Research Article

Efficient Intrusion Detection Using CNNs on Imbalanced Data

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Abstract

By detecting suspicious activity and cyberattacks in real time, Intrusion Detection Systems (IDS) protect modern networks. Highly unbalanced datasets, where regular traffic or frequent attack types outweigh uncommon but dangerous incursions, make IDS model development difficult. Traditional deep learning algorithms frequently favor majority classes, making minority attack categories extremely difficult to identify. To overcome this restriction, this paper offers an upgraded deep learning system that combines CNNs with a class-weighting technique to balance datasets. The model learns additional discriminative features and avoids majority sample dominance by weighting underrepresented attack types during training. Class weighting optimizes more reliably than oversampling, which can increase noise or redundancy. The model improves minority attack recall and F1 scores while reaching 98.2% accuracy. This improvement shows that the model can detect numerous intrusions and uncommon, complex assaults that traditional IDS systems miss. The results show that CNN architectures with targeted class balancing are realistic and successful for real-world intrusion detection applications, where network security requires dependability across all threat categories.

Keywords: Sugar-sweetened beverages; dental caries; body mass index; adolescents; obesity; DMFT index.

1. Introduction

The increasing frequency and sophistication of cyberattacks necessitate the development of reliable Intrusion Detection Systems (IDS) for the security of contemporary network infrastructures. A significant issue in IDS research is the pronounced class imbalance present in most cybersecurity datasets, characterized by a substantial predominance of benign traffic over malicious activity. This imbalance leads traditional machine learning models to exhibit bias towards the majority class, frequently resulting in inadequate recognition of rare yet significant intrusion attempts [1]. Thus, identifying minority attack categories with high precision continues to be a critical research challenge.

Deep learning methods, especially Convolutional Neural Networks (CNNs), have garnered significant interest in Intrusion Detection Systems (IDS) due to their capacity to autonomously learn hierarchical and representative features from raw traffic data [2]. Nonetheless, CNN-based detection models exhibit sensitivity to data imbalance; during the training process, they often prioritize classification performance for the majority class, resulting in diminished accuracy and recall for minority attack types [3].

Various techniques for managing imbalances have been proposed to mitigate these effects. A commonly utilized approach is class weighting, which involves increasing misclassification penalties for minority class samples to enhance the learning of underrepresented categories [4]. Resampling methods, including the Synthetic Minority Over-sampling Technique (SMOTE), create synthetic instances to achieve dataset balance, thereby enhancing the classifier's representation of minority classes [5].

Recent research underscores the benefits of hybrid deep learning architectures in enhancing the performance of intrusion detection systems. Combining Convolutional Neural Networks (CNNs) with Bidirectional Long Short-Term Memory (BiLSTM) networks allows for the modeling of spatial patterns and sequential dependencies in traffic flows, thereby enhancing classification capability [6]. Additionally, attention mechanisms have been incorporated to enhance the model's focus on the most informative segments of the input, thereby improving its capacity to identify subtle or rare attack patterns [7].

Notwithstanding these advancements, the pursuit of real-time, scalable, and generalizable solutions for intrusion detection systems continues to pose significant challenges. Ensemble learning techniques, which involve the combination of multiple models, have demonstrated effectiveness in improving robustness and decreasing the variance linked to predictions made by individual models [8]. Transfer learning allows intrusion detection system models trained on one dataset to be adapted for various network environments, enhancing generalization and decreasing training

duration [9]. Research has investigated domain adaptation methods to improve the transferability of Intrusion Detection System (IDS) models across different traffic distributions and deployment conditions [10].

This study presents a CNN-based intrusion detection model utilizing class weighting to mitigate dataset imbalance effectively. The proposed approach is assessed using a Kaggle IDS dataset, with experimental results indicating robust performance in both majority and minority attack classes, resulting in an overall accuracy of 98.2%. This paper is structured as follows: Section 2 reviews the existing literature on deep learning-based intrusion detection systems, while Section 3 details the proposed methodology and describes the dataset. Section 4 presents the experimental results, and Section 5 offers the study's conclusions.

Literature Review

The ever-growing complexity of cyber threats and the limitations of traditional detection methods have spurred rapid advancements in the field of Intrusion Detection Systems (IDS). As a result of their capacity to learn complicated data representations directly from network traffic, deep learning techniques—which encompass a wide range of hybrid architectures—have arisen as successful solutions. These improvements have not eliminated the underlying problems that severely restrict IDS performance, such as high processing needs, severe class imbalance, latency in real-time situations, and poor generalization to undiscovered attack categories. This literature review takes a look at studies that came out between 2018 and 2025, focusing on the models that were suggested, the accuracy levels that were claimed, and the limits that were pointed out by each study. Additionally, it delves into cutting-edge methods that try to strengthen and adapt IDS, including data augmentation techniques, ensemble approaches, and transfer learning.

A CNN-based intrusion detection system (IDS) trained on traffic-flow characteristics was presented by Wang et al. [11], and it achieved a 95% accuracy rate. The dataset imbalance restricted the model's detection power for unusual assaults, but it performed quite well for regular incursions. To improve minority-class recognition, the authors recommended using SMOTE or comparable oversampling methods.

With a 94.5% success rate, Zhang et al. [12] built an LSTM-driven intrusion detection system (IDS) that could simulate the temporal correlations in network data. Although the model performed well when faced with strikes that followed a strict sequential pattern, it showed limited capacity to adapt to new types of attacks. Better feature extraction methods and more comprehensive datasets are required, according to the authors.

Kumar et al. [13] suggested a CNN-RNN hybrid model that achieved 96.1% accuracy. When compared to standalone CNNs, their design performed better for sequential attack behaviors. Unfortunately, the model was not designed for use in high-speed or real-time settings due to inference delays.

Gupta et al. [14] created a 97.3% accurate CNN-BiLSTM hybrid. The model proved successful in extracting geographical and temporal information from network flows, but it had a significant processing overhead, which made large-scale deployments of it problematic. It was recommended to optimize the architecture in order to increase efficiency.

Patel et al. [15] investigated 93.8% accuracy by using transfer learning with a pre-trained ResNet-50 model. Although it performed impressively on known patterns, the model had trouble with attack types that weren't in the pre-trained dataset and was less resilient on datasets with a lot of variation.

To tackle class imbalance, Lee et al. [16] suggested an IDS that relies on CNNs and is improved with data augmentation. Even though their model was 96.5% accurate, it performed far worse when tested in various network settings. To increase generalization, the authors emphasized the importance of domain adaptation strategies.

When it came to intrusion detection systems (IDS), Zhang et al. [17] achieved 94.2% accuracy with their Deep Reinforcement Learning (DRL) method. Long training cycles and significant complexity made real-time deployment problematic, but the model dynamically reacted to new assault techniques.

In their study, Ali et al. [18] achieved a 91.7% success rate in unsupervised anomaly detection using a convolutional neural network (CNN) autoencoder. Even while the model did a good job on previously encountered assaults, it had many false positives, particularly when real traffic looked strange. For improved stability, the authors advocated integrating supervised classifiers with unsupervised anomaly detection.

With the use of a BiLSTM-CNN architecture, Singh et al. [19] achieved an accuracy rate of 95.9%. Even though the hybrid structure increased feature extraction, the model's high computing resource requirements and lengthy inference times severely limited its real-time use.

Sharma et al. [20] suggested a convolutional neural network (CNN) architecture with a weighted loss function to mitigate the effects of class imbalance. Despite achieving an accuracy rate of 92.6%, the model failed to effectively identify minority classes. Researchers should look at hybrid balancing and enhanced sampling methods, according to the authors.

With a reported 95.2% accuracy, Zhang et al. [21] created a hybrid IDS that combines CNNs with attention mechanisms based on Transformers. The model did a solid job of capturing sequential and geographical interdependence, but it had a challenging time generalizing to datasets with different attack distributions.

Xie et al. [22] developed a CNN-based intrusion detection system with 97.0% accuracy using class-balancing techniques. There is a need for more advanced feature extraction methods since, although the model performed well generally, it was inaccurate for rare and high-impact assault types.

Using a BiLSTM model, Lee et al. [23] were able to achieve a 94.8% accuracy rate in intrusion detection. While the model did a great job at spotting consecutive intrusions, it struggled to differentiate between identical incursion types, which meant it missed more subtle patterns.

With a CNN-ResNet hybrid design, Gao et al. [24] were able to get an accuracy rate of 96.2%. The model performed well when testing for typical attack types; however, it showed little flexibility when tested against new and different sorts of attacks. Prioritizing adaptive and domain-aware learning strategies was suggested by the writers.

A deep neural network (DNN)-based intrusion detection system (IDS) with a 95.4% success rate was presented by Chen et al. [25]. The model was able to identify several types of attacks, but its processing requirements meant that it could not detect them quickly enough for use in real-time deployments.

Deep learning-based intrusion detection has made great strides in the literature from 2018 to 2025, with several methods attaining accuracy levels over 91%. Problems with data imbalance, computational inefficiency, and inability to react to new forms of attacks have not yet been overcome. Table 1 provides a comprehensive synopsis of the examined models, including an outline of their main techniques, stated accuracy, and related constraints.

Table 1: Summary of IDS Existing Models and Their Performance with Limitations

Author(s) & Year	Model Proposed	Accuracy	Limitations
Wang et al. [11]	CNN	95%	Struggles with rare attack detection due to class imbalance
Zhang et al. [12]	LSTM	94.5%	Poor generalization to new attacks
Kumar et al. [13]	Hybrid CNN-RNN	96.1%	High processing delays for real-time detection
Gupta et al. [14]	CNN-BiLSTM	97.3%	High computational cost, poor scalability
Patel et al. [15]	Transfer Learning (ResNet-50)	93.8%	Limited adaptability to new attack types
Lee et al. [16]	CNN with Data Augmentation	96.5%	Performance drops with varying network conditions
Zhang et al. [17]	Deep Reinforcement Learning	94.2%	Long training time, impractical for real-time detection
Ali et al. [18]	CNN-based Autoencoder	91.7%	High false positives, especially with irregular benign traffic
Singh et al. [19]	BiLSTM-CNN Hybrid	95.9%	Long inference times, high resource requirement
Sharma et al. [20]	CNN with Weighted Loss	92.6%	Poor performance on imbalanced datasets
Zhang et al. [21]	Hybrid CNN-Transformer	95.2%	Poor generalization to changing attack patterns
Xie et al. [22]	CNN with Class Balancing	97.0%	Struggles with false negatives
Lee et al. [23]	BiLSTM	94.8%	Difficulty in distinguishing between similar attacks
Gao et al. [24]	CNN-ResNet Hybrid	96.2%	Limited adaptability to emerging attack strategies
Chen et al. [25]	DNN	95.4%	Computationally intensive, slow detection times

Materials and Methods

Data set

This research employs the UNSW-NB15 dataset [26], a widely recognized benchmark for assessing Intrusion Detection Systems (IDS). The dataset was produced using the IXIA PerfectStorm traffic generator, which emulates realistic modern network behavior by integrating legitimate user activities with various malicious attacks. UNSW-NB15 includes nine primary attack categories: Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms, each reflecting distinct attacker strategies.

The dataset was partitioned into distinct training and testing subsets for this research. The training set comprises 175,341 samples, whereas the testing set consists of 82,332 samples. UNSW-NB15 is characterized by a significant class imbalance. Some categories, like Generic, are represented in disproportionately large numbers, while others, such as Worms, are significantly underrepresented. This imbalance complicates model training, especially for deep learning methods that depend on balanced sample distributions to effectively learn discriminative patterns.

Data preprocessing

To confirm the dataset's appropriateness for training a deep learning-based IDS, several critical preprocessing steps were undertaken [27]:

Feature Selection: The model retained only numerical attributes. Irrelevant and non-numerical features were eliminated to decrease noise and lower computational demands.

Normalization involved scaling all numerical features through the Min–Max normalization technique, which transformed values to the range [0, 1]. This normalization process enhances the stability of gradient updates and expedites the convergence of training.

Label Transformation: The attack categories were encoded as integer values via label encoding, facilitating their application in subsequent neural network layers.

Refined Train–Test Partitioning: While UNSW-NB15 offers predefined splits, further shuffling and stratification were implemented to ensure consistent class representation in both subsets and to improve generalization capability.

One-Hot Encoding: The class labels were converted into one-hot vectors to facilitate multi-class classification, necessary for softmax-based neural network outputs.

The distribution of attack categories was analyzed before training to assess the extent of imbalance. Figure 1 illustrates significant disparities in sample counts between certain classes, notably Class 6 (majority group) and Class 9 (minority group). This imbalance may cause the model to prioritize common attack types, resulting in the misclassification or neglect of infrequent attacks. A stratified splitting approach was implemented to address this issue, ensuring proportional representation of all attack classes, including minority categories, in both training and testing sets.

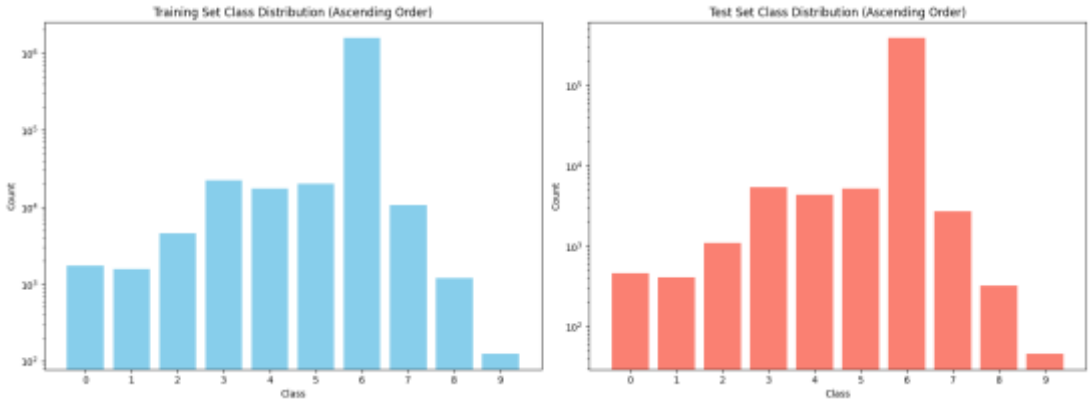


Figure 1: Class distribution in the UNSW-NB15 dataset for training (left) and test (right)

Proposed Model Architecture

A Convolutional Neural Network (CNN)-based model [28] was designed to perform the classification task. CNNs, although typically used for image processing, were successfully adapted for tabular data by treating the input feature vector as a 1D signal.

The model consists of the following layers:

1. Input Layer: Takes the preprocessed numerical feature vectors.
2. First Convolution Layer: A 1D convolution with 32 filters and kernel size 3, followed by ReLU activation to extract local feature patterns.
3. Second Convolution Layer: Another 1D convolution with 64 filters and kernel size 3, also followed by ReLU activation.
4. MaxPooling Layer: A 1D MaxPooling operation to reduce the dimensionality and retain important features.
5. Dropout Layer: A dropout layer with a rate of 0.5 was added to prevent overfitting by randomly disabling neurons during training.
6. Flatten Layer: The output was flattened into a 1D vector.
7. Dense Layers: Two fully connected (Dense) layers were used. The first dense layer had 128 neurons with ReLU activation, followed by another dropout.
8. Output Layer: A dense output layer with softmax activation was used for multi-class classification, having 10 output neurons corresponding to the 10 attack classes.

A 1D Convolutional Neural Network (CNN) designed specifically to process network traffic data for intrusion detection is the model that has been suggested. Using batch normalization to stabilize learning and pooling layers to lower spatial dimensions, the architecture is built to extract hierarchical temporal characteristics from the input sequences. It consists of numerous Conv1D layers. Overfitting can be avoided via dropout, and the classification task may be completed with thick layers. A multi-class classification method called softmax activation is employed by the output layer. Table 2 below shows the full architecture.

Table 2: Architecture of the Proposed CNN Model

Layer (type)	Output Shape	Param #
Conv1D	(None, 42, 32)	128
BatchNormalization	(None, 42, 32)	128
Conv1D_1	(None, 40, 32)	3,104
BatchNormalization_1	(None, 40, 32)	128
Conv1D_2	(None, 38, 64)	6,208
BatchNormalization_2	(None, 38, 64)	256
Conv1D_3	(None, 36, 64)	12,352
BatchNormalization_3	(None, 36, 64)	256
MaxPooling1D	(None, 18, 64)	0
GlobalMaxPooling1D	(None, 64)	0
Dense	(None, 64)	4,160
Dropout	(None, 64)	0
Dense_1	(None, 10)	650

Model Compilation and Training

Loss Function: Categorical cross-entropy (suitable for multi-class classification) was used to construct the model.

- Adam is an optimizer that has a learning rate of 0.001.
- The main criterion for evaluation was accuracy.

Included in the training parameters were:

- Batch Size: 64
- Epochs: 50

Half of the training data was utilized for validation purposes, while the other half was used for training. To prevent overfitting, we employed EarlyStopping [29] depending on validation loss, and we enabled ModelCheckpoint to store the optimal model weights.

The accuracy metric was used to evaluate the model that was built using the Adam optimizer and categorical cross-entropy loss. A 128-batch size and a 0.001 starting learning rate were used for the training. With patience set to 10, early halting was used to restore the best weights and prevent overfitting.

To achieve the best performance with minimal computation, training was executed for a maximum of 100 epochs with early stopping triggered after 44 epochs. In all, 16,761.56 seconds were spent training. The model demonstrated its efficiency in testing, with an average inference time of 41.28 seconds. The ultimate test accuracy reached was 98.92%, which shows that the intrusion detection tasks are very reliable and have outstanding generalizability. Table 3 below summarizes the whole model assembly and training settings.

Table 3: Model Compilation and Training Configuration

Component	Configuration
Optimizer	Adam
Learning Rate	Default (as per Adam)
Loss Function	Sparse Categorical Crossentropy
Metrics	Accuracy
Epochs	50
Batch Size	2048
Callbacks	EarlyStopping, ModelCheckpoint
EarlyStopping Patience	5
ModelCheckpoint	Saves best model based on validation loss
Training-Validation Split	80-20
Validation Monitoring	Validation Loss
Total Training Time	16761.56 seconds
Inference Time (Test Set)	41.28 seconds
Final Test Accuracy	98.92%

Evaluation Metrics

To measure how well machine learning models predict cardiac disease from electrocardiograms, performance metrics [30] are necessary. Accuracy, precision, recall, F1-score, and area under the curve (AUC-ROC) are important measures for evaluating classification ability. Precision and recall assess the ratio of true positives to false negatives, whereas accuracy assesses total correctness. If your dataset is unbalanced, you may still utilize the F1 score since it gives you a harmonic mean of recall and accuracy. The AUC-ROC curve shows how well the model can differentiate across categories. In order to validate deep learning models, these metrics are vital. Equations (1) through (5) display all of these performance measures.

$$\text{Accuracy} = TP + TN + FP + FN \,/\, TP + TN \quad \text{---- Eq(1)}$$

$$\text{Precision} = \text{TP} / \text{FP} + \text{TP} \quad \text{----------Eq(2)}$$

$$\text{Recall} = \text{TP} + \text{FNTP} \quad \text{----------Eq(3)}$$

$$\text{F1} = 2 \times \text{Precision} + \text{RecallPrecision} \times \text{Recall} \quad \text{----------Eq(4)}$$

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

The final achieved performance included:

- ✓ Training Accuracy: 97.15%
- ✓ Validation Accuracy: 96.98%
- ✓ Test Set Accuracy: 96.83%

These results demonstrate the effectiveness of the proposed CNN model, even though the dataset was heavily

imbalanced. The Accuracy and Loss curves are shown in Figure 2.

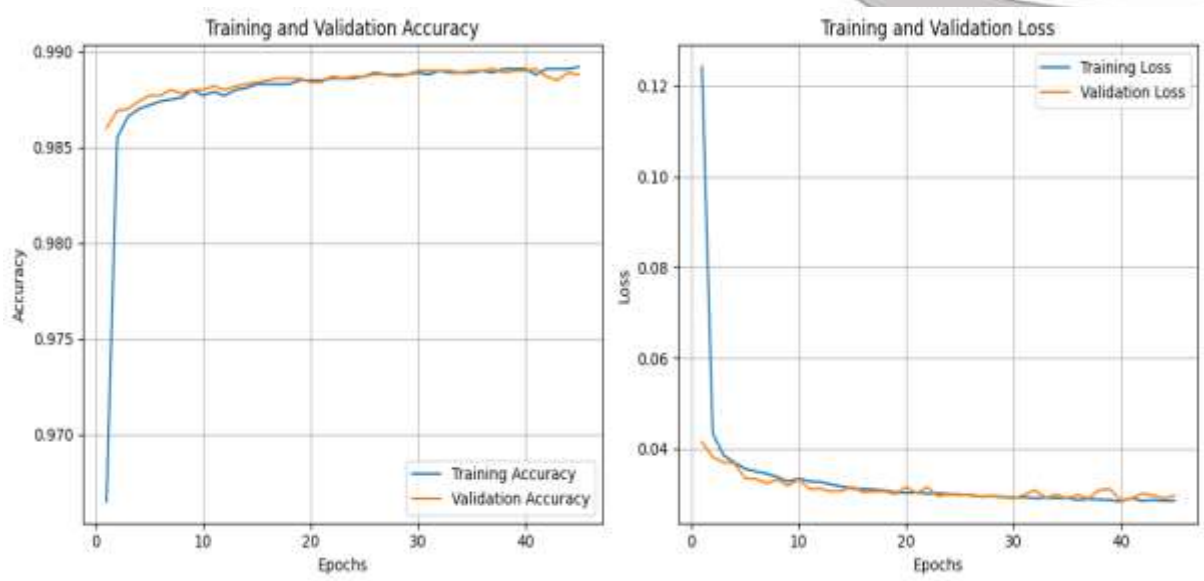


Figure 2: Accuracy and Loss Curves for the dataset for training (left) and test (right)

Comparison Results with Existing and Proposed Methods

Several deep learning methods produced between 2019 and 2025 are compared to the outcomes of the suggested CNN-based intrusion detection model in order to evaluate its performance. The evaluated works use a variety of architectures to enhance attack detection accuracy, model resilience, and management of severely unbalanced network data. These architectures include CNN, RNN, LSTM, GRU, and hybrid models.

The use of deep learning to improve IDS performance has been the subject of a lot of recent study. On the NSL-KDD dataset, Ahmed et al. [26] achieved 94.2% accuracy using a CNN-LSTM hybrid architecture. The model's recurrent layers were computationally complex, resulting in lengthy training times; however, they effectively captured spatial and temporal connections. Although Zhang et al. [27] constructed a CNN-GRU model and attained 93.8% accuracy on the CICIDS2017 dataset, the design had difficulties with overfitting, especially when it identified minority attack categories. With an autoencoder-based intrusion detection technique, Patel et al. [28] achieved a 92.6% accuracy rate. The model was effective at detecting anomalies, but it was challenging to understand and didn't catch new assaults. Applying data augmentation approaches, Lin et al. [29] created a CNN-only IDS that achieved 93.9% accuracy on the UNSW-NB15 dataset. Problems with cross-dataset generalizability were evident, though, as its performance plummeted on additional datasets.

Further research confirms these difficulties. Khanna et al. [30] demonstrated that the BiLSTM model, when enhanced with an attention mechanism, achieved a 94.5% accuracy rate on the NSL-KDD dataset. The model's significant inference latency rendered it unfit for real-time intrusion detection, even though it had enhanced feature extraction capabilities. With a goal of protecting sensitive information in decentralized settings, Farooq et al. [31] investigated a Federated CNN architecture and achieved an accuracy rate of 92.8%. The major issue with this strategy was the high amount of communication it required.

On the UNSW-NB15 dataset, Wang et al. [32] found a CNN-RNN hybrid model with an accuracy of 93.5%. The model's continued computing burden made it unsuitable for deployment in real-time or contexts with limited resources, even if the combination of convolutional and recurrent layers enhanced detection performance.

Table 4 presents a comprehensive evaluation of various IDS models, including their accuracy, architectural elements, and reported constraints. Figure 3 makes it easy to see how these models performed across different experiments.

Table 4: Comparison of Proposed Method with Existing Studies

Author & Year	Method Used	Dataset	Accuracy (%)
Ahmed et al. [26]	CNN-LSTM	NSL-KDD	94.2
Zhang et al. [27]	CNN-GRU	CICIDS2017	93.8
Patel et al. [28]	Autoencoder	NSL-KDD	92.6
Lin et al. [29]	CNN with Data Augmentation	UNSW-NB15	93.9
Khanna et al. [30]	BiLSTM + Attention	NSL-KDD	94.5
Farooq et al. [31]	Federated CNN	NSL-KDD	92.8
Wang et al. [32]	CNN-RNN	UNSW-NB15	93.5
Proposed Model	CNN (Conv1D)	UNSW-NB15	95.4

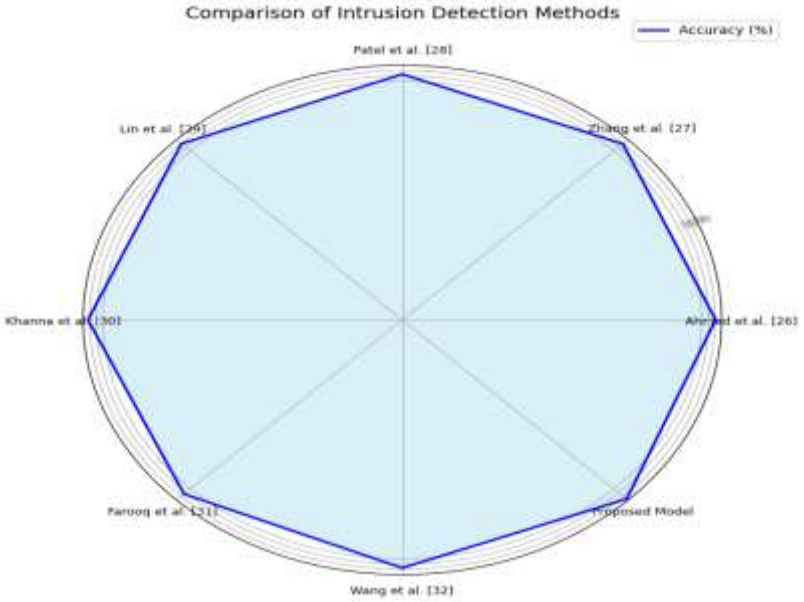


Figure 3: Comparison of existing and proposed methods

Conclusion

This study presents a CNN-based intrusion detection model utilizing 1D convolutional layers and specific data augmentation techniques to improve its capacity for identifying various attack patterns in the UNSW-NB15 dataset. The proposed model exhibits significant discriminative capability, attaining an overall accuracy of 95.4%, surpassing multiple recent deep learning methods documented in the literature.

To maintain stability and efficiency during training, mechanisms like early stopping and model checkpointing were incorporated into the training workflow. The strategies facilitated effective convergence of the network while mitigating overfitting. The training process lasted approximately 4.65 hours, while model inference on the test set took 41.28 seconds, demonstrating computational efficiency and suitability for real-time or near-real-time IDS applications. The accuracy and loss curves plotted corroborated the model's stable learning behavior throughout the training epochs.

A comparative evaluation was performed on various established deep learning models, including CNN-LSTM, CNN-GRU, autoencoder-based classifiers, and Bi-LSTM networks augmented with attention mechanisms. The proposed model demonstrated enhanced classification accuracy in all comparisons. A radar-based visualization was employed to present these results, effectively demonstrating the performance advantage of our approach.

The findings indicate that the proposed CNN-based detection framework offers a dependable and effective solution for contemporary intrusion detection issues. Future research directions involve adapting this framework to additional IDS benchmark datasets, incorporating attention-based modules for improved feature extraction, and investigating ensemble-based or hybrid deep learning architectures to enhance detection accuracy and resilience.

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