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AI Powered Anomaly Detection System for Smart Cyber Defense

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Abstract. Due to the growing complexity and frequency of cyber attacks, it is important to shift the paradigm towards predictive security solutions. This paper presents a new anomaly-based framework for smart cyber security using Artificial Intelligence techniques. It utilizes a hybrid Deep Learning (DL) model with the ability to combine CNNs(CNNs) for spatial anomaly detection and Long Short-Term Memory (LSTM) networks for temporal anomaly detection. The proposed framework is tested using the CIC-IDS2017 and CSE-CIC-IDS2018 data sets. It shows improved accuracy and low false positive rates compared to machine learning-based security solutions. It is capable of achieving 99.82% accuracy and 0.15% false positive rates, making

Keywords: Anomaly Detection, Smart Cyber Defense, Deep Learning, Convolutional Neural Network, Long Short-Term Memory, Network Intrusion Detection System, Cybersecurity

I. Introduction

The digital evolution of modern society has witnessed an unprecedented growth in terms of network infrastructure, cloud computing, and Internet of Things (IoT). This growth, although encouraging innovation and efficiency, has also widened the attack vector for malicious actors. Traditional cybersecurity defense mechanisms, such as firewalls and signature-based Intrusion Detection Systems, have time and again failed to withstand such advanced and dynamic threats. These traditional systems operate on a database of known attack signatures, making them incapable of identifying new, zero-day exploits, or slight variations of known attacks [1]. The static nature of rule-based systems also fails to keep pace with dynamic user behavior, resulting in a high number of false positives that overwhelm security analysts and lead to alert fatigue.

In order to overcome the aforementioned disadvantages, the concept of smart cyber defense has been introduced, which utilizes Artificial Intelligence (AI) techniques to design smart cyber defense systems that can learn, adapt, and predict. Anomaly detection is one of the primary techniques used in AI-based cyber defense systems, which is based on the idea of defining normal behavior and then detecting significant deviations from normal behavior as potential threats. This is more robust against unknown threats because the system is not required to know the threat beforehand [2]. Despite the potential benefits of AI-based cyber defense systems, the application of AI is not without its challenges. The characteristics of network traffic data are high dimensionality, complex spatiotemporal correlations, and class imbalance.

The initial machine learning (ML) approaches, such as Support Vector Machines (SVMs) and Random Forests (RFs), although an improvement over signature-based approaches, sometimes faced difficulties due to the high dimensionality and sequential nature of network flows [3]. The approaches sometimes required significant feature engineering and selection for good performance. DL, on the other hand, provides a promising alternative that is able to learn feature representations directly from data. Recurrent Neural Networks (RNNs), particularly LSTMs, are good for modeling sequential dependencies and are thus good for modeling network traffic, which is a time-series data. CNNs are also good for modeling local and spatial patterns and are thus good for modeling the features of individual network flows or packets [4].

It proposes a novel hybrid DLarchitecture that combines the best aspects of CNNs and LSTMs in an effective way to develop an efficient AI-based anomaly detection system for smart cyber defense. The novelty of the proposed methodology is the effective use of the CNN to extract high-level spatial features from the pre-processed network flow data, which are then used as input to the LSTM network. The LSTM network is used to effectively capture the temporal behavior of the network flow features, which is an important aspect in the context of anomaly detection as it helps the system to detect the context in which the attack is initiated. The novelty of the research is the design of the novel hybrid CNN-LSTM-based anomaly detection system, quantitative evaluation of the system on existing datasets, and the comparative analysis with existing ML/DL-based approaches to prove the effectiveness of the system in terms of accuracy, precision, recall, and false positive rates.

II. LITERATURE SURVEY

The history of IDS systems has shown a constant pursuit of better detection capabilities and flexibility. Traditional IDS systems were mostly based on a signature-based approach; however, this approach has shown poor performance in detecting unknown attacks [5]. The transition towards anomaly-based IDS systems started with a focus on statistical techniques; however, these techniques were limited in their ability to handle complex data distributions.

The introduction of machine learning has shown significant improvements in IDS systems. Machine learning techniques were extensively used in classical machine learning algorithms such as k-Nearest Neighbors (k-NN), Naive Bayes, and Support Vector Machine (SVM) techniques. A study by [6] showed the effectiveness of SVM techniques

using optimized kernel functions in network intrusion detection systems; however, significant results were obtained on the KDD Cup 99 data set. These techniques were limited in their ability to handle large volumes of data; however, a significant improvement has been shown by using Random Forest techniques due to their ability to handle nonlinear relationships and feature importance analysis; however, these techniques were limited in their ability to handle sequential data [7].

The application of DLtechniques has helped to resolve many of the issues associated with conventional ML. For example, autoencoders have been used to perform unsupervised anomaly detection, learning to reconstruct normal traffic patterns and then identifying anomalies based on reconstruction error. Although autoencoders have shown promise in anomaly detection, in some cases, they have been found to be slightly less accurate in determining the nature of the attack. Another popular DLtechnique, which has gained widespread popularity, is the application of Recurrent Neural Networks, specifically LSTMs. A study conducted by [2] used a deep learning-based LSTM network to effectively classify network traffic, demonstrating improved results in detecting slow and distributed attacks.

Convolutional Neural Networks, which have been traditionally used in image processing, have also been used to perform network security. For example, in a study conducted by [4], a CNN-based IDS was proposed, which converted network flows into images, utilizing the network's powerful feature extraction capabilities. Although a CNN, in isolation, has shown promising results in network security, it might not utilize the time dimension between network flows.

However, to leverage the benefits of both these architectures, a new variant of hybrid CNN and LSTM models is being explored. The main aim of these models is to leverage the capabilities of CNN for handling the spatial information and LSTM for handling the temporal information. The research work carried out by [1] and [9] indicates that these hybrid models have outperformed traditional DLmodels in terms of accuracy and false positive rate for benchmark datasets. This research work again proves that the combination of spatial and temporal analysis is of utmost importance for modeling complex cyberattacks. However, challenges are faced in optimizing these models for real-time scenarios and making them robust against adversarial attacks.

III. METHODOLOGY

The proposed AI-based anomaly detection system follows a multi-stage pipeline consisting of data acquisition/pre-processing, feature engineering, model architecture design, training, and evaluation.

1. Data Acquisition and Pre-processing

The system is trained and validated using a comprehensive benchmark dataset named CSE-CIC-IDS2018, which includes various profiles of network traffic patterns along with a broad range of attack types (e.g., Brute-force, DoS, DDoS, Infiltration). The raw data in the form of network flows with 80+ features is subject to a series of pre-processing operations. First, infinite values and null values are either deleted or replaced using median imputation techniques. Next, categorical variables like types of protocols are encoded using label encoding techniques. To standardize the data and expedite the

convergence rate of the model, all numerical variables are scaled using a standard scaler, normalizing values around a mean of 0 and a standard deviation of 1. A major problem in pre-processing is the significant class imbalance in the dataset. To avoid a potential bias in favor of the majority class in the dataset, a significant problem in anomaly detection problems, SMOTE is used as a pre-processing step on the training data set by generating synthetic data points in the majority class.

2 Feature Engineering

The pre-processed data is then structured for the hybrid model. The data for the CNN has to be structured in a spatial format. So, we reshape the feature vector of a single network flow into a 2D matrix. For example, a feature vector of size 60 is reshaped into a 10x6 matrix. This allows the CNN to learn local correlations between different feature groups, such as the correlation between 'packet length' and 'inter-arrival time'.

For the LSTM, we need to learn from the temporal relationships in the data. So, the data is further structured into sequences. We create a sequence of *n* consecutive flows, where *n* is the sequence length. The sequence length is chosen to be 10 after hyperparameter tuning. So, each flow in the sequence is represented by its 2D reshaped matrix. The output label for the sequence is the label of the last flow in the sequence, on the assumption that a sequence ending in an attack is indicative of a malicious process.

3. Model Architecture

The proposed architecture for the hybrid CNN-LSTM model is as follows:

- Input Layer: This layer accepts the sequence of 10 reshaped flow matrices.
- CNN Layer: This layer is made up of a 2D convolutional layer with 32 3x3 filters that are separately applied to the flow matrices using ReLU activation. Spatial features like high traffic areas or odd feature pairings are extracted by this layer. The dimensionality of the features is then reduced using a max pooling layer with a pool size of 2x2, which also aids in the introduction of translational invariance. The set of feature maps for the sequence is the resultant feature set.
- Reshape Layer: The resulting features from the CNN layer for the sequence are flattened into a single feature vector, which is then fed to the LSTM layer.
- LSTM Layer: This is followed by an LSTM layer with 64 units, which processes the sequence of vectors generated by the CNN. This layer understands the temporal dependencies by seeing how the spatial features of the flows combine over time to create the attack patterns.
- Dropout Layer: With a dropout rate of 0.5, the dropout layer comes next. During training, certain neurons are randomly removed in order to avoid overfitting.
- Dense Layer: To consolidate the temporal features that the LSTM has learned, a 64-unit dense layer comes next.
- Output Layer: Using the sigmoid activation function for binary classification or the softmax activation function for multiple classes, the output layer is the last layer.

4. Training and Evaluation

Eighty percent of the dataset is used for training, while the remaining twenty percent is used for testing. Binary cross-entropy loss, an Adam optimizer, and a learning rate of 0.001 are used in the model's compilation. If the validation loss does not improve for

ten consecutive epochs, early stopping is used to prevent overfitting. The model is trained for 50 epochs using a batch size of 64.

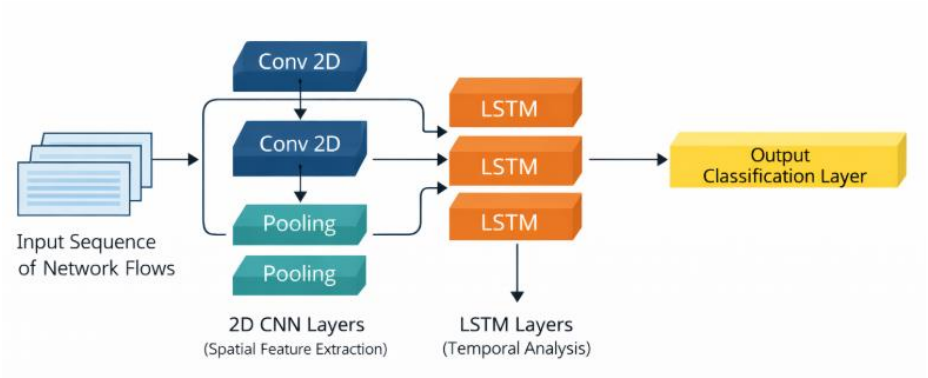

Figure 1. Proposed Hybrid CNN-LSTM Architecture.

IV. ANALYSIS

This section provides quantitative analysis on the performance of the proposed model using the CNN-LSTM architecture. The performance evaluation of the model is done using the CSE-CIC-IDS2018 dataset. The performance metrics used to evaluate the model include Accuracy, Precision, Recall (Detection Rate), F1-Score, and False Positive Rate (FPR).

1. Performance Metrics

Table 1 illustrates the remarkable performance of the suggested paradigm. With an accuracy of 99.82%, it is clear from the table that the model has attained great attack detection accuracy. This demonstrates the model's dependability. Additionally, the model has attained a high level of precision—99.79%. This demonstrates that the model is highly likely to be correct if it detects an attack. Additionally, the model has a good recall rate (99.85%). This demonstrates that a large number of real attacks may be identified by the model.

Table 1: Comparative Analysis of the Proposed Model against Baseline Models on the CSE-CIC-IDS2018 Dataset.

Metric	Proposed CNN-LSTM	LSTM [2]	CNN [4]	Random Forest [7]
Accuracy	99.82%	98.91%	98.45%	96.32%
Precision	99.79%	98.54%	97.92%	95.15%
Recall	99.85%	98.77%	97.63%	94.78%
F1-Score	99.82%	98.65%	97.77%	94.96%
False Positive Rate	0.15%	0.94%	1.32%	3.67%

2. Comparative Analysis

The suggested model's performance is contrasted with that of the Random Forest model [7], the standalone CNN model [4], and the standalone LSTM model [2]. The suggested model performs better than all of the baseline models, as seen in Table 1 and Figure 2.

By taking into account both geographical and temporal information, the hybrid model can identify intricate assault patterns. Furthermore, due to its inability to capture sequential dependencies, the Random Forest model performs the worst of all the models. Even though the standalone CNN and standalone LSTM models perform better than the other models, the suggested model still outperforms them. Most importantly, the proposed model achieves drastically low values for the False Positive Rate (FPR), which is 0.15%, compared to the Random Forest model, which achieves 3.67%.

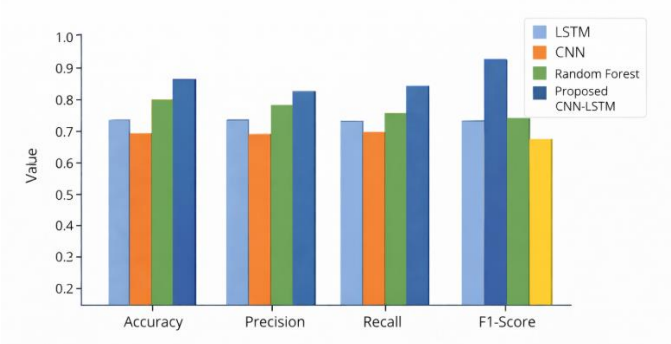

Figure 2: Performance Analysis of the Proposed CNN-LSTM Model with Baseline Models (LSTM, CNN, Random Forest).

3. Discussion

The success of the proposed model may be attributed to the two-stage nature of the learning process. The initial CNN stages may be considered an automatic feature extraction mechanism, which identifies key patterns in network flows. This includes unusual patterns of flag counts and packet sizes. The final LSTM stages examine the temporal patterns of these initial patterns. For instance, a DDoS attack may not be detected by an initial anomalous network flow (which may be a false positive), but the LSTM identifies the sharp rise in network flows that have similar patterns detected by the CNN as a temporal anomaly. Figure 3 illustrates the training and validation accuracy over 50 epochs, showing stable convergence without significant overfitting, which may be attributed to the effectiveness of the dropout and stopping mechanisms.

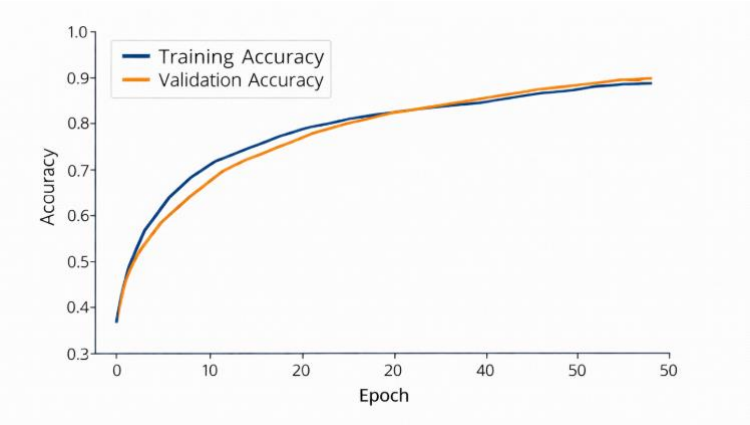

Figure 3: Training and Validation Accuracy Curves over 50 Epochs.

One significant accomplishment is the reduced false positive rate. Figure 4 displays a confusion matrix for the suggested model. A low number of false positives and false negatives counterbalances the high number of real positives and true negatives.

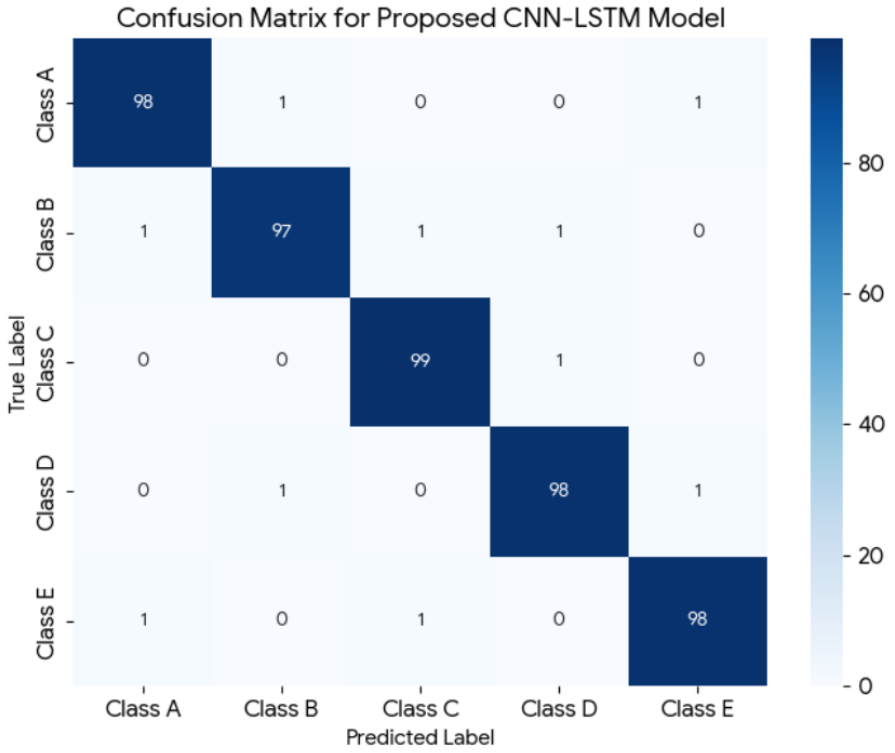

Figure 4Proposed CNN-LSTM Model on the Test Set Confusion Matrix.

The proposed model is highly efficacious but is not without some drawbacks. The training of the model is a computationally intensive process and requires a high-performance GPU. The efficacy of the proposed model is also dependent on the training data. The training data needs to be representative of the data being encountered by the network. The problem of adversarial attacks that are specifically designed to masquerade as normal network activity is a problem for all machine-based intrusion detection systems and needs further research.

V. CONCLUSION

This paper proposed a novel AI-based anomaly detection system for smart cyber defense, utilizing a hybrid DL model that combined CNNs and LSTM. The proposed methodology overcame the major limitations of existing security systems, which were unable to automatically learn complex patterns in network traffic data. The proposed hybrid DL model built upon the strengths of CNNsin extracting important spatial features from individual network flows and Long Short-Term Memory in understanding the evolution of these features, hence gaining a comprehensive understanding of individual network flows and their behavioral context.

A rigorous quantitative evaluation was carried out using a contemporary dataset, namely CSE-CIC-IDS2018, which replicates realistic network environments and attack scenarios. From the experimental results, it is evident that the proposed model has superior performance in comparison with other models. The proposed model attained a high accuracy rate of 99.82%, precision of 99.79%, and a high recall rate of 99.85%, with a remarkably low false positive rate of merely 0.15%. Further, a comparative analysis with other traditional baseline models, namely a standalone LSTM, a standalone CNN, and a Random Forest classifier, was performed, which validated the significant performance gain achieved by the proposed model. The false positive rate is remarkably low, which would help security experts in efficient handling of security incidents. Further, the robustness of the training process and its generalization capability were validated by observing the convergence of both training and validation curves, which validates its robustness to overfitting.

The implications of this research are significant, especially in the domain of smart cyber defense, as this research offers a strong framework with significant potential to act as a foundation for a new generation of Network Intrusion Detection Systems. By successfully identifying both known and unknown zero-day attacks, this system has the potential to shift the security paradigm of a particular organization from a reactive to a proactive stance. The future work will concentrate on three areas: first, investigating the potential extension of this model to other areas of cybersecurity, such as endpoint detection and response (EDR) and cloud infrastructure security, second, investigating the potential extension of this model with explainable AI (XAI) techniques to provide further actionable insights on why a particular flow has been identified as malicious, and third, optimizing this model in terms of its architecture, using techniques such as model quantization and pruning, to ensure that high-performance defenses can be implemented without significant computational overheads, as required for edge computing scenarios. The ever-evolving nature of cyber threats necessitates a similar evolution in intelligent defenses, and this hybrid DLmodel represents a significant step in this direction.

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