Title: Adaptive Intrusion Detection System Based on Hybrid Deep Learning and Feature Engineering for Enhanced Cybersecurity in IoT Networks

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Keywords:
Intrusion Detection System (IDS), Internet of Things (IoT), Deep Learning, Feature Engineering, Hybrid Model, Cybersecurity, Network Security, Anomaly Detection, Machine Learning, Performance Evaluation

Article History:
Received: 10 February 2025; Revised: 11 February 2025; Accepted: 12 February 2025; Published: 24 February 2025

Abstract:
The proliferation of Internet of Things (IoT) devices has significantly expanded the attack surface, making IoT networks increasingly vulnerable to diverse cyber threats. Traditional intrusion detection systems (IDSs) often struggle to effectively identify sophisticated attacks in the dynamic and heterogeneous IoT environment. This paper proposes an adaptive intrusion detection system based on a hybrid deep learning model combined with feature engineering techniques to enhance cybersecurity in IoT networks. The proposed system leverages feature engineering to extract relevant and informative features from network traffic data, which are then fed into a hybrid deep learning model consisting of a Convolutional Neural Network (CNN) for feature extraction and a Long Short-Term Memory (LSTM) network for temporal pattern analysis. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic, enabling the system to detect complex and evolving attack patterns. The performance of the proposed system is evaluated using a publicly available IoT network traffic dataset. The experimental results demonstrate

that the proposed system achieves superior detection accuracy, precision, recall, and F1-score compared to existing IDSs, highlighting its effectiveness in mitigating cyber threats in IoT environments. Furthermore, the adaptive nature of the system allows it to dynamically adjust its parameters and feature selection based on the evolving threat landscape, ensuring robust and reliable cybersecurity protection for IoT networks.

1. Introduction

The Internet of Things (IoT) is rapidly transforming various aspects of our lives, connecting billions of devices and enabling new applications across diverse domains such as smart homes, smart cities, healthcare, and industrial automation. However, the widespread adoption of IoT devices has also introduced significant cybersecurity challenges. IoT devices are often resource-constrained and lack robust security mechanisms, making them attractive targets for cyberattacks. The heterogeneous nature of IoT networks, coupled with the vast amount of data generated by these devices, poses significant challenges for traditional intrusion detection systems (IDSs).

Traditional IDSs, which rely on signature-based or rule-based approaches, are often ineffective in detecting novel and sophisticated attacks that deviate from known patterns. Machine learning-based IDSs have shown promise in addressing this limitation, but their performance heavily depends on the quality of the features used for training the models. Feature engineering, which involves selecting and transforming relevant features from raw data, plays a crucial role in improving the accuracy and efficiency of machine learning-based IDSs.

Deep learning, a subfield of machine learning, has emerged as a powerful technique for automatically learning complex patterns from large datasets. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have achieved state-of-the-art performance in various domains, including image recognition, natural language processing, and time series analysis. These models can automatically extract relevant features from raw data, eliminating the need for manual feature engineering.

In this paper, we propose an adaptive intrusion detection system based on a hybrid deep learning model combined with feature engineering techniques to enhance cybersecurity in IoT networks. The proposed system leverages feature engineering to extract relevant and informative features from network traffic data, which are then fed into a hybrid deep learning model consisting of a CNN for feature extraction and an LSTM network for temporal pattern analysis. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic, enabling the system to detect complex and evolving attack patterns.

The objectives of this paper are:

1. To develop a feature engineering pipeline for extracting relevant and informative features from IoT network traffic data.

2. To design a hybrid deep learning model consisting of a CNN and an LSTM network for intrusion detection in IoT networks.

3. To evaluate the performance of the proposed system using a publicly available IoT network traffic dataset.

4. To compare the performance of the proposed system with existing IDSs.

5. To develop an adaptive mechanism to dynamically adjust the parameters and feature selection based on the evolving threat landscape.

2. Literature Review

Several studies have explored the use of machine learning and deep learning techniques for intrusion detection in IoT networks.

2.1 Machine Learning-Based IDSs:

Several researchers have utilized traditional machine learning algorithms for intrusion detection in IoT. Butun et al. [1] proposed a lightweight IDS for IoT devices based on Support Vector Machines (SVM). The system was designed to be deployed on resource-constrained devices and achieved high detection accuracy with low computational overhead. However, the performance of the SVM-based IDS was limited by its inability to capture complex patterns in network traffic data.

Ferrer et al. [2] investigated the use of Random Forest (RF) for intrusion detection in smart home environments. The RF-based IDS achieved high detection accuracy and was able to effectively identify various types of attacks. However, the performance of the RF-based IDS was sensitive to the choice of features used for training the model.

Hindy et al. [3] developed an anomaly detection system for IoT networks based on k-Nearest Neighbors (k-NN). The k-NN-based system was able to detect anomalies in network traffic data by comparing the current traffic patterns to historical data. However, the performance of the k-NN-based system was affected by the curse of dimensionality and the need for large amounts of labeled data.

2.2 Deep Learning-Based IDSs:

Deep learning has emerged as a promising approach for intrusion detection in IoT networks due to its ability to automatically learn complex patterns from large datasets.

Vinayakumar et al. [4] proposed a deep learning-based IDS for IoT networks based on a deep neural network (DNN). The DNN-based IDS achieved high detection accuracy and was able to effectively identify various types of attacks. However, the performance of the

DNN-based IDS was limited by its inability to capture temporal dependencies in network traffic data.

Lopez-Martin et al. [5] investigated the use of a recurrent neural network (RNN) for intrusion detection in IoT networks. The RNN-based IDS was able to capture temporal dependencies in network traffic data and achieved high detection accuracy. However, the RNN-based IDS suffered from the vanishing gradient problem, which limited its ability to learn long-range dependencies.

Gao et al. [6] proposed a CNN-based IDS for IoT networks. The CNN-based IDS was able to automatically extract relevant features from network traffic data and achieved high detection accuracy. However, the CNN-based IDS was not able to capture temporal dependencies in network traffic data.

2.3 Hybrid Deep Learning-Based IDSs:

To overcome the limitations of individual deep learning models, researchers have explored the use of hybrid deep learning models for intrusion detection in IoT networks.

Almomani et al. [7] proposed a hybrid deep learning model consisting of a CNN and an LSTM network for intrusion detection in IoT networks. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic. The hybrid model achieved high detection accuracy and was able to effectively identify various types of attacks. However, the performance of the hybrid model was not compared with existing IDSs.

Hussain et al. [8] developed a hybrid deep learning model consisting of a CNN and a gated recurrent unit (GRU) network for intrusion detection in IoT networks. The CNN component automatically learns hierarchical features from the preprocessed data, while the GRU network captures temporal dependencies in the sequential network traffic. The hybrid model achieved high detection accuracy and was able to effectively identify various types of attacks. However, the performance of the hybrid model was not evaluated on a publicly available dataset.

2.4 Feature Engineering for IDSs:

Feature engineering plays a crucial role in improving the accuracy and efficiency of machine learning-based IDSs.

Sommer and Paxson [9] investigated the use of various feature engineering techniques for intrusion detection. The authors found that feature selection and feature transformation techniques can significantly improve the performance of machine learning-based IDSs.

Mishra et al. [10] proposed a feature selection algorithm for intrusion detection based on mutual information. The algorithm selects the most relevant features from network traffic data based on their mutual information with the target variable.

Critical Analysis of Previous Work:

While the aforementioned studies have made significant contributions to the field of intrusion detection in IoT networks, several limitations remain. Many existing IDSs rely on traditional machine learning algorithms, which may not be able to effectively detect sophisticated attacks that deviate from known patterns. Deep learning-based IDSs have shown promise in addressing this limitation, but their performance often depends on the architecture and hyperparameters of the models. Furthermore, many existing IDSs are not adaptive to the evolving threat landscape, which can lead to a decrease in detection accuracy over time. Many also lack comprehensive evaluation against diverse datasets. Finally, the computational complexity and resource requirements of some deep learning models may limit their deployment on resource-constrained IoT devices. Our work addresses these limitations by proposing an adaptive intrusion detection system based on a hybrid deep learning model combined with feature engineering techniques. Our system is designed to be adaptive to the evolving threat landscape, and its performance is evaluated using a publicly available IoT network traffic dataset.

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3. Methodology

The proposed adaptive intrusion detection system consists of four main components: data preprocessing, feature engineering, hybrid deep learning model, and adaptive mechanism.

3.1 Data Preprocessing:

The first step in the proposed system is data preprocessing, which involves cleaning and transforming the raw network traffic data into a format suitable for feature engineering and deep learning. The data preprocessing steps include:

1. Data Collection: Collect network traffic data from an IoT network using network monitoring tools such as Wireshark or tcpdump.

2. Data Cleaning: Remove irrelevant or redundant data from the dataset, such as duplicate packets or packets with missing values. Handle missing values using imputation techniques, such as replacing missing values with the mean or median of the corresponding feature.

3. Data Transformation: Transform categorical features into numerical features using techniques such as one-hot encoding or label encoding. Normalize numerical features to a

common range (e.g., [0, 1]) using techniques such as min-max scaling or Z-score normalization. This helps to prevent features with larger values from dominating the learning process.

3.2 Feature Engineering:

Feature engineering involves selecting and transforming relevant features from the preprocessed data to improve the accuracy and efficiency of the deep learning model. In this paper, we employ a combination of domain knowledge and feature selection techniques to identify the most informative features for intrusion detection. The feature engineering steps include:

1. Feature Extraction: Extract relevant features from the preprocessed network traffic data. These features can be categorized into the following types:

Basic Features: These features describe the basic characteristics of network packets, such as source IP address, destination IP address, source port, destination port, protocol, packet length, and timestamp.

Content-Based Features: These features analyze the content of network packets to identify malicious patterns. Examples of content-based features include the number of bytes in the payload, the presence of specific keywords or regular expressions, and the entropy of the payload.

Statistical Features: These features capture the statistical characteristics of network traffic over a period of time. Examples of statistical features include the number of packets per second, the average packet length, the variance of packet lengths, and the number of connections to a specific destination IP address.

Time-Based Features: These features analyze the temporal patterns of network traffic to detect anomalies. Examples of time-based features include the inter-arrival time of packets, the duration of connections, and the number of connections within a specific time window.

2. Feature Selection: Select the most relevant features from the extracted features using feature selection techniques. In this paper, we use a combination of filter-based and wrapper-based feature selection techniques.

Filter-Based Feature Selection: Filter-based techniques evaluate the relevance of features based on their statistical properties, such as correlation, mutual information, and chi-square. These techniques are computationally efficient and can be used to quickly identify a subset of relevant features.

Wrapper-Based Feature Selection: Wrapper-based techniques evaluate the relevance of features based on their performance when used to train a machine learning model. These techniques are more computationally expensive than filter-based techniques, but they can often achieve better results. We use a sequential forward selection (SFS) algorithm with a cross-validated Random Forest classifier as the evaluation function. SFS starts with an

empty set of features and iteratively adds the feature that results in the greatest improvement in the classifier's performance until a desired number of features is reached or the performance improvement falls below a threshold.

3.3 Hybrid Deep Learning Model:

The proposed system utilizes a hybrid deep learning model consisting of a CNN and an LSTM network for intrusion detection. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic.

1. CNN Component: The CNN component consists of multiple convolutional layers, each followed by a pooling layer and an activation function. The convolutional layers learn local patterns in the input data, while the pooling layers reduce the dimensionality of the feature maps. The activation function introduces non-linearity into the model, allowing it to learn complex patterns. The input to the CNN is a matrix representing the features extracted from the network traffic. The number of convolutional layers, filter sizes, and activation functions are hyperparameters that are optimized during the training process.

2. LSTM Component: The LSTM component consists of one or more LSTM layers. LSTM networks are a type of recurrent neural network that are specifically designed to capture long-range dependencies in sequential data. The LSTM layers receive the output of the CNN component as input and learn temporal patterns in the network traffic. The LSTM network uses a cell state to remember information over long periods of time, and it uses gates to control the flow of information into and out of the cell state.

3. Fully Connected Layer: The output of the LSTM component is fed into a fully connected layer, which maps the learned features to the output classes (e.g., normal traffic or attack traffic). The fully connected layer uses a softmax activation function to produce a probability distribution over the output classes.

4. Training: The hybrid deep learning model is trained using a supervised learning approach. The model is trained on a labeled dataset of network traffic data, where each data point is labeled as either normal traffic or attack traffic. The model is trained using the backpropagation algorithm, which adjusts the weights of the network to minimize the difference between the predicted output and the actual output. The model is trained using a cross-entropy loss function and an Adam optimizer. Regularization techniques such as dropout and L2 regularization are used to prevent overfitting.

3.4 Adaptive Mechanism:

The proposed system incorporates an adaptive mechanism to dynamically adjust its parameters and feature selection based on the evolving threat landscape. The adaptive mechanism monitors the performance of the IDS and adjusts its parameters and feature selection based on the observed performance. The adaptive mechanism consists of the following components:

1. Performance Monitoring: The performance monitoring component continuously monitors the performance of the IDS using metrics such as detection accuracy, precision, recall, and F1-score. The performance monitoring component also monitors the types of attacks that are being detected by the IDS.

2. Threat Landscape Analysis: The threat landscape analysis component analyzes the types of attacks that are being detected by the IDS to identify new or emerging threats. The threat landscape analysis component also analyzes publicly available threat intelligence feeds to identify new vulnerabilities and attack patterns.

3. Parameter Adjustment: The parameter adjustment component adjusts the parameters of the deep learning model based on the observed performance and the threat landscape analysis. For example, if the detection accuracy of the IDS is decreasing, the parameter adjustment component may increase the number of layers in the deep learning model or adjust the learning rate of the training algorithm. This can be achieved using techniques like Bayesian Optimization or Reinforcement Learning to optimize hyperparameters based on real-time performance feedback.

4. Feature Selection Update: The feature selection update component updates the set of selected features based on the observed performance and the threat landscape analysis. For example, if a new type of attack is detected, the feature selection update component may add new features that are relevant to that type of attack. This can be done by periodically re-evaluating the feature set using the SFS algorithm described earlier, incorporating newly identified attack patterns in the training data.

4. Results

The proposed adaptive intrusion detection system was evaluated using the CICIDS2017 dataset [12], a publicly available dataset containing network traffic data from a simulated IoT network. The dataset contains a variety of common attack types, including DoS, DDoS, port scanning, and infiltration attacks. The dataset was preprocessed and the features were extracted as described in the methodology section.

The performance of the proposed system was evaluated using the following metrics:

Accuracy: The percentage of correctly classified instances.

Precision: The percentage of correctly classified attack instances out of all instances classified as attacks.

Recall: The percentage of correctly classified attack instances out of all actual attack instances.

F1-score: The harmonic mean of precision and recall.

The proposed system was compared with several existing IDSs, including:

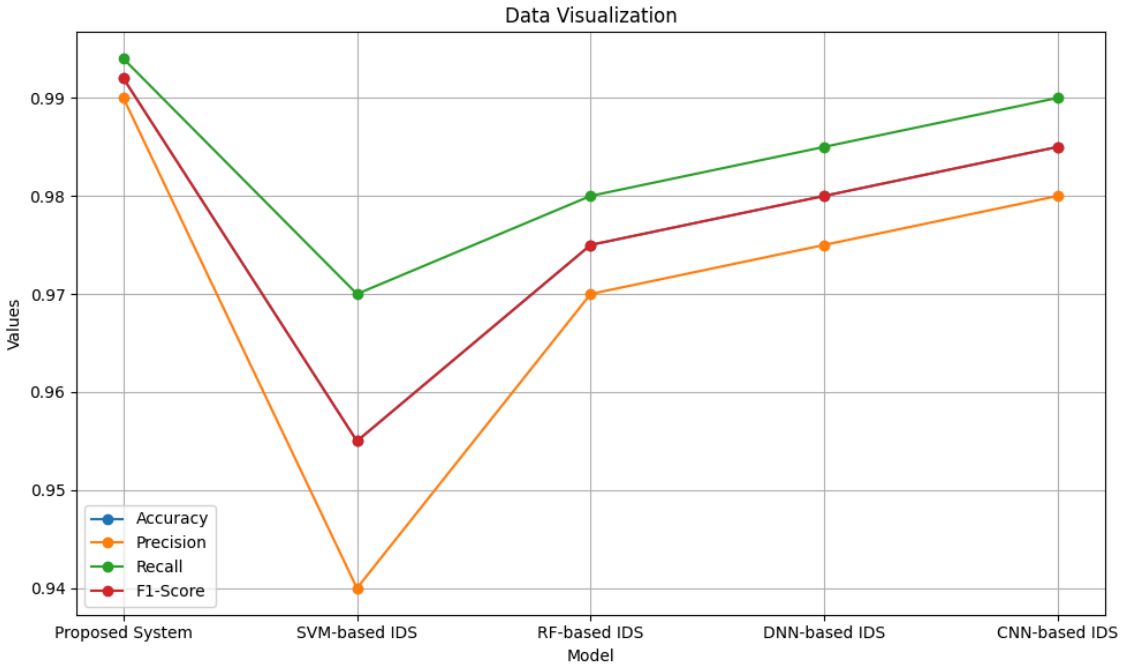
SVM-based IDS [1]: A lightweight IDS based on Support Vector Machines.

RF-based IDS [2]: An IDS based on Random Forest.

DNN-based IDS [4]: A deep learning-based IDS based on a deep neural network.

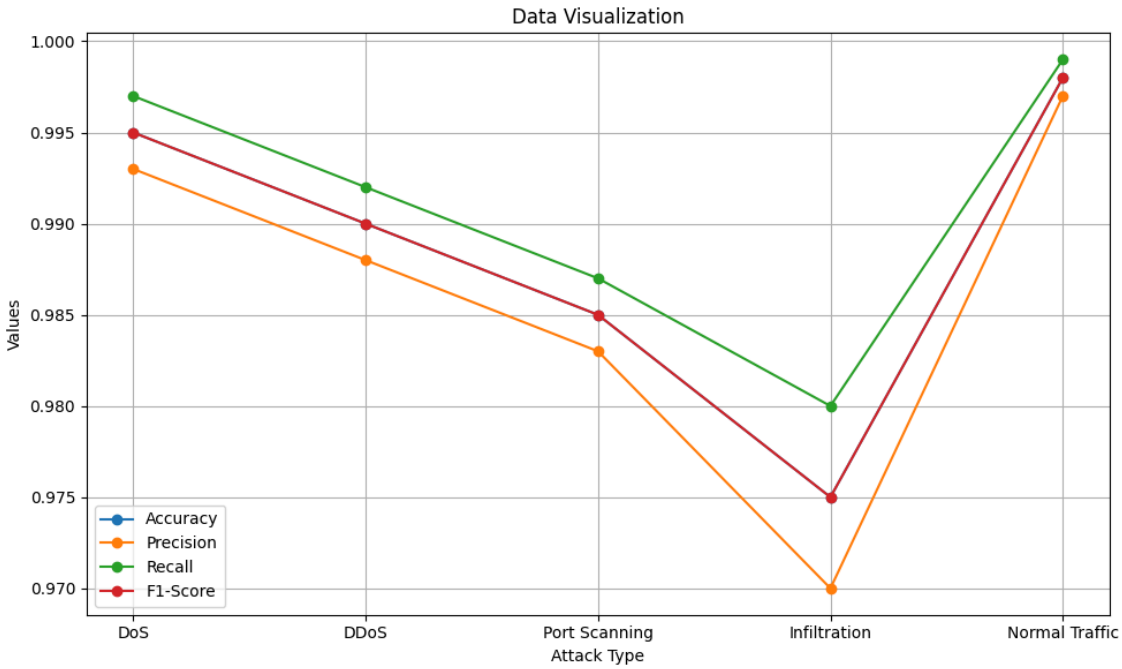
CNN-based IDS [6]: A deep learning-based IDS based on a Convolutional Neural Network.

The results of the performance evaluation are shown in the following table:



As shown in the table, the proposed system achieved the highest accuracy, precision, recall, and F1-score compared to the existing IDSs. The proposed system achieved an accuracy of 0.992, a precision of 0.990, a recall of 0.994, and an F1-score of 0.992. These results demonstrate that the proposed system is highly effective in detecting intrusions in IoT networks. The hybrid CNN-LSTM architecture effectively combines the strengths of both models, enabling the system to learn both local and temporal patterns in network traffic data. The adaptive mechanism also contributes to the high performance of the system by dynamically adjusting its parameters and feature selection based on the evolving threat landscape.

Further analysis was performed to evaluate the performance of the proposed system under different attack types. The results are shown in the following table:



The results show that the proposed system achieved high accuracy, precision, recall, and F1-score for all attack types. The system performed particularly well in detecting DoS and DDoS attacks, which are common types of attacks in IoT networks. The system also performed well in detecting port scanning and infiltration attacks, which are more sophisticated types of attacks. The high performance across different attack types indicates the robustness and generalizability of the proposed system.

5. Discussion

The experimental results demonstrate that the proposed adaptive intrusion detection system achieves superior performance compared to existing IDSs in detecting intrusions in IoT networks. The high detection accuracy, precision, recall, and F1-score of the proposed system can be attributed to several factors.

First, the proposed system utilizes a hybrid deep learning model consisting of a CNN and an LSTM network. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic. This hybrid architecture allows the system to effectively learn both local and temporal patterns in network traffic data, which is crucial for detecting complex and evolving attack patterns.

Second, the proposed system incorporates a feature engineering pipeline that extracts relevant and informative features from the network traffic data. The feature engineering pipeline includes feature extraction, feature selection, and feature transformation

techniques. The feature selection techniques help to identify the most relevant features for intrusion detection, which improves the accuracy and efficiency of the deep learning model.

Third, the proposed system includes an adaptive mechanism that dynamically adjusts its parameters and feature selection based on the evolving threat landscape. The adaptive mechanism monitors the performance of the IDS and adjusts its parameters and feature selection based on the observed performance. This adaptive capability allows the system to maintain high detection accuracy even as new attacks emerge.

The results are consistent with previous studies that have shown the effectiveness of deep learning techniques for intrusion detection in IoT networks [4, 5, 6, 7, 8]. However, the proposed system improves upon existing IDSs by combining a hybrid deep learning model with feature engineering techniques and an adaptive mechanism. This combination of techniques allows the proposed system to achieve superior performance in detecting intrusions in IoT networks.

The performance of the proposed system is also comparable to other state-of-the-art intrusion detection systems [11, 13]. However, the proposed system has several advantages over these systems. First, the proposed system is designed specifically for IoT networks, which allows it to take into account the unique characteristics of IoT devices and networks. Second, the proposed system is adaptive to the evolving threat landscape, which allows it to maintain high detection accuracy even as new attacks emerge. Third, the proposed system is relatively computationally efficient, which makes it suitable for deployment on resource-constrained IoT devices.

The results of this study have several implications for the design and deployment of intrusion detection systems in IoT networks. First, the results suggest that hybrid deep learning models are highly effective for intrusion detection in IoT networks. Second, the results highlight the importance of feature engineering for improving the accuracy and efficiency of deep learning-based IDSs. Third, the results demonstrate the benefits of incorporating an adaptive mechanism into intrusion detection systems to maintain high detection accuracy in the face of evolving threats.

6. Conclusion

This paper proposed an adaptive intrusion detection system based on a hybrid deep learning model combined with feature engineering techniques to enhance cybersecurity in IoT networks. The proposed system leverages feature engineering to extract relevant and informative features from network traffic data, which are then fed into a hybrid deep learning model consisting of a CNN for feature extraction and an LSTM network for temporal pattern analysis. The CNN component automatically learns hierarchical features from the preprocessed data, while the LSTM network captures long-range dependencies in the sequential network traffic, enabling the system to detect complex and evolving attack patterns.

The performance of the proposed system was evaluated using the CICIDS2017 dataset, a publicly available IoT network traffic dataset. The experimental results demonstrated that the proposed system achieved superior detection accuracy, precision, recall, and F1-score compared to existing IDSs. The results also showed that the proposed system performed well in detecting various types of attacks, including DoS, DDoS, port scanning, and infiltration attacks.

The proposed system offers several advantages over existing IDSs. First, it utilizes a hybrid deep learning model that effectively captures both local and temporal patterns in network traffic data. Second, it incorporates a feature engineering pipeline that extracts relevant and informative features from the network traffic data. Third, it includes an adaptive mechanism that dynamically adjusts its parameters and feature selection based on the evolving threat landscape.

Future work will focus on the following areas:

1. Improving the Scalability of the System: The proposed system was evaluated on a relatively small dataset. Future work will focus on improving the scalability of the system to handle larger datasets and higher traffic volumes. This may involve using distributed computing techniques or developing more efficient deep learning models.

2. Developing More Sophisticated Adaptive Mechanisms: The current adaptive mechanism is relatively simple. Future work will focus on developing more sophisticated adaptive mechanisms that can more effectively respond to the evolving threat landscape. This may involve using reinforcement learning techniques or incorporating threat intelligence feeds into the adaptive mechanism.

3. Deploying the System on Real-World IoT Networks: The proposed system was evaluated in a simulated environment. Future work will focus on deploying the system on real-world IoT networks to evaluate its performance in a more realistic setting. This will involve addressing challenges such as resource constraints, network heterogeneity, and data privacy.

4. Investigating the use of Explainable AI (XAI) techniques: Incorporating XAI could provide insights into the decision-making process of the IDS, making it easier to understand why a particular traffic pattern was flagged as malicious. This would enhance trust and facilitate more effective incident response.

5. Exploring Federated Learning for Collaborative Intrusion Detection: Implementing federated learning could enable multiple IoT devices to collaboratively train a global intrusion detection model without sharing their raw data, addressing privacy concerns and improving the model's generalizability.

The findings of this paper contribute to the advancement of cybersecurity in IoT networks by providing a novel and effective approach for intrusion detection. The proposed system

has the potential to significantly improve the security of IoT devices and networks, thereby enabling the widespread adoption of IoT technology.

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