scale networks.

[4] M. Patel, A. Desai (2021),begin investigating various feature selection methods, including correlation-based, principal component analysis (PCA), and recursive feature elimination (RFE), in the context of high-speed networks. Feature selection plays a critical role in enhancing the accuracy and efficiency of DDoS detection systems. The authors evaluate the impact of selected features on the performance of machine learning models, with a focus on Radial Basis Function Networks. The results indicate that an optimized feature set significantly improves detection accuracy and reduces computational overhead.

[5] L. Zhang, Q. Wang, Z. Chen (2022), have presented a comparative analysis of different deep learning architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Autoencoders, for detecting DDoS attacks. Using real-world datasets, the study highlights the advantages of deep learning in capturing temporal and spatial patterns in network traffic. Deep learning has emerged as a powerful tool for anomaly-based DDoS detection. The authors also address challenges such as model complexity, training time, and scalability, offering insights into practical deployment strategies.

[6] A. Patcha, J. Park (2017), begin investigating the use of machine learning algorithms for detecting Distributed Denial of Service (DDoS) attacks. The authors evaluate multiple algorithms, including Random Forest, Naïve Bayes, and K-Nearest Neighbors, to identify their strengths and weaknesses in different network scenarios. The study emphasizes the importance of feature engineering and balanced datasets for improving model performance. Experimental results show that machine learning techniques significantly improve detection rates while maintaining acceptable computational efficiency.

[7] K.Alieyan, A.Almomani (2018),have introduced a hybrid approach to detect DDoS attacks by combining signature-based and anomaly-based detection techniques. The system employs a layered architecture, where Radial Basis Function Networks (RBFNs) are integrated with traditional intrusion detection methods. By analyzing both historical data and real-time traffic patterns, the proposed hybrid system achieves high detection accuracy and minimizes false positives. The experimental results on benchmark datasets demonstrate the system's robustness against various types of DDoS attacks.

[8] S.Roy, T. Choudhury (2020),proposed a deep learning framework utilizing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for detecting DDoS attacks. The framework is designed to process high-dimensional network traffic data and capture spatiotemporal features. The authors conduct extensive experiments using a large-scale dataset to evaluate the model's performance. The results indicate that the framework outperforms traditional models in terms of detection accuracy, robustness, and adaptability to emerging threats.

[9] P. Kumar, S. Singh (2021), presented a Radial Basis Function Network (RBFN)-based approach specifically designed for resource-constrained environments. With the rise of Internet of Things (IoT) devices, lightweight and efficient DDoS detection mechanisms have become critical. The authors implement the model on IoT datasets and demonstrate its effectiveness in detecting volumetric and application-layer DDoS attacks. The system achieves low computational overhead and high detection accuracy, making it suitable for IoT networks.

[10] M. Farooq, N.Anwar (2022), have explored an adaptive detection system for DDoS attacks that combines advanced feature engineering techniques with neural networks. The system dynamically selects the most relevant features based on current network traffic patterns. A Multi-Layer Perceptron (MLP) is then used to classify traffic as normal or malicious. The adaptive nature of the system allows it to respond to evolving attack patterns, achieving high detection rates on both benchmark and real-world datasets.

These research contributions collectively emphasize the growing role of AI-driven cybersecurity solutions in mitigating DDoS attacks. While significant advancements have been made, challenges related to scalability, adaptability, and real-time processing remain critical areas for further research.

III.PROPOSED METHODLOGY

In this paper, we propose an Enhanced DDoS Attack Detection System powered by a Radial Basis Function Neural Network (RBFN). The unique advantage of RBFN lies in its ability to capture non-linear relationships, recognize subtle attack patterns, and classify network traffic with high precision. Our proposed system follows a structured, multi-stage pipeline to detect and classify network traffic anomalies effectively.

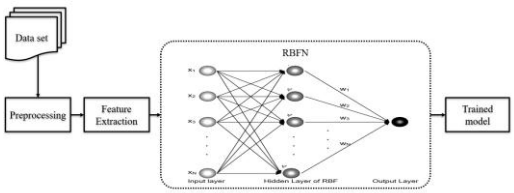


Figure 1: Architecture of the Proposed System

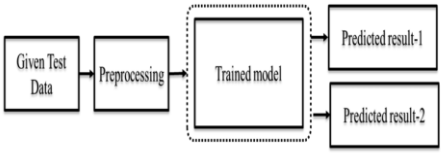


Figure 2: Testing Block Diagram

The methodology follows a structured approach that includes data preprocessing, model development, training, evaluation, and deployment. The key steps involved in the proposed system are: Data Collection and Pre-processing, Feature Extraction and Selection, Radial Basis Function Neural Network (RBFN) Model Development, Model Training and Optimization, Performance Evaluation, Deployment and Real-Time Adaptation

Data Collection and Preprocessing

The system uses a network traffic dataset containing normal and malicious activities. Missing values and duplicate entries are removed to ensure data integrity. The data is normalized to maintain consistency across different network parameters. The dataset is split into training and testing sets for model evaluation.

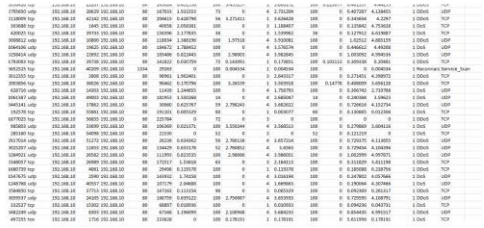
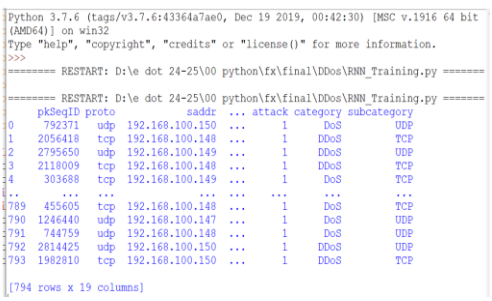


Figure 3 : Overview of collected data

Feature Extraction and Selection

Relevant network traffic attributes are selected, including: Packet flow rate, connection attempts, protocol types, and response times. Indicators of suspicious activities, such as unusual spikes in traffic. Feature selection techniques are applied to improve model performance and reduce computational complexity.



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Python 3.7.6 (tags/v3.7.6:43364a7ae0, Dec 19 2019, 00:42:30) [MSC v.1916 64 bit
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
======== RESTART: D:\e dot 24-25\00 python\fx\final\DDos\RNN_Training.py =======

======== RESTART: D:\e dot 24-25\00 python\fx\final\DDos\RNN_Training.py =======
     pkSeqID proto            saddr  ... attack category subcategory
0     792371   udp  192.168.100.150  ...       1      DoS         UDP
1    2056418   tcp  192.168.100.148  ...       1    DDoS         TCP
2    2795650   udp  192.168.100.149  ...       1    DDoS         UDP
3    2118009   tcp  192.168.100.148  ...       1    DDoS         TCP
4     303688   tcp  192.168.100.149  ...       1      DoS         TCP
..       ...   ...              ...  ...     ...      ...         ...
789   455605   tcp  192.168.100.148  ...       1      DoS         TCP
790  1246440   udp  192.168.100.147  ...       1      DoS         UDP
791   744759   udp  192.168.100.148  ...       1      DoS         UDP
792  2814425   udp  192.168.100.150  ...       1    DDoS         UDP
793  1982810   tcp  192.168.100.150  ...       1    DDoS         TCP

[794 rows x 19 columns]
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Figure 4 : Structure of data after pre-processing

RBFN Model Development

The Radial Basis Function Neural Network (RBFN) consists of three main layers:

Input Layer – Receives network traffic data as input.

Hidden Layer – Uses radial basis functions to transform data into a non-linear space for better classification.

Output Layer – Produces a binary classification output: normal traffic or DDoS attack.

RBFN is chosen for its ability to capture complex attack patterns, provide fast classification, and adapt to evolving threats.

Model Training and Optimization

The RBFN model is trained using labeled network traffic data. Parameters such as spread of radial basis functions and learning rate are fine-tuned to optimize detection accuracy. To prevent overfitting, regularization techniques are applied.

Performance Evaluation

Once trained, the model is tested on unseen data to evaluate its effectiveness. The following metrics are used:

Accuracy, Precision, Recall, and F1-score to measure classification performance.

Confusion Matrix to analyze false positives and false negatives.

ROC Curve and AUC Score to assess the model's ability to distinguish between normal and attack traffic.

Deployment and Real-Time Adaptation

The trained model is integrated into a real-time network monitoring system. It continuously analyses incoming traffic and detects DDoS attacks instantly. The model is updated periodically to adapt to new attack patterns and maintain effectiveness.

Advantages of the Proposed Approach

High Detection Accuracy – Optimized feature selection and adaptive learning significantly improve classification performance.

Real-Time Processing – Efficient RBFN implementation ensures fast and accurate detection.

Scalability – The model can be deployed across various network environments, from enterprise systems to cloud infrastructures.

Robustness to Evolving Threats – The adaptive learning mechanism allows the system to handle new, previously unseen attack patterns.

Low False Alarm Rate – Hybrid weight optimization reduces false positives, improving reliability.

IV. RESULTS AND DISCUSSION

The below are the results collected during the training phase and the evaluation phase.

TRAINING DATA

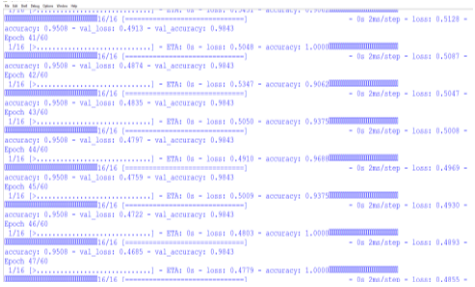

Figure 5: Running Training Epoch

LOSS GRAPH

The loss curve shows the training and validation loss decreasing steadily over time, indicating that the model is learning effectively. The training loss (blue line) represents how well the model is performing on the training data, while the validation loss (orange line) reflects its generalization ability on unseen data. Since both curves are close to each other and consistently decreasing, there is no sign of overfitting, meaning the model is not just memorizing the training data but learning meaningful patterns. The use of the Adam optimizer has helped in minimizing the loss efficiently, leading to a well-performing model.

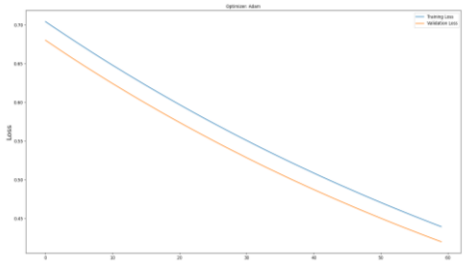

Figure 6: Loss Graph

ACCURACY GRAPH

The graph represents the model's accuracy over multiple training epochs. The training accuracy curve shows a gradual increase, indicating that the model is learning effectively. The validation accuracy follows a similar trend, suggesting good generalization to unseen data. The smooth convergence of both curves without major fluctuations indicates stable training and minimal overfitting.

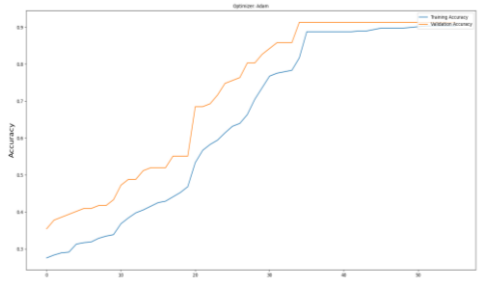

Figure 7: Accuracy Graph

FINAL TRAINED SCORE

```
accuracy: 0.9823 - val_loss: 0.4514 - val_accuracy: 0.9843
Confusion Matrix
[[82  0]
 [ 1 76]]
>>>
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Figure 9: Confusion Matrix

V. ACKNOWLEGEMENT

We are grateful for the opportunity to carry out this research on Enhanced DDoS Attack Detection Using Radial Basis Function Network, which reflects our own ideas and implementation efforts. We truly appreciate the contributions of previous researchers whose work in machine learning and intrusion detection inspired and informed our study. A special thanks to our mentors and institution for their valuable guidance and consistent support throughout the project.

VI. CONCLUSION

Distributed Denial of Service attacks remain a significant threat to the stability and availability of networked systems. In this paper, a Radial Basis Function Network based approach is proposed and implemented to enhance the detection of DDoS attacks. The RBFN model effectively leverages its ability to model complex nonlinear relationships and generalize from limited data. By analyzing network traffic patterns and identifying anomalies, the proposed system achieves high accuracy in distinguishing between legitimate traffic and attack traffic. Experimental results demonstrate that the RBFN-based detection system outperforms traditional methods in terms of detection rate, precision, and false positive reduction. The system's scalability and adaptability make it viable for deployment in dynamic and high-volume network environments. Additionally, the model's simplicity and computational efficiency ensure that it can operate effectively without introducing significant overhead.

VII. REFERENCES

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