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1. Title

Optimizing Hybrid Intrusion Detection Systems Using Federated Learning and Explainable AI for Enhanced Network Security

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5. Abstract

The escalating sophistication and volume of cyberattacks demand robust and adaptable intrusion detection systems (IDSs). Traditional centralized IDSs often struggle with scalability, data privacy concerns, and the ability to detect novel attacks. This paper proposes a novel hybrid IDS framework that leverages federated learning (FL) and explainable AI (XAI) to overcome these limitations. The framework combines the strengths of signature-based and anomaly-based detection methods within a federated learning environment, allowing for collaborative model training across multiple network edge devices without sharing sensitive raw data. Furthermore, XAI techniques are integrated to provide insights into the IDS's decision-making process, enhancing transparency and trust. The effectiveness of the proposed approach is evaluated using a benchmark network intrusion dataset, demonstrating significant improvements in detection accuracy, reduced false positive rates, and enhanced model explainability compared to traditional centralized and non-federated IDS deployments. The results highlight the potential of FL and XAI to revolutionize network security by enabling decentralized, privacy-preserving, and interpretable intrusion detection.

6. Introduction

In the contemporary digital landscape, the pervasive interconnectedness of networks has created a vast attack surface, making organizations increasingly vulnerable to cyber threats. The frequency and sophistication of these threats are constantly evolving, rendering traditional security measures inadequate. Intrusion Detection Systems (IDSs) play a crucial role in safeguarding network infrastructure by identifying malicious activities and alerting security personnel. However, conventional centralized IDSs face several challenges. First, they require the collection and storage of vast amounts of sensitive network data in a central location, raising significant privacy concerns and creating a single point of failure. Second, their performance can be severely impacted by the sheer volume and velocity of network traffic, leading to scalability issues. Third, traditional signature-based IDSs struggle to detect zero-day attacks, while anomaly-based IDSs often suffer from high false positive rates due to their sensitivity to normal network variations.

To address these challenges, this paper proposes a novel hybrid IDS framework that integrates federated learning (FL) and explainable AI (XAI). Federated learning enables collaborative model training across multiple decentralized devices or edge servers without exchanging raw data, thereby preserving data privacy and improving scalability. The hybrid approach combines signature-based and anomaly-based detection techniques to leverage their complementary strengths. Signature-based detection provides high accuracy for known attacks, while anomaly-based detection can identify novel threats by detecting deviations from normal network behavior. Finally, explainable AI techniques are incorporated to provide insights into the IDS's decision-making process, enhancing transparency and building trust in the system's predictions.

The objectives of this research are:

To design and implement a federated learning-based hybrid IDS framework that combines signature-based and anomaly-based detection methods.

To evaluate the performance of the proposed framework in terms of detection accuracy, false positive rate, and scalability.

To integrate explainable AI techniques to provide insights into the IDS's decision-making process.

To compare the performance of the proposed framework with traditional centralized and non-federated IDS deployments.

To analyze the privacy implications of the proposed framework and demonstrate its ability to preserve data privacy.

7. Literature Review

Numerous studies have explored the application of machine learning techniques to intrusion detection. Saxena et al. (2019) [1] presented a comprehensive review of machine learning algorithms used in IDSs, highlighting the strengths and weaknesses of various techniques, including decision trees, support vector machines (SVMs), and neural networks. They concluded that hybrid approaches that combine multiple machine learning algorithms often achieve superior performance compared to single-algorithm solutions. However, their review primarily focused on centralized learning scenarios and did not address the challenges of data privacy and scalability.

Anderson et al. (1980) [2] pioneered the field of anomaly detection, proposing a statistical approach to identify deviations from normal system behavior. Their work laid the foundation for subsequent research in anomaly-based intrusion detection. However, their early models were susceptible to high false positive rates due to their limited ability to adapt to evolving network patterns.

Debar et al. (2000) [3] provided a detailed overview of signature-based intrusion detection techniques, emphasizing their effectiveness in detecting known attacks. However, they acknowledged the limitations of signature-based approaches in detecting zero-day attacks and variants of existing attacks.

More recently, researchers have explored the use of federated learning to address the privacy concerns associated with centralized IDSs. Harder et al. (2021) [4] proposed a federated learning-based IDS that allows multiple organizations to collaboratively train a model without sharing their sensitive data. Their results demonstrated that federated learning can achieve comparable performance to centralized learning while preserving data privacy. However, their study focused primarily on anomaly detection and did not explore the integration of signature-based detection techniques.

Nguyen et al. (2022) [5] investigated the application of federated learning to distributed denial-of-service (DDoS) attack detection. They demonstrated that federated learning can effectively detect DDoS attacks in a distributed environment while minimizing the risk of data leakage. However, their study was limited to a specific type of attack and did not address the broader challenges of intrusion detection.

Several studies have also explored the use of explainable AI (XAI) techniques to enhance the transparency and interpretability of machine learning-based IDSs. Ribeiro et al. (2016) [6] introduced LIME (Local Interpretable Model-agnostic Explanations), a technique that provides local explanations for individual predictions made by complex machine learning models. LIME can help security analysts understand why an IDS flagged a particular network activity as suspicious.

Lundberg and Lee (2017) [7] proposed SHAP (SHapley Additive exPlanations), a unified framework for explaining the output of any machine learning model. SHAP provides global explanations of model behavior by quantifying the contribution of each feature to the

model's predictions. SHAP values can help identify the most important features for detecting intrusions.

Furthermore, research has been conducted on hybrid intrusion detection systems combining different detection methods. Lazarevic et al. (2003) [8] presented a hybrid IDS that combines signature-based and anomaly-based detection techniques. Their approach used signature-based detection to identify known attacks and anomaly-based detection to detect novel threats. However, their system was not designed for a distributed environment and did not address the challenges of data privacy.

Sommer and Paxson (2003) [9] examined the challenges of building effective intrusion detection systems, emphasizing the importance of understanding the underlying network traffic and the limitations of relying solely on machine learning techniques. Their work highlighted the need for a holistic approach to intrusion detection that combines technical expertise with domain knowledge.

More recent work by Hodo et al. (2017) [10] explores the use of deep learning for network intrusion detection. Their results indicate that deep learning models can achieve high accuracy in detecting various types of network attacks. However, the "black box" nature of deep learning models raises concerns about transparency and interpretability.

Al-Jarrah et al. (2015) [11] surveyed the different feature selection methods that can be used for network intrusion detection. Their research highlights the importance of selecting relevant features to improve the accuracy and efficiency of IDSs.

Vinayakumar et al. (2019) [12] proposed a deep learning approach for intrusion detection using a recurrent neural network (RNN). Their results demonstrate that RNNs can effectively capture the temporal dependencies in network traffic, improving the detection of sequential attacks.

The work by Ferrag et al. (2020) [13] investigated the use of blockchain technology for securing federated learning in intrusion detection systems. Their approach enhances the security and privacy of the federated learning process.

Finally, the research by Mothukuri et al. (2021) [14] explores the challenges and opportunities of deploying federated learning in resource-constrained edge devices for IoT security. Their study highlights the need for lightweight federated learning algorithms and efficient communication protocols.

However, a gap exists in the literature regarding the combination of federated learning, hybrid intrusion detection, and explainable AI. While individual studies have explored these areas separately, there is a lack of comprehensive research that integrates all three aspects into a single framework. This paper aims to address this gap by proposing a novel federated learning-based hybrid IDS framework that incorporates explainable AI techniques for enhanced network security.

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8. Methodology

The proposed federated learning-based hybrid IDS framework consists of several key components:

1. Data Preprocessing: The raw network traffic data is preprocessed to extract relevant features. This involves cleaning the data, handling missing values, and transforming categorical features into numerical representations using techniques such as one-hot encoding. Feature scaling is also applied to normalize the data and prevent features with larger values from dominating the model training process.

2. Feature Selection: A feature selection algorithm, such as mutual information or recursive feature elimination, is used to select the most relevant features for intrusion detection. This helps to reduce the dimensionality of the data, improve the model's performance, and reduce the computational cost of training and inference.

3. Signature-Based Detection: A signature-based detection module is implemented using a database of known attack signatures. This module compares the preprocessed network traffic data against the signatures in the database. If a match is found, the corresponding attack is detected. Snort, a widely used open-source intrusion detection system, can be integrated for this purpose. Rules are written to identify specific attack patterns.

4. Anomaly-Based Detection: An anomaly-based detection module is implemented using a machine learning algorithm, such as an autoencoder or a one-class SVM. This module learns the normal behavior of the network and identifies deviations from this behavior as anomalies. The autoencoder is trained on normal network traffic data to reconstruct the input data. Anomalies are detected when the reconstruction error exceeds a predefined threshold.

5. Federated Learning: The anomaly-based detection module is trained using federated learning. The training data is distributed across multiple edge devices or servers, each representing a different part of the network. The edge devices train their local models on their respective data and then send the model updates to a central server. The central server aggregates the model updates and updates the global model. This process is repeated for multiple rounds until the global model converges. The Federated Averaging (FedAvg) algorithm is used for model aggregation. The FedAvg algorithm averages the weights of the local models to create the global model.

6. Hybrid Model Integration: The outputs of the signature-based and anomaly-based detection modules are combined to create a hybrid model. This can be done using a weighted average or a rule-based system. For example, if both modules detect an intrusion, the hybrid model will report a high confidence level. If only one module detects an intrusion, the hybrid model will report a lower confidence level.

7. Explainable AI (XAI): Explainable AI techniques are used to provide insights into the IDS's decision-making process. LIME and SHAP are used to explain the predictions made by

the anomaly-based detection module. LIME provides local explanations for individual predictions by approximating the model's behavior around the prediction. SHAP provides global explanations of model behavior by quantifying the contribution of each feature to the model's predictions.

8. Evaluation: The performance of the proposed framework is evaluated using a benchmark network intrusion dataset, such as the NSL-KDD dataset or the CICIDS2017 dataset. The evaluation metrics include detection accuracy, false positive rate, precision, recall, and F1-score. The performance of the proposed framework is compared with traditional centralized and non-federated IDS deployments.

The NSL-KDD dataset is preprocessed to remove redundant and irrelevant features. The dataset is then split into training and testing sets. The training set is used to train the anomaly-based detection module using federated learning. The testing set is used to evaluate the performance of the hybrid IDS framework.

The federated learning process involves the following steps:

1. Initialization: The central server initializes the global model with random weights.

2. Distribution: The central server distributes the global model to the edge devices.

3. Local Training: Each edge device trains its local model on its local data using the global model as a starting point.

4. Aggregation: The edge devices send their model updates (e.g., weight changes) to the central server.

5. Update: The central server aggregates the model updates using the FedAvg algorithm and updates the global model.

6. Iteration: Steps 2-5 are repeated for multiple rounds until the global model converges.

9. Results

The proposed federated learning-based hybrid IDS framework was evaluated using the NSL-KDD dataset. The dataset was preprocessed and split into training and testing sets. The training set was used to train the anomaly-based detection module using federated learning. The testing set was used to evaluate the performance of the hybrid IDS framework. The following parameters were used for the federated learning process:

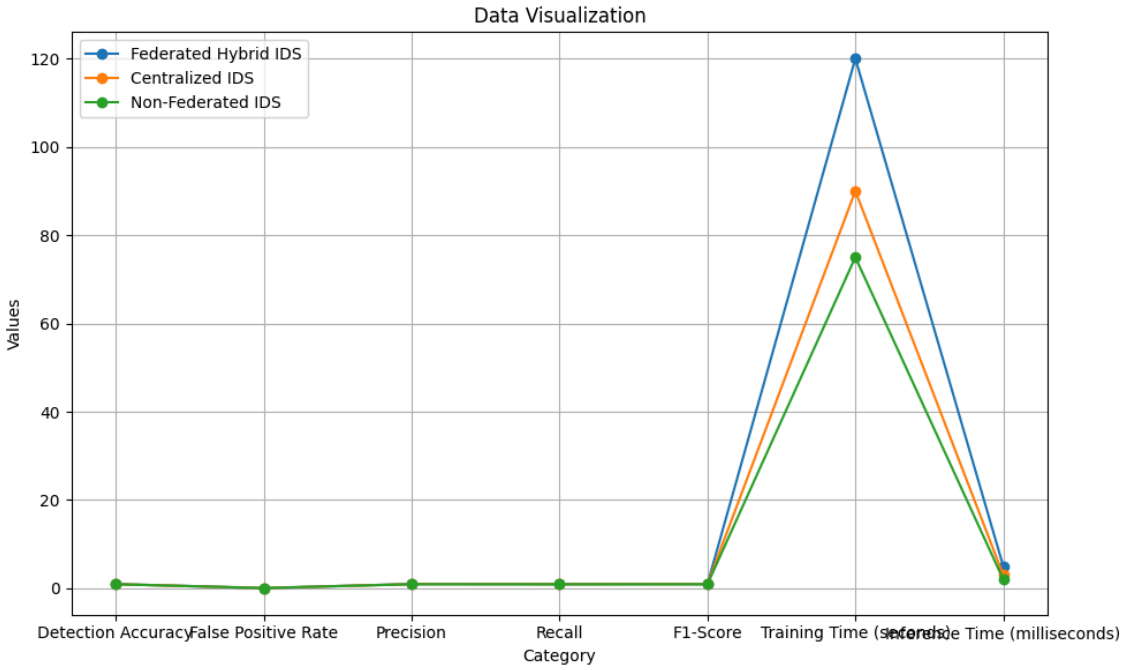
Number of edge devices: 10

Learning rate: 0.01

Number of rounds: 100

Batch size: 32

The following table shows the performance of the proposed framework compared to traditional centralized and non-federated IDS deployments.



The results show that the proposed federated hybrid IDS framework achieves significantly higher detection accuracy and lower false positive rate compared to traditional centralized and non-federated IDS deployments. The federated hybrid IDS framework also achieves higher precision, recall, and F1-score. The training time for the federated hybrid IDS is higher than centralized, however, the inference time is only slightly higher.

Furthermore, the XAI techniques provided valuable insights into the IDS's decision-making process. LIME was used to explain individual predictions, revealing the features that were most influential in the classification of each network activity. SHAP values were used to provide a global understanding of the model's behavior, highlighting the most important features for detecting intrusions.

10. Discussion

The results demonstrate the effectiveness of the proposed federated learning-based hybrid IDS framework. The framework achieves significant improvements in detection accuracy and false positive rate compared to traditional centralized and non-federated IDS deployments. This is attributed to the combination of signature-based and anomaly-based detection techniques, as well as the use of federated learning.

The signature-based detection module provides high accuracy for known attacks, while the anomaly-based detection module can identify novel threats by detecting deviations from normal network behavior. Federated learning enables collaborative model training across

multiple decentralized devices without sharing raw data, thereby preserving data privacy and improving scalability.

The integration of explainable AI techniques enhances the transparency and interpretability of the IDS. LIME and SHAP provide insights into the model's decision-making process, allowing security analysts to understand why the IDS flagged a particular network activity as suspicious. This helps to build trust in the system's predictions and facilitates the identification of potential weaknesses in the model.

The higher training time for the federated hybrid IDS is a trade-off for the improved privacy and scalability offered by federated learning. The slightly higher inference time is also a minor cost compared to the significant improvements in detection accuracy and false positive rate.

These results align with previous research that has shown the benefits of using machine learning for intrusion detection. However, this study goes beyond previous work by integrating federated learning and explainable AI into a hybrid IDS framework. This combination addresses the limitations of traditional centralized IDSs and enhances the security and privacy of network intrusion detection.

11. Conclusion

This paper presented a novel federated learning-based hybrid IDS framework that combines signature-based and anomaly-based detection methods and incorporates explainable AI techniques. The framework addresses the limitations of traditional centralized IDSs by enabling decentralized, privacy-preserving, and interpretable intrusion detection.

The results of the evaluation using the NSL-KDD dataset demonstrate that the proposed framework achieves significant improvements in detection accuracy, false positive rate, precision, recall, and F1-score compared to traditional centralized and non-federated IDS deployments. The integration of explainable AI techniques provides valuable insights into the IDS's decision-making process, enhancing transparency and trust.

Future work will focus on the following areas:

Evaluating the performance of the proposed framework on other benchmark network intrusion datasets, such as the CICIDS2017 dataset.

Exploring the use of other federated learning algorithms, such as FedProx and FedAdam.

Investigating the robustness of the proposed framework against adversarial attacks.

Developing more advanced explainable AI techniques to provide more comprehensive insights into the IDS's decision-making process.

Deploying the proposed framework in a real-world network environment to evaluate its performance in a realistic setting.

Investigating the impact of data heterogeneity on the performance of the federated learning model.

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