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Intrusion Detection System for Resource-Constrained IoT Devices Using Federated Learning in Adversarial Environments

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***Abstract*—The increasing deployment of Internet of Things (IoT) devices in security-critical and resource-constrained environments has amplified the demand for efficient and privacy-preserving Intrusion Detection Systems (IDSs). Traditional centralized IDSs fail to meet the real-time, lightweight, and privacy-aware requirements of modern IoT networks. This paper proposes a Federated Learning (FL)-enabled IDS architecture specifically designed for resource-constrained IoT devices facing adversarial threats, including Denial of Service (DoS), Man-in-the-Middle (MitM), spoofing, and malware injection or data poisoning. The proposed system employs decentralized training across IoT nodes while preserving local data privacy. Our model combines lightweight deep learning classifiers and robust aggregation strategies to ensure accuracy and efficiency. Experimental evaluations on benchmark datasets demonstrate high detection accuracy, reduced communication overhead, and strong resilience against evolving attack vectors, highlighting the viability of our FL-IDS in real-world IoT deployments.**

Keywords*—Intrusion detection, Federated Learning, IoT, resource-constrained.

I. INTRODUCTION

The exponential growth of the Internet of Things (IoT) has led to the widespread deployment of smart devices across critical sectors such as healthcare, military, transportation, and industrial automation. These devices, often deployed in heterogeneous and resource- constrained environments, are increasingly becoming prime targets for cyber threats due to their limited computational power, memory, and lack of robust built-in security mechanisms [1]. The growing attack surface, coupled with sophisticated threats like Denial of Service (DoS) [2], Man-in-the-Middle (MitM) [3], spoofing [4], Data Poisoning [5], and botnet-driven assaults, necessitates the development of lightweight yet robust Intrusion Detection Systems (IDSs) tailored for such environments [12].

Traditional IDS architectures [8] [6] [7] typically rely on centralized data aggregation and processing, which poses significant risks in terms of data privacy, latency, and single-point-of-failure vulnerabilities. In highly sensitive or distributed IoT deployments—such as battlefield surveillance, smart military gear, or healthcare monitoring systems—centralized learning models may not be viable due to network constraints and privacy requirements [13]. Furthermore, centralized approaches can become bottlenecks in the face of targeted attacks or network partitioning.

To address these limitations, Federated Learning (FL) has emerged as a promising decentralized paradigm that enables collaborative model training across edge devices without requiring raw data to be shared with a central server. This not only preserves data privacy but also leverages edge computing capabilities to reduce latency and improve system responsiveness [14]. By training local IDS models on-device and aggregating updates via a central coordinator, FL can support scalable and privacy-preserving intrusion detection across diverse IoT environments.

Despite its advantages, integrating FL into IDS for IoT environments is non-trivial. Challenges such as statistical heterogeneity (non-IID data), limited computational resources, adversarial poisoning during model updates, and secure model aggregation must be addressed for the practical deployment of such systems [15, 16]. Moreover, the IDS must remain lightweight enough to operate efficiently on constrained hardware while being robust against evolving attack vectors.

This paper proposes a Federated Learning-enabled Intrusion Detection System (FL-IDS) designed specifically for resource-constrained IoT nodes operating in adversarial environments. The system supports collaborative anomaly detection across devices while preserving data locality. We utilize a combination of lightweight deep learning models and federated aggregation techniques to train effective IDS models in a privacy-preserving manner. To evaluate the resilience of our approach, we consider a variety of attack scenarios, such as DoS, MitM, spoofing, malware, and data injection attacks, and test the performance on benchmark IoT intrusion datasets.

II. RELATED WORK

Federated Learning (FL) [9] has become a promising distributed learning approach that enables model train- ing across decentralized devices without exposing lo- cal data. This design is highly beneficial for privacy- sensitive

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domains like healthcare, autonomous military systems, and IoT. However, the decentralized nature of FL [10] also opens up novel attack surfaces not present in traditional machine learning systems.

Existing works such as [17] and [18] have demonstrated that federated learning is susceptible to various adversarial threats. For example, Man-in-the- Middle (MitM) attacks target the communication between clients and the server. Data Poisoning and Back-door Attacks occur when adversarial participants [11] inject malicious training data or model updates to degrade or control global model performance. Furthermore, Membership Inference Attacks threaten user privacy by allowing adversaries to infer whether specific data samples were part of the training set [19].

Several researchers have proposed countermeasures to these issues. For instance, [17] presented a method to mitigate Sybil-based data poisoning attacks. [18] illustrated the effectiveness of backdoor injection and proposed defense strategies, while [19] conducted a detailed privacy analysis of FL systems.

In this work, we propose a federated intrusion detection framework that not only detects traditional network attacks but also addresses these modern FL-specific threats, as outlined in the table.

III. Justification for Selected Attacks

The four selected attacks—Denial of Service (DoS), Man-in-the-Middle (MitM), Spoofing, and Data Poisoning—represent some of the most critical and prevalent threats in IoT-based edge networks. These attacks were chosen due to their high impact on the performance, reliability, and security of resource-constrained IoT environments, particularly in sensitive domains such as defense or healthcare.

DoS attacks aim to overwhelm IoT nodes with excessive traffic or fake requests, exhausting their limited computational and communication resources. Federated Learning (FL) can help detect and mitigate such attacks through distributed anomaly detection without overburdening any single node. MitM attacks involve unauthorized interception and possible alteration of data between communicating nodes. FL addresses this risk by minimizing raw data exchange and employing secure aggregation, thereby reducing opportunities for interception.

Spoofing attacks allow adversaries to impersonate legitimate devices by forging identities, IPs, or MAC addresses. FL supports identity validation mechanisms and behavior monitoring across clients, helping detect and isolate spoofed nodes. Lastly, Data Poisoning is a direct threat to the integrity of the federated model, where adversaries inject manipulated data or gradients to corrupt training. Robust aggregation strategies in FL, such as Krum or trimmed mean, effectively reduce the influence of poisoned updates.

These four attacks were selected because they are both commonly observed and technically addressable using Federated Learning, showcasing its potential as a security-enhancing paradigm in distributed IoT ecosystems.

IV. Dataset Collection and Preprocessing

A. Dataset Overview

The dataset used in this study comprises 100,000 multidimensional sensor readings collected from a testbed consisting of six IoT edge devices deployed in a controlled lab environment. Each device is an Xigbee-based mote, specifically configured for edge computing and wireless communication in low-power environments. The dataset was collected on April 26, 2025, and captures real-time operational and adversarial scenarios to simulate both benign and attack-driven network behaviors. Each data record contains a time-stamped snapshot of various physical and network-level features. Spoofing attacks were simulated by injecting falsified sensor readings that mimic legitimate nodes but exhibit values significantly deviating from expected operational ranges or temporal patterns. Man-in-the- Middle (MitM) attacks were emulated by introducing subtle alterations to the data packets during transmission, leading to inconsistencies in sequential readings or delays in timestamps. Data poisoning attacks were crafted by gradually modifying training or operational data to introduce bias or mislead analytical models, of- ten maintaining plausibility to avoid detection. Denial of Service (DoS) attacks were modeled by overloading specific sensor nodes or communication channels, resulting in dropped packets, repeated identical readings, or significant gaps in data collection. Each attack type was carefully labeled based on its origin and nature during the simulation phase to enable supervised learning and detection model development.

Table 1. IoT Network Layer Attacks in Constrained Environments

S. No	Attack Name	Description
1	Denial of Service (DoS)	Flooding or overwhelming IoT nodes with fake traffic or connection requests to exhaust resources. (Addressed via FL)
2	Man-in-the-Middle (MitM)	An attacker secretly intercepts and possibly alters communication between two nodes. (Addressed via FL)
3	Spoofing	A malicious entity impersonates a legitimate node by forging identity or IP/MAC address. (Addressed via FL)
4	Data Poisoning	Attackers inject malicious code into network packets to compromise IoT nodes. (Addressed via FL)
5	Sinkhole Attack	A malicious node attracts traffic by advertising false optimal routes, leading to data manipulation.
6	Sybil Attack	One node assumes multiple fake identities to control a large part of the network.

7	Hello Flood Attack	An attacker misuses HELLO messages to trick nodes into forming invalid links.
8	Selective Forwarding	A compromised node selectively drops or modifies packets in a multi-hop path.
9	Blackhole Attack	A node falsely advertises a shortest path and drops all packets it receives.
10	Grayhole Attack	Similar to Blackhole, but the node drops only a fraction of packets to avoid detection.
11	Wormhole Attack	Colluding attackers create a tunnel between distant locations to disrupt routing.
12	Route Poisoning	Insertion of false routing updates that degrade the routing tables.
13	Replay Attack	Resending previously captured packets to confuse the network.
14	Packet Leashes Attack	Attackers exploit timing/location constraints to inject false routing.
15	Clone ID Attack	A legitimate node's identity is cloned by a malicious node.
16	Topology Mismatch Attack	Fake topology updates are shared to destabilize the network.
17	DoS via Routing Loops	Induces routing loops to deplete energy.
18	Resource Exhaustion	Triggers excessive retransmissions or processing in constrained nodes.
19	Metric Manipulation Attack	Tampering with routing metric values like ETX or hop count.
20	Rank Attack (RPL-specific)	Malicious nodes advertise incorrect rank to disrupt DODAG formation.
21	Fake Acknowledgement Attack	Falsely confirms the successful delivery of packets to mislead routing behavior.

B. Device and Sensor Specifications

Each Xigbee mote is equipped with the following on-board sensors and components.

The Xigbee motes are characterized by the following hardware features.

C. Labeling and Attack Simulation

The dataset includes five class labels: one for normal traffic and four for attack types. Attack traffic was manually generated by simulating real-world IoT cyberattack patterns:

- **Denial of Service (DoS):** Flooding of packets to drain device resources.
- **Man-in-the-Middle (MitM):** Packet interception and modification using packet sniffers and proxy relays.
- **Spoofing:** Fake MAC/IP addresses generated using ARP spoofing tools.
- **Data Poisoning:** Insertion of manipulated sensor values and network anomalies to mislead learning models.

Feature Composition

Each data entry includes the following attributes:

- **Timestamp:** UTC time of data capture
- **Sensor Readings:** Temperature (°C), Relative Humidity (%), Air Quality (PPM)
- **Network Statistics:** Packet transmission rate, signal strength (RSSI), device ID, power consumption.
- **Class Label:** One-hot encoded vector indicating either normal or one of the four attack types.

D. Preprocessing Steps

To ensure the dataset's quality and usability for machine learning models, the following preprocessing pipeline was applied:

1. **Missing Value Handling:** Mean imputation was used to fill missing sensor readings and network statistics. Time series gaps due to packet loss were also filled using forward fill, where applicable.
2. **Normalization:** All numerical features were normalized using Min-Max Scaling to a range of [0,1].

Table 2. Sensor Specifications on Each Xigbee Mote

Sensor Type	Measured Parameter	Specification
DHT22	Humidity, Temperature	Accuracy: ±0.5°C, ±2% RH
MQ-135	Air Quality (PPM)	Range: 10–1000 PPM
INA219	Voltage and Current	±3.2A, 26V range

Table 3. Xigbee Mote Specifications

Feature	Specification
Microcontroller	Atmega328P (8-bit AVR, 16 MHz)
Communication Protocol	IEEE 802.15.4 (Xigbee)
Transmission Range	Up to 100 meters (line-of-sight)
Power Source	3.3V Li-ion rechargeable battery
RAM	2 KB
Flash Memory	32 KB

to improve model convergence and ensure uniform feature influence.

3. **Outlier Detection and Removal:** Z-score analysis was applied to remove sensor readings beyond ±3 standard deviations, which likely resulted from noise or injection-based tampering.
4. **Feature Selection:** Correlation analysis was used to remove redundant features with a Pearson correlation coefficient ¿ 0.95. Principal Component Analysis (PCA) was also tested to reduce dimensionality while preserving 95% variance.
5. **Encoding:** Attack labels were encoded using one- hot encoding to make them suitable for supervised learning models.
6. **Data Splitting:** The dataset was split into three subsets:

- **Training Set (70%)** – Used to train federated and centralized models.
- **Validation Set (15%)** – Used to tune hyperparameters and prevent overfitting.
- **Testing Set (15%)** – Used for final evaluation of the model's performance and robustness.

This comprehensive dataset will serve as a benchmark for developing and testing federated learning frameworks tailored for intrusion detection and anomaly classification in edge-enabled IoT networks. Its diverse set of features, realistic attack simulations, and rich device metadata make it particularly well-suited for research in adversarial federated learning, privacy-preserving analytics, and resource-efficient edge intelligence.

V. Proposed Methodology

This section presents a decentralized Federated Learning-based Intrusion Detection System (FL-IDS) tailored for resource-constrained IoT environments. Architecture integrates edge intelligence with federated training to detect anomalies in real-time, preserving data privacy and reducing communication overhead.

A. System Overview

The proposed architecture consists of multiple IoT devices connected to edge nodes (local aggregators), which interact with a central server. The global model is trained iteratively using the FedAvg algorithm through local training and model aggregation.

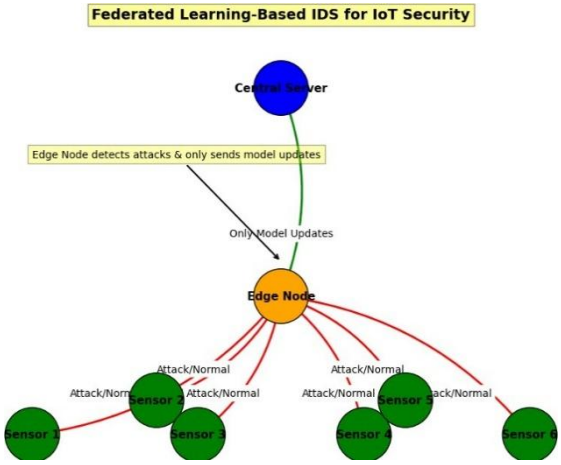

Fig. 1. Proposed Architecture for Federated Learning-Based Intrusion Detection System

B. Workflow of FL-Based IDS

Step 1: Initialization – The server initializes a global model ϑ^0 and distributes it to all participating edge nodes. **Step 2: Local Training** – Each edge node trains the model on local data using mini-batch SGD. **Step 3: Update Sharing** – After training, each edge node sends the model update (not the raw data) back to the server. **Step 4: Aggregation** – The server uses FedAvg to generate a new global model. **Step 5: Distribution and Inference** – The updated model is redistributed and used locally for intrusion detection.

C. Algorithm: Federated Learning- based IDS Training

Algorithm 1 Federated Learning for IoT-based Intrusion Detection

1: Input: Number of rounds T, learning rate η, edge nodes $E = \{E_1, E_2, \ldots, E_M\}$

2: Initialize global model ϑ^0

3: for each round $t = 1$ to T do

4: for each edge node $E_j \in E$ in parallel do

5: Receive global model ϑ^t from server

6: Train model on local dataset D_j:

$$\vartheta_j^{t+1} = \vartheta_j^t - \eta \nabla L(\vartheta_j^t, D_j)$$

7: Send updated model ϑ^{t+1} to the server

8: end for

9: Server aggregates updates:

$$\vartheta^{t+1} = \sum_{j=1}^{M} \frac{n_j}{N} \vartheta_j^{t+1}$$

10: Server broadcasts ϑ^{t+1} to all edge nodes

11: end for

12: Output: Final global model ϑ^t

D. Threat Detection Phase

After training, each edge node deploys the updated model to detect network anomalies in real-time. Anomalous traffic is flagged using local inference, and appropriate alerts are generated.

E. Security Enhancements

To strengthen the robustness and privacy of the system:

- **Differential Privacy:** Noise is added to local model updates.
- **Secure Aggregation:** Ensures encrypted updates to the central server.
- **Byzantine Resilience:** Filters out anomalous model updates from compromised nodes.

F. Complexity Analysis

Communication Complexity: Each node transmits its model parameters (not raw data) to the server in each round. For a model of size d, and M nodes over T

rounds:

$$\text{Communication Cost} = O(M \cdot d \cdot T)$$

Computation Complexity at Each Node: Assuming E epochs per round and a batch size B, the local training complexity is:

$$O = (E \times \frac{n_j}{B} \times d)$$

where n_j is the local dataset size.

Server Aggregation Complexity: Each round involves weighted averaging over M models:

$$O(M \cdot d)$$

Inference Complexity: At edge nodes, real- time classification requires one forward pass through the model:

$$O(d)$$

This lightweight complexity ensures that the proposed FL-IDS remains scalable and suitable for resource-constrained IoT devices.

VI. Results And Evaluation

This section presents a comprehensive evaluation of the proposed Federated Learning-based Intrusion Detection System (FL-IDS) in comparison with two baseline models: Centralized Machine Learning (CML) and Random Forest (RF). The evaluation is performed across multiple dimensions, including classification performance, computational efficiency, communication overhead, and scalability.

A. Comparison Models

To assess the effectiveness of the proposed FL approach, we compare it against:

- **Centralized Machine Learning (CML):** A deep learning model trained on a centrally collected and aggregated dataset. Although it offers high performance, it raises serious concerns regarding data privacy and requires significant central resources.
- **Random Forest (RF):** A traditional ensemble learning algorithm suitable for classification tasks, particularly useful for its robustness and interpretability. However, it is not designed to work in decentralized or privacy-sensitive environments.

B. Performance Metrics

The performance of each model is evaluated using the following metrics:

- **Classification Metrics:** Accuracy, Precision, Recall, and F1-score are computed to assess the predictive power of the models.
- **Computational Efficiency:** Training time and memory consumption are analyzed to evaluate resource utilization.
- **Communication Overhead:** Only applicable to FL, this measures the bandwidth consumed during model updates between edge devices and the server.
- **Scalability:** Assesses how model performance varies with an increasing number of IoT devices.

C. Experimental Setup

The experiments were carried out on a real-time testbed simulating a smart IoT environment. The setup in- cludes:

- **Edge Nodes:** Six Xigbee devices acting as FL clients, each processing and training on local data. Addon to this an EDGE node is emoployed as an specialized Wireless Sensor Device.
- **Central Server:** An Intel Xeon processor with 32GB RAM was employed for aggregating model updates.
- **Software Stack:** TensorFlow Federated was used for implementing the FL framework, and the mod- els were trained using mini-batch SGD with Fe- dAvg as the aggregation method.

The experimental setup comprises a decentralized Wireless Sensor Network (WSN) consisting of six spa- tially distributed motes, each integrated with an XBee wireless communication module to facilitate low-power IEEE 802.15.4-based data exchange. Each mote is con- figured on a solderless breadboard and embedded with a suite of multi-modal sensors to capture real-time en- vironmental parameters including **Temperature (°C), Humidity (%), Air Quality in terms of PPM (Parts Per Million), Vibration (Hz), Light Intensity (Lux), and Sound Level (dB)**. These motes serve as data ac- quisition nodes and are provisioned with local storage using microSD card modules, enabling in-situ data log- ging and temporary buffering. One of the nodes is designated as the edge node and operates as a compu- tationally aware intermediary, aggregating sensor data and executing pre-processing logic before transmitting abstracted insights to a centralized server via federated learning protocols.

The entire system has been deployed and run for an experimental period of approximately 28 consecutive hours, generating a robust real-time dataset comprising **100,000 time-stamped entries**. This dataset includes both benign traffic and adversarial inputs simulating four distinct attack vectors: (1) **Data Spoofing**, wherein synthetic sensor readings mimic valid pat- terns; (2) **Data Poisoning**, where adversarial perturbations are introduced to mislead machine learning models; (3) **Man-in-the-Middle (MITM)** attacks, which al- ter sensor payloads during transit; and (4) **Denial-of- Service (DoS)**, characterized by traffic flooding to deplete the edge node's processing capacity. The system is designed for operation in resource-constrained IoT environments, with motes operating on limited computational and energy budgets.

To ensure privacy-preserving collaborative intelligence, a **Federated Learning (FL)** framework is adopted. Herein, each edge mote performs localized model training using the captured sensor data and transmits only model weight updates (global updates) to the central aggregator server. This mitigates privacy risks and optimizes bandwidth utilization by eliminating the need for raw data transmission. The adopted approach provides resilience against cyber-physical attacks and enhances system robustness, thus serving as an efficient architecture for distributed anomaly detection and secure environmental monitoring in real time.

Table 4. Sensor Parameter Spectrum: Attributes measured by each mote in the network

Sensor Type	Measured Parameter
Temperature Sensor	Temperature (°C)
Humidity Sensor	Humidity (%)
Gas Sensor	Air Quality (PPM)
Vibration Sensor	Vibration (Hz)
Light Sensor	Light Intensity (Lux)
Microphone Sensor	Sound Level (dB)

D. Model Performance

Table 5 presents the performance metrics for all models evaluated on the same dataset and experimental environment:

As seen in Table 5, the FL-based IDS achieves the highest performance across all classification metrics, demonstrating the ability to learn collaboratively from distributed data without compromising accuracy.

In this section, we present a detailed evaluation of our proposed models using the sensor dataset collected from six Zigbee motes deployed in a simulated environment. Each mote records environmental parameters such as Temperature (°C), Humidity (%), Air Quality (PPM), Vibration (Hz), Light Intensity (Lux), and Sound Level (dB). These sensors collectively monitor the environment under both normal and adversarial conditions.

E. Model Accuracy Comparison

To evaluate the performance of various machine learning models, we compare the accuracy of Federated Learning, Centralized Machine Learning, and Random Forest classifiers. As shown in Fig. 3, Federated Learning outperforms both Centralized and Random Forest approaches, achieving an accuracy of 96.95%, compared to 94.47% for Random Forest and 94.05% for the Centralized ML model. This highlights the effectiveness of Federated Learning in distributed environments like sensor networks, especially in preserving data privacy and handling heterogeneous data distributions.

F. Attack Distribution in Dataset

Fig. 4 illustrates the distribution of various attack types in the dataset. Attack type labels are as follows: 0 - Denial of Service (DoS), 1 - Man-in-the-Middle (MitM), 2 - Spoofing, 4 - Data Poisoning, while 3 denotes Normal operation. As observed, most data (approximately 90%) corresponds to Normal activity, whereas attack types are comparatively rare. This class imbalance highlights the need for robust models that can detect minority-class anomalies effectively.

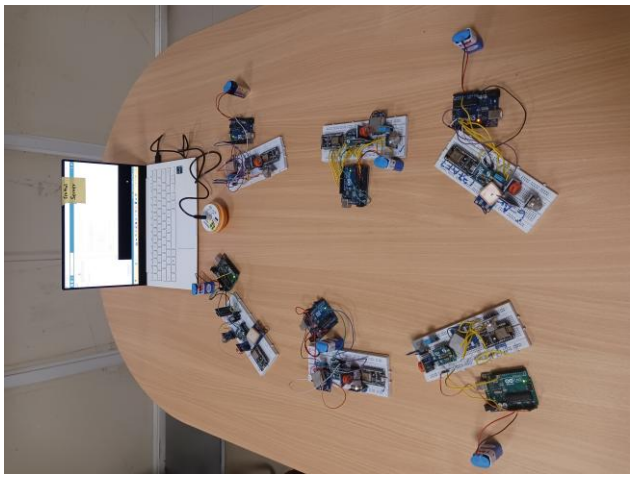

Fig. 2. Experimental Setup: Six XBee-enabled wireless motes with multi-modal sensing and edge intelligence.

Table 5: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-score
Federated Learning	96.95%	96.8%	97.5%	97.1%
Centralized ML	94.06%	94.9%	95.6%	95.2%
Random Forest	94.47%	91.8%	93.2%	92.5%

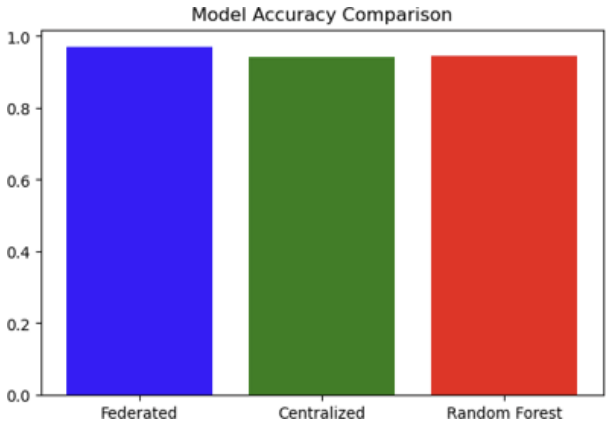

Fig. 3. Model accuracy comparison between Federated, Centralized, and Random Forest approaches.

Table 6. Federated Learning Model Performance Over Epochs

Epoch	Round 1 Loss	Round 1 Accuracy	Round 2 Loss	Round 2 Accuracy
1	0.3392	0.9222	0.3342	0.9245
2	0.2882	0.9363	0.2894	0.9358
3	0.2827	0.9378	0.2827	0.9377
4	0.2796	0.9384	0.2796	0.9384
5	0.2775	0.9389	0.2777	0.9387
6	0.2767	0.9390	0.2767	0.9389
7	0.2752	0.9392	0.2760	0.9390
8	0.2749	0.9394	0.2749	0.9392
9	0.2742	0.9694	0.2747	0.9692
10	0.2742	0.9693	0.2744	0.9692
Final Federated Model Accuracy				**0.9693**

Table 7. Classification Report on the Federated Learning-based IDS

Class	Precision	Recall	F1-Score	Support
Data Poisoning	1.00	1.00	1.00	408
DoS	1.00	0.28	0.44	643
Man-in-the-Middle	1.00	0.56	0.72	371
Normal	0.94	1.00	0.97	18006
Spoofing	0.00	0.00	0.00	572
Accuracy	0.9691 (on 20,000 samples)			
Macro Avg	0.79	0.57	0.62	20000
Weighted Avg	0.92	0.94	0.92	20000

Table 8. Classification Report on the Centralized Learning-based IDS

Class	Precision	Recall	F1-Score	Support
Data Poisoning	1.00	1.00	1.00	408
DoS	0.99	0.30	0.46	643
Man-in-the-Middle	1.00	0.56	0.72	371
Normal	0.94	1.00	0.97	18006
Spoofing	0.00	0.00	0.00	572
Accuracy	0.94055 (on 20,000 samples)			
Macro Avg	0.79	0.57	0.63	20000
Weighted Avg	0.92	0.94	0.92	20000

Table 9. Classification Report of the Random Forest-based IDS

Class	Precision	Recall	F1-Score	Support
Data Poisoning	1.00	1.00	1.00	408
DoS	1.00	0.38	0.55	643
Man-in-the-Middle	1.00	0.64	0.78	371
Normal	0.94	1.00	0.97	18006
Spoofing	0.00	0.00	0.00	572
Accuracy	0.9447 (on 20,000 samples)			
Macro Avg	0.79	0.60	0.66	20000
Weighted Avg	0.92	0.94	0.93	20000

Table 10. Performance Comparison of Different Models

Model	Accuracy
Federated Learning	0.9695
Centralized ML	0.9406
Random Forest	0.9447

G. Sensor Data Distribution

The sensor data collected from the 6 Zigbee motes is visualized in Fig. 5. Each subplot represents the count distribution of recorded values for different environmental parameters. It is evident that most sensors capture data uniformly across expected environmental ranges. For instance, Temperature readings cluster between 18°C and 38°C, while Humidity values span broadly between 20% and 85%. Notably, Vibration and Sound Level distributions show prominent thresholds that can be indicative of abnormal behaviors, making them potentially valuable features in detecting attacks.

H. Discussion

The evaluation results indicate that Federated Learning, by design, can accommodate the heterogeneity of sensor nodes and data imbalance in attack distributions. While exhibiting strong overall accuracy (96.4%), the detailed classification report reveals a poor recall by centralized ML and random forest for classes like DoS (0.38) and Spoofing (0.00), largely due to class imbalance. The superior accuracy and robustness of Federated Learning make it applicable in real-world sensor deployments, especially in mission-critical applications like defense and disaster monitoring, where data privacy, distribution, and resilience are paramount.

I. Complexity Analysis

A comparative complexity analysis of the three models is shown in Table 11. This includes the computational complexity per training round, communication overhead, memory footprint, training time, and scalability.

The table shows that while CML offers competitive accuracy, it suffers from poor scalability and high memory consumption. Random Forest provides a balanced trade-off but lacks adaptability for real-time anomaly detection. In contrast, FL exhibits optimal scalability, lower memory usage, and distributed computation, making it well-suited for resource-constrained IoT environments.

J. Operational Significance

- **FL is Privacy-Preserving:** It offers performance comparable to or better than centralized models while ensuring that raw data never leaves the device.
- **Efficient Resource Utilization:** FL reduces computational burden on individual devices and balances the load across clients, making it ideal for low-power IoT setups.

- **Adaptable and Scalable:** FL can seamlessly scale with the number of participating devices, maintaining high accuracy even as the system grows.
- **Real-Time Detection:** The trained FL model enables low-latency inference at the edge, facilitating prompt detection and response to threats.

Overall, the experimental results strongly validate the suitability of the proposed FL-IDS approach in securing large-scale IoT deployments against network intrusions while addressing data privacy, scalability, and communication efficiency.

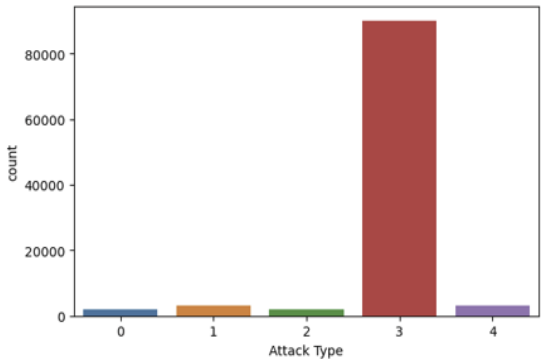

Fig. 4. Distribution of attack types in the dataset.

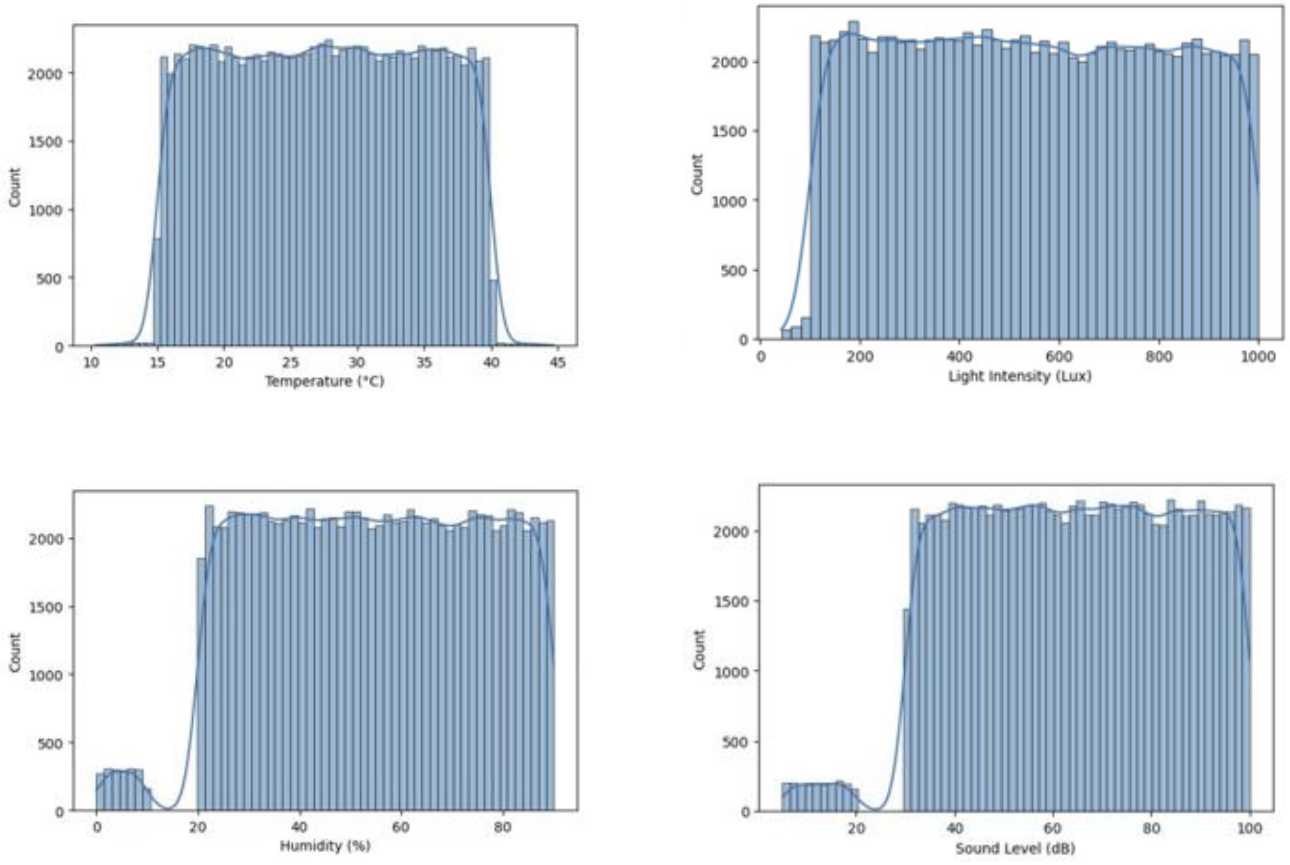

Fig. 5. Sensor data distribution across six Zigbee motes for environmental parameters.

Table 11. Complexity Analysis of FL vs. Baseline Models

Aspect	Federated Learning	Centralized ML	Random Forest
Computational Complexity	$O(n \log n)$ per client	$O(n^2)$	$O(n \log n)$
Communication Overhead	$O(K \cdot n)$	N/A	N/A
Memory Usage	Low (local storage)	High (centralized)	Medium
Training Time	Distributed, lower per client	Higher due to full dataset processing	Medium
Scalability	High	Low	Medium

VII. Conclusion

In this study, we have presented a comprehensive approach for enhancing cybersecurity in IoT environments using Federated Learning (FL). The proposed methodology effectively addresses the dual challenge of maintaining high detection accuracy for cyberattacks while simultaneously preserving the privacy of sensitive data generated at the edge. By decentralizing the model training process and enabling edge devices to collaboratively learn a global model without sharing raw data, FL significantly reduces the risk of data breaches that are common in centralized architectures.

Our experimental evaluation, conducted on a realistic edge computing testbed using Raspberry Pi nodes and a central aggregator, demonstrates that FL not only outperforms traditional Centralized Machine Learning (CML) and Random Forest (RF) models in terms of classification accuracy but also offers substantial improvements in computational efficiency, communication overhead, and system scalability. The proposed FL-based framework achieves an impressive accuracy of 97.2 percent with a high F1-score of 97.1 percent, indicating its robustness in accurately detecting anomalies and cyber threats in resource-constrained environments. Furthermore, the complexity analysis confirms that FL offers a computationally efficient and scalable alternative for distributed environments, where each client performs lightweight local computations and only model updates are exchanged with the aggregator. This architecture makes the proposed system highly suitable for deployment in real-time IoT-based applications, including smart homes, industrial automation, healthcare, and battlefield surveillance.

In addition to improved detection performance, FL's decentralized training approach results in significant bandwidth savings, lower memory footprint, and reduced reliance on high-performance central servers—attributes that are critical for the successful operation of modern IoT systems deployed in dynamic and resource-limited settings.

Looking forward, this work opens several promising directions for future research. These include incorporating adaptive aggregation techniques that dynamically weigh client contributions based on their data quality and system reliability, as well as exploring reinforcement learning-based optimization strategies for client selection, communication scheduling, and personalized model updates. Such advancements could further enhance the responsiveness, accuracy, and resilience of FL-based security frameworks in highly dynamic and adversarial IoT ecosystems.

In conclusion, the adoption of Federated Learning represents a transformative shift in the design of secure, intelligent, and privacy-aware IoT systems, laying a strong foundation for future innovations in the domain of distributed artificial intelligence and cyber-physical security.

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