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ENHANCING NETWORK SECURITY THROUGH INTEGRATED DEEP LEARNING ARCHITECTURES AND ATTENTION MECHANISMS

***[1,2]Ahmed, A. A., [1]Aliyu, A. A., [1]Ibrahim, M., [1]Abdulkadir, S., [1]Ahmad, M. A., [1]Tanko, S. A. and [1]Umaru, I. A.**

[1]Department of Informatics, Faculty of Science, Kaduna State University
[2]Department of Computer Science, Federal Polytechnic Kaltungo, Gombe

*Corresponding authors' email: binahmad60@gmail.com

ABSTRACT

With the widespread integration of the Internet into our daily life, ensuring network security has become crucial for applications like online retail, auctions, and file processing. By examining network process logs, intrusion detection and classification are crucial for spotting threats. The issue of network infiltration is made worse by the increasing volume and complexity of contemporary network traffic data, making traditional intrusion prevention methods insufficient. Therefore, low false alarm rates and effective intrusion detection systems are essential. In order to increase efficacy and efficiency, the model uses Convolution Neural Network-Long Short Time Memory (CNN-LSTM) for feature extraction and classification. The attention mechanism is used to choose the most discriminative features. Metrics including accuracy, precision, recall, and the F1-score are used to assess the model's performance. These metrics reveal how well the model detects intrusions (true positives), prevents harmful traffic from being mistakenly labelled as normal (true negatives), and classifies data overall. About 99.9% accuracy is attained by the model, with a precision of 0.98, recall of 1.0, and F1-score of 0.99. These results reflect its ability to effectively identify both normal traffic and intrusion attempts. The high accuracy underscores the model's strong performance in distinguishing malicious from benign activities. This work contributed to cybersecurity by presenting an innovative solution to intrusion detection challenges. It highlights the importance of balanced datasets and advanced deep learning architectures to improve detection capabilities. The results highlight how well the model can handle the intricacies of contemporary network security risks.

Keywords: Intrusion detection system, Cyber security, Attention mechanism, Convolution Neural Network, Long Short-Term Memory

INTRODUCTION

Understanding that the complexity of huge network traffic data and the growing size of contemporary networks make the network intrusion problem a serious danger, traditional intrusion prevention system solutions frequently fail. New approaches are therefore needed for intrusion detection that is both effective and efficient while minimising false alarm rates. Because of the digital revolution's rising reliance on digital systems and networks due to automation and internet-connected objects, it is critical to safeguard the security and integrity of these infrastructures (Kadam et al., 2022). Apart from the fact that cybercriminals are always improving their intrusion techniques, there are many advantages to such innovation (Rullo et al., 2023). Vijay et al.,(2020) Added that, all systems must implement an Intrusion Detection System (IDS) for security maintenance since cybersecurity threats, such as unauthorised access, data breaches, and network intrusions, represent serious hazards to both persons and organisations. There is interest in using advances in machine learning (ML) and artificial intelligence (AI) to fight cybercrime (Shone et al., 2018).

Meghdouri et al. (2018) used a Deep Neural Network, whereas Kim et al. (2016) used the Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) classifier. These methods seek to simplify the input feature space in order to lower computational cost and improve classification performance; they have been evaluated on datasets such as UNSW-NB15, KDDCup99, and NSL-KDD (Khalid et al., 2014). By utilising their ability to extract useful and hierarchical features, deep learning algorithms enable effective processing in a lower-dimensional space.

Researchers and practitioners have been investigating novel strategies to enhance the identification and prevention of such intrusions in response to these difficulties. Cybersecurity breaches are a major worldwide concern, according to a World Economic Forum report (Ghani et al., 2023). Numerous security solutions, including firewalls, intrusion prevention systems (IDS), authorisation procedures, antivirus software, encryption, and intrusion prevention systems (IPS), have been created to safeguard systems and networks in response to the increasing frequency of network attacks (Awujoola et al., 2020). Since it enables objects to connect over networks and spurs new business processes, the Internet of Things has seen increased acceptance in recent years (Lee, 2019). However, because of the rapid growth of cyber dangers, this development has also brought about difficulties in the areas of finance, credibility, enforcement, and operations (Lee, 2020). Because it provides a flexible framework that offers a variety of resources and services catered to customer demands, cloud computing is frequently the preferred storage medium for IoT data. Finding anomalies in network traffic through signature-based and anomaly-based techniques is one way to stop cyberattacks.

Understanding that the complexity of huge network traffic data and the growing size of contemporary networks make the network intrusion problem a serious danger, traditional intrusion prevention system solutions frequently fail. New approaches are therefore needed for intrusion detection that is both effective and efficient while minimising false alarm rates.

Ghani et al. (2023) highlighted the escalating dependence on networks across various sectors, resulting in a heightened threat of cyberattacks and the urgent need for robust detection mechanisms. They introduced an innovative approach using deep learning-based feedforward neural networks (FFNN) with multiple hidden layers to improve intrusion detection. However, their reliance on FFNN for classification suggests exploring other deep learning architectures to potentially achieve better results.

Building upon the groundwork laid by Ghani et al. (2023), this study proposes an approach to improve IDS by integrating feature fusion of both CNN and LSTM networks, along with an attention mechanism. CNNs excel at feature extraction from spatial data, identifying patterns and structures within network traffic. LSTMs, on the other hand, capture temporal dependencies within sequential data, tracking changes and trends over time. By combining these architectures, Feature fusion enhances detection accuracy by enabling the model to efficiently incorporate temporal and spatial trends in network traffic data.

Incorporating an attention mechanism further enhances the CNN-LSTM model by focusing on salient features while disregarding irrelevant information. This mechanism dynamically adjusts the weighting of input features, prioritizing those most important for intrusion detection. Through feature fusion and attention, the model gets more resilient and flexible, ability to make more accurate judgements between normal network behavior and anomalous activities. A more thorough and efficient intrusion detection system is produced by combining the advantages of the CNN and LSTM architectures.

A limitation in Ghani et al. (2023) was their approach to training the model using different epochs for distinct datasets, lacking generality and potentially leading to suboptimal performance on unseen data. This study advocates for a more generic model trained uniformly across all datasets to achieve greater robustness and generalization capabilities.

Additionally, this work draws inspiration from the dataset balancing technique pioneered by Awujoola et al. (2021). Ensuring a more equitable distribution of data across different classes mitigates how class disparity affects model performance. Integrating dataset balancing aims to further refine the classification accuracy of the CNN-LSTM model, increasing its efficacy in actual intrusion detection situations.

Hence, the aim of this study is to enhance network security by integrating deep learning architectures, specifically through the fusion of CNN and LSTM networks, with the incorporation of attention mechanisms.

MATERIALS AND METHODS

The methodological flow is visually shown in Figure 1, which provides a detailed explanation of the procedure used in this investigation. The availability of labelled documents is the foundation of the technique because the machine learning algorithms used are supervised.

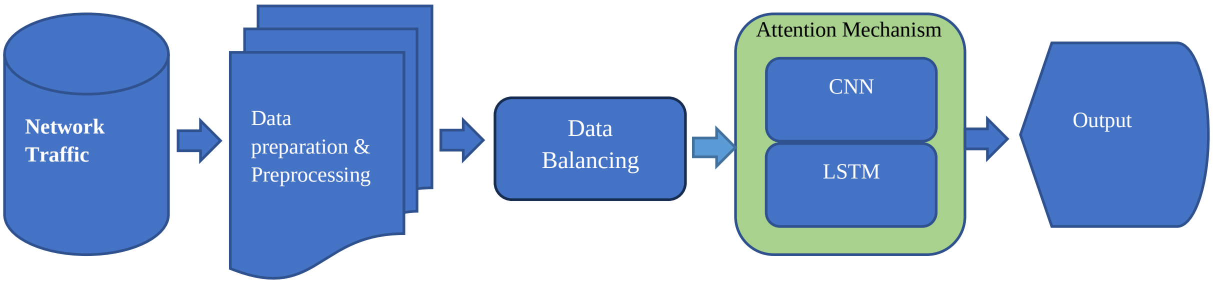


Figure 1: Methodology Flow

The model employs CNN-LSTM for both feature extraction and classification, leveraging the attention mechanism to guide the selection of the most discriminant features, thereby enhancing the effectiveness and efficiency of classification.

Data Preparation and Preprocessing for Intrusion Traffic Analysis

Data preparation and preprocessing are essential stages in data analysis, particularly when handling intrusion traffic data for cybersecurity. These steps transform unstructured network traffic data into a clean and organized format, enabling effective analysis and modeling. This document emphasizes the importance of these processes in building a deep learning-based intrusion detection model, utilizing CNNs, LSTMs, and attention mechanisms.

The process began with data cleaning, where irrelevant or redundant elements like unnecessary headers, metadata, and artifacts were removed to eliminate noise and discrepancies that could hinder model performance. Next is normalization or standardization, which scales numerical values to a uniform range, ensuring all features contribute equally to the analysis. For example, scaling features like packet size and inter-arrival times improves the model's ability to detect subtle intrusion patterns.

Feature selection refines the dataset further by identifying the most relevant attributes for detecting malicious activities. Techniques like mutual information, chi-square tests, and machine learning-based assessments reduced dimensionality, speeding up training and improving the model's generalization. Encoding is then applied to categorical variables (e.g., protocol types or service flags), converting them into numerical formats through methods like one-hot encoding or neural network embedding layers.

Given that network traffic data may contain partial records, handling missing values is equally crucial. Techniques include imputation and the removal of incomplete records; the decision affects the efficiency and accuracy of the model. Finally, class imbalances were addressed by data balancing, as incursion instances are frequently much lower than typical ones. By creating artificial samples of the minority class, methods such as SMOTE or ADASYN guarantee that the model can successfully identify infrequent intrusion occurrences.

The structured dataset has been preprocessed and was prepared for training. Complex incursion patterns can be recognised by the model thanks to CNNs for feature extraction, LSTMs for temporal pattern identification, and attention methods to prioritise important aspects. The creation of strong cybersecurity systems that can counteract changing cyberthreats was ensured by this thorough approach to data preparation.

Training and Testing in Intrusion Detection Model Development

The training and testing stages are crucial to confirming the model's efficacy, precision, and generalisability in many network contexts when creating an intrusion detection system with network traffic data. These stages are required to assess the model's precision and efficacy in detecting network intrusions.

Training Phase: The training phase involves the model learning from a curated dataset, which includes network traffic data labeled as normal or malicious. This phase enables the model to identify patterns, characteristics, and anomalies associated with network intrusions. Typically, a substantial portion of the dataset, usually around 70-80%, was allocated for training. Through iterative processing, the model adjusts its parameters to reduce errors and enhance its ability to predict network intrusions accurately. A high-quality and diverse training dataset is essential to the training phase's performance since it exposes the model to a variety of intrusion scenarios.

***Testing Phase*:** The testing stage assesses how well the model function on untested data after training. In order to evaluate the model's generalisation skills and the capacity to identify network traffic intrusions in the real world that were not included in the training dataset, this step is essential. An objective evaluation of the model's predicted accuracy and preparedness for implementation in real-world settings was provided by the remaining 20–30% of the dataset, which is put aside for testing.

Evaluation Metrics

Accuracy, specificity, sensitivity, and error rate were used as performance metrics for the experimental comparison of classification algorithms. The model was assessed using the following metrics:

Confusion Matrix

A table that compares a classification model's projected labels with the actual ground truth labels is called a confusion matrix (Gron, 2019). The genuine labels are represented by rows in this matrix-formatted table, while the predicted labels are represented by columns.

The table shows the number or frequency of cases that fit into each category for each combination of true and anticipated labels. The matrix's off-diagonal elements show examples that were incorrectly classified, while the diagonal elements show occurrences that were successfully classified.

Table 1: Confusion matrix for a two-class model (Heydarian, 2022)

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

TP represents the instances correctly predicted as positive, FN represents the instances incorrectly predicted as negative, FP represents the instances incorrectly predicted as positive, and TN represents the instances correctly predicted as negative.

By analyzing the values in the confusion matrix, we can compute various evaluation metrics such as accuracy, precision, recall, and F1 score, which provide insights into the model's performance and its ability to correctly classify instances belonging to different classes.

Accuracy

It is the percentage of accurate predictions i.e the ratio of number of correctly classified instances to the total number of instances and it can be defined as: (Santamaria et al., 2018).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \quad (1)$$

where TP- True Positive, FP- False Positive, TN- True Negative, FN- False Negative

False Positive rate (FPR)

This measures the rate of wrongly classified instances. A low FP-rate signifies that the classifier is a good one (Santamaria et al., 2018).

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (2)$$

Sensitivity

It is the proportion of positives that are correctly identified (Gad, 2021).

$$\text{Sensitivity} = \text{TP} / \text{TP} + \text{FN} \quad (3)$$

Precision

Precision is the ratio of positively predicted instances among the retrieved instances (Gad, 2021).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

Specificity

It is the proportion of negatives that are correctly identified. It is calculated as the number of correct negative predictions divided by the total number of negatives. It is also called true negative rate. The worst is 0.0 while the best is 1.0 (Gad, 2021).

$$\text{Specificity} = \text{TN} / \text{TN} + \text{FP} \quad (5)$$

Recall

Is the ratio of positively predicted instances among all the instances (Gad, 2021).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6)$$

Error Rate

It is equivalent to 1 minus Accuracy. (Platanios et al., 2017).

Dataset

To provide a positive comparison, the same datasets used in the benchmark study by Ghani et al. (2023) was used in this work. In particular, we will concentrate on NSL-KDD, one of the two datasets. IXIA Perfect Storm tool captured raw network traffic to make up the UNSW-NB15 dataset, which is widely used in cyber security research. It provides a blend of realistic everyday activities and simulated modern attack behaviours, which makes it ideal for in-depth examination and assessment. Furthermore, the cyber security community largely acknowledges both dataset as a standard dataset for IDS. By leveraging these two datasets, we conducted a thorough and rigorous evaluation of our proposed approach, ensuring robustness and effectiveness in comparison to existing methods.

The testing set has 82,332 records, including both normal activities and different types of attacks, whereas the training set consists of 175,341 data (Choudhary and Kesswan, 2020). Furthermore, the KDD Cup dataset's shortcomings were solved by the NSL-KDD dataset, a brand-new dataset that has been suggested. Selected records from the whole KDD Cup'99 dataset make up NSL-KDD. NSL-KDD has a number of advantages over the KDD Cup'99 dataset (Choudhary and Kesswan, 2020).

RESULTS AND DISCUSSION

In order to verify the generalisability of the created model and to guarantee a comprehensive comparison with current benchmarks, the study utilised two well-known datasets. In the first experiment, the NSL-KDD dataset was utilised because it is a common benchmark in intrusion detection studies. In the second experiment, the UNSW-NB15 dataset which is renowned for its varied and contemporary network traffic features was used to evaluate the model's generalisability across various intrusion situations and network conditions.

Additionally, the model addresses the issue of dataset imbalance a challenge not tackled in the benchmark studies through a novel hybrid preprocessing technique that combines ADASYN with undersampling. This innovative approach enhances the model’s performance by effectively managing class imbalance, thus ensuring more reliable and generalizable results.

Evaluation of the Attention guided CNN with the LSTM on the NSL-Kdd Dataset

The classification report generated by testing the model on the unbalanced dataset is shown in Table 2, and the results obtained after the dataset was balanced are shown in Table 3. Furthermore, the confusion matrices for the balanced and imbalanced datasets are displayed in Figures 2 and 3, respectively.

Table 2: Classification Report on Imbalance Data.

Class	Precision	Recall	F1-Score	Support
Normal	0.90	0.75	0.82	283
Intrusion	0.99	1.00	1.00	10686
Accuracy			0.99	10969
Macro Avg	0.95	0.88	0.91	10969
Weighted Avg	0.99	0.99	0.99	10969

Table 3: Classification Report on balance Data

Class	Precision	Recall	F1-Score	Support
normal	1.00	1.00	1.00	10722
intrusion	1.00	1.00	1.00	10677
Accuracy			1.00	21399
Macro Avg	1.00	1.00	1.00	21399
Weighted Avg	1.00	1.00	1.00	21399

The quality and features of the dataset used for training and assessment have a significant impact on how well a machine learning model for intrusion detection works. To demonstrate how dataset balance affects model results, this study evaluates how well a deep learning intrusion detection model performs on balanced and unbalanced datasets. Although the model's accuracy on the unbalanced dataset was good at 0.99, performance differed greatly between classes. In contrast to the normal class (minority class), the intrusion class (majority class) demonstrated much higher precision, recall, and F1-Score. As an example, the intrusion class scored perfect recall and an F1-Score of 1.00, whereas the normal class got an F1-Score of 0.82 and a recall of 0.75. These results highlight that the model was biased toward the majority class, making the high overall accuracy misleading and reducing the model's generalizability.

Tests conducted on the balanced dataset, however, showed notable gains in every performance indicator. The precision, recall, and F1-Score scores for the normal and intrusion classes were all perfect at 1.00. The model's ability to generalise successfully and deliver consistent performance across all classes was made possible by the balanced dataset. In order to address class imbalance difficulties and provide a more robust and dependable model, strategies like combining ADASYN and undersampling were successful. Weighted average and macro metrics highlight these results even more. Macro averages were lower for the unbalanced dataset (e.g., F1-Score of 0.91 and recall of 0.88), indicating difficulties with the minority class. Because of the dominance of the majority class, weighted averages were distorted. The balanced dataset, on the other hand, obtained flawless macro and weighted averages of 1.00, confirming the positive impact of balancing on model performance.

The study comes to the conclusion that creating machine learning models that can successfully detect intrusions across all classes requires balancing datasets. Although models that have been trained on unbalanced data may perform well for majority classes, they are unable to provide trustworthy intrusion detection solutions. For strong cybersecurity applications, balancing guarantees a more reliable and equitable architecture.

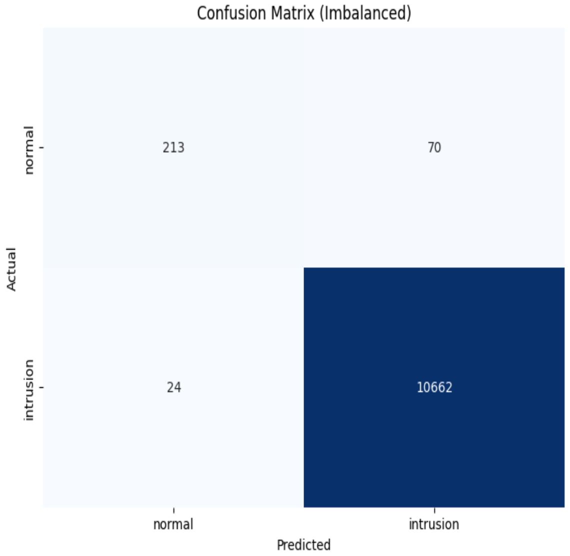


Figure 2: Confusion Matrix for Imbalance Data

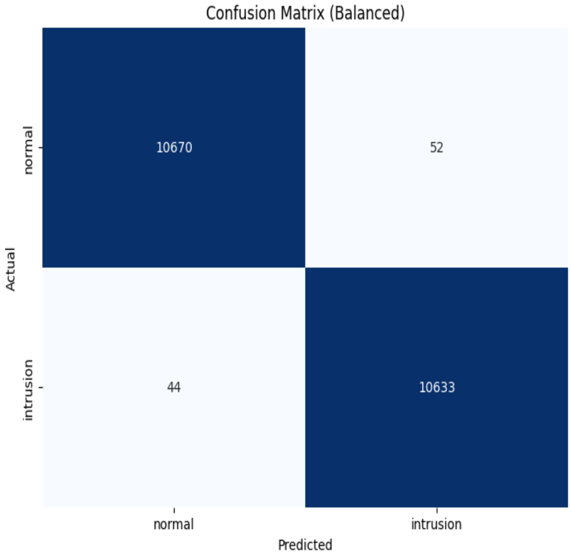


Figure 3: Confusion Matrix for Balanced Data

Confusion matrix evaluations provide detailed information on a machine learning model's performance in intrusion detection, with a focus on false positives, false negatives, true positives, and true negatives and more. Model output was tested on both balanced and unbalanced datasets, revealing significant differences in performance and classification accuracy. The confusion matrix for the balanced dataset indicated that the model accurately detected 10,670 normal occurrences and 10,633 intrusion instances, with just 52 normal cases being wrongly categorised as intrusions and 44 intrusion cases being incorrectly labelled as normal. Due to effective balancing techniques like ADASYN and undersampling, the model's balanced performance in both classes and good accuracy are demonstrated here. There are very few misclassifications, indicating that the model can generalise equally well for everyday operations and intrusion. However, the results of the dataset that was not balanced revealed a biased performance. Despite properly classifying 10,662 intrusion occurrences and 213 normal instances, the model incorrectly classified 70 normal cases as intrusions and 24 intrusions as normal respectively. The model's preference for the majority class (intrusions) highlighted the challenges brought forth by class imbalance by producing a higher false positive rate for the normal class and a larger false negative rate for the intrusion class. Although the accuracy of the model was excellent overall, the unbalanced dataset affected its ability to identify minority-class cases. The confusion matrices from the two datasets are compared to emphasise the significance of data balance. The balanced dataset enabled the model to operate consistently across both classes, allowing for a fair evaluation of its capabilities. The unbalanced dataset's misleadingly high accuracy ratings hid the model's struggles with the minority class.

These findings demonstrate how crucial data balance is to precise and practical IDS performance evaluations. Balancing ensures that the model can handle class imbalances, resulting in accurate and dependable evaluations and improved performance across all classes. However, a model's effectiveness may be overestimated if measurements are distorted due to unbalanced data.

Evaluation of the Attention guided CNN with the LSTM on the UNSW-NB15 Dataset: The second experiment assesses the effectiveness of an Attention-guided CNN combined with LSTM on the UNSW-NB15 dataset, confirming the advantages of using a balanced dataset. The classification report in Table 4 shows the model's high precision, recall, and F1-scores for both normal and intrusion classes, along with overall accuracy, demonstrating its effectiveness in differentiating between malicious and normal network traffic under balanced conditions. The confusion matrix in Figure 4 clearly illustrates the model's ability to correctly classify normal and intrusion instances, with balanced data contributing to fewer misclassifications. Training and Validation Metrics in Figures 4 & 5 demonstrate that; Accuracy Curve: Shows the model's capacity to generalise to unseen data. Loss Curve: Indicates effective minimisation of errors during training, reflecting steady learning progress.

The results show that the model's classification performance was greatly improved by balancing the dataset. A strong solution for intrusion detection in cybersecurity, the Attention-guided CNN with LSTM technique shown the ability to handle both normal and intrusion instances with high accuracy. The significance of dataset preparation and the efficiency of attention mechanisms in deep learning for handling intricate cybersecurity issues are highlighted by this thorough analysis.

Table 4: Classification report for the evaluation of the developed model on UNSW-NB15 dataset

Class	Precision	Recall	F1-Score	Support
Normal	1.00	0.98	0.99	70834
Intrusion	0.98	1.00	0.99	64105
Accuracy	-	-	0.99	134939
Macro Avg	0.99	0.99	0.99	134939
Weighted Avg	0.99	0.99	0.99	134939

The developed model's exceptional performance in identifying and categorising normal and intrusion cases with high precision, recall, and F1-scores is demonstrated in the classification report on the UNSW-NB15 dataset. Precision for the typical class was 1.00 (everything that was categorised as normal was actually normal). Recall was 0.98, meaning that 98% of real, typical cases were correctly identified. Strong classification performance is shown by the F1-Score of 0.99 and 70,834 instances were supported. The precision for the intrusion class was 0.98, meaning that 98% of the classified incursions were correct and Recall of 1.00 (every instance of an incursion was accurately located). High effectiveness is shown by the F1-Score of 0.99 and 64,105 instances were supported. The overall performance indicate that 99% of all cases were correctly classified with the accuracy of 0.99. Precision, recall, and F1-score, the macro and weighted average metrics, were all 0.99, showing consistent and balanced performance in both classes.

The outcomes demonstrate how robust and dependable the model is in identifying both typical and intrusion cases. Its steady performance across criteria points to real-world intrusion detection systems' practical applicability, providing a workable answer to cybersecurity issues.

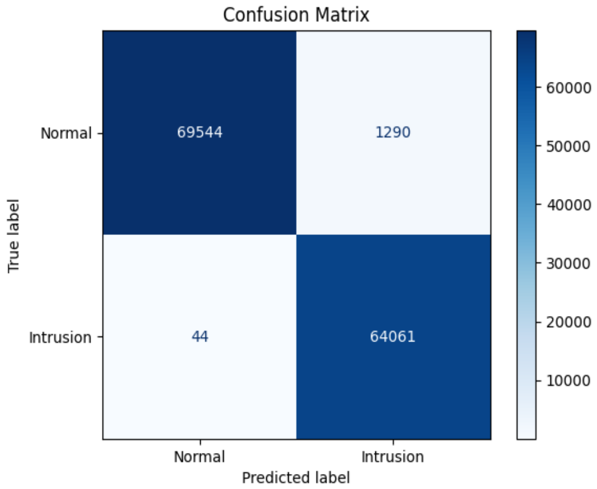


Figure 4: Confusion Matrix obtained from the evaluation of the model on UNSW-NB15

The confusion matrix analysis highlights the constructed model's performance on the UNSW-NB15 dataset, showcasing its strengths and areas for improvement in intrusion detection. Key findings include: Classification Results: 6,954 instances were correctly classified as Normal traffic while 1,290 instances were false positives (Normal misclassified as Intrusion). 64,061 instances were correctly classified as Intrusions while 44 instances were false negatives (Intrusions misclassified as Normal).

Performance Metrics: Accuracy of ~0.99, reflecting the model's overall reliability in classifying both Normal and Intrusion traffic. Precision (Intrusion) of ~0.98, indicating most instances classified as Intrusions were correct. Recall (Intrusion) was 1.00, demonstrating the model's ability to identify all Intrusions without missing any cases. F1-Score of ~0.99, balancing precision and recall for a comprehensive performance measure and Specificity (Normal) of ~0.84, showing strong but slightly lower performance in identifying benign traffic.

The Strengths for this class includes; High recall ensures that no intrusions are overlooked and strong F1-Score and precision highlight the model’s effectiveness in predicting malicious activity.

The Challenges for this class was 1,290 false positives which suggest a need to refine the model to better distinguish Normal traffic from Intrusion attempts. While specificity is solid, reducing false positives could further enhance accuracy.

In conclusion, the model demonstrates excellent performance in detecting intrusions with high accuracy, precision, recall, and F1-Score, making it highly effective for cybersecurity applications. However, addressing the false positive rate could further improve its ability to accurately differentiate between benign and malicious network activity, enhancing its practical utility in real-world scenarios.

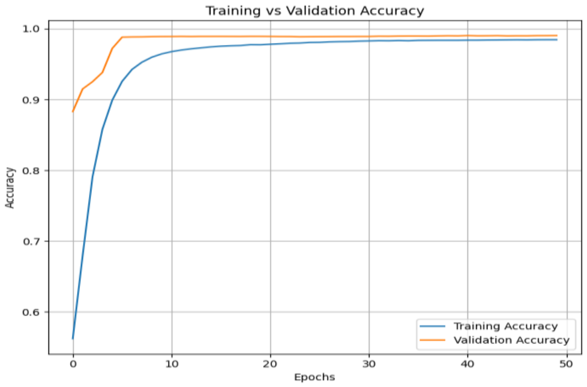


Figure 5: Training versus Validation Accuracy

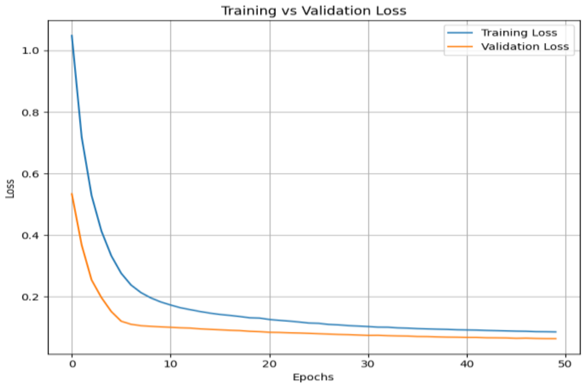


Figure 6: Training versus Validation loss

The performance of the machine learning model of over 50 epochs, as depicted in Figures 5 and 6, demonstrates effective learning and generalization. Figure 5 indicate that Training accuracy starts below 0.6 and rapidly increases, surpassing 0.9 by the 10th epoch, eventually nearing 1.0 while, Validation accuracy follows a similar trajectory, starting slightly higher than training accuracy and converging to near 1.0, indicating efficient learning and strong generalization to unseen data. In Figure 6, Training loss begins above 1.0, decreases sharply in early epochs, and drops below 0.2 by the 10th epoch, stabilizing at a low value. Validation loss mirrors this pattern, starting lower than training loss, decreasing rapidly, and aligning closely with training loss, demonstrating no overfitting and effective generalization. The high accuracy and low loss values for both training and validation sets, along with their convergence, indicate a successful training process. The model demonstrates strong generalization, robust learning, and reliability, suggesting its suitability for practical applications.

Model Perormance Comparison

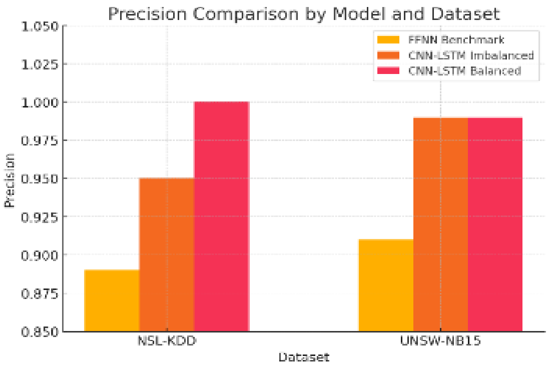
We compared the CNN-LSTM model with attention mechanisms' performance to that of a benchmark FFNN model in order to assess the model's efficacy. A thorough basis for testing and verifying intrusion detection models is provided by these datasets, which include a variety of network intrusion situations.

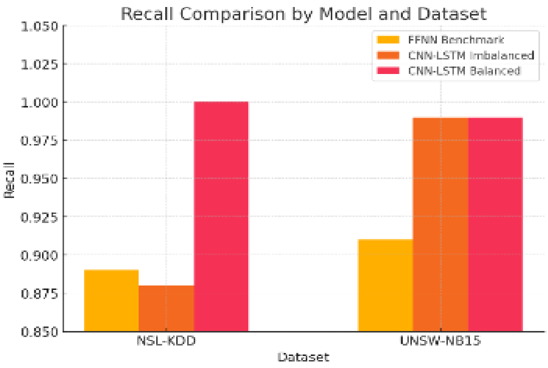
The benchmark FFNN model was selected due to its established performance in network intrusion detection, where it demonstrated reliable classification on imbalanced data with a smaller feature set. However, the rapid advancement of deep learning architectures has allowed for more complex models, such as the CNN-LSTM architecture, which integrates spatial and temporal feature extraction capabilities. The addition of an attention mechanism in the developed model further enhances feature selection, prioritizing relevant data points for improved classification accuracy.

Table 5 Comparison between the benchmark and proposed model

Dataset	Model	Data Balance	Precision (Macro Avg)	Recall (Macro Avg)	F1-Score (Macro Avg)	Accuracy
NSL-KDD	FFNN (Benchmark)	Imbalanced	0.89	0.89	0.89	89.03%
NSL-KDD	CNN-LSTM and attention (Our model)	Imbalanced	0.95	0.88	0.91	99.00%
NSL-KDD	CNN-LSTM and attention (Our model)	Balanced	1.00	1.00	1.00	100.00%
UNSW-NB15	FFNN (Benchmark)	Imbalanced	0.91	0.91	0.91	91.29%
UNSW-NB15	CNN-LSTM and attention (Our model)	Imbalanced	0.99	0.99	0.99	99.00%
UNSW-NB15	CNN-LSTM and attention (Our model)	Balanced	0.99	0.99	0.99	99.00%

The benchmark FFNN model shows an accuracy of 89.03% with macro-averaged scores around 0.89 for precision, recall, and F1-score on imbalanced data. Our model (CNN-LSTM and attention) significantly outperforms the benchmark on both imbalanced and balanced data. It achieves perfect classification of 100% accuracy when trained and evaluated on balanced data, and a high accuracy of 99% on imbalanced data. The benchmark FFNN model achieves 91.29% accuracy with macro-averaged scores of 0.91. The model reaches 99% accuracy, precision, recall, and F1-score on both imbalanced and balanced data. This improvement highlights the model's strong generalization and robustness across different data distributions.





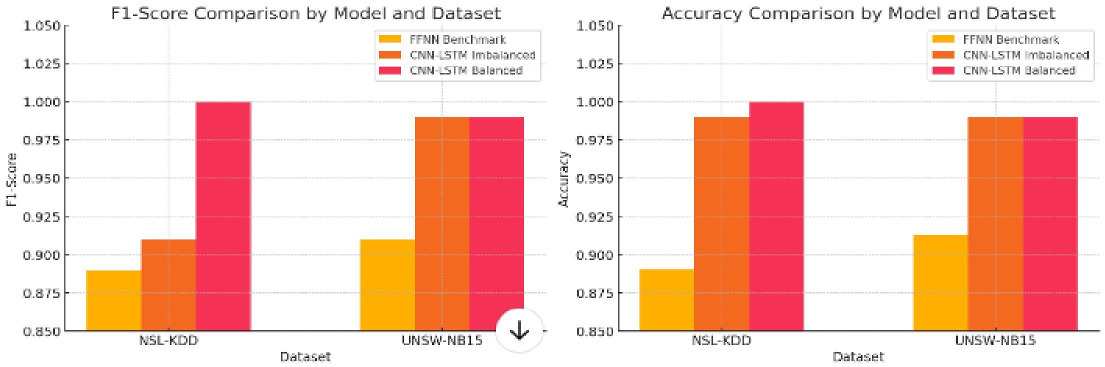


Figure 7: Bar chart comparison between benchmark and proposed model

The CNN-LSTM model, particularly on balanced data, consistently outperforms the FFNN benchmark in precision and recall, reflecting its ability to accurately classify both normal and intrusion instances. The F1-score for the CNN-LSTM model remains high across both datasets and conditions, indicating that the model is not only precise but also consistent in capturing true positives, especially when dataset balancing is applied. The balanced datasets significantly boost the CNN-LSTM model's performance across all metrics, especially in the NSL-KDD dataset. This underscores the importance of data balancing in enhancing model accuracy and reliability.

Discussion

A deep CNN is combined with LSTM networks in this work, and an attention mechanism is integrated to guide the features extracted before the fusion of all the extracted features. This innovative approach aims to leverage the strengths of both CNNs and LSTMs, with the Attention mechanism enhancing the model's focus on significant features during the learning process. The dataset used in this study presents a challenge due to its imbalance, which is a common issue in intrusion detection datasets. To address this, a hybrid preprocessing technique combining ADASYN and undersampling is employed. This method aims to balance the dataset, enhancing the model's ability to detect intrusions effectively.

The experiments aim to explore the effectiveness of this combined deep learning approach in detecting and counteracting various types of intrusions. By utilizing complex patterns and unique signatures found in network traffic, the model aims to proactively identify potential security threats. This approach seeks to strengthen the network's defense mechanisms against cyber-attacks, ensuring a more secure and resilient communication system.

The analysis focuses on evaluating the performance of the proposed model in terms of its ability to detect intrusions with high accuracy. Various metrics, including precision, recall, and overall accuracy, are used to assess the model's effectiveness. The discussion highlights the strengths and potential limitations of the model, providing insights into its practical applications in cybersecurity.

CONCLUSION

The research demonstrated that integration of CNN, LSTM, and attention mechanisms proved to be a highly effective approach for extracting and focusing on significant features in network traffic, enhancing the model's ability to detect complex intrusion patterns. The model's performance is evaluated with metrics such as accuracy, precision, recall, and the F1-score, which provide insights into its ability to identify intrusions (true positives), avoid false labeling of normal traffic as malicious (true negatives), and overall classification efficiency. The model achieves an accuracy of approximately 99.9%, with a precision of 0.98, recall of 1.0, and F1-score of 0.99. These results reflect its ability to effectively identify both normal traffic and intrusion attempts. The high accuracy underscores the model's strong performance in distinguishing malicious from benign activities.

Suggestion for more research can be made in light of the study's results and conclusions in order to enhance cybersecurity protocols and progress the field of intrusion detection. Future research should focus on implementing the developed model in real-time environments to assess its performance in detecting intrusions as they occur. This involves optimizing the model for low-latency responses and ensuring it can handle continuous data streams effectively.

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