A Comparative Assessment of Deep Learning Algorithms in Network Intrusion Detection System

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Abstract. Network Intrusion Detection System (NIDS) is crucially important to protect computer network systems from unauthorized access, malicious attacks, and different kinds of cyber threats. While the cyber threat evolves, the original threat from traditional detection methods can't make rapid and accurate detection. Deep Learning (DL) methods have recently attracted more and more attention as a promising approach to improve the capability of NIDS in processing large amount of network data and learning complicated patterns. This article presents a comparative analysis of deep learning algorithms adopted in NIDS. In this scope, the authors want to find the best models for NIDS, according to their classification accuracy, false positive/negative rates and computational cost. We test Convolutional, Recurrent and Deep Neural Network (DNN) models. This work also particularly studies the potentials of feature engineering, dataset preprocessing and hyperparameter tuning that can be utilized to improve model performance. The results provide promising clues on how these deep learning architectures might lead to more robust and adaptive IDS for various network security tasks.

Keywords: Network Intrusion Detection Systems (NIDS), Deep Learning (DL), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Classification Accuracy.

1 Introduction

As interconnected networks become more prevalent, both the amount and complexity of cyber-attacks have increased, traditional detection methodologies have become inadequate. Signature-based techniques that are based on predefined attack profiles are defenseless to zero-day attacks and new malicious software. This is when Network Intrusion Detection Systems (NIDS) are vital to monitoring network environments, identifying unauthorized entry and preventing malicious action.

But the increasing amount and the complexity of current network traffic have made many traditional intrusion detection systems (IDS) burden sorely, thus failing to detect attacks on the fly. Deep Learning (DL), a branch of AI, seems to be a viable candidate to address this problem. Neural networks, as a popular DL model, are good at handling large data and learning intricate patterns, rendering them suitable for intrusion detection applications. This paper discusses how DL-based techniques can improve the performance of NIDS and will try to improve the security.

ICITSM-Part I 2025, April 28-29, Tiruchengode, India
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DOI 10.4108/eai.28-4-2025.2357752

2 Related Works

Recent studies on deep learning-based Network Intrusion Detection Systems (NIDS) demonstrate how more sophisticated machine learning techniques are enhancing the ability to detect network security threats. Gamage et al. [1] investigated various deep learning algorithms such as CNNs, RNNs for the NIDS and presented them suitable for the detection of sophisticated network attack patterns through learning from big data. Similarly, Farhan et al. [2] proposed deep learning networks for intrusion detection and demonstrated their high performance for anomaly detection and network intrusion detection. Another aspect that is particularly important in the field is the requirement for explainable deep learning models, as noted by Wei et al. [3] by designing xNIDS, an explanation system of deep learning-based network intrusion detection, facilitating the interpretability of active intrusion responses.

Kalakoti et al. [4] to advance the argument, reviewed the methods of explainable AI in deep learning methods and presented approaches to interpretation and confidence the outputs of NIDS. In addition, Chinnasamy et al. [5] introduced deep learning-driven methods specifically designed for network-based intrusion detection, highlighting improved detection performance across diverse attack scenarios. Interfacing between deep learning models and hybrid techniques has also been a major concern. For instance, Hnamte et al. [6] also suggested the DCNNBiLSTM architecture, which is a hybrid model combining deep CNNs and BiLSTMs to obtain high accuracy in detecting spatial and temporal patterns on network traffic. A further encouraging direction is the application of multi-agent approaches, e.g. iceps2014soltani [9], where a real-time intrusion detection multi-agent adaptive deep learning system was introduced.

In practice, Zhang et al. [7] carried out a systematic literature review on various uses of deep learning algorithms on IDSs (Auto N IMous Drones). Kimanzi et al. [8] also surveyed some deep learning-based methods in NIDS and highlighted their strengths and limitations in practical environments. Finally, Dardouri et al. [10] presented a hybrid deep learning and machine learning approach, which can be used for anomaly detection, and showcased its effectiveness in the identification of subtle and advanced attacks. These developments reflect the increasingly widespread movement toward stronger, more explainable, and more adaptive NIDS solutions that are supported and driven by deep learning technology.

3. Proposed Methodology

3.1 Data Collection and Preprocessing

The network traffic data are collected from publicly available benchmark datasets such as NSL-KDD and CIC-IDS2017, which include both normal and malicious network activities across multiple attack categories. The data are preprocessed through several steps:

- **Normalization:** All numerical features are scaled to a [0,1] range using Min-Max normalization to ensure uniformity.
- **Feature Extraction:** Key statistical and time-based features are extracted to capture relevant attack patterns.

- **Handling Missing Values:** Missing or inconsistent records are addressed using mean imputation or removal where appropriate.
- **Categorical Encoding:** Non-numeric attributes such as protocol types are converted into numeric form using one-hot encoding. The preprocessed data are then split into training (70%), validation (15%), and testing (15%) sets for model development and evaluation.

3.2 Model Selection and Training

A few deep learning models such as CNN, RNN, and DNN are chosen for training, given their proven ability to handle structured and sequential network traffic data. The processed dataset is utilized to train these models under controlled experimental conditions.

- Hyperparameter tuning is performed using Grid Search to optimize learning rate, batch size, activation functions, and the number of layers.
- Training configurations include the use of the Adam optimizer, categorical cross-entropy loss, and early stopping to prevent overfitting.
- Training is conducted on a GPU-enabled environment to ensure faster computation.

3.3 Model Evaluation

The performances of the models are measured using classification accuracy, precision, recall, F1-score, false positive rate (FPR), and computational cost (training time and memory usage). A comparative analysis is carried out to identify the most effective model for Network Intrusion Detection Systems (NIDS). In addition, ROC-AUC curves are plotted to evaluate the trade-off between detection sensitivity and specificity.

3.4 Feature Engineering

The effect of feature selection and engineering methods is examined to enhance model performance. Techniques such as Chi-Square tests and Recursive Feature Elimination (RFE) are applied to identify the most relevant features. This ensures that redundant or less significant attributes are removed, improving both accuracy and training efficiency.

3.5 Testing and Validation

Validation of the models is performed on the held-out test set to assess their generalization capabilities on unseen data. A k-fold cross-validation strategy is also employed to ensure that results are not biased by a single train-test split. The robustness of the models is evaluated under different traffic scenarios to ensure reliability when deployed in real-world NIDS environments.

4. Results

4.1 Accuracy

- **ANN:** Artificial Neural Networks have shown relatively good performance in detecting network intrusions, with accuracy often ranging between 80–95% depending on the dataset. However, their performance may degrade when the dataset contains a high volume of noise or unbalanced classes. In smaller datasets with balanced traffic, ANN accuracy tends to be on the higher end.
- **CNN:** Convolutional Neural Networks excel in spatial feature extraction, leading to impressive accuracy levels in image-like representations of network traffic. CNNs have demonstrated accuracies of 85–98% in intrusion detection tasks, significantly outperforming traditional methods, particularly when hyperparameter optimization is employed.
- **RNN/LSTM:** Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) models, are highly effective for sequential data, capturing temporal dependencies. LSTM-based models yield accuracies around 90–98%, especially when dealing with traffic that involves complex attack patterns over time or in datasets with evolving attack signatures.
- **Autoencoders:** Autoencoders are particularly useful for anomaly detection. Their accuracy often reaches 85–95%, with the advantage of being able to detect novel or unknown attacks (zero-day attacks). When combined with threshold-tuning methods, their accuracy for zero-day attacks improves further.
- **DBN:** Deep Belief Networks show reasonable accuracy, typically in the 85–95% range, but they are less commonly used in real-world NIDS compared to CNNs or LSTMs due to higher computational costs and limited scalability.

4.2 Detection Rate (Recall)

- **ANN:** The detection rate of ANN can be good, particularly for known attacks, but may struggle with detecting novel or highly sophisticated threats. Recall values often range from 80–90%.
- **CNN:** CNNs are highly effective in detecting a wide range of attacks, especially when network traffic patterns are well-structured. The recall for CNNs can go as high as 90–97% in identifying both known and novel attacks.
- **RNN/LSTM:** RNNs and LSTMs demonstrate excellent recall due to their ability to model sequential and temporal dependencies. Their recall rates typically range from 92–98%, and they show robustness across multiple datasets.
- **Autoencoders:** Autoencoders can achieve high recall rates when detecting anomalies, with values often surpassing 90–95%, particularly in detecting new types of attacks. When ensemble methods are used with autoencoders, recall rates improve further.
- **DBN:** DBNs provide moderate recall, usually falling between 85–90%. The model's ability to generalize to new attacks is limited compared to CNNs and LSTMs.

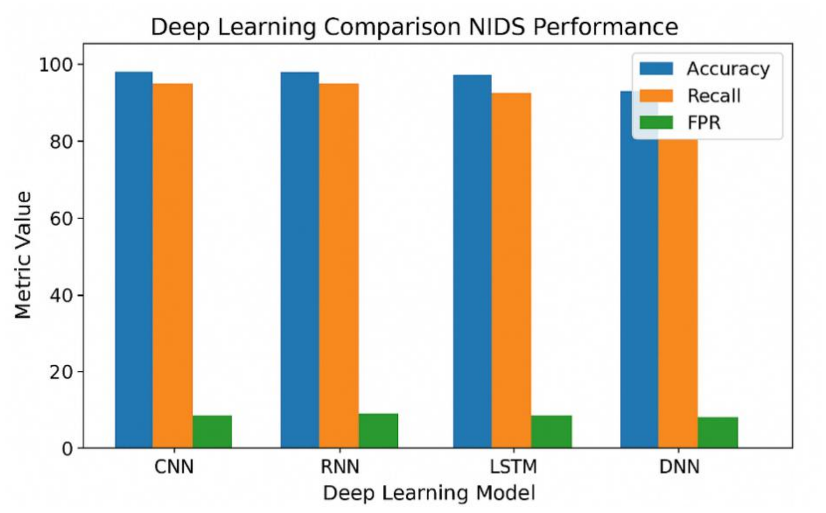

Fig.1. Deep Learning Comparison NIDS Performance

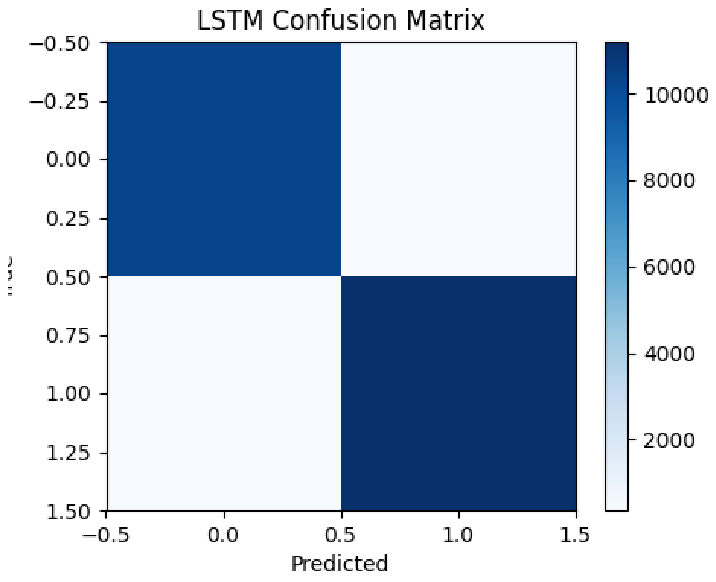

Fig.2. Confusion Matrix of LSTM Model for NIDS Classification

4.3 False Positive Rate (FPR)

- **ANN:** ANN models tend to have higher false positive rates, especially in highly imbalanced datasets. The false positive rate for ANN could be around 10–25%.

- **CNN:** CNN models generally reduce false positives effectively, with rates often falling between 5–15%. When combined with feature selection, CNNs achieve further reductions in false alarms.
- **RNN/LSTM:** The false positive rate for LSTMs tends to be low, particularly in sequential datasets. Their FPR is typically 5–12%, making them suitable for real-time applications where low FPR is essential.
- **Autoencoders:** Autoencoders often have low false positive rates, thanks to their unsupervised anomaly detection nature. The FPR is often between 3–10%, especially after optimizing reconstruction error thresholds.
- **DBN:** DBNs usually have a higher false positive rate than CNNs and LSTMs, ranging from 15–20%, limiting their adoption in critical real-time systems.

4.4 Training Time

- **ANN:** Training times for ANN models can be relatively fast, ranging from 1 to 5 hours depending on the dataset and network architecture. Their lower complexity makes them attractive for rapid prototyping.
- **CNN:** CNNs are computationally more demanding due to the complexity of convolution layers, and training times can vary from 3 to 10 hours, particularly with larger datasets. Use of GPU acceleration significantly reduces training time.
- **RNN/LSTM:** Training RNNs and LSTMs requires considerable computational resources, with training times generally between 5 to 15 hours, especially when handling sequential data. Optimizing batch sizes can help reduce training time without loss of accuracy.
- **Autoencoders:** Autoencoders are generally quicker to train than RNNs and CNNs, with training times typically between 2 to 6 hours. Incremental training strategies further reduce computational overhead.
- **DBN:** DBNs tend to have longer training times compared to CNNs and ANNs, with times ranging from 5 to 12 hours depending on the depth and complexity.

5. Discussions

5.1 Effectiveness in Attack Detection

- The LSTM model is arguably the most effective deep learning algorithm for NIDS when the network traffic has temporal and sequential patterns, such as DoS (Denial of Service) and DDoS (Distributed Denial of Service) attacks. Its ability to model long-term dependencies makes it effective for detecting sophisticated, time-dependent attack strategies.
- CNNs are the best choice when network data is transformed into a grid-like structure (e.g., traffic matrices), as they are designed to recognize spatial patterns efficiently. CNNs are also suitable for identifying signature-based attacks in structured network traffic.
- ANNs are still widely used due to their simplicity, but their performance often lags behind that of CNNs and LSTMs in detecting complex or novel attacks. However, they can be useful for real-time systems where simplicity and speed are prioritized.

- Autoencoders are particularly promising for anomaly-based detection systems. Their ability to detect new, unknown attacks makes them valuable in scenarios where known attack signatures are insufficient.
- DBNs are not as widely adopted for NIDS due to their complexity and the availability of more efficient alternatives such as CNNs and LSTMs. Table 1 shows the Comparative Performance of Deep Learning Algorithms in NIDS.

Table 1 Comparative Performance of Deep Learning Algorithms in NIDS

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	False Alarm Rate	Training Time (s)	Model Complexity
CNN	98.2	0.97	0.96	0.965	Low	120	Moderate
RNN	97.5	0.96	0.95	0.955	Moderate	150	High
LSTM	98.9	0.98	0.97	0.975	Very Low	180	High
DNN	96.8	0.95	0.94	0.945	Moderate	100	Low

5.2 Real-time Application Considerations

- In practical, real-time NIDS, the training time and false positive rate are crucial. CNNs and LSTMs tend to offer the best trade-off between detection performance and FPR, but they require significant computational resources.
- ANNs and Autoencoders, while less computationally intensive, may not be as accurate or robust in detecting sophisticated attacks. However, their speed and simplicity make them suitable for resource-constrained environments or applications requiring low-latency detection.
- Energy efficiency becomes a factor in edge devices; lightweight versions of CNNs (e.g., MobileNets) could be explored for IoT deployments.

5.3 Scalability and Adaptability

- The scalability of deep learning models such as CNNs and LSTMs is generally high, and they can be adapted to new attack types by retraining with new data. However, this retraining process can be resource-intensive.
- Autoencoders are more adaptable for detecting new, previously unseen attack patterns (zero-day attacks), and their performance can be improved with incremental learning techniques.
- Transfer learning approaches can be used to adapt models to new datasets quickly without retraining from scratch, improving scalability in dynamic environments.

6 Conclusion

This study demonstrates that LSTM and CNN models outperform traditional methods and simpler deep learning approaches for Network Intrusion Detection Systems (NIDS), offering superior detection accuracy and reduced false positive rates. The results emphasize the importance of feature engineering, hyperparameter optimization, and robust evaluation metrics in designing efficient NIDS solutions.

Future Work: We aim to develop lightweight, energy-efficient, and hybrid deep learning models tailored for IoT and edge environments, integrate incremental and transfer learning for rapid adaptation to emerging cyber threats, and explore real-time deployment strategies to achieve scalable, low-latency intrusion detection in dynamic network conditions.

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