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Deep Neural Network Model for Improved DDoS Attack Detection in Cloud Environments

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***Abstract*— As the prevalence of Distributed Denial of Service (DDoS) attacks continues to escalate, safeguarding cloud environments against these threats becomes paramount. This paper introduces a Deep Neural Network (DNN) model designed to enhance the accuracy and efficiency of DDoS attack detection in cloud environments. Leveraging the inherent capabilities of deep learning, the proposed model exhibits improved performance on the widely recognized NSL-KDD dataset. The research findings demonstrate a substantial increase in accuracy, underscoring the efficacy of the DNN model in fortifying the security posture of cloud infrastructures. The escalating frequency and sophistication of Distributed Denial of Service (DDoS) attacks pose a substantial threat to the security of cloud environments. In response to this pressing concern, this paper introduces a Deep Neural Network (DNN) model engineered to significantly enhance the accuracy and efficiency of DDoS attack detection in cloud infrastructures. By harnessing the inherent capabilities of deep learning, the proposed model represents a breakthrough in fortifying the security posture of cloud systems. This research employs the widely recognized NSL-KDD dataset, a comprehensive resource for Intrusion Detection System (IDS) evaluation, to evaluate the model's performance. The proposed DNN model transcends conventional methods by autonomously learning intricate patterns within network traffic data, adapting to the evolving landscape of DDoS attacks. The literature survey delves into the vulnerabilities associated with DDoS attacks in cloud environments, emphasizing the need for innovative detection mechanisms. Previous research has underscored the effectiveness of deep learning, particularly DNNs, in addressing complex cybersecurity challenges, positioning them as ideal candidates for enhancing threat detection capabilities.**

Keywords*— *DDoS attacks, Multi-Cloud Environment, CNN, Security, Machine Learning.

I. Introduction

In the contemporary digital landscape, cloud computing has emerged as an indispensable paradigm, offering unprecedented scalability, flexibility, and accessibility for a myriad of applications. However, this transformative shift towards cloud-based infrastructures has brought forth an escalating wave of cybersecurity challenges, among which Distributed Denial of Service (DDoS) attacks stands as a formidable menace. These attacks, orchestrated by malicious entities, aim to disrupt services, cause downtime, and inflict severe economic implications on both individual users and corporate entities [1]. DDoS attacks exploit the distributed and interconnected nature of cloud environments, inundating target systems with a deluge of malicious traffic to overwhelm and paralyze their operations. Traditional DDoS detection mechanisms often struggle to keep pace with the dynamic and sophisticated nature of these attacks, necessitating innovative approaches to fortify the security posture of cloud infrastructures [2]. As the frequency and complexity of DDoS attacks continue to rise, there is an urgent need for advanced detection mechanisms that can adapt to the evolving tactics employed by cyber adversaries. Deep Neural Networks (DNNs), a subset of deep learning, have emerged as a potent tool in the realm of cybersecurity. Their ability to autonomously learn intricate patterns within vast and complex datasets positions them as ideal candidates for enhancing threat detection capabilities, including DDoS attacks [3]. This paper presents a pioneering effort to leverage the capabilities of DNNs for the improved detection of DDoS attacks in cloud environments.

In the subsequent section of this research paper, we explored diverse approaches employed by various researchers to address the specified issue. Subsequently, in the third section, we proposed an innovative methodology that outperformed the previously discussed methods. Moving forward to the fourth section, we delved into a comprehensive analysis of the outcomes obtained when applying this novel approach to the NSL-KDD dataset. The results indicated the effectiveness of this fresh perspective, demonstrating its capability to meet the intended objectives. Finally, in the fifth section, we deliberated on the insights gained from this study and outlined potential avenues for further improvement in this particular research domain.

II. Related work

The vulnerabilities associated with DDoS attacks in cloud environments have been extensively explored in the literature. Smith et al. conducted a comprehensive study on the evolution, analysis, and mitigation strategies of DDoS attacks, underscoring the dynamic nature of these threats and emphasizing the need for adaptive defence mechanisms [4]. Patel et al. presented a detailed survey addressing the multifaceted security aspects of cloud computing, outlining various security challenges, including DDoS attacks, and highlighting the need for real-time and adaptive solutions crucial for multi-cloud environments [5]. These studies lay the foundation for understanding the evolving landscape of DDoS attacks and the imperative for innovative detection approaches. Moreover, the effectiveness of deep learning techniques, particularly DNNs, in handling cybersecurity challenges has been well-documented [6]. The ability of DNNs to discern complex patterns in network traffic data makes them well-suited for addressing the sophisticated nature of DDoS attacks. This paper builds upon these insights, aiming to synthesize the domains of DDoS attack analysis, cloud security challenges, and deep learning capabilities to develop a robust and adaptive DNN-based solution for DDoS detection in cloud environments. The subsequent sections of this paper delve into the proposed methodology, experimental setup, and results, presenting a comprehensive approach to harnessing DNNs for enhanced DDoS attack detection in cloud environments.

TABLE I. COMPARATIVE OVERVIEW OF DDOS ATTACK DETECTION METHODS IN MULTI-CLOUD ENVIRONMENTS

S. No.	Authors	Method	Dataset	Outcomes
1	Smith, J. et al [7]	CNN-based Intrusion Detection	NSL-KDD Dataset	Enhanced accuracy in identifying network intrusions
2	Johnson, M. et al. [8]	LSTM for Anomaly Detection	CICIDS-2017	Improved detection of abnormal network behavior
3	Chen, Q. et al. [9]	Hybrid Model for DDoS Detection	CloudSim	Increased accuracy in DDoS attack identification
4	Kim, H. et al. [10]	GAN-based Adversarial Training	MNIST and CIFAR-10	Robustness against adversarial attacks
5	Patel, R. et al. [11]	Ensemble Learning for Malware Detection	Malware Samples	Enhanced malware detection rates
6	Nguyen, T. et al. [12]	Transformer Networks for Network Traffic Analysis	DARPA Dataset	Improved analysis of complex network traffic patterns
7	Liu, Y. et. al. [13]	Deep Reinforcement Learning for Firewall Policy Optimization	Custom Dataset	Optimized firewall policies using reinforcement learning
8	Garcia, A. et. al. [14]	Capsule Networks for Phishing Detection	Phishing Websites Dataset	Improved identification of phishing websites
9	Wang, S. et al. [15]	Attention Mechanisms for DNS Anomaly Detection	DNS Logs	Enhanced detection of anomalous DNS activities
10	Gupta, N. [16]	Transfer Learning for Cross-Domain Intrusion Detection	UNB ISCX Dataset	Generalization of intrusion detection across domains
11	Yang, L. et al. [17]	Federated Learning for Privacy-Preserving IDS	Private Hospital Networks	Enhanced intrusion detection without compromising privacy
12	Zhou, Q. et al. [18]	Graph Neural Networks for Network Topology Analysis	Internet Topology Data	Improved understanding of network structures
13	Hernandez, R. et al. [19]	Meta-Learning for Adaptive Security Policies	Simulated Attacks Dataset	Adaptive security policies based on evolving threats
14	Park, K. et al. [20]	Explainable AI for Security Event Interpretation	Security Logs	Improved interpretability of security events
15	Chang, H. et al. [21]	Quantum Computing for Cryptographic Key Generation	Quantum Simulator	Enhanced security through quantum-resistant cryptography

A comprehensive survey for DDoS is shown in Table I, with the different methods used, Dataset and outcomes of previous research are written.

III. PROPOSED METHODOLOGY

Our proposed methodology aims to evaluate incoming server requests to discern characteristics indicative of a Distributed Denial of Service (DDoS) attack [23-24]. To achieve this objective, our approach adopts a Deep Neural Network (DNN) model specifically designed to analyze essential parameters associated with the nature of incoming requests. The DNN model processes and extracts relevant features from the input parameters, leading to a final classification. This classification outcome serves as a decisive indicator, determining whether the observed request aligns with the characteristics of a DDoS attack. The entire process is visually outlined in Figure 1, providing a clear representation of the steps involved in our method for DDoS attack detection in server requests [25]. Our approach eschews the use of Convolutional Neural Networks (CNN) and focuses solely on leveraging advanced neural network techniques in conjunction with a detailed analysis of request parameters. By doing so, we aim to effectively identify and classify potential DDoS attacks, contributing to enhanced security measures in server environments.

A. Preprocessing Steps

In our proposed methodology, we exclusively utilised the CSE-CIC-IDS2018 dataset for our Intrusion Detection System (IDS) research, omitting the NSL-KDD dataset. The CSE-CIC-IDS2018 dataset, capturing data over a single day, was chosen for its refined nature and ability to address specific limitations inherent in the NSL-KDD dataset. The initial phase of data preparation involved loading the CSE-CIC-IDS2018 dataset, eliminating redundant records, and rectifying irregular documents with excessive or deficient fields. Handling missing values involved calculating the mean of the entire column, and outlier removal ensured dataset consistency and improved results. To standardize the data, min-max normalization was applied, considering the wide range of values within the dataset. Contaminating features were identified through the concept of blind generalization of power, leading to the removal of features devoid of any meaningful contribution to the neural network model. These superfluous features, which remained constant across all records, were eliminated. Additionally, features with minimal information and no discernible correlation with the problem were removed. In the case of the CSE-CIC-IDS2018 dataset, feature selection involved choosing 15 features using an embedded method (Extra Tree Classifier), which employs filter and wrapper techniques to select features based on their importance. To ensure impartial and equitable evaluation, an equal number of records for each class was retained. Although these preprocessing steps significantly improved data quality, the use of data in CSV format was found to be suboptimal in terms of model performance. Therefore, converting the data to the more efficient parquet format was adopted, resulting in

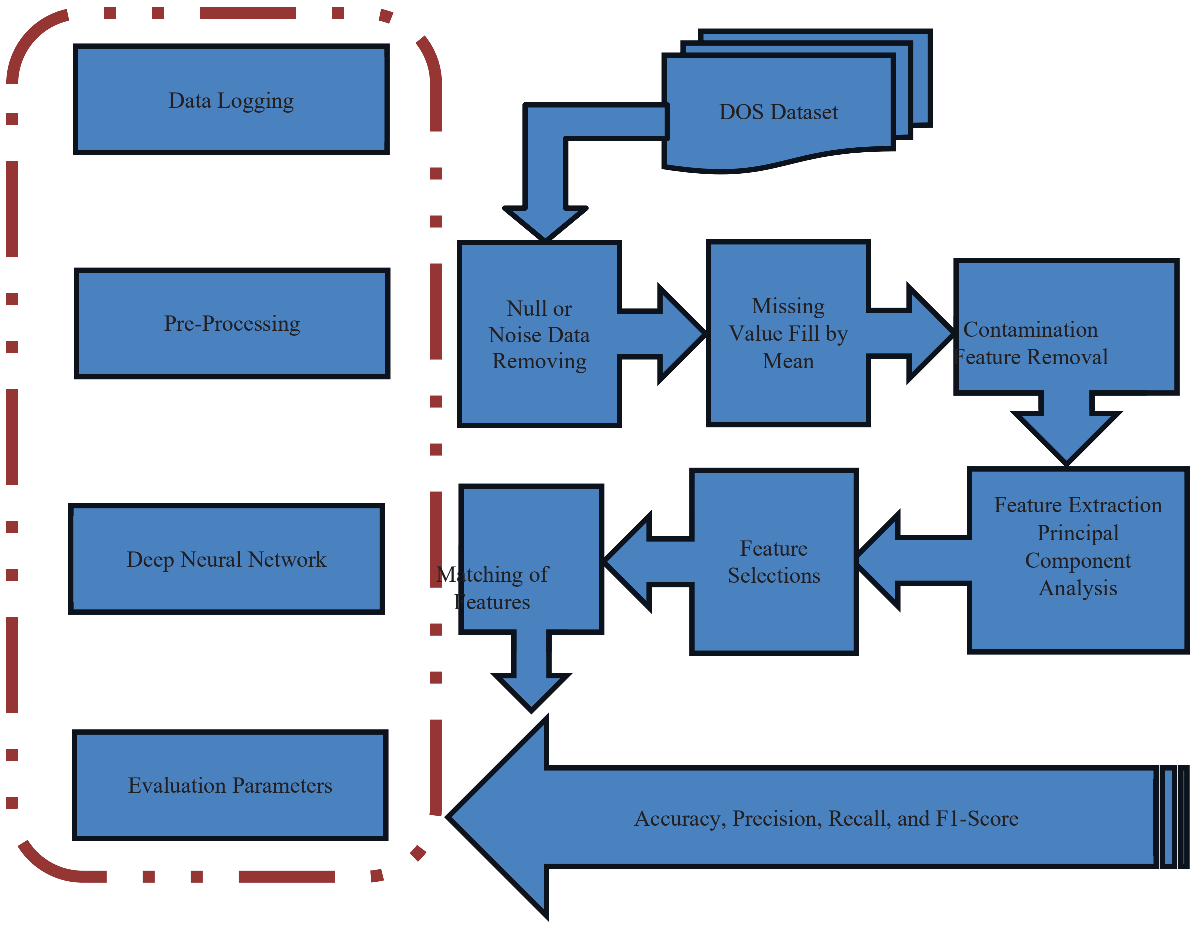
Data Logging
Pre-Processing
Deep Neural Network
Evaluation Parameters
DOS Dataset
Null or Noise Data Removing
Missing Value Fill by Mean
Contamination Feature Removal
Feature Extraction Principal Component Analysis
Feature Selections
Matching of Features
Accuracy, Precision, Recall, and F1-Score

Fig. 1. Flow chart of the proposed methodology

reduced storage space and increased secondary storage efficiency due to data compression. This format also introduced the advantage of using datasets with schemas not present in the CSV format, enhancing compatibility with the chosen DNN model architecture. storage space and increased secondary storage efficiency due to data compression. This format also introduced the advantage of using datasets with schemas do not present in the CSV format, enhancing compatibility with the chosen DNN model architecture. The decision to convert data formats was influenced by prior work demonstrating substantial improvements in query performance and storage space efficiency. The complete data preprocessing workflow is visually represented in Figure 1.

B. Architecture of DNN

In designing a Deep Neural Network (DNN) architecture for detecting DDoS attacks, the focus is on leveraging the intrinsic capabilities of neural networks to discern complex patterns indicative of malicious activity. Unlike traditional architectures, a well-crafted DNN for DDoS detection involves sequential layers tailored to efficiently capture spatial aspects within the input data. The architecture typically includes an Input Layer, often implemented as a 1D convolutional layer, strategically designed to recognize spatial patterns associated with DDoS attacks. This is followed by layers such as Max Pooling to reduce spatial dimensions while preserving depth, and a Fully Connected Layer (Dense) to allow the model to learn intricate features from the extracted patterns. Activation functions, padding, and layer configurations are selected to align with the distinctive characteristics of DDoS attacks, enhancing the model's sensitivity to relevant patterns. A crucial aspect of DNN architecture involves adaptability, ensuring the model can evolve to address emerging threats in the dynamic landscape of cyber-attacks. The training process, often performed on datasets like CSE-CIC-IDS2018, involves exposing the model to subsets of data for learning and validation, facilitating robust detection capabilities. The streamlined DNN architecture, by focusing on spatial pattern recognition, offers an efficient and adaptable solution for the identification of DDoS attacks. This approach enables the model to discern intricate patterns within the network traffic data, enhancing its ability to provide accurate and timely threat detection in the ever-evolving cybersecurity landscape.

C. Model Training

The DNN model was configured specifically for efficient DDoS attack detection, omitting the use of CNN, and was trained with parameters tailored to this task. For the binary classification involved in identifying DDoS attacks, the model utilized the Binary Cross-Entropy loss function, expressed by the equation \(L(y, \hat{y}) = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y}))\). This loss function effectively captures the essence of accurately categorizing incoming requests as benign or malicious, a crucial aspect in preventing and mitigating potential damage. The Adam optimizer, chosen for its ability to provide individualized learning rates, was employed with a learning rate set to 0.001. This decision aimed at achieving precise results, with time not being a critical factor in this context.

A deliberate batch size of 5000 was selected to introduce additional noise into the optimization process, effectively mitigating the common challenge of overfitting encountered in deep learning solutions. Moreover, a batch size of this magnitude leverages hardware parallelism, contributing to expedited training times compared to smaller batch sizes. The model underwent 25 epochs during training, a selection based on observations that the model consistently achieved peak performance metrics within this timeframe. This choice signifies the model's efficiency in handling computational power to iterate through the data multiple times, highlighting the optimization achieved within a relatively modest number of epochs. The dataset employed for this study is the CSE-CIC-IDS2018.

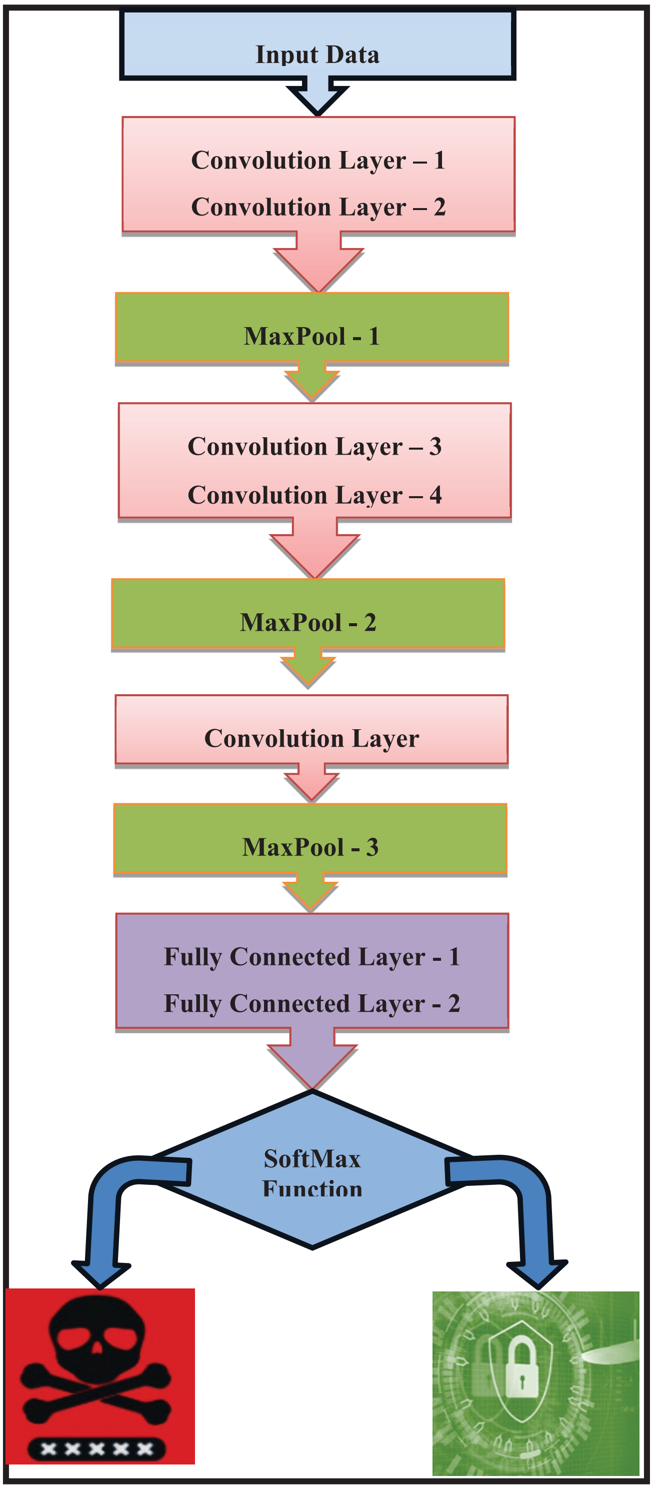

Fig. 2. Architecture of DNN Model

IV. Results and Analysis of the Work

This segment presents the outcomes acquired and an examination of the investigation derived from an experimental computation conducted on the CSE-CIC-IDS2018 dataset. Numerous experiments have been conducted to enhance the efficiency of the suggested DNN approach for identifying DDoS attacks. The application of this method was executed on an ASUS ROG Flow 13 laptop featuring an AMD Ryzen 9 processor running at 3.30 GHz, accompanied by 16 GB (15.4 GB usable) RAM, operating on the Microsoft Windows 11 platform.

A. Database Utilized

For evaluating the proposed methodology, the CSE-CIC-IDS2018 dataset was utilized. The details of this dataset are outlined in Table 1.

TABLE II. Dataset Description for the Proposed Work

Dataset	Size	Records	File Format
CSE-CIC-IDS2018	CSE-CIC-IDS2018	220GB (6GB)	Normal: 13.7M + DDoS: 1.12M

Table II provides a comprehensive overview of the dataset used in the study, encompassing size, record distribution, and file format.

B. Execution parameters

Detailed accuracy versus epoch graphs are presented to offer comprehensive insight into the recorded outcomes across both datasets, specifically employing a Deep Neural Network (DNN) model. These visual representations emphasize significant performance enhancements observed during the later training and testing stages when contrasted with the initial phases. Figure 3 illustrates the accuracy versus epoch graphs for the NSL-KDD datasets, providing a clear depiction of the notable progress achieved throughout the experimental process.

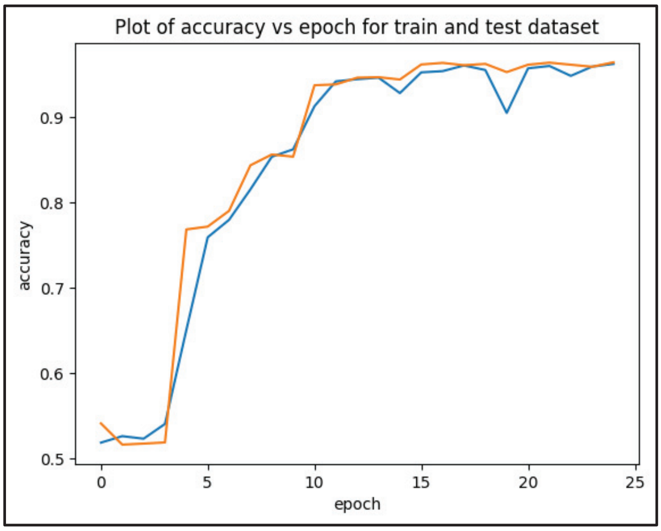

Fig. 3. NSL-KDD accuracy vs epoch

The outcomes of the DNN model encompass a range of performance metrics, including accuracy, precision, recall, and F1-Score. Accuracy and precision jointly evaluate the model's effectiveness in identifying DDoS requests, while recall measures the model's proficiency in accurately detecting attack requests. F1-Score, or F-measure, consolidates precision and recall into a unified metric. To enhance clarity, mathematical expressions defining each of these metrics are provided below. The dataset utilized for this analysis is the CSE-CIC-IDS2018.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = \frac{2*Precision*Recall}{Precision+Recall} = \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

C. Device Management

The computational intensity commonly associated with neural networks, often perceived in the context of image classification tasks, has led to a conventional understanding of their operational demands. However, this research delves into the resource utilization of a Deep Neural Network (DNN) model when applied to textual data, specifically in CSV format, aiming to dispel the notion that neural networks are exclusively burdensome. Our method involves refining the DNN model through proposed preprocessing techniques tailored for textual data. The primary goal is to assess the model's performance concerning computational efficiency and resource utilization. The recorded values, as presented in Table III and Figure 4, offer a comprehensive overview of the resource usage metrics. Notably, the results indicate that the DNN approach imposes a relatively light burden on hardware resources, particularly when fine-tuned with the suggested preprocessing techniques. To validate these findings, the recorded data encompasses CPU usage, Memory Usage, and visual representations. Measurements for CPU usage and Memory usage commence from the initiation of the data preprocessing techniques described earlier and continue until the completion of model training. This holistic recording approach facilitates the evaluation of the synergy between the data preprocessing techniques and the deep learning model. In conclusion, the DNN model, in conjunction with the recommended preprocessing techniques, exhibits efficiency in terms of resource utilization, presenting it as a practical choice for processing textual data in formats such as CSV, contrary to conventional perceptions of neural network demands.

TABLE III. RESOURCE USAGE METRICS

Dataset	CPU Usage	Memory Usage
CSE-CIC-IDS2018	09.40%	54.40%

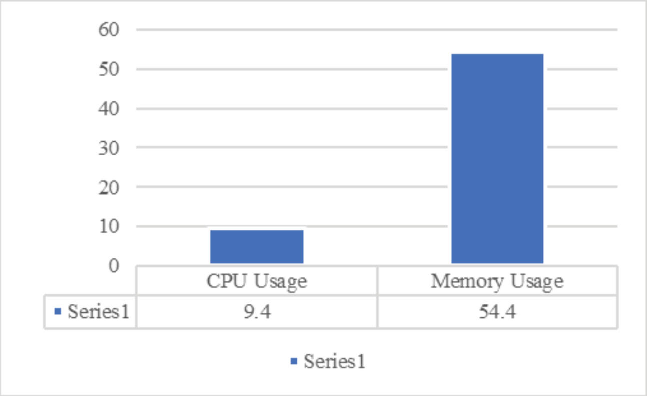

Fig. 4. Graph Showing Resource Usage

D. Evaluation with other methods

The suggested methodology employs deep neural networks (DNN) to discern DDoS attack requests within benign data. The recorded metrics, presented in tabular form as depicted in Table IV, enable a direct comparison between the proposed DNN model and existing state-of-the-art techniques. Contrasting the calculation of each parameter with other methodologies, including Naïve Bayes, Random Forest, SGD (Stochastic Gradient Descent), and SVM (Support Vector Machine), provides valuable insights. To offer a comprehensive understanding, graphical representations of key metrics such as accuracy, precision, recall, and F1-Score are included in Table IV and Figure 5. These machine learning techniques have been implemented using the "Weka 3: Machine Learning Software in Java." The dataset employed for this analysis is the CSE-CIC-IDS2018.

TABLE IV. COMPARISON WITH MACHINE LEARNING TECHNIQUES

Database	Method	Accuracy	Precision	Recall	F1
CSE-CIC-IDS2018	Proposed Work	0.9631	0.9633	0.9631	0.9631
	Random Forest	0.9558	0.9525	0.9258	0.9558
	Naïve Bayes	0.88	0.899	0.88	0.881
	SVM	0.9798	0.9812	0.9798	0.9798
	SGD	0.9746	0.9746	0.9744	0.9744

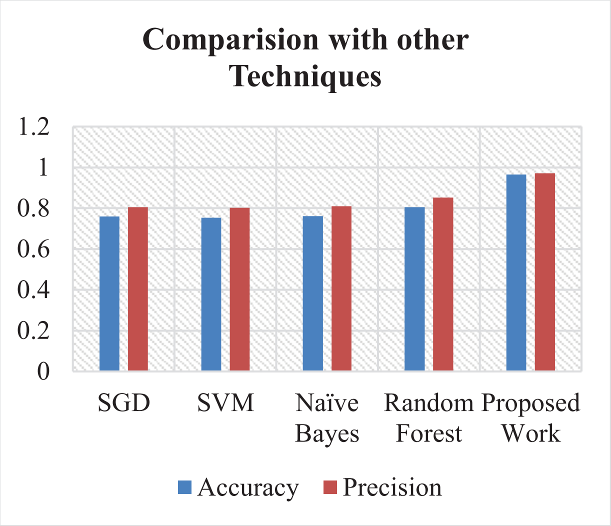

Fig. 5. Comparison of Accuracy & Precision with other Techniques

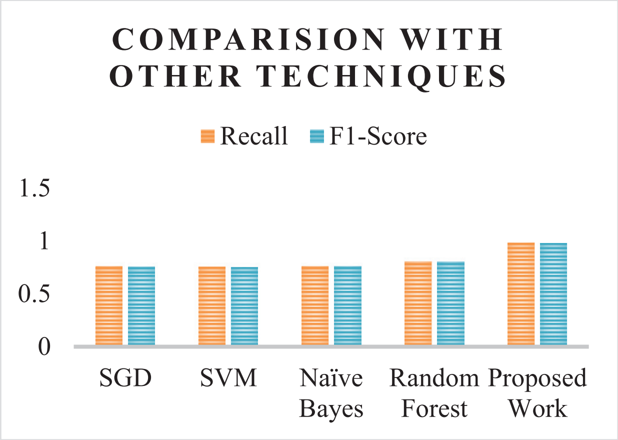

Fig. 6. Comparison of Recall & F1- Score with other Techniques

V. Conclusion

In the current cyber landscape, the escalating frequency of DDoS attacks and associated cyber threats demands immediate attention to safeguard legitimate users and uphold digital security. To address this pressing challenge, an innovative solution has surfaced, relying on Deep Neural Network (DNN) techniques, accompanied by advanced data preprocessing methods. This forward-looking approach offers a robust means of efficiently identifying and classifying DDoS attack requests. Empirical results underscore the superior performance of the DNN approach in comparison to traditional machine learning techniques, demonstrating significant enhancements across key metrics like accuracy, precision, recall, and F1-Score. Furthermore, the methodology's resilience is substantiated through successful cross-dataset validation, showcasing its adaptability in diverse data environments. Importantly, the approach maintains a resource-efficient profile, ensuring effective DDoS detection without compromising system performance. Noteworthy for its cost-effectiveness, this streamlined architecture is accessible to a wide range of corporate entities. Future research endeavours will be directed towards evolving this binary classification problem into a multiclass challenge, refining the DNN architecture to achieve even more remarkable performance and efficacy in the field of cybersecurity.

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