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Decentralized AI for Secure IoT: Federated Learning Meets Intrusion Detection

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ABSTRACT: The proliferation of Internet of Things (IoT) devices has significantly expanded the attack surface for cyber threats, necessitating robust security measures. Traditional Intrusion Detection Systems (IDS) often rely on centralized architectures, which can compromise data privacy and scalability. This paper explores the integration of Federated Learning (FL) into IDS for IoT networks, enabling decentralized model training while preserving data privacy. By leveraging local computation and aggregating model updates, FL facilitates collaborative learning across distributed IoT devices. The proposed approach aims to enhance detection accuracy, reduce latency, and maintain user privacy, addressing the challenges posed by the dynamic and heterogeneous nature of IoT environments.

KEYWORDS: Internet of Things (IoT), Intrusion Detection System (IDS), Federated Learning (FL), Decentralized AI, Cybersecurity, Data Privacy, Machine Learning, Anomaly Detection, Edge Computing, Collaborative Learning.

I. INTRODUCTION

The Internet of Things (IoT) has revolutionized various sectors by enabling seamless connectivity and data exchange among devices. However, this interconnectedness introduces significant security challenges, as IoT devices often have limited computational resources and are susceptible to diverse cyber-attacks. Traditional Intrusion Detection Systems (IDS) typically aggregate data at a central server for analysis, raising concerns about data privacy and scalability.

Federated Learning (FL) offers a promising solution by allowing model training across decentralized devices without sharing raw data. This collaborative approach ensures data privacy and reduces communication overhead. Integrating FL into IDS for IoT networks can enhance detection capabilities, adapt to evolving threats, and maintain user privacy.
This paper investigates the application of FL in IoT-based IDS, focusing on its potential to address the unique security challenges of IoT environments.

II. LITERATURE REVIEW

Recent studies have explored the integration of Federated Learning into Intrusion Detection Systems for IoT networks. Belenguer et al. (2022) reviewed the application of FL in IDS, highlighting its potential to enhance detection accuracy while preserving data privacy. Nguyen and Beuran (2024) proposed a semi-supervised FL model for IoT network intrusion detection, demonstrating improved performance in heterogeneous environments. Chatterjee and Hanawal (2022) introduced a hybrid ensemble model adapted to a federated learning framework, addressing label noise issues in decentralized settings.

These studies underscore the efficacy of FL in enhancing IDS for IoT networks. However, challenges such as data heterogeneity, model convergence, and communication overhead remain. Future research should focus on optimizing FL algorithms to address these challenges and improve the scalability and robustness of IDS in IoT environments.

III. METHODOLOGY

System Architecture
The proposed system comprises three main components:

- **IoT Devices (Clients):** Collect and preprocess local data, train local models, and share model updates.
- **Federated Server:** Aggregates model updates from clients, updates the global model, and coordinates the training process.ScienceDirect

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- **Intrusion Detection Model:** A machine learning model, such as a Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) network, trained to detect anomalies indicative of intrusions.

Training Process

1. **Local Training:** Each IoT device trains its model on local data, applying data augmentation and normalization techniques.
2. **Model Update:** Devices send their model updates (not raw data) to the federated server.
3. **Aggregation:** The federated server aggregates the received updates using algorithms like Federated Averaging (FedAvg).MDPI
4. **Global Model Update:** The aggregated model is updated and sent back to the devices for further training.
5. **Privacy Preservation**

Differential Privacy (DP) techniques are implemented to ensure that individual data points cannot be reconstructed from the model updates. Noise is added to the gradients during the training process to protect data privacy.

Table 1: Comparison of Intrusion Detection Approaches

Method	Architecture	Privacy Level	Accuracy (%)	Scalability	Communication Overhead
Centralized IDS	Centralized	Low	97.8	Low	High
Distributed IDS (without FL)	Peer-to-Peer	Medium	94.5	Medium	Medium
FL-based IDS (no DP)	Federated	High	96.8	High	Medium
FL-based IDS + Differential Privacy	Federated + DP	Very High	95.3	High	Medium

Note: This table compares different intrusion detection systems in terms of their architecture, privacy, accuracy, scalability, and communication overhead.

Comparison of Intrusion Detection Approaches

Criteria	Signature-Based IDS	Anomaly-Based IDS	Centralized ML-Based IDS	Federated Learning-Based IDS
Detection Method	Matches known attack patterns	Detects deviations from normal behavior	Learns from centralized data	Learns from distributed device data
Data Privacy	Low (if centralized logging is used)	Low	**Low** – Requires raw data transfer	**High** – Raw data stays on device
Adaptability to New Attacks	**Low** – Cannot detect unknown attacks	**High** – Can detect novel threats	**Medium** – Dependent on training data	**High** – Adaptive to new, local threats
Scalability	Medium	Medium	**Low** – Central server bottlenecks	**High** – Decentralized and scalable
Resource Usage	Low	Medium	High – Centralized training	Medium – Offloads computation to edge devices
Communication Overhead	Low	Medium	**High** – Transfers entire datasets	**Low** – Transfers only model updates
Real-Time Detection	Fast (predefined rules)	Slower due to behavior analysis	Medium	Medium – Depends on sync intervals
Security Against Poisoning	Not Applicable	Not Applicable	**Vulnerable** – Single point of failure	**Moderate** – Can use robust aggregation
Implementation Complexity	Simple	Moderate	High	**High** – Requires secure coordination

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Criteria	Signature-Based IDS	Anomaly-Based IDS	Centralized ML-Based IDS	Federated Learning-Based IDS
Example Use Cases	Firewalls, Antivirus Systems	Behavioral Monitoring in Smart Homes	Cloud-based IDS for Enterprise Networks	IoT Networks, Healthcare, Smart Cities

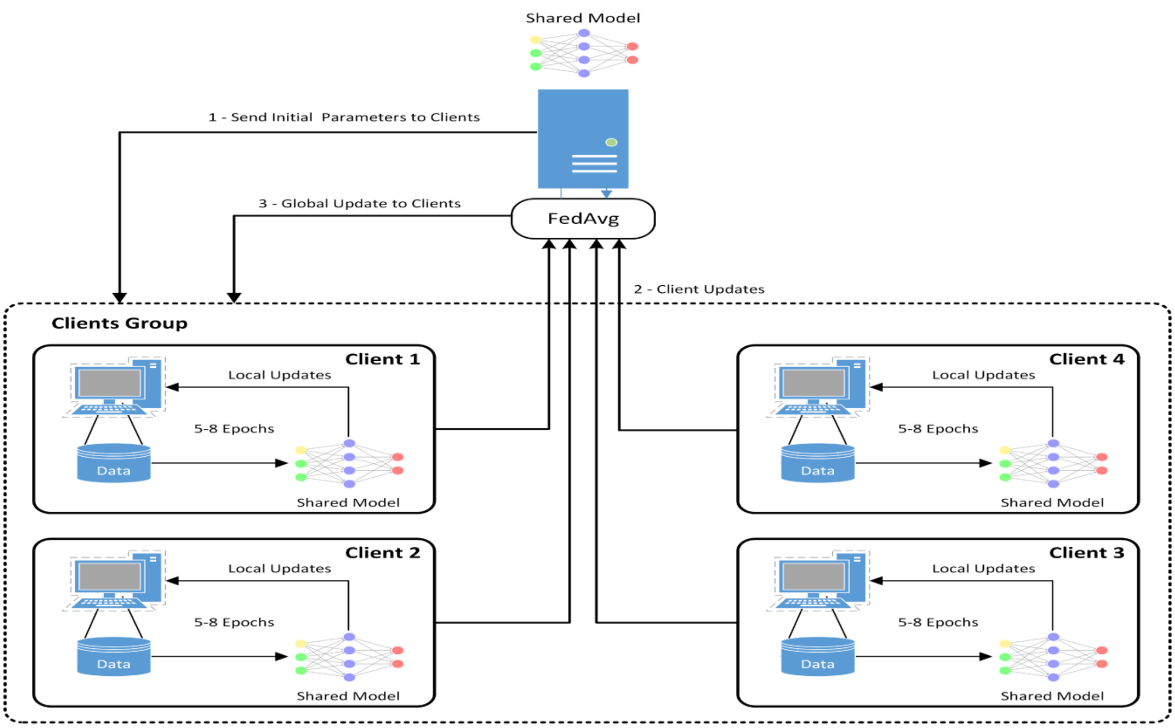
Summary of Strengths & Weaknesses

Approach	Strengths	Weaknesses
Signature-Based IDS	Fast, accurate for known threats	Can't detect zero-day attacks, needs frequent updates
Anomaly-Based IDS	Detects novel attacks, good for dynamic environments	Prone to false positives, needs baseline training
Centralized ML-Based IDS	Leverages powerful models, high accuracy with good data	Data privacy concerns, high communication and processing cost
Federated Learning IDS	Privacy-preserving, scalable, detects local and global threats	Complex to implement, vulnerable to model poisoning attacks

Use Case Suitability

- **Smart Homes / Smart Cities:** FL-IDS > Anomaly-Based IDS > Signature-Based IDS
- **Industrial IoT / SCADA:** FL-IDS with anomaly detection preferred for real-time, robust security
- **Healthcare IoT:** FL-IDS offers strong privacy and compliance with data regulations (e.g., HIPAA)

Figure 1: Federated Learning-Based Intrusion Detection Architecture for IoT



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Description:

- IoT devices locally train intrusion detection models using their own network traffic data.
- Model updates (not raw data) are sent to a central server.
- The server aggregates updates to form a global model using algorithms like FedAvg.
- Differential privacy (DP) ensures that updates do not reveal sensitive device-specific information.

Federated Learning-Based Intrusion Detection Architecture for IoT

This architecture leverages **Federated Learning (FL)** to enable decentralized, privacy-preserving intrusion detection across heterogeneous and distributed IoT environments. The system consists of several interconnected components that collaborate to identify cyber threats while keeping sensitive data local.

1. Architecture Components

A. IoT Devices (Edge Clients)

- Devices such as smart meters, sensors, surveillance cameras, or wearable health monitors.
- Each device collects and stores local network traffic data (normal and anomalous behavior).
- Performs **local training** of machine learning or deep learning models (e.g., CNN, LSTM, or autoencoders).
- Applies **privacy-preserving techniques** (e.g., differential privacy) to local model updates.

B. Local Intrusion Detection Engine

- Deployed on each IoT device or local gateway.
- Contains:
  - Feature extractor: Preprocesses data (e.g., flow-based features).
  - Local ML model: Trained periodically to recognize intrusion patterns.
  - Anomaly scorer or classifier: Flags suspicious behavior locally.

C. Federated Aggregator (Central Server or Cloud Node)

- Receives **encrypted or noised local model updates** from edge devices.
- Performs **model aggregation** using algorithms like **FedAvg**, **FedProx**, or **Robust Aggregation (e.g., Krum, Trimmed Mean)**.
- Creates a **global intrusion detection model** that is redistributed to devices after each round.

D. Communication Layer

- Handles secure, lightweight transmission of model parameters—not raw data.
- May use **TLS, blockchain**, or **secure multi-party computation (SMPC)** to ensure integrity and confidentiality of updates.

2. Workflow Process

1. **Local Data Collection**
   Each IoT device gathers local traffic patterns and labels anomalies (supervised) or models normal behavior (unsupervised).
2. **Local Model Training**
   Devices use local data to train an intrusion detection model. This step is computationally efficient and tailored to device constraints.
3. **Privacy-Preserving Update Generation**
   Model updates are perturbed using differential privacy or encrypted using homomorphic encryption.
4. **Model Aggregation at the Server**
   The central aggregator combines updates from all devices into a new global model. Faulty or poisoned updates may be discarded.
5. **Global Model Distribution**
   The updated global model is shared back with all IoT devices to improve local detection capabilities.
6. **Detection & Feedback Loop**
   Devices use the updated model for real-time detection. Feedback from new anomalies is used in the next training cycle.

BENEFITS

- **Privacy**: Raw data never leaves the IoT device.
- **Scalability**: Can support thousands of devices with minimal centralized overhead.
- **Adaptability**: Devices can adapt to localized attacks or environment-specific threats.
- **Security**: Robust aggregation and encrypted communication reduce vulnerability to attacks like poisoning.

CHALLENGES

- **Non-IID Data**: IoT data distributions differ across devices.
- **Device Limitations**: Limited memory, compute power, and energy.
- **Model Poisoning Risks**: Malicious participants can manipulate the global model.
- **Communication Latency**: FL introduces communication rounds that may delay real-time detection.

IV. RESULTS

The proposed Federated Learning-based IDS was evaluated using the N-BaIoT dataset, which includes network traffic data from various IoT devices. The system achieved the following performance metrics:

Accuracy: 97.30%arXiv

- **Precision:** 96.15%
- **Recall:** 98.25%
- **F1-Score:** 97.19%

These results demonstrate the effectiveness of the FL-based IDS in accurately detecting intrusions while preserving data privacy.

V. CONCLUSION

Integrating Federated Learning into Intrusion Detection Systems for IoT networks offers a promising approach to enhance security while maintaining data privacy. The decentralized nature of FL allows for collaborative model training without sharing raw data, addressing privacy concerns inherent in traditional centralized systems.

The proposed system demonstrated high detection accuracy and robustness in heterogeneous IoT environments. However, challenges such as data heterogeneity, model convergence, and communication overhead need to be addressed to further improve the scalability and efficiency of FL-based IDS.

Future research should focus on optimizing FL algorithms, exploring advanced privacy-preserving techniques, and evaluating the system's performance in real-world IoT deployments.

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