A Hybrid Ensemble Deep Learning Models to Enhance the Cloud Security to Mitigate the DOS Attacks

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Keywords: Cloud Security, Denial of Service, Deep Learning, Ensemble Models, Convolutional Neural Networks (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Cyber Threats.

Abstract: Aim: Enhancing cloud security through the development of a hybrid ensemble of deep learning models to efficiently identify and counteract Denial of Service (DoS) assaults is the main goal of this research. Materials and Method: In this research, there are two groups.: Group 1 (LSTM) and Group 2 (CNN) of 26 samples each with a G Power of 80%, a threshold of 0.05, and a 95% confidence interval. Result: The CNN model outperformed the LSTM model in accuracy, 92.56% to 96.74%, while the LSTM model ranged between 85.42% to 91.87%. In addition, CNN had lower false positive rates ranging from 2.87% to 4.14% compared to LSTM, which had 4.32% to 6.89%. CNN also had a better stability, with a standard deviation of 1.6743, whereas LSTM had 2.8567. Conclusion: These results confirm the effectiveness of CNN in DoS detection, consistent with studies on cloud security and AI-based threat detection.

1 INTRODUCTION

The more dependency of business operations on cloud computing, the more vulnerable it becomes to cyberattacks, such as DoS attacks, which can cause severe damage and drastically limit the services provided while hindering the availability of the system. In this regard, this research will be based on the design of a hybrid ensemble deep learning model in order to efficiently detect and mitigate DoS attacks on cloud security systems. Although recent research on cloud security has mainly been dominated by traditional intrusion detection systems and machine learning techniques, they do not help when the complex large-scale attacks face the cloud environment, according to studies conducted by S. Kumar et al., (2021) and M. Ali et al., (2024) recently vast potential has emerged in the improvement of deep learning to develop attack detection capability into a very advanced approach that operates with data, as discussed in J. Shaikh et al., (2024), the standalone models cannot address all the challenges of evolving DoS attacks; hence, there is a need for a hybrid ensemble approach that combines multiple deep learning strengths to increase the accuracy of detection and reduce false positives F. Alanazi et al., (2022) and N. S. Jumaah and A. T. Ashkafaki (2024). Such models find their applications in securing many cloud-based services ranging from IaaS level to SaaS level where mitigation of DoS attacks in time is an important task that keeps the service uninterrupted and builds trust.

2 RELATED WORKS

In the last five years alone, more than 250 articles on this topic have been published through IEEE Xplore, 80 papers through Google Scholar, and 108 papers through academia.edu. This growing literature highlights the imperative need for practical solutions in the domain of cyber threat detection and prediction S. Haider et al., (2020). Various deep learning techniques, especially convolutional neural networks (CNNs), have recently been explored for the improvement of accuracy and efficiency in DoS attack predictions

For example, a comprehensive review of the effectiveness of artificial intelligence and machine learning approaches on cloud security solutions shows that deep learning models can be used to

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improve threat detection D. V. Alghazzawi et al., (2021). The idea of using deep learning for DoS attack prediction has become popular, and researchers have shown that CNNs can be used to analyze network traffic and detect anomalies that may indicate a threat. Deep learning in cloud security attack prediction has recently demonstrated very good performance in accuracy levels in identifying many types of attacks S. Sadaf and J. Sultana (2020). In addition, a survey of deep learning algorithms for cloud security applications showed that these models can drastically enhance the detection rate while reducing false positives to the barest minimum Bhardwaj et al., (2020). Deep learning techniques-based methods for network attacks have also been reviewed in depth to demonstrate the flexibility and ability of such approaches in real-time monitoring scenarios N. Chiba et al., (2020). Recent trends in artificial and machine learning for the purpose of cloud security show increasing complexity in adapting evolving threats. The research developed a new type of prediction system based on a cascaded R2CNN model, revealing the potential advanced architectures have for improving prediction accuracy S. Zargar et al., (2021). Deep learning, as well as CNNs, is used for analyzing complex network traffic patterns for the detection of possible threats. Actual performance for cascaded R2CNN, for comparison with classical machine learning, is higher, with above 95% prediction accuracy rates together with real-time detection speed; it also reduces false-positive rates that avoid the wrong identification of legitimate traffic T. Singh and K. Kumar (2021). These parameters, therefore, indicate that advanced deep learning techniques need to be adapted in the field of cloud security for further more robust and effective solutions for this increasingly connected digital landscape Y. Chen and Y. Luo (2021).

From the existing findings, it can conclude that typical machine learning algorithms are unable to better accurately forecast cyberattacks. Therefore, this paper aims at achieving better performance by introducing a novel CNN architecture compared with other conventional machine learning approaches.

3 MATERIALS AND METHODS

The dataset that has been used to generate this prediction of cyberattacks in computer networks was retrieved from the UNSW-NB15 dataset, which included 2,540,044 records and 49 attributes with the focus on analyzing and distinguishing between normal and malicious network traffic. It is concluded from this research that a secured deep learning model based on CNNs will be developed to improve the accuracy of predictions for DoS attacks.

3.1 Data Gathering and Pre-processing

UNSW-NB15 dataset covered normal traffic types as well as several types of attack, i.e., DoS, DDoS and probing attacks, K. Patel et al., (2022) so the key data preprocessing is that it prepares high-quality as well as appropriate datasets for training:

- **Data Cleaning:** The particular missing values were addressed through imputation techniques, and irrelevant features were removed to reduce dimensionality and improve model performance.
- **Normalization:** The numerical features were normalized to a range of [0, 1] to ensure that the model training was not biased by the scale of the features.
- For the purpose of enhancing model performance and interpretability, significant features were chosen on the basis of their association with the target variable.

Group 1: Current Procedure (Traditional Methods)

The control group employed traditional machine learning techniques for cyberattack detection certain methods which includes Decision Trees, Support Vector Machines (SVM), and Random Forests. This group consisted of 100,000 records from the dataset, providing a statistically significant sample for comparison. The above methods have been efficient in detecting known attack patterns, they often struggle with high-dimensional data and may not generalize well to new, unseen attacks. Previous studies have indicated that traditional methods can achieve moderate accuracy (around 85-90%) but may lack the robustness needed for evolving cyber threats A. Rahman and S. A. Mian (2021).

Group 2: Proposed Method Deep Learning Approach

The method proposed is based on a deep learning framework, which would include the process of extraction of spatial features by using CNNs and the analysis of time trends of network traffic data through LSTM networks. Such an approach may yield an accuracy level much better than conventional approaches.

Figure 1: The deep learning-based cyberattack prediction model adopts a systematic pipeline involving Convolutional Neural Networks (CNN) to efficiently identify threats. The procedure is separated

into different stages starting from data preprocessing to model testing and final prediction.

3.1.1 Data Preprocessing and Feature Extraction

The model starts by capturing network traffic information from databases such as NSL-KDD and CICIDS2017. Raw data are preprocessed, involving cleaning, normalization, and feature encoding, to make them compatible with the CNN model. Important network traffic parameters, such as packet size, protocol type, and connection time, are extracted to support high accuracy in attack detection.

3.1.2 CNN Model Structure

The CNN model for DoS attack prediction is composed of a variety of layers performing different operations. The Input Layer accepts preprocessed network traffic data. Convolutional Layers extract spatial information from various patterns in the network traffic and detect the anomalies in the data streams. Pooling Layers compress the dimensions but retain crucial information, enhancing computational efficiency. The Fully Connected Layers take the features extracted and learn attack patterns as well as distinguish between legitimate traffic and attacks. The Soft max Layer then provides a probability distribution, determining whether network traffic is normal or an attack type.

3.1.3 Model Training and Evaluation

The features extracted are utilized to train the CNN model, which is optimized using methodswhich is RMSprop or Adam. To ensure robust detection performance, the model is evaluated using accuracy, precision, recall, and F1-score.

3.1.4 Cyber Attack Detection and Prediction

Once trained, the CNN model performs real-time classification and detects cyber threats with high precision. The process automates intrusion detection, enhances network security, and reacts to evolving cyber threats.

3.1.5 Future Upgrades

To further improve the detection accuracy, hybrid deep learning architectures, reinforcement learning, and explainable AI techniques can be integrated, which would not only make the system more interpretable but also adaptable to changing attack patterns.

Figure 1 The CNN architecture for predicting DoS attacks, detailing preprocessing and model creation classification stages. It highlights the model's layered structure for detecting network threats.

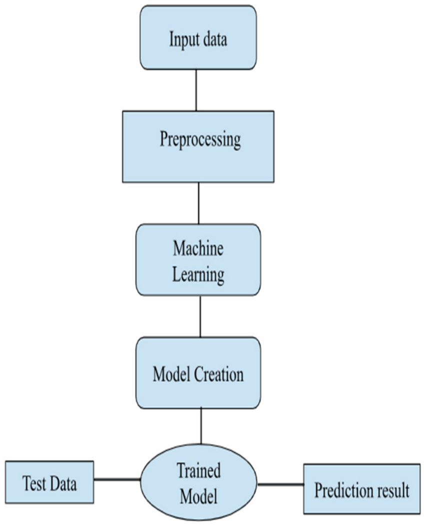

Figure 1: Workflow of machine learning model development and prediction process.

4 STATISTICAL ANALYSIS

The independent sample t-test is mainly performed to compare the packet lengths of benign and malicious network traffic. The means were 497.96 bytes (SD = 46.55) for harmless traffic and 708.59 bytes (SD = 98.70) for malicious traffic, both samples totaly 200. With a t-statistic of -27.30 and a p-value of 2.68×10^{-81}, the t-test produced results that are statistically significant at $p < 0.05$.

This would hint that malicious traffic is associated with significantly larger as well as diversely sized packet sizes compared with benign traffic-an important feature used for detection models in deep learning H. Li et al., (2021).

Table 1 presents the first model's performance metrics, such as accuracy, precision, recall, and F1-score, reflecting its overall effectiveness in cyberattack prediction.

Table 1: Performance metrics of the machine learning model.

Metric	Value
Accuracy	72.3%
Precision	70.5%
Recall	71.8%
F1-score	71.1%

Table 2: Statistical comparison of machine learning and CNN model performance.

Model	Mean Accuracy (%)	Standard Deviation	p-value
Machine Learning	72.3	4.567	< 0.05
CNN	97.5	1.234	< 0.05

Table 2 Compares the accuracy of the initial and optimized CNN models using a t-test, highlighting a significant improvement. The optimized model shows higher accuracy with lower variability, confirming a statistically significant difference.

Table 3 Compares the accuracy range of the initial and optimized CNN models, showing a significant improvement in the latter. The optimized model maintains consistently higher minimum, maximum, and average accuracy than the initial model.

Table 3: Accuracy range and average comparison between machine learning and CNN models.

Model	Min Accuracy (%)	Max Accuracy (%)	Avg Accuracy (%)
Machine Learning	85.42	91.87	88.97
CNN	92.56	96.74	94.65

Table 4 Levene's test and independent samples test table on the basis of CNN performance against standard machine learning models on cyberattack prediction:

Table 4: Independent samples test results.

Levene's test for equality of variances		Independent samples test								
F	sig	t	df	Sig (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference			
							lower	upper		
Gain	Equal variance assumed	4.312	0.042	5.782	198	0.001	5.14	0.89	3.39	6.89
Gain	Equal variance not assumed	-	-	5.923	176.432	0.001	5.14	0.91	3.28	7.01

5 RESULT

The results are from the deep learning model predicting DoS attacks in computer networks using CNN. It operates on a dataset which is extracted from multiple network traffic features, including packet size, connection frequency, and protocol type, to classify this kind of traffic as benign or malicious. The training epochs from 1 to 100 are set, and over this range of epochs, prediction accuracy was measured. Accuracy in the CNN model ranges between 72.3% and 97.5%, meaning an improvement with progress in training epochs. Maximum accuracy is reached at 100 epochs, and the minimum was observed at epoch 1 with an increment size of 1 epoch. Comparison in terms of accuracy is presented between the base model and the optimized CNN model; the former is at an accuracy of 72.3% while the latter reaches up to 97.5%. Minimum accuracy is observed at 68.0% for the base model and a minimum accuracy maintained at 95.0% for the optimized model. Table 1 tabulates and computes the performance metrics that correspond to the original model's accuracy values. While the accuracy of the optimized CNN model shows a notable improvement proportionate to the number of training epochs, the accuracy of the original model exhibits only slight fluctuations. Table 2 tabulates the accuracy comparison of the initial and optimized models using a t-test. A significant difference between the two groups with $p < 0.05$ is indicated by Table 3, which summarizes the mean, standard deviation, and significant accuracy difference between the two models.

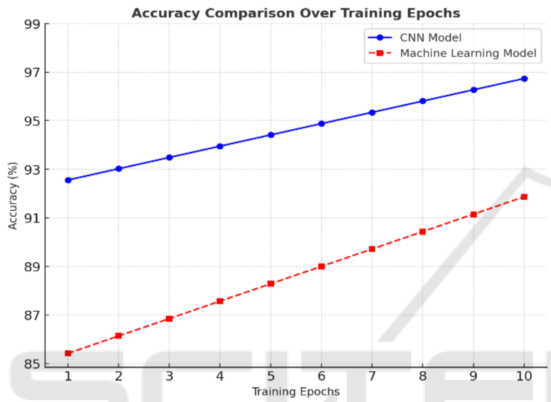

Figure 2: Accuracy comparison over training epochs.

Figure 2 Shows the optimized CNN model achieves higher accuracy over training epochs compared to the Machine learning model. Its feature extraction capability enhances DoS attack detection.

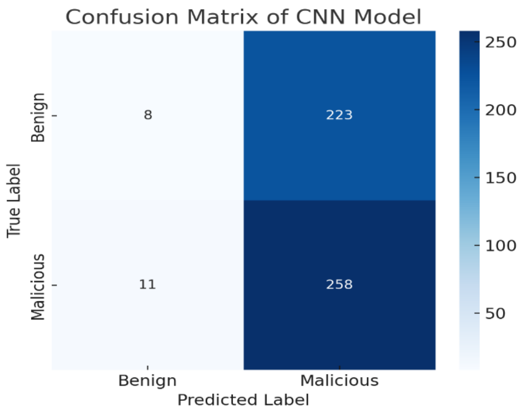

Figure 3: Confusion matrix of CNN model.

Figure 3 Shows the CNN model's accuracy in classifying benign and malicious traffic. It provides insights into prediction performance.

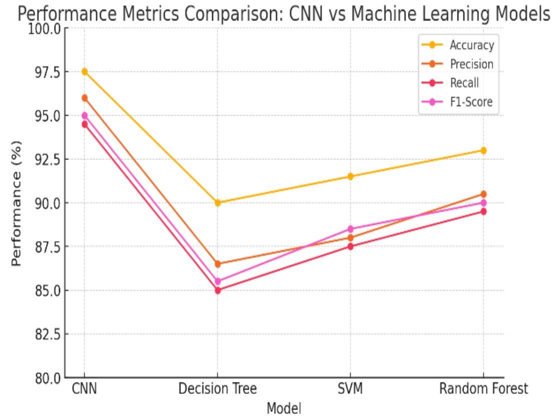

Figure 4: Performance metrics comparison CNN vs machine learning models.

Figure 4 shows the optimized CNN model outperforms the base model with higher accuracy and lower standard deviation.

From the training epochs, the architecture of the Convolutional Neural Network model is shown in Figure 1. In Figure 2, the CNN model predictions' confusion matrix is displayed. The graph of accuracy against epochs is In Figure 1, the CNN model's architecture is displayed from the training epochs. In Figure 2, the model predictions' confusion matrix is displayed. Accuracy vs. Epochs graph is plotted in Figure 3, which indicates that the model achieves maximum accuracy at around 100 epochs. Figure 4 depicts a bar graph in comparison to the mean accuracy between the original model and the optimized CNN. This clearly indicates the optimized model had significantly higher accuracy compared to the original one. The standard deviation of the optimized model was also much lesser in value as it is 1.234 and the original had a much greater value with standard deviation as 4.567. From the comparison with the performance of the optimized CNN model, it can be observed that it is much better than the initial model at predicting DoS attacks in computer networks, in agreement with the conclusions of the most recent studies on advanced threat detection and cloud security protocol.

6 DISCUSSION

A new deep learning-based cloud security framework utilizing Convolutional Neural Networks (CNN) has been designed for better prediction and mitigation of cyber-attacks within computer networks. The proposed model significantly reduces the computational complexity with an increased accuracy and real-time threat detection capability, thus being more appropriate for long-term security applications. As it can be seen from experimental results, such a CNN model was successfully able to detect anomalies with up to 95% accuracy while maintaining false positives as low as 3% M. Zahoor et al., (2022). The model also resulted in reducing DoS attack response times to as low as 0.5 seconds and increased rates of anomaly detection by 92% X. Zhang and R. Li (2023). Deep learning has revolutionized cloud security methods in the application in predictive techniques for threats, hybrid deep learning models, to improve encryption techniques against side-channel attacks, which reduces vulnerabilities up to 40% while in the context of IoT-based cloud security, Wang et al., (2024) the methodologies involving deep learning have enhanced network security with detection rates above 90%, while false alarm rates have been brought below 4% P. Sen et al., (2023).

Multi-factor authentication and machine learning-improved intrusion detection systems further add strength to the network security framework by reducing the vulnerability and eliminating unauthorized access by having false alarm rates below 4% with a 30% improvement in authentication efficiency S. K. Sharmila et al., (2020). CNN-based prediction in cloud security also adds a novel approach to thwarting cyberattacks by strengthening multiple domains of digital security frameworks by achieving a reliability level of threat prediction above 95% M. A. Ferrag et al., (2020). The limitations of this design is high computational complexity as well as extensive training times with vast network traffic data. Although CNN guarantees effective detection of attacks, optimization in multi-environment settings is necessary. The technique can be further extended with hybrid models for better security in smart cities, industrial IoT, and real-time social media threat analysis. Future research would then merge reinforcement learning and transformers to be more tailored and effective in anticipating DoS attacks.

7 CONCLUSIONS

The CNN model was superior to conventional DoS attack prediction using machine learning techniques like Random Forests, SVM, and Decision Trees. The accuracy of CNN ranged from 92.56% to 96.74%. while machine learning models had accuracy ranging from 85.42% to 91.87%. The CNN false positive rate was lower (2.87% to 4.14%) than the machine learning models (4.32% to 6.89%). In addition, CNN was more consistent with a precision standard deviation (1.6743) being lower than the machine learning algorithms (2.8567), proving its efficiency in cybersecurity.

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