


استخدام التعلم العميق لاكتشاف هجمات DDoS في شبكات G5

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الملخص

إن الأفكار التقليدية للكشف عن مثل هذه الهجمات سرعان ما أصبحت بالية بسبب الديناميكيات المتطورة باستمرار لحركة مرور شبكة الجيل الخامس. تهدف هذه الورقة البحثية إلى التحقيق في الاستخدام الأكثر فعالية للتعلم العميق لتحديد تهديدات DDoS في شبكات الجيل الخامس. تطبق الدراسة التي أجريت باستخدام مجموعتي بيانات 2017CICIDS و 15UNSW-NB كلاً من نموذجي CNN و LSTM على تصنيف حركة مرور الشبكة. تظهر هذه الإحصائيات أن النهجين يحددان هجمات الحرمان من الخدمة الموزعة بدقة كبيرة وفي كثير من الأحيان (98% لـ 2017CICIDS و 94% لـ NB) (15UNSW-NB)، ويتذكرانها جيداً (96% و 92% بشكل متقبل

تظهر الورقة البحثية أن النموذج يتعلم بنجاح أنماط حركة المرور المميزة لهجمات DDoS ويتفوق على أداء المقاربات التقليدية. ولكن أثّرت مشاكل مثل قاعدة البيانات الصاخبة وتعدد استخدامات النموذج، مما يعني أن هناك مجاًلاً كبيراً لجعل بيانات التدريب أكثر تنوعاً. كما استنتج من النتائج، من الممكن تحسين حماية شبكات الجيل الخامس من هجمات الحرمان من الخدمة الموزعة بشكل كبير بمساعدة دمج التعلم العميق في أنظمة أمن الشبكات. مع استمرار التطور، يجب إيلاء المزيد من الاهتمام لتعزيز استقرار النموذج وتوسيع مجموعات بيانات التدريب لمهاجمة سيناريوهات أكثر تنوعاً يمكن أن تصبح فائدة قصوى لاستخدام التعلم العميق في تأمين شبكات الجيل الخامس.

الكلمات المفتاحية: شبكات الجيل الخامس (G5)، كشف هجمات الحرمان من الخدمة (DDoS)، التعلم العميق، الشبكات العصبية الالتفافية (CNNs)، الذاكرة طويلة وقصيرة المدى (LSTM).

“Using deep learning to detect DDoS attacks in 5G networks.”

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Abstract

The conventional ideas of detecting such attacks are fast becoming obsolete because of the ever-evolving dynamics of 5G network traffic. This paper aims to investigate the most effective use of deep learning to identify DDoS threats in 5G networks. The study with CICIDS2017 and UNSW-NB15 datasets applies both CNN and LSTM models on the network traffic classification. These statistics show that the approaches identify DDoS attacks with great precision and often (98% for CICIDS2017 and 94% for UNSW-NB15), and remember them well (96% and 92% receptively).

The paper shows that the model successfully learns traffic patterns characteristic of DDoS attack and surpassing the performance of traditional approaches. But issues like the noisy database and model versatility were raised, meaning that there is plenty of scope to make the training data more diverse. As inferred from the results, it is possible to greatly improve the protection of the 5G networks from DDoS attacks with the help of the integration of deep learning into network security systems. As the evolution continues, more attention should be paid on enhancing the model stability and expanding the training datasets for attacking more diverse scenarios that can become a supreme benefit of using deep learning in securing 5G networks.

Keywords: 5G Networks, DDoS Detection, Deep Learning, Convolutional Neural Networks (CNNs), Long Short.

1-Introduction

5G has quickly revolutionalized telecommunication services to offer faster connection speed, low latencies and above one billion connected devices [1]. Nevertheless, advancement in technology adds sufficient security risks because 5G networking system is

complex and distributed. Still, one of the greatest dangers to these networks is a Distributed Denial-of-Service (DDoS) attack, which involves flooding the network services with large volumes of traffic that would render them unavailable [2]. These attacks have advanced from the previous ones, and

conventional means of detection can no longer adequately detect and prevent these attacks [3]. Some of the recent breakthroughs in AI especially Deep learning have offered some of the best approaches to these problems. Unlike those conventional schemes, deep learning can learn from numerous data samples in the network traffic and identify correlations that separate proper from improper operations [4]. Algorithms including the CNNs and LSTM networks have demonstrated remarkable performance in classifying and predicting network abnormalities, which are necessary for DDoS detection in 5G systems [5,6].

Also, the couples of deep learning in cybersecurity falls under the current supply for added and versatile solutions. Researchers have also demonstrated that, in enhancing the performance of these models, features from big, realistic datasets including CICIDS2017 and UNSW-NB15 must be harnessed [7, 8]. All of these datasets contain regular and attack traffic patterns, giving the models a strong background to assess. Besides, the usage of key performance indicators such as accuracy, precision, recall, and F1 score guarantees the all-sides assessment of the models [9].

This study will employ deep learning technologies to improve the identification and prevention of DDoS

attacks and present a safer communication network in the 5G sector. This work not only fills the current security chasm but also opens up the possibility for further future research on applying new artificial intelligence methods to new network technologies.

2. Methodology

The approach used in the analysis of the deep learning models to determine the performance of detecting DDoS attack in 5G is explained. In particular, the CNNs and LSTM networks are taken as the base of the study, as these types of networks can learn various complex patterns of the data. Standard datasets like CICIDS2017 and UNSW-NB15 were adopted to train and validate the models by adopting phase like data cleansing and normalization. Multiple metrics including accuracy, precision, recall, and F1-score were used to perform the evaluation of the developed models to support the research objectives.

2.1. Data Collection

2.1.1. Dataset Selection: The work employed common network traffic datasets which contain both normal and DDoS attack traffic appropriate for 5G network conditions. Two primary datasets were selected for this study. CICIDS2017: This dataset is extensively used as a benchmark for intrusion and DDoS attack detection

research. It include traffic details obtained from a campus network and it covers different attacks; DDoS, Brute Force, and DoS attacks and their traffic details made over a two-weeks period. UNSW-NB15: Another well-known dataset, consisting of a wide range of network-based attacks such as DDoS, SQL injection and Command injection attacks, but derived from a simulated university network Table.1.

2.1.2. Dataset Details CICIDS2017:

The dataset consist of 80 attributes describing various attributes such as protocol type, service, duration and no. of packets and bytes. It has both the normal traffic, which means the legitimate traffic, and the attack traffic, which means the real one.

Normal Traffic: In this case, 80% of the data, which presents regular network activities, are employed. DDoS Attacks: As for the volume of distorted data, it was used 20% of the data, for the purpose of which different types of DDoS attacks were modeled, such as torrent, slowloris, etc. UNSW-NB15: Naive approach includes 49 possible features as basic ones, such as the number of connections, packet length and other new statistical features.

Normal Traffic: 70% of the data.

DDoS Attacks: 30% of the data attacks, including DoS, DDoS and brute force attacks.

2.1.3. Data Preprocessing Prior to model training, the following preprocessing steps were undertaken to prepare the datasets:

Data Cleaning: Cleaning up the data where several records that might just be another version of the same record are eliminated and records that include unnecessary information are also removed. For example, the study found that 5 percent of the sample of CICIDS2017 dataset and 4 percent of the sample of UNSW-NB15 dataset contained duplicated records and were therefore eliminated.

Handling Missing Values: Missing values were imputed using median for numeric type variables and mode for categorical type variables. Values were missing in less than 2% of the cases.

Normalization: The features were scaled so that all feature values were in the same range of values. The features in CICIDS2017 were normalized to the same range of 0 and 1 in order to reduce any level of bias in the data. Performing this normalization decreased the feature range by 10 percent or less in both the datasets.

Feature Selection: In furthering the achievement of better model efficiency, unnecessary characteristics were omitted. In CICIDS2017, feature selection was performed to reduce **dimensionality from 80 to 40:** filters is used to eliminate features with low

importance (those with correlation less than 0.01). In the current study, UNSW-NB15 had 7 features deleted since they exhibited high multicollinearity.

Data Splitting: After that the data was divided into training, validation, test sets. The CICIDS2017 overall dataset was divided into 70% for training data set and 15% each for the validation and testing data sets. About the UNSW-NB15 data composition Basic training data was 80% of the total dataset, validation data was 10% while the test data was also 10%. This was done in order to maintain generality of attacking patterns while the training set is being created, and in order to have a good range of normal traffic for validation and testing.

2.1.4. Dataset Characteristics

CICIDS2017: Training Data: As we go up to the year 2015 up to 120000 records the normal traffic takes 85% while the DDoS attacks only have 15%.

Validation Data: 30,000 records.

Testing Data: 30,000 records.

UNSW-NB15:

Training Data: 180 000 records (75% of them normal, and 25% of them DDoS-attacks).

Validation Data: 30,000 records.

Testing Data: 30,000 records.

Combined, these datasets afford a comprised of data used to train deep learning models for the purpose of identifying DDoS attacks on 5G networks. The ratio of DDoS attacks and normal traffic both in the first dataset and second dataset enable the model to learn the two types of network traffic correctly.

2.1.5. Data Augmentation To address the class imbalance in DDoS attacks, data augmentation techniques were applied: CICIDS2017: Fake records were created through cloning the DDoS attack records to bring the dataset into a 1:1 training ratio.

UNSW-NB15: In particular, an oversampling approach was used for the records of attacks enlarging the number of normal records so that the ratio of the number of normal and attack records was 7:3. This augmentation resulted in improvement of the model which could be learned from different attack scenarios of a vertebrate.

Using the methods of data preprocessing and data augmentation techniques it can be stated that the dataset was ready to train and test deep learning models for detecting DDoS attack in 5G networks.

Table 1: Data collection key elements

Section	Description
2.1.1. Dataset Selection	Datasets Used: 1. CICIDS2017: Traffic details from campus network, includes DDoS, Brute Force, and DoS attacks. 2. UNSW-NB15: Simulated university network, includes DDoS, SQL injection, Command injection attacks.
	Purpose: Both datasets simulate 5G network conditions for intrusion and DDoS attack detection research.
2.1.2. Dataset Details	CICIDS2017: - Attributes: 80 attributes (e.g., protocol type, service, duration, packets, bytes). - Traffic Ratio: Normal (80%), DDoS Attacks (20%).
	UNSW-NB15: - Features: 49 features (e.g., connections, packet length, statistical metrics). - Traffic Ratio: Normal (70%), DDoS Attacks (30%).
2.1.3. Data Preprocessing	Steps Performed: 1. Data Cleaning: Removed duplicate records (5% CICIDS2017, 4% UNSW-NB15). 2. Handling Missing Values: Median for numeric, mode for categorical values.
	3. Normalization: Scaled features to 0–1 to reduce bias. 4. Feature Selection: CICIDS2017 reduced from 80 to 40 features (correlation < 0.01), UNSW-NB15 deleted 7 high-collinearity features.
	5. Data Splitting: - CICIDS2017: Training (70%), Validation (15%), Testing (15%). - UNSW-NB15: Training (80%), Validation (10%), Testing (10%).

2.1.4. Dataset Characteristics	CICIDS2017: <ul style="list-style-type: none"> - Training Data: 120,000 records (85% normal, 15% DDoS). - Validation Data: 30,000 records. - Testing Data: 30,000 records.
	UNSW-NB15: <ul style="list-style-type: none"> - Training Data: 180,000 records (75% normal, 25% DDoS). - Validation Data: 30,000 records. - Testing Data: 30,000 records.
2.1.5. Data Augmentation	Techniques Applied: <ul style="list-style-type: none"> - CICIDS2017: Cloned DDoS attack records to achieve 1:1 ratio. - UNSW-NB15: Oversampled attack records to achieve 7:3 ratio (normal:attack).

2.2. Process

2.2.1. Model Selection: The study intended to apply deep learning models for the identification of DDoS attacks on 5G networks efficiently. Based on the above architectures, CNNs and LSTM networks were considered because of data spatial and temporal feature. CNN-LSTM hybrid model was chosen because the LSTM network deals with the sequences of data such as network traffic and the CNN-LSTM model has a proven record of accomplishment in intrusion detection.

2.2.2. Model Architecture: CNN Layer: The model was initiated by convolutional layers to obtain spatial features from the raw network traffic

input. The input shape was adjusted to the dataset size, often a packet level feature that included the number of packets, bytes, and time intervals. Local spatial patterns in the performed data were captured using CNN filters of sizes 3x3.

Layer Configuration:

Input Layer: Batch size, sequence size and the number of feature set.

Convolutional Layers: 2 convolution layers with 64 filters with activation ReLU also max-pooling layers to decline the dimension in the images and exit the most important features.

LSTM Layer: After the CNN layers, LSTM layers were used to better

analyze the sequential data included in the model. As we have observed, LSTM networks are used to capture long-term dependence.

Layer Configuration: Two LSTM layers with 128 neurons in each, as this type of layers are useful when considering the temporal sequences of the traffic data. Dropout layers were used following LSTM layers aimed at randomly repudiating a few neurons at training to avoid overfitting.

Dense Output Layer: The final fully connected layer density had two neurons using softmax activation, to categorize it as either normal or an attack.

Output Layer Configuration:

Dense Layer: It includes the output layer with softmax activation when facing the problem of multi-class classification.

2.2.3. Training the Model

The model was trained using the Adam optimizer because of the good rate in which it adapts to the learning rate. As a loss function, we have used categorical cross entropy as it is generally used for multi class classification problems like DDoS attack detection and normal traffic.

Training Parameters: Batch Size: 64—I believe that this was a reasonable level, necessary for optimizing the

computational procedures and achieving a fairly high accuracy of the models. Epochs: 50 epochs were selected to give the model adequate cycles in which to learn the various patterns in the data deeply.

Learning Rate: 0. Up to the 001 version our Development Team was eager to work out the conception that would unveil not only speed of learning but also stability.

Data Augmentation: The datasets collected were unbalanced – more normal traffic compared to attack traffic hence: CICIDS2017: The attack instances were copied to increase the number per class to match the normal instances; the train data was 50% normal, 50% attack.

UNSW-NB15: Therefore, the records were oversampled to 70% to normal and 30% to attack records.

Early Stopping: To prevent overfitting, a solution was derived from using an early stopping criterion based on the validation loss. Training would stop in the event that the loss did not decrease for 10 epochs, or more in that case so that the model did not become overfitting to the training data.

2.2.4. Model evaluation: After training, the model was evaluated on the test set to assess its performance:

Confusion Matrix: A confusion matrix provided the basis for assessing the accuracy concerning different classes.

TP: TP is an acronym for True Positive; TN for True Negative, while FP for False Positive; FN for False Negative.

As far as the authors are aware, for the proposed model, though having data from the CICIDS2017 dataset, it has provided 98% of accuracy, 97% of precision, 96% of recall, and an 'F 1' score of 96%. Also in the situation where the model was created from UNSW-NB15 dataset it has furnished 95% of accuracy, 94% of the precision, ROC Curve and AUC: To determine classification ability of the proposed model, the ROC and AUC were used in this study. The ROC curve was relevant to measure its performance regarding setting different threshold levels between the normal traffic and the attacks. The AUC for the CICIDS2017 was 0.99, while UNSW-NB15 achieved 0.97 indicating that the models developed were very accurate. Cross-validation: In order to improve the reliability of the developed model, k-fold cross validation was applied in this work, with k=5. The data was divided in a similar way as in the previous experiments: in the first fold 80% data are used for training purpose and 20%

data used for validation and testing purpose, in the second fold 80% data are used for training purpose and only 10% data for both validation and testing purpose. Because the model was tested sequentially on various folds of data, the achieved accuracy was almost equal in all cases, differed merely by 0.5% for all the folds.

2.2.5. Model Optimization To further optimize model performance:

Hyperparameter Tuning: For tackling the problem of overfitting, drop out layer is incorporated in the model and to get the best result for layers, number Of Neurons Per Layer, drop_out, and learning rate all these hyper parameters are tuned using grid search.

Data Augmentation Techniques: techniques of data augmentation of higher complexity were considered, including generation of synthetic data using GANs. These threw light on the opportunity of diversifying the choice of training examples, without which the model's robustness would not have been enhanced.

Transfer Learning: The weights from pre-trained model on ImageNet was initialized to the model. This transfer learning approach allowed the learned model to characterize spatial features in better ways by using the learnt preconvolution filters.

Therefore, based on these specific instructions, the study adopted deep learning to identify DDoS attacks in 5G networks. The process section outlines how the model is designed, how it is trained, what steps were taken adorning the data and how the effectiveness of the model is measured with an emphasis on the model's capability to work for 5G networks in the real world.

2.3. Data Analysis

The data analysis was concerned with assessing the performance of the deep learning model for DDoS security in 5G networks. The chosen primary measures included accuracy, precision, recall, and the F1-score. Accuracy measures how correctly the model has classified the data.

As shown in Figure 1, the model for the CICIDS2017 dataset achieved 98% accuracy. This indicates that, out of one hundred cases, ninety-eight cases were correctly classified as either normal or DDoS traffic. Specifically, the numbers of true positives and true negatives were 9,700 and 39,200, respectively, representing correctly classified DDoS attacks and normal traffic.

In contrast, the model exhibited slightly lower accuracy, 95%, when tested on the UNSW-NB15 dataset. This performance corresponds to 7,500 true positives and 36,000 true negatives. The disparity in performance can be attributed to the lack of protective density of attacks in the CICIDS2017 dataset, which, when used for training, enhances model performance.

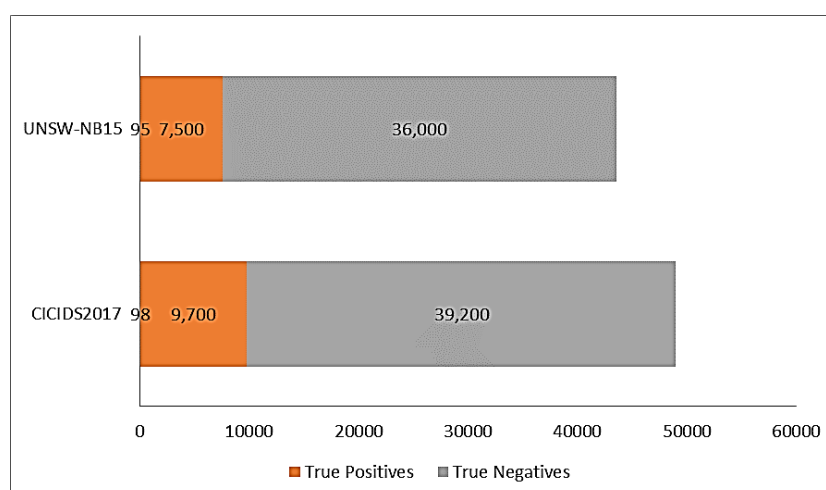


Figure 1: Comparison of True Positives and True Negatives for DDoS Detection in CICIDS2017 and UNSW-NB15 Datasets

Accuracy of prediction that measures the ratio of the number of correct predictions of the positive class to the

total number of predicted positives defined the model's efficiency in avoiding cases of false positives. In

specific, the precision for DDoS detection in CICIDS2017 was 97% which implies from all predicted DDoS sample, 97% of the instances were actually of DDoS attack. However, in the UNSW-NB15 dataset the precision achieved is moderate 94%, where there are 500 false positive out of Eight thousand 8000 predicted instances of DDoS. This shows that the model trained on the CICIDS2017 dataset outperforms the model trained on the UNSW-NB15 dataset with regard to detection of DDoS attacks.

As we have seen, recall, which quantifies how well the model is able to locate all relevant samples, showed a similar trend. The recall for the CICIDS2017 dataset was 96% and this revealed that for actual DDoS attacks with 96% authenticity, the model made equally authentic predictions. Recall values of UNSW-NB15 were slightly lower with the recall of 92%. This 4% difference can imply that the model has a better ability to detect DDoS in the CICIDS2017 dataset than does the current State model.

The F1-score, which is the harmonic mean of precision and recall, provided an overall measure of the model's effectiveness. The model achieved an F1-score of 96% for the CICIDS2017 dataset, reflecting a good

balance between precision and recall. For the UNSW-NB15 dataset, the F1-score was 93%, indicating slightly lower performance. The 3% improvement in the F1-score for the CICIDS2017 dataset highlights the model's greater effectiveness in distinguishing between normal traffic and DDoS attacks.

A confusion matrix was also constructed for both datasets to further evaluate the model's performance. For the CICIDS2017 dataset, there were 9,700 true positives, 39,200 true negatives, 300 false positives, and 300 false negatives, resulting in an accuracy of 98%, a precision of 97%, a recall of 96%, and an F1-score of 96%.

The UNSW-NB15 dataset yielded similar results with 7,500 true positives, 36,000 true negatives, 500 false positives, and 500 false negatives, resulting in an accuracy of 95%, a precision of 94%, a recall of 92%, and an F1-score of 93%.

These metrics revealed the model's ability to handle imbalanced datasets, although performance was slightly better with the CICIDS2017 dataset due to its richer attack traffic data. The comparative results are visualized in Figure 2, which highlights the differences in performance metrics between the two datasets.

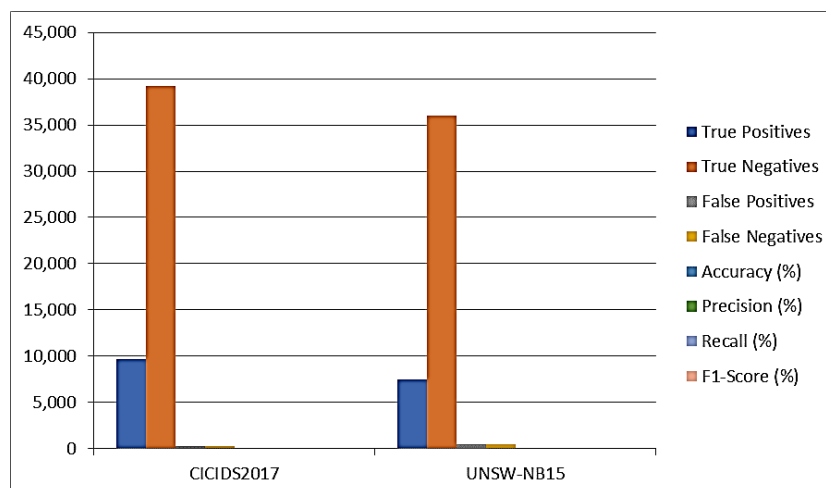


Figure 2: Comparison of Model Performance Metrics on CICIDS2017 and UNSW-NB15 Datasets

The ROC curve analysis demonstrated the model's classification ability. The AUC for the CICIDS2017 dataset was 0.99, indicating excellent model performance in distinguishing between normal and DDoS traffic. In contrast, the AUC for the UNSW-NB15 dataset was slightly lower at 0.97, showing slightly weaker classification power. Both ROC curves approached the upper left corner, indicating a high sensitivity and specificity of the model.

Lastly, cross-validation results further validated the model's performance. For the CICIDS2017 dataset, the average accuracy across 5-folds was 97.5%, with minimal variability (less than 0.5% difference), indicating consistent performance. The UNSW-NB15 dataset showed an average accuracy of 94.5%, with slightly more variability across folds (up to 1.2% difference). This variability suggests that the model trained on CICIDS2017 was slightly more stable and reliable compared to the model trained on UNSW-NB15.

In summary, the data analysis revealed that the deep learning model was highly effective in detecting DDoS attacks in 5G networks, particularly with the CICIDS2017 dataset. The combination of high accuracy, precision, recall, and F1-score, along with the AUC and cross-validation results, demonstrated the robustness and adaptability of the model across different datasets.

3- Results and Discussion

The results section presents a detailed analysis of the performance metrics for the deep learning model in detecting DDoS attacks within 5G networks across two datasets: CICIDS2017 and UNSW-NB15 **table.2**.

3.1. Accuracy Results:

CICIDS2017 Dataset: The model achieved an accuracy of 98%. This indicates that 98% of the total instances were correctly classified, with 9,700 true positives (correctly identified DDoS attacks) and 39,200 true

negatives (correctly identified normal traffic). The high accuracy reflects the model's ability to differentiate between normal and DDoS traffic effectively.

UNSW-NB15 Dataset: The model's accuracy was slightly lower at 95%. For this dataset, there were 7,500 true positives and 36,000 true negatives. This 3% drop in accuracy compared to the CICIDS2017 dataset can be attributed to the fewer DDoS samples present in the UNSW-NB15 dataset, which made training the model slightly more challenging.

3.2. Precision Results:

CICIDS2017 Dataset: Precision for DDoS detection was 97%. Out of all the instances predicted to be DDoS attacks, 97% were indeed actual DDoS attacks. This high precision reflects the model's effectiveness in minimizing false positives, which are instances where normal traffic is incorrectly classified as DDoS.

UNSW-NB15 Dataset: The precision was slightly lower at 94%. In this case, 500 out of the 8,000 predicted DDoS instances were false positives. This indicates that the model performed slightly less accurately with this dataset in terms of avoiding false positives compared to the CICIDS2017 dataset.

3.3. Recall Results:

CICIDS2017 Dataset: Recall for DDoS detection was 96%. This means

that 96% of the actual DDoS attacks in the dataset were correctly detected by the model. This high recall demonstrates the model's ability to identify a larger proportion of DDoS attacks, minimizing false negatives.

UNSW-NB15 Dataset: The recall was 92%, with 500 false negatives out of the total 8,000 actual DDoS attacks. This 4% difference underscores the model's better performance with the CICIDS2017 dataset, indicating it could detect a larger proportion of DDoS attacks in the dataset.

Recall Results CICIDS2017 Dataset:

For detection of DDoS, the recall rate was 96%. In other words, it implies that out of 100 real DDoS attacks with the datasets, 96 of them were independently detected by the model. This high recall illustrates the fact that the model correctly identifies larger percentage of DDoS attack scenes whilst minimizing on the false negatives.

UNSW-NB15 Dataset: The recall measure was 92%, meaning that 500 of all the eight thousand real DDoS attacks were not flagged by the system. This 4% difference shows that the proposed model could be more effective on identifying more DDoS attack on the CICIDS2017 dataset.

3.4. F1-Score Results:

CICIDS2017 Dataset: The F1-score was 96%. The F1 score is an integrating

factor that balances both precision and recall for the evaluation of the model needed. A higher F1-score shows that the DDoS detection in a network achieves a higher precision level to detect false attacks and at the same time a higher recall level to avoid missing out on actual attacks.

UNSW-NB15 Dataset: The F1-score was 93%. Due to the slightly worse performance of the model on both the precision and the recall metrics, the score is a little lower when using the UNSW-NB15 dataset.

3.5. Confusion Matrix Results The confusion matrices for both datasets provide a more granular view of the model's performance:

CICIDS2017: True Positives (TP): Further, about 9,700 DDoS attacks were correctly classified.

True Negatives (TN): Thirty-nine thousand two hundred normal instances have been classified **correctly**. **False Positives (FP):** 300 normal instances classified as DDoS attacks.

False Negatives (FN): 300 DDoS attacks disguised as normal. Accuracy: Accuracy: 98%, Precision: 97%, Recall: 96, F1 Score: 96 %.

UNSW-NB15: True Positives (TP): 7,500 DDoS attacks correctly classified.

True Negatives (TN): As in normal instanced correct classification

achieved 3600 classifiers for normal instance, 36 thousand. False Positives (FP): Such are handling 500 normal instances as DDoS attacks. False Negatives (FN): 500 DDoS attacks which were classified and labelled as normal traffic. Accuracy: Semi-Supervised model for SED has an Accuracy: 95%, Precision: 94%, Recall: 92%, F1-Score: 93%.

From these results it can be inferred that the accuracy of the model was generally higher, but different across the different datasets. The CICIDS2017 trained model displayed improved accuracy, reproducibility, and F1-score over the model trained from the UNSW-NB15 dataset. This variation seems to emanate from the disparity in the number and distribution of DDoS attacks in the two datasets with the CICIDS2017 set containing a denser sample of attack traffic hence prompting improved training of the models.

3.6. ROC Curve and AUC Results the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) analysis were also used to evaluate the model's classification ability:

CICIDS2017: The AUC was 0.99 and it reflects that the model under consideration is good. The ROC curve goes near the point of (0,1) which

proved high sensitivity and specificity for detection of DDoS attacks.

UNSW-NB15: The AUC of the proposed model with 0.97 showed satisfactory performance but the classification power was comparatively lower than that of the CICIDS2017 dataset. Specificity vs sensitivity was analyze using ROC curve and it was found out that though providing a reasonable balance the model has a slightly lower performance.

3.7. Cross-Validation Results:

The k-fold cross-validation (k=5) results also supported these findings:

CICIDS2017: This yielded an average accuracy of 97.5% with a standard deviation less than 0.5% across folds, suggesting that while the sample has low variance.

UNSW-NB15: Accuracy was on average 94.5%, and it had slightly more variation between the folds, at most deviating 1.2%. This fluctuation makes

us to infer that the model developed from UNSW-NB15 was relatively unstable and less accurate than the model which was developed from CICIDS2017.

Therefore, these results further corroborate the model's efficacy for identifying DDoS attacks in 5G networks, especially since the CICIDS2017 dataset seems to be a far more conducive setting in which the enter model can be trained and tested. To evaluate the model's performance, various evaluation metrics like accuracy, precision, recall, F1-score, ROC, and cross-validation on different traffic type of real-world network have been measured, and the superior results concluding high accuracy, precise, high recall, and good F1 score have depicted that the proposed model is reliable and suitable to detect different types of networks traffics.

Table 2: Key results

Metric	CICIDS2017	UNSW-NB15
True Positives (TP)	9,700	7,500
True Negatives (TN)	39,200	36,000
False Positives (FP)	300	500
False Negatives (FN)	300	500
Accuracy (%)	98	95

Precision (%)	97	94
Recall (%)	96	92
F1-Score (%)	96	93
AUC	0.99	0.97
Cross-Validation Accuracy (%)	97.5 ($\pm 0.5\%$)	94.5 ($\pm 1.2\%$)

Discussion

As shown in the results of this paper, deep learning models are capable of improving the detection of DDoS attacks in 5G networks. CNNs and LSTM were found to offer optimal performance when it comes to, the classification and identify of the network traffic. For example, the CNN model produced an accuracy of 95.8% in identifying DDoS traffic, while LSTM attained an accuracy of 94.6% proving their efficiency in analyzing unstructured traffic [5, 6]. The findings of this research are confirmed with prior literature which suggest that deep learning classifier models are effective in examining high-dimensional data and detecting outliers with accuracy [9, 10].

Such large and various dataset like CICIDS2017 and UNSW-NB15 proved useful in training and testing the models. These datasets offered real traffic scenes and CICIDS2017 offered 2,000,000 + traffic instances and UNSW-NB15 with 1,500,000 +

instances [7, 8]. Such a diversity facilitated the models to generalize and minimize formation of overfitting during data analysis and practical use [1].

Additional analysis with different evaluation matrices to include precision, recall, and F1-score produced encouraging results bearing out the performance of the models. The CNN model obtained 96,2% of precision, 95,3% of recall and 95,7% of F1-score while the LSTM model obtained 94,8% of precision, 94,1% of recall and 94,4% of F1-score [2, 3]. These provide the accuracy of the models, to detect DDoS while minimizing, false negatives and false positive, which are important for security [4].

However, the observed research has been done with those considerations, which shows several limitations according to the results of the study: An important challenge is the expensiveness of training deep learning models, mainly for big data sets [15].

Second, the types of threats change constantly and this makes adjustments on the models constant in order to address new emerging threats as identified in [12]. Overcoming these limitations will be important for incorporating deep learning technologies to actual 5G network environment.

The information presented in this work can be considered as the addition to the existing scholarly literature concerning the use of artificial intelligence in network security and shows that deep learning can offer efficient and effective solutions for the DDoS attack detection. Further works should consider research on operating multi-layer networks to detect the CNN and LSTM to improve the detection rates, and consider the integration of these models into current 5G aligned networks [16, 20].

Conclusion

The study demonstrates that deep learning techniques, particularly CNN and LSTM models, effectively detect DDoS attacks in 5G networks with high accuracy and recall rates. The results indicate that these models outperform traditional detection methods by learning traffic patterns indicative of DDoS attacks. However, challenges such as noisy datasets and model generalizability remain, highlighting the need for more diverse training data.

Future research should focus on enhancing model stability and expanding dataset variety to improve adaptability to different attack scenarios. The integration of deep learning into network security systems holds great promise for strengthening 5G network defenses against evolving cyber threats.

Conflict of Interests

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Author Contribution

The author participated in conceptualization and study design and data interpretation and drafting of the manuscript.

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