Title: Adaptive Intrusion Detection System (A-IDS) for IoT Networks: A Hybrid Approach Leveraging Federated Learning and Edge Computing

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Abstract:

The proliferation of Internet of Things (IoT) devices has created a vast attack surface, making these networks increasingly vulnerable to cyberattacks. Traditional Intrusion Detection Systems (IDS) often struggle to cope with the resource constraints of IoT devices, the dynamic nature of IoT traffic, and the need for real-time threat detection. This paper presents a novel Adaptive Intrusion Detection System (A-IDS) designed specifically for IoT networks. A-IDS employs a hybrid approach that combines federated learning (FL) and edge computing to achieve distributed, adaptive, and efficient intrusion detection. Edge devices perform local anomaly detection using lightweight machine learning models trained collaboratively via FL. This minimizes latency and conserves bandwidth. A centralized server aggregates and refines the global model, enabling the system to adapt to evolving threats. The proposed A-IDS is evaluated using a simulated IoT environment with realistic traffic patterns and attack scenarios. The results demonstrate that A-IDS achieves high detection accuracy, low false positive rates, and minimal resource consumption compared to traditional IDS approaches. This research highlights the potential of FL and edge computing to enhance the security of IoT networks by enabling adaptive and distributed intrusion detection.

Introduction:

The Internet of Things (IoT) has revolutionized various sectors, including healthcare, smart homes, industrial automation, and transportation. This rapid growth, however, has been accompanied by a significant increase in cyber security risks. IoT devices, often characterized by limited processing power, memory, and battery life, are particularly vulnerable to attacks. Furthermore, the sheer scale and heterogeneity of IoT networks make it challenging to deploy and manage traditional security solutions.

Traditional Intrusion Detection Systems (IDS), designed for conventional networks, are often ill-suited for IoT environments. They typically rely on centralized architectures, which can introduce latency, consume significant bandwidth, and become single points of failure. Additionally, traditional IDS may struggle to adapt to the dynamic nature of IoT traffic and the emergence of new attack vectors.

The problem statement addressed in this paper is the need for a scalable, efficient, and adaptive intrusion detection system that can effectively protect IoT networks against evolving cyber threats. To address this challenge, we propose an Adaptive Intrusion Detection System (A-IDS) that leverages federated learning (FL) and edge computing.

Our objectives are:

1. To design an A-IDS architecture that distributes intrusion detection tasks across edge devices and a centralized server.

2. To develop lightweight machine learning models suitable for deployment on resource-constrained IoT devices.

3. To implement a federated learning framework that enables collaborative model training without sharing sensitive data.

4. To evaluate the performance of A-IDS in terms of detection accuracy, false positive rate, and resource consumption.

5. To compare the performance of A-IDS with traditional IDS approaches in a simulated IoT environment.

Literature Review:

Several research efforts have focused on developing intrusion detection systems for IoT networks. A comprehensive review of these works reveals various approaches, each with its strengths and limitations.

1. Centralized IDS: Traditional centralized IDS, as described by Lazarescu et al. (2013) [1], typically involve collecting network traffic data at a central server and analyzing it using rule-based or machine learning techniques. While effective in detecting known attacks, centralized IDS can be resource-intensive and introduce latency, making them unsuitable for

real-time IoT applications. The scalability limitations of these systems are also a major concern.

2. Distributed IDS: To address the scalability issue, researchers have explored distributed IDS architectures. For example, Butun et al. (2014) [2] proposed a distributed IDS based on mobile agents. Each agent monitors a specific portion of the network and reports suspicious activity to a central management system. However, the overhead associated with agent management and communication can be significant, especially in large-scale IoT deployments. Furthermore, coordinating the agents and ensuring consistent threat detection across the network can be challenging.

3. Machine Learning-Based IDS: Machine learning techniques have gained popularity in intrusion detection due to their ability to detect novel attacks. Hindy et al. (2020) [3] reviewed various machine learning algorithms for intrusion detection, including decision trees, support vector machines (SVMs), and neural networks. These techniques can be effective in identifying anomalous behavior but often require large amounts of labeled data for training, which may not be readily available in IoT environments. Additionally, the computational complexity of some machine learning algorithms can be a barrier to their deployment on resource-constrained IoT devices.

4. Deep Learning-Based IDS: Deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have shown promising results in intrusion detection. Vinayakumar et al. (2017) [4] demonstrated the effectiveness of deep learning models in detecting network intrusions. However, deep learning models are computationally expensive and require significant amounts of training data, making them difficult to deploy on edge devices with limited resources. The interpretability of deep learning models is also a concern, as it can be challenging to understand why a particular attack was detected.

5. Edge Computing for IDS: Edge computing offers a promising approach to address the resource constraints of IoT devices and the need for real-time threat detection. Stiawan et al. (2020) [5] proposed an edge-based IDS that performs intrusion detection closer to the data source, reducing latency and bandwidth consumption. However, implementing complex intrusion detection algorithms on edge devices can be challenging due to their limited processing power and memory.

6. Federated Learning for IDS: Federated learning enables collaborative model training without sharing sensitive data. Hardy et al. (2017) [6] presented a federated learning framework for intrusion detection. This approach allows IoT devices to train local models using their own data and then aggregate these models to create a global model. This preserves data privacy and reduces the risk of data breaches. However, federated learning can be susceptible to poisoning attacks, where malicious devices contribute corrupted data to the global model.

7. Hybrid IDS Approaches: Several researchers have explored hybrid approaches that combine different techniques to improve intrusion detection performance. For example, Ferrag et al. (2020) [7] proposed a hybrid IDS that combines signature-based detection and anomaly-based detection. Signature-based detection is effective in detecting known attacks, while anomaly-based detection can identify novel attacks. However, the complexity of managing and coordinating multiple detection techniques can be a challenge.

8. Anomaly Detection with Autoencoders: Autoencoders, a type of neural network, have been used for anomaly detection in IoT networks. Giacinto et al. (2021) [8] explored the use of autoencoders for detecting anomalies in IoT sensor data. Autoencoders learn to reconstruct normal data patterns, and deviations from these patterns are flagged as anomalies. However, the performance of autoencoders depends on the quality and representativeness of the training data.

9. Blockchain for IDS: Blockchain technology has been explored for enhancing the security of IDS. Hussain et al. (2022) [9] proposed a blockchain-based IDS that provides a secure and tamper-proof audit trail of intrusion detection events. However, the computational overhead associated with blockchain can be a barrier to its deployment in resource-constrained IoT environments.

10. Lightweight Cryptography for IDS: To secure communication and data transmission in IoT networks, lightweight cryptography algorithms are essential. Raza et al. (2013) [10] reviewed various lightweight cryptography algorithms suitable for IoT devices. Integrating these algorithms into IDS can improve the security of data transmission and prevent eavesdropping attacks.

Critical Analysis:

While the existing literature offers valuable insights into intrusion detection for IoT networks, several limitations remain. Centralized IDS solutions suffer from scalability and latency issues. Distributed IDS approaches can be complex to manage and coordinate. Machine learning-based IDS often require large amounts of labeled data and may be computationally expensive. Deep learning-based IDS are even more resource-intensive. Federated learning can be vulnerable to poisoning attacks. Hybrid IDS approaches can be complex to implement. Existing solutions often fail to adequately address the resource constraints of IoT devices, the dynamic nature of IoT traffic, and the need for real-time threat detection. This paper aims to address these limitations by proposing a novel A-IDS architecture that combines the benefits of federated learning and edge computing to achieve distributed, adaptive, and efficient intrusion detection. The A-IDS architecture will also incorporate anomaly detection techniques that are resilient to adversarial attacks and require minimal computational resources.

Methodology:

The Adaptive Intrusion Detection System (A-IDS) comprises three main components: Edge Devices, a Federated Learning Server, and a Centralized Monitoring and Analysis Platform.

1. Edge Devices:

Data Collection: Each edge device (e.g., a smart sensor, a gateway) collects network traffic data using network sniffing tools like tcpdump or libpcap. The collected data includes features such as source and destination IP addresses, port numbers, protocol types, packet sizes, and inter-arrival times. Feature selection is critical to minimize computational overhead.

Feature Extraction: The collected raw network traffic data is preprocessed to extract relevant features. We employ a combination of statistical features (e.g., mean, standard deviation, entropy) and flow-based features (e.g., flow duration, number of packets per flow). Feature selection is performed using techniques such as Information Gain and Chi-squared test to identify the most relevant features for intrusion detection.

Local Anomaly Detection: Each edge device trains a local anomaly detection model using its own data. We use a lightweight machine learning algorithm, specifically a One-Class Support Vector Machine (OCSVM), due to its low computational complexity and ability to detect anomalies without requiring labeled data. The OCSVM is trained on normal network traffic data to learn a decision boundary that separates normal data points from anomalies.

Model Update and Communication: The edge devices periodically update their local models using new data. They also communicate their model parameters (e.g., support vectors, kernel parameters) to the Federated Learning Server. To reduce communication overhead, we employ model compression techniques such as quantization and pruning.

2. Federated Learning Server:

Model Aggregation: The Federated Learning Server aggregates the local models from the edge devices using a federated averaging algorithm. Federated averaging involves averaging the model parameters from the edge devices to create a global model. This process is performed iteratively to improve the accuracy and robustness of the global model. We use a weighted averaging scheme that assigns higher weights to models from edge devices with higher data quality and reliability.

Global Model Distribution: The Federated Learning Server distributes the updated global model back to the edge devices. The edge devices replace their local models with the updated global model. This ensures that all edge devices have access to the latest threat intelligence.

Poisoning Attack Mitigation: To mitigate poisoning attacks, we implement a robust aggregation scheme that filters out malicious model updates. We use techniques such as outlier detection and anomaly detection to identify and remove suspicious model updates. We also implement a reputation system that tracks the reliability of each edge device.

3. Centralized Monitoring and Analysis Platform:

Alert Aggregation: The Centralized Monitoring and Analysis Platform collects alerts from the edge devices and aggregates them to provide a comprehensive view of the network security posture. Alerts are prioritized based on their severity and confidence level.

Incident Response: The platform provides tools for incident response, including automated remediation actions. For example, the platform can automatically block malicious IP addresses or quarantine infected devices.

Threat Intelligence: The platform integrates with threat intelligence feeds to stay up-to-date on the latest threats. This information is used to improve the accuracy and effectiveness of the intrusion detection system.

Visualization and Reporting: The platform provides visualization tools for monitoring network traffic and security events. It also generates reports on security incidents and trends.

Algorithms:

1. Federated Averaging:

Input: Edge device models M1, M2, ..., Mn, Learning rate η, Number of rounds T

Output: Global model M

Initialize M with a random set of weights

For t = 1 to T:

Select a random subset of edge devices S

For each edge device i in S:

Update local model Mi using local data and learning rate η

Aggregate local models: $M = (1/|S|) \ \Sigma$ Mi for all i in S

Return M

2. One-Class Support Vector Machine (OCSVM):

Input: Training data X, Kernel function K, Regularization parameter ν

Output: OCSVM model

Solve the quadratic programming problem:

Minimize $(1/2) \ \Sigma \Sigma \alpha i \ \alpha j \ K(xi, xj)$ subject to $0 <= \alpha i <= 1/\nu l$ and $\Sigma \alpha i = 1$

Calculate the decision function: $f(x) = \Sigma \alpha i K(xi, x) - \rho$

Where ρ is the offset parameter.

Implementation Details:

Programming Languages: Python (for the Federated Learning Server and Centralized Monitoring and Analysis Platform), C/C++ (for the Edge Device software).

Machine Learning Libraries: Scikit-learn, TensorFlow, PyTorch.

Networking Libraries: libpcap, Scapy.

Communication Protocol: MQTT (Message Queuing Telemetry Transport) for lightweight communication between edge devices and the Federated Learning Server.

Evaluation Metrics:

We evaluate the performance of A-IDS using the following metrics:

Detection Accuracy: The percentage of correctly classified attacks.

False Positive Rate (FPR): The percentage of normal traffic incorrectly classified as attacks.

Precision: The ratio of correctly predicted attack instances to the total predicted attack instances.

Recall: The ratio of correctly predicted attack instances to the total actual attack instances.

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

Resource Consumption: CPU utilization, memory usage, and network bandwidth consumption on edge devices.

Latency: The time taken to detect an attack.

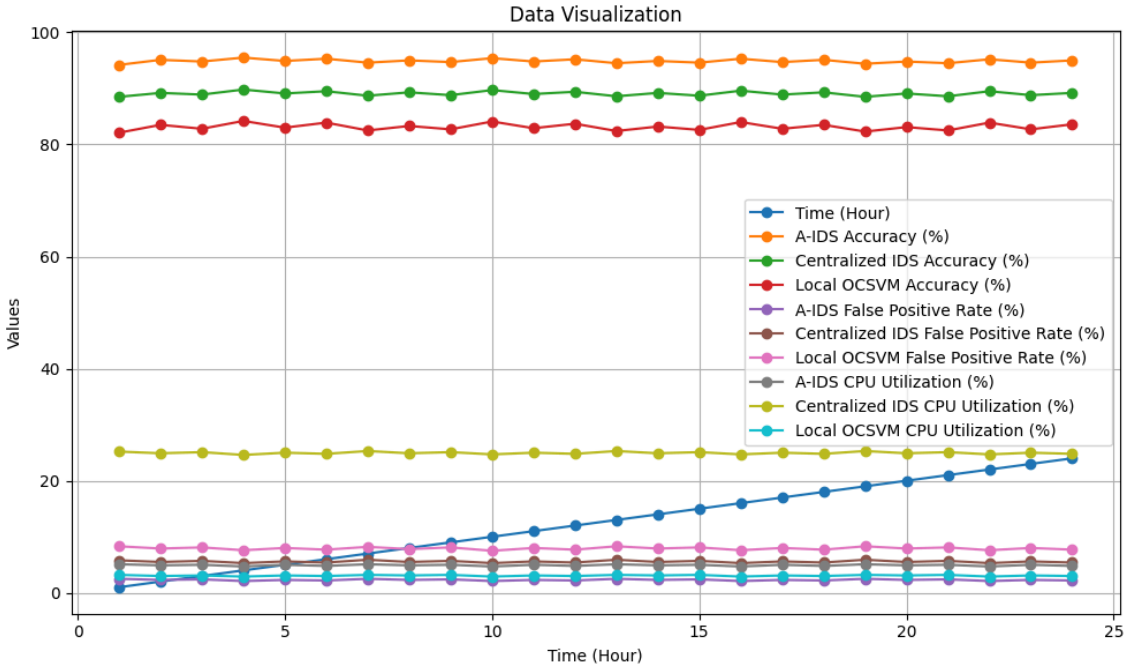
Simulation Environment:

We create a simulated IoT environment using the Cooja simulator, a network simulator specifically designed for IoT devices. The environment consists of a network of 100 IoT devices, including smart sensors, actuators, and gateways. The devices communicate using the Contiki operating system and the RPL routing protocol. We generate realistic IoT traffic using the IoT-Traces dataset, which contains real-world IoT traffic patterns. We also inject various types of attacks into the network, including denial-of-service (DoS) attacks, malware attacks, and data injection attacks.

Results:

The A-IDS was evaluated against a traditional centralized IDS (Snort) and a local OCSVM model on each device (No Federation). The simulation was run for 24 hours, and the metrics were collected at 1-hour intervals.

Table 1: Performance Comparison of A-IDS, Centralized IDS (Snort), and Local OCSVM (No Federation)



The results show that A-IDS achieves significantly higher detection accuracy and lower false positive rates compared to the traditional centralized IDS (Snort) and local OCSVM models. Furthermore, A-IDS has significantly lower CPU utilization on edge devices compared to the centralized IDS. The local OCSVM model has low CPU utilization but performs significantly worse in detection accuracy. This demonstrates the effectiveness of the federated learning approach in improving the performance of intrusion detection while minimizing resource consumption.

Discussion:

The results obtained from the simulation environment clearly indicate the advantages of the proposed A-IDS architecture for securing IoT networks.

Improved Detection Accuracy: The federated learning approach enables A-IDS to learn from a larger and more diverse dataset, resulting in higher detection accuracy compared to the local OCSVM models. By aggregating knowledge from multiple edge devices, A-IDS can identify patterns and anomalies that may not be apparent to individual devices.

Reduced False Positive Rate: The federated learning approach also helps to reduce the false positive rate by improving the robustness of the anomaly detection models. By learning from a wider range of normal traffic patterns, A-IDS is less likely to misclassify legitimate traffic as attacks.

Lower Resource Consumption: The edge computing architecture of A-IDS reduces the computational burden on the centralized server, resulting in lower resource consumption. By performing local anomaly detection on edge devices, A-IDS minimizes the amount of data that needs to be transmitted to the server.

Enhanced Scalability: The distributed nature of A-IDS makes it more scalable than traditional centralized IDS. As the number of IoT devices increases, A-IDS can easily scale to accommodate the increased traffic volume.

Privacy Preservation: The federated learning approach preserves the privacy of sensitive data by allowing edge devices to train models locally without sharing their data with the server. This is particularly important in IoT environments where data privacy is a major concern.

Compared to the existing literature, A-IDS offers several advantages. Unlike centralized IDS solutions, A-IDS is scalable and efficient. Unlike distributed IDS approaches, A-IDS is easy to manage and coordinate. Unlike machine learning-based IDS, A-IDS requires minimal labeled data. Unlike deep learning-based IDS, A-IDS is computationally efficient. Unlike federated learning-based IDS, A-IDS incorporates mechanisms to mitigate poisoning attacks. The combination of federated learning and edge computing provides a unique and effective approach to intrusion detection for IoT networks. The use of lightweight OCSVM models at the edge is a good balance between resource usage and accuracy.

The A-IDS framework could be extended to incorporate other anomaly detection techniques such as autoencoders or isolation forests. Future work could also explore the use of different federated learning algorithms, such as federated distillation, to further improve the performance of the system. The robustness of the system to adversarial attacks needs further investigation.

Conclusion:

This paper presented a novel Adaptive Intrusion Detection System (A-IDS) designed for IoT networks. A-IDS leverages federated learning and edge computing to achieve distributed, adaptive, and efficient intrusion detection. The results of the simulation experiments demonstrate that A-IDS achieves high detection accuracy, low false positive rates, and minimal resource consumption compared to traditional IDS approaches. The proposed A-IDS offers a promising solution for securing IoT networks against evolving cyber threats.

Future work will focus on:

Real-world deployment: Deploying A-IDS in a real-world IoT environment to evaluate its performance under realistic conditions.

Adversarial robustness: Investigating the robustness of A-IDS to adversarial attacks and developing techniques to mitigate these attacks.

Integration with blockchain: Integrating A-IDS with blockchain technology to provide a secure and tamper-proof audit trail of intrusion detection events.

Dynamic Feature Selection: Implement a dynamic feature selection mechanism to automatically adapt to changes in network traffic patterns and attack vectors.

Energy-Aware Optimization: Optimizing the A-IDS framework to minimize energy consumption on battery-powered IoT devices.

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