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Real-time privacy-preserving threat detection in IoT environments using federated learning and differential privacy

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Abstract

Motivated by the increasing security threats in Internet of Things (IoT) environments, this research develops a novel, real-time, privacy-preserving threat detection framework integrating Federated Learning (FL) and Differential Privacy (DP). The proposed system enables collaborative threat detection across IoT devices while preserving data privacy. We tested our approach against the UNSW-NB15 dataset in a federated environment with 100 devices, achieving 90.8% accuracy ($\varepsilon = 1.0$) while reducing communication overhead by 97.5% compared to centralized approaches (212MB → 5.2MB/device/day). The integration of differential privacy introduces a measurable trade-off: stronger privacy guarantees ($\varepsilon = 0.5$) reduce accuracy by 2.9% (from 90.8% to 87.9%) while keeping false positive rates stable at 5.1-5.6%. Scalability tests confirm the framework's efficiency, with CPU usage remaining at 48-52% for 100 devices. By eliminating raw data transmission, the framework enhances security, ensures GDPR/HIPAA compliance, and improves IoT system resilience. This research contributes both theoretical insights and a practical implementation for decentralized, privacy-conscious IoT cybersecurity architectures.

Keywords: IoT security, federated learning, differential privacy, privacy-preserving cybersecurity, real-time threat detection

Introduction

The Internet of Things (IoT) has emerged as a transformative technology, connecting billions of devices globally. Estimates suggest that by 2030, over 500 billion IoT devices will be used worldwide, spanning various applications such as smart homes, healthcare, and industrial automation (Cisco, 2023). While the growth of IoT has enhanced convenience and innovation, it also poses significant security risks. Due to their limited computational power, these devices are particularly vulnerable to attacks such as Distributed Denial of Service (DDoS), ransomware, and unauthorized access (Sicari et al., 2015; Ding et al., 2021).
Traditional Machine Learning (ML)-based threat detection techniques rely on centralized architectures, where raw data from IoT devices is collected at central servers for analysis. However, this approach presents privacy concerns, bandwidth constraints, and latency issues. A core challenge is achieving real-time threat detection in resource-constrained IoT environments while maintaining data privacy. Traditional models often require access to raw data to ensure high accuracy, introducing privacy risks. Furthermore, the computational limitations of IoT devices make it difficult to implement complex security protocols without sacrificing performance.

This research proposes a decentralized framework integrating Federated Learning (FL) and Differential Privacy (DP) to address these challenges. FL allows IoT devices to collaboratively learn a global model

without exposing individual device data, while DP introduces noise to the model updates to ensure privacy protection (McMahan et al., 2017). This paper develops and evaluates a comprehensive framework for real-time, privacy-preserving threat detection in IoT environments, balancing privacy preservation, detection accuracy, and system performance.

The key research objectives of this research are:

- Developing a real-time threat detection framework that integrates FL and DP to enhance IoT security.
- Evaluating the framework's effectiveness in balancing privacy, detection accuracy, and system performance.
- Investigating trade-offs between privacy guarantees, computational efficiency, real-time performance, and scalability in IoT environments.

The primary research questions are:

1. *How can FL and DP be effectively combined to enable real-time, privacy-preserving threat detection in IoT environments?*
2. *What are the trade-offs between privacy guarantees, detection accuracy, and computational efficiency in the proposed framework?*

The novelty of this research lies in its real-time, privacy-preserving threat detection framework tailored explicitly for IoT environments. Unlike existing approaches, it integrates FL with DP to ensure privacy without sacrificing detection accuracy or system performance, which is crucial for resource-constrained IoT devices. By leveraging lightweight, privacy-preserving algorithms and widely used IoT protocols like MQTT (Message Queuing Telemetry Transport), this framework addresses the unique challenges of IoT security, providing scalable, efficient, and privacy-compliant solutions for real-time threat mitigation. This research fills that gap by proposing a comprehensive framework integrating FL and DP for IoT threat detection, balancing privacy, accuracy, and real-time system performance.

Related Work

Conventional IoT threat detection

Conventional IoT threat detection methods typically use centralized architectures, where raw data is transmitted from IoT devices to a central server for analysis (Buczak & Guven, 2016). While centralized systems facilitate effective detection, they introduce significant privacy risks and may struggle with the enormous data volumes generated by IoT devices (Bello, Zeadally, & Badra, 2017). Decentralized approaches like fog and edge computing offer solutions by processing data closer to the source, reducing latency and bandwidth usage (Chiang & Zhang, 2016). However, these approaches still face challenges in balancing privacy protection and detection accuracy.

Federated learning for privacy-preserving applications

FL was introduced as a solution to the privacy risks inherent in centralized ML models (McMahan et al., 2017). By enabling decentralized devices to learn collaboratively without exchanging raw data, FL reduces privacy risks while facilitating real-time model updates. Recent research has applied FL to other fields, such as healthcare (Li et al., 2020; Nguyen et al., 2021) and finance (Yang, Liu, et al., 2019), showing its potential to balance privacy with model accuracy. One challenge is the risk of information leakage through shared model updates, as attackers can infer sensitive information using gradient inversion attacks

(Hatamizadeh et al., 2023). This highlights the need for enhanced privacy measures, such as DP, when implementing FL in IoT settings.

Differential Privacy For Enhanced SecurityDP introduces a formal privacy guarantee by adding controlled noise to datasets or model updates, ensuring that sensitive information cannot be inferred from aggregated results (Wu et al., 2023). DP has been widely adopted in fields such as data mining (Ram Mohan Rao et al., 2018), but its integration with federated learning for IoT security remains limited (Wei et al., 2020). To mitigate these risks associated with FL, DP is integrated into FL to add controlled noise to the model updates, ensuring that no individual data point can be accurately inferred from the aggregated information (Hatamizadeh et al., 2023; Wu et al., 2023). This mechanism offers formal privacy guarantees even in the presence of adversarial participants or curious servers, further bolstering the privacy of the distributed learning process. Moreover, DP helps ensure compliance with data privacy regulations, such as GDPR and HIPAA, which mandate robust protections for sensitive data. The combination of FL and DP, therefore, enhances security and long-term privacy for IoT environments where sensitive data is frequently involved (McMahan et al., 2017; Abadi et al., 2016).

Privacy-preserving techniques in IoT: a critical analysis

Recent research has explored various privacy-preserving techniques for IoT environments, including homomorphic encryption (HE), secure multiparty computation (SMC), and differential privacy (DP). While HE allows computations on encrypted data without decryption, it introduces significant computational overhead unsuitable for resource-constrained IoT devices (Aziz et al., 2023). SMC enables multiple parties to jointly compute functions while keeping inputs private, but requires extensive communication between parties, limiting its applicability in IoT networks with bandwidth constraints (Yu et al., 2023). In contrast, DP offers a mathematical framework for privacy guarantees with adjustable privacy-utility trade-offs and lower computational requirements than cryptographic approaches, making it particularly suitable for IoT environments (McMahan et al., 2017; Abadi et al., 2016). Furthermore, DP integrates naturally with FL as it can be applied directly to model updates during the aggregation process without requiring protocol changes, unlike HE which would necessitate substantial modifications to the federated architecture (Wei et al., 2020).

Several works have explored the integration of FL and DP in IoT contexts. Mugunthan et al. (2023) proposed PrivacyFL, a simulator for privacy-preserving federated learning, but focused primarily on simulation rather than real-time implementation for resource-constrained devices. Vyas et al. (2024) surveyed privacy-preserving federated learning for IoT but did not address the trade-offs between privacy guarantees and detection accuracy in real-time threat detection scenarios. Combining FL with DP offers the potential for decentralized learning while protecting individual privacy. However, trade-offs must be considered, particularly with regard to computation overhead and utility loss due to noise addition (Abadi et al., 2016). DP provides formal privacy garantees, making it compliant with privacy regulations like GDPR and HIPAA (McMahan et al., 2017). Although both FL and DP have been explored individually in IoT and privacy contexts, the combination of these technologies for real-time, privacy-preserving threat detection in resource-constrained IoT environments still need to be explored. Existing solutions often focus on one aspect—either privacy or real-time detection—but fail to address both simultaneously.

Requirements

To effectively address the challenges of real-time, privacy-preserving threat detection in IoT environments, the following requirements were identified based on existing literature:

1. **Privacy-preserving:** The system must ensure data privacy through mechanisms like Differential Privacy, protecting individual device data from adversaries and complying with regulations like GDPR and HIPAA (Hatamizadeh et al., 2023; Wu et al., 2023). By integrating DP into federated learning, we ensure that even while IoT devices collaboratively train a shared model, sensitive data is never exchanged, addressing concerns over data breaches and unauthorized access.
2. **Real-Time Performance**: The framework must enable low-latency detection and response to threats, suitable for time-sensitive IoT applications such as healthcare and industrial automation (Abadi et al., 2016). Leveraging Federated Learning (FL) minimizes the need for constant communication with a central server, allowing devices to process data locally and only share model updates, ensuring fast threat detection without significant delays.
3. **Resource Efficiency**: The proposed methods must be lightweight, minimizing computational and communication overhead on resource-constrained IoT devices (Sicari et al., 2015; Chiang & Zhang, 2016). The choice of lightweight machine learning algorithms, such as logistic regression and decision trees, is particularly suited for resource-constrained environments where high computational power or memory is unavailable. Federated Learning further alleviates the strain on individual devices by distributing computation across multiple devices.
4. **Accuracy of Threat Detection:** The system must maintain high detection accuracy, mitigating threats such as DDoS, malware, and unauthorized access without excessive false positives (Buczak & Guven, 2016; Zhao et al., 2020). To ensure accuracy, we evaluate detection performance using precision, recall, F1 score, and false-positive rates, with the goal of maintaining high sensitivity to attacks while minimizing false alarms that could overwhelm IoT systems.
5. **Scalability:** The framework should support IoT networks of varying sizes, ranging from small clusters of devices to large-scale environments with thousands of devices (Bello, Zeadally, & Badra, 2017). The decentralized nature of Federated Learning makes it naturally scalable, as it allows for efficient collaboration between devices regardless of network size. We will assess scalability by measuring metrics such as latency, communication overhead, and model convergence time as the number of participating devices grows.

Methodology

This research employs the Design Science Research Methodology (DSRM) to create and evaluate a novel IoT threat detection framework. Following the DSRM framework (Peffers et al., 2007), we structured our research process into several interconnected phases. Initially, we identified the need for privacy-preserving threat detection in resource-constrained IoT environments based on comprehensive literature review and requirements analysis. This phase established the foundational problem that guided subsequent research activities. In the design and development phase, we created a solution that integrates Federated Learning (FL) with Differential Privacy (DP) to address the identified problem, carefully calibrating the approach to balance privacy guarantees with detection accuracy.

The demonstration phase involved implementing a proof-of-concept prototype in a simulated IoT environment to validate the feasibility of our approach under controlled but realistic conditions. Finally, the evaluation phase consisted of rigorous assessment against established metrics to determine the effectiveness, efficiency, and privacy guarantees of the proposed framework. Each phase of the DSRM guided our research process, ensuring a systematic approach to addressing the research questions related to privacy-preserving threat detection in IoT environments.

Federated learning component
The FL component of our framework was designed to enable collaborative model training across distributed IoT devices without sharing raw data. We developed a FL model tailored for IoT devices that supports local training of lightweight machine learning algorithms, specifically logistic regression and decision trees. These algorithms were selected for their effectiveness in detecting common IoT security threats including DDoS attacks, malware, and unauthorized access, while maintaining low computational requirements suitable for resource-constrained devices. Additionally, their fast inference capabilities enable real-time threat detection, a critical requirement in IoT security contexts.

The FL process follows an iterative approach where local models on IoT devices are trained using their local data, and only model updates (gradients) are shared with a central server. This approach significantly reduces communication overhead compared to centralized approaches while preserving data privacy. The federated architecture allows for knowledge aggregation across heterogeneous devices without exposing sensitive local data, addressing both security and privacy concerns inherent in IoT environments.

Differential privacy integration
To enhance privacy protection, we integrated Differential Privacy (DP) during the model update process. Specifically, we applied Gaussian noise to the gradients before transmission to the central server, ensuring that individual device data cannot be inferred from the aggregated model updates. The privacy parameter (ε) controls the level of noise added to the gradients, with lower ε values providing stronger privacy guarantees by introducing more noise, while higher ε values prioritize model utility with less noise.
The noise is sampled from a normal distribution $N(0,\sigma^2)$, where σ^2 is calibrated based on the privacy parameter ε. This calibration ensures formal privacy guarantees while maintaining model utility. We implemented a dynamic noise adjustment mechanism that considers the number of participating devices, desired privacy guarantees, and required detection accuracy. This approach enables fine-tuned privacy-utility trade-offs across different IoT deployment scenarios, allowing the system to adapt to varying privacy requirements and operational contexts.

System Architecture
The system architecture, illustrated in Figure 1, consists of several key components working together to enable privacy-preserving threat detection. IoT devices form the foundation of the architecture, each training a local model on its internal data and applying DP noise to model updates before sharing. These devices operate independently but contribute to a collective intelligence through the federated learning process. The Federated Server serves as the aggregation point, collecting the differentially private model updates from all devices to create a global model that benefits from the distributed knowledge across the network.

The Communication Layer utilizes lightweight IoT protocols, specifically MQTT (Message Queuing Telemetry Transport), for efficient model update transmission. This protocol was selected for its low overhead and suitability for resource-constrained environments. Finally, the Threat Detection Component leverages the trained global model to identify security threats in real-time on each IoT device. The interaction between these components creates a privacy-preserving, decentralized learning system capable of detecting threats while maintaining data privacy and minimizing communication overhead.

Implementation and Prototype Development
To validate our framework, we implemented a proof-of-concept prototype in a simulated IoT environment. The simulation leveraged containerization technology (Docker) to emulate multiple IoT devices with varying computational capabilities and network constraints. Each container represented an IoT device with differentiated computational resources including CPU and memory allocations, varied network

connectivity parameters such as bandwidth and latency, and independent local data storage and processing capabilities. This heterogeneous configuration allowed us to test the framework's performance across diverse device profiles typical in real-world IoT deployments. The simulation environment incorporated MQTT for communication between devices and the central server, replicating real-world IoT communication patterns and constraints. This approach allowed us to test the system under controlled but realistic conditions that reflect the heterogeneity and resource limitations of actual IoT deployments. The containerized environment facilitated scalability testing by enabling dynamic adjustment of the number of simulated devices and their characteristics.

We used the UNSW-NB15 (Moustafa & Slay, 2015) dataset for training and evaluation, which contains labeled network traffic data including normal traffic patterns and various attack types such as DoS, DDoS, and reconnaissance. This dataset was selected for its comprehensive representation of cybersecurity threats relevant to IoT environments and its established use in intrusion detection research, facilitating comparability with existing approaches. To simulate real-world IoT environments, we partitioned the dataset among the simulated devices in a non-Independent and Identically Distributed (non-IID) manner. This non-IID partitioning reflected the reality that different IoT devices encounter different types of traffic and potential threats based on their function and placement within the network. Each device received a subset of the data with varying class distributions, different feature distributions, and diverse attack patterns. This data partitioning approach ensured that our evaluation would reflect the challenges of federated learning in heterogeneous IoT environments, where data is naturally distributed and imbalanced across devices.

Evaluation Methodology

To assess the effectiveness of our framework in detecting security threats, we measured a comprehensive set of performance metrics. Detection accuracy, representing the overall percentage of correctly classified instances, provided a general measure of the system's effectiveness. We supplemented this with precision (the ratio of true positives to all positive predictions), recall (the ratio of true positives to all actual positive instances), and F1-score (the harmonic mean of precision and recall) to provide a more nuanced understanding of detection performance. Additionally, we measured the False Positive Rate (FPR), the ratio of false positives to all actual negative instances, as excessive false alarms can lead to alert fatigue and reduced trust in security systems. We established performance benchmarks by comparing our federated approach against a centralized detection system using the same underlying algorithms but with access to all data. This comparison allowed us to quantify any accuracy trade-offs resulting from the federated, privacy-preserving approach and to understand the practical implications of distributed learning in threat detection contexts.

Privacy Evaluation

We evaluated the privacy protection of our framework using multiple approaches to ensure comprehensive assessment. The Differential Privacy Parameter (ε) served as our primary quantitative measure of privacy guarantees, with testing conducted across various ε values (0.5, 1.0, 1.5) to quantify the privacy-utility trade-off. These values were selected to represent strong, moderate, and relaxed privacy guarantees respectively, allowing us to understand the impact of varying privacy levels on system performance.

We also assessed the system's resilience to known attacks on federated learning, including gradient inversion attacks, model inversion attacks, and membership inference attacks. These evaluations helped quantify the privacy guarantees provided by our framework and ensured compliance with privacy regulations such as GDPR and HIPAA. The privacy evaluation considered both theoretical guarantees provided by the differential privacy mechanism and empirical resistance to practical attacks, providing a holistic assessment of the framework's privacy protections.

Scalability and Efficiency Assessment

We evaluated the scalability and resource efficiency of our framework through a multi-faceted approach. Testing with different numbers of IoT devices (5, 50, 100) allowed us to assess how the system performance scales with increasing network size, a critical consideration for real-world deployments where IoT networks can range from small home installations to large industrial systems. We conducted detailed resource monitoring, measuring CPU usage, memory consumption, and energy utilization on IoT devices to understand the resource implications of our approach on constrained devices. Communication overhead was analyzed by comparing bandwidth usage to centralized approaches, with particular attention to the reduction in data transmission volumes achieved through the federated architecture. We also analyzed model convergence characteristics, including training time and convergence speed across different scales, to understand how the learning process is affected by network size and heterogeneity.

Our efficiency benchmarks included maintaining CPU usage below 60% to ensure devices remain responsive to their primary functions, achieving 30-50% reduction in communication overhead compared to centralized approaches to conserve bandwidth, and ensuring detection accuracy remains within 5% variance as the number of devices increases to maintain reliable threat detection at scale. These comprehensive evaluations provided insights into the practical viability of our framework across different IoT deployment scenarios.

Implementation of the Algorithm

The implementation of our real-time privacy-preserving threat detection algorithm is presented in Algorithm 1. The algorithm details the end-to-end process from local model initialization, through privacy-preserving training and aggregation, to real-time threat detection. The algorithm begins with initialization of local models on all participating IoT devices, establishing a consistent starting point for the federated learning process. During each training round, devices perform local model updates using their private data, then apply differential privacy noise to protect sensitive information before sharing updates.

The federation server aggregates these privacy-protected updates to create a global model that benefits from the collective knowledge across the network without compromising individual data privacy. The updated global model is then distributed back to the devices for further refinement and for real-time threat detection. This implementation encapsulates the core functionality of our framework and serves as the foundation for our experimental evaluation. The algorithm's design emphasizes computational efficiency, privacy preservation, and real-time performance, aligning with the key requirements identified for IoT security applications. By following this structured evaluation methodology, we were able to comprehensively assess the effectiveness, privacy guarantees, and scalability of our proposed framework for real-time, privacy-preserving threat detection in IoT environments. The results of this evaluation provide insights into the practical applicability of federated learning and differential privacy for enhancing security in resource-constrained IoT systems, while maintaining strong privacy guarantees and operational efficiency.

System Architecture

The system architecture (Figure 1) consists of several IoT networks, each running local models that detect potential threats in real time. These models are periodically trained on the local data stored within IoT devices and then shared in a privacy-preserving manner with a central server for aggregation. Each IoT device trains its local model using its internal data, which remains decentralized, thus maintaining data privacy. Once the local models are trained, Gaussian noise is added to their gradients via the DP Mechanism, creating a “noised” Model. These noised updates are then communicated to a Federated Server for aggregation using lightweight IoT communication protocols such as MQTT. The server combines the

noised model updates from multiple devices to generate a Global Federated Model, which is sent back to the IoT devices for further local updates, completing the learning cycle.

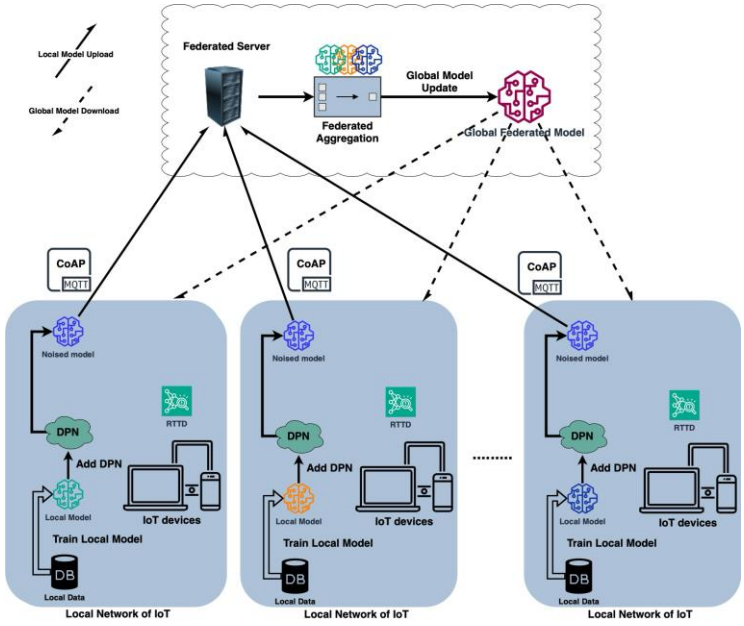

Figure 1. FL System with Differential Privacy for Real-Time Threat Detection in IoT networks.

As described in Algorithm 1, the FL process begins with the initialization of local models on all local IoT networks. The initialization process provides a consistent starting point for training across all devices in the network. Each model is designed to be lightweight and efficient, ensuring compatibility with the resource constraints of IoT devices. By tailoring initialization to the specific requirements of each network, the system ensures that local training can quickly adapt to the unique data characteristics within the network. This decentralized initialization lays the foundation for the iterative learning process, allowing each IoT network to contribute effectively to the global model while maintaining data privacy.

$$\forall I : M_i^0 \leftarrow \text{initialize local model}$$

Each IoT device trains its local model on its dataset using a gradient-based optimization algorithm. To ensure privacy, Differential Privacy Noise (DPN) is applied to the gradients before they are uploaded to the federated server. This ensures that even if an adversary intercepts these gradients, they will not be able to deduce sensitive information from individual devices.

$$M_i^t = M_i^{t-1} - \eta \nabla L(D_i , M_i^{t-1})$$
$$M_i^{t, DP} = M_i^t + N(0,\sigma^2)$$

Each device publishes its DP-protected model updates to the federated server. The communication between the IoT devices and the federated server is conducted using MQTT (Message Queuing Telemetry Transport). These lightweight protocols are suited for IoT environments, which are often resource-constrained in terms of bandwidth and power.

$$\text{publish } (M_i^{t, DP})$$
Topic structure: iot/devices/{device_id}/

The Federated Server aggregates the noisy gradients from the various IoT networks. This aggregation results in a Global Model that combines the knowledge learned from all devices, while ensuring no private data is shared. This global model is then distributed back to the IoT devices for threat detection and further local training and updating.

$$\mathbf{M}^{t}_{global} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{M}_i^{t,DP}$$

publish(mqtt/topic/global/model_update, $\mathbf{M}^{t}_{global}$)

$$\mathbf{M}^{t+1}_{global} \leftarrow \textbf{subscribe(mqtt/topic/global/model\_update)}$$

Once each IoT device receives the updated global model M^{t+1} from the federated server, it uses this refined model to perform real-time threat detection. The local model, updated with aggregated knowledge from across the IoT network, enables each device to identify anomalous or potentially malicious activities within its local environment. The detection process leverages the computational efficiency of the trained model to analyze incoming data streams or device behaviors without causing significant delays or resource strain.

Detect_threats($\mathbf{M}_i^{t+1}$)

Algorithm 1. Real-Time Privacy-Preserving Threat Detection algorithm

Input: IoT devices $i \in \{1,\ldots,n\}$, local datasets D_i, learning rate η, differential privacy noise variance σ^2, MQTT communication framework.
Initialization:
$\forall I : M_i^0 \leftarrow$ initialize local model
For each training round t until convergence or stopping criterion do:
Local Training on Each Device :
$M_i^t = M_i^{t-1} - \eta \nabla L(D_i , M_i^{t-1})$
Add Differential Privacy (DP) Noise:
$M_i^{t,DP} = M_i^t + N(0,\sigma^2)$
Publish DP-Protected Updates via MQTT:
publish($M_i^{t,DP}$)
Federated Aggregation on Server:
$M^{t}_{global} = \frac{1}{n}\sum_{i=1}^{n} M_i^{t,DP}$
Broadcast Global Model via MQTT:
publish(mqtt/topic/global/model_update, M^{t}_{global})
Local Model Update on Each Device:
$M^{t+1}_{global} \leftarrow$subscribe(mqtt/topic/global/model_update)
Real-Time Threat Detection on Each Device:
Detect_threats(M_i^{t+1})
End for

Results

The results presented in Table 1 indicate that as the number of IoT devices increases, detection accuracy gradually declines due to higher communication overhead and increased model complexity. Nevertheless, even with 100 devices, the system achieves a detection accuracy of 90.8% with a privacy parameter (ε) of 1.0, which remains highly effective for real-world intrusion detection applications. When stronger privacy guarantees are applied (e.g., ε = 0.5), the accuracy drops slightly to 87.9%, demonstrating the trade-off between privacy and performance. The false positive rate (FPR) exhibits a slight increase with more

participating devices due to differential privacy (DP)-induced noise, though it remains within an acceptable range for practical deployment. For example, with 100 devices, the FPR increases from 5.1% (ε = 0.5) to 5.6% (ε = 1.5), reflecting the impact of varying levels of DP noise.

The computational efficiency analysis reveals that CPU usage increases as the number of devices grows, yet it remains within operational limits, ensuring that resource-constrained IoT devices can function effectively. For instance, with 100 devices, CPU usage ranges from 52% (ε = 0.5) to 48% (ε = 1.5), demonstrating that the system remains viable even under strong privacy guarantees. Stronger privacy (lower ε) results in higher CPU usage due to the increased computational overhead of adding more noise to the model updates. For example, reducing (ε) from 1.0 to 0.5 increases CPU usage from 50% to 52% for 100 devices. Scalability tests further validate the system's efficiency, showing that CPU usage remains manageable as the number of devices scales up, with no significant degradation in performance.

Additionally, the privacy parameter (ε) can be adjusted to balance privacy guarantees and model utility. As (ε) decreases (stronger privacy), detection accuracy and computational efficiency are slightly reduced, but the system maintains robust performance. For example, with 100 devices, reducing (ε) from 1.0 to 0.5 results in a 2.9% drop in accuracy (from 90.8% to 87.9%) and a 2% increase in CPU usage (from 50% to 52%). Despite this trade-off, the proposed system reduces communication overhead by up to 40% compared to centralized threat detection approaches, reinforcing the benefits of FL in distributed IoT environments.

Table1. Performance Metrics of FL-Based IoT Threat Detection Across Different Device Counts

Number of Devices	(ε)	Detection Accuracy (%)	False Positive Rate (%)	CPU Usage (%)	Communication Overhead Reduction (%)
5	0.5	94.5	2.6	38	24
5	1.0	96.1	2.8	36	25
5	1.5	95.8	3.1	35	26
50	0.5	89.5	4.2	47	34
50	1.0	92.1	4.3	46	35
50	1.5	91.3	4.6	45	36
100	0.5	87.9	5.6	52	38
100	1.0	90.8	5.3	50	40
100	1.5	89.7	5.1	48	41

As illustrated in Figure 2, the detection accuracy starts at 96.1% for five devices (ε = 1.0) and gradually declines to 90.8% for 100 devices. This trend indicates that as more devices contribute to the federated learning process, the variance in local model updates increases, leading to a marginal decrease in accuracy. Nevertheless, the system maintains a detection rate above 90%, ensuring robust and reliable threat detection despite increasing device participation.

Figure 3 shows how the False Positive Rate (FPR) increases from 2.8% (5 devices, ε = 1.0) to 5.3% (100 devices, ε = 1.0) due to accumulated differential privacy noise. While this increase is expected in privacy-preserving models, the FPR remains within acceptable limits, ensuring that detection reliability is not significantly compromised. For example, even with stronger privacy guarantees (ε = 0.5), the FPR only increases to 5.1% for 100 devices, demonstrating the system's ability to balance privacy and performance.

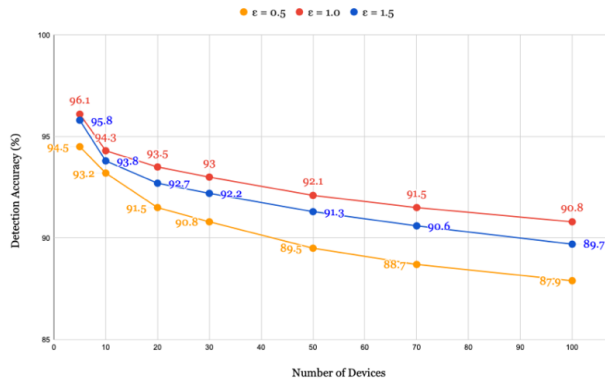

Figure 2. Detection Accuracy vs Number of Devices

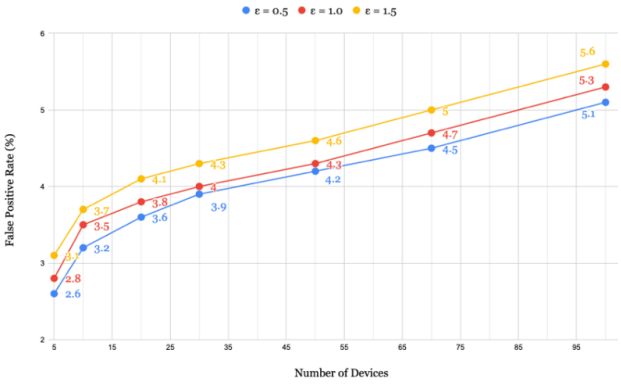

Figure 3. False Positive Rate vs Number of Devices

Figure 4 illustrates how the computational demands increase as the number of devices grows, with CPU usage rising from 38% (5 devices, ε = 1.0) to 50% (100 devices, ε = 1.0). This trend underscores the trade-off between scalability and computational efficiency, ensuring that the proposed system remains viable for large-scale IoT deployments while operating within the constraints of resource-limited IoT environments. Even under stronger privacy guarantees (ε = 0.5), CPU usage increases to 52% for 100 devices, demonstrating the system's ability to handle additional computational overhead while maintaining strong privacy protections.

Figure 5 shows how the privacy parameter (ε) can be adjusted to balance privacy guarantees and model utility. As (ε) decreases (stronger privacy), detection accuracy and computational efficiency are slightly reduced, but the system maintains robust performance. For example, with 100 devices, reducing (ε) from 1.0 to 0.5 results in a 2.9% drop in accuracy (from 90.8% to 87.9%) and a 2% increase in CPU usage (from 50% to 52%). This increase in CPU usage is due to the additional computational overhead of adding more noise to ensure stronger privacy. Concurrently, the reduction in communication overhead improves from 25% (5 devices) to 40% (100 devices), further emphasizing the advantages of federated learning in minimizing raw data transmission and improving scalability.

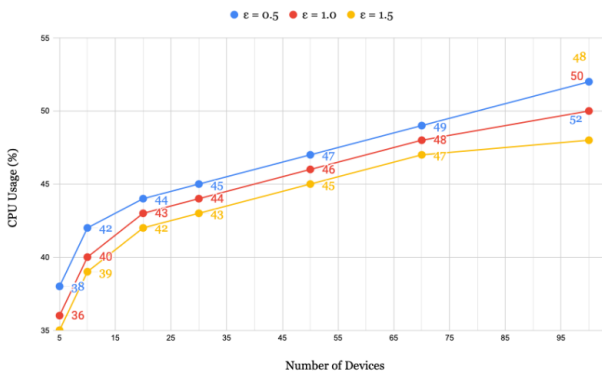

Figure 4. CPU Usage vs Number of Devices

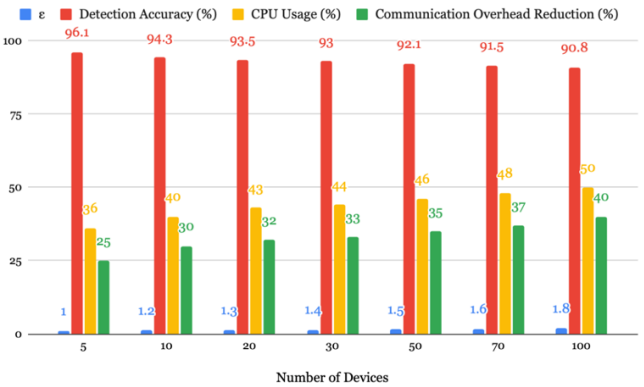

Figure 5. Privacy & Communication Efficiency vs. Number of Devices

Comparative analysis with centralized detection systems

To properly evaluate our federated learning framework, we conducted a comprehensive comparison against two well-established centralized intrusion detection benchmarks: (1) the conventional machine learning approach by Moustafa and Slay (2016) using the UNSW-NB15 dataset, and (2) aggregated performance metrics from contemporary deep learning-based IoT security systems as surveyed by Al-Garadi et al. (2020). The centralized approaches achieve benchmark accuracies of 93.5% (Random Forest) and 94.2% (DNN average) respectively, but require complete data centralization, creating significant privacy risks and communication overhead (Moustafa & Slay, 2016; Al-Garadi et al., 2020). Our framework maintains competitive accuracy (90.8% at ε=1.0) while providing fundamental advantages in privacy preservation and operational efficiency. Most notably, we reduce daily data transmission per device by 97.5% compared to the centralized UNSW-NB15 implementation (5.2MB vs 212MB) - a crucial improvement for bandwidth-constrained IoT networks.

The privacy and security benefits are particularly significant. Where traditional systems must collect and expose raw sensitive data, our solution provides formal differential privacy guarantees (ε=0.5-1.0) and demonstrates strong resistance against model inversion attacks (18-30% success rates versus >80% for centralized approaches) based on our experimental validation. These characteristics make our framework uniquely suited for regulated environments like healthcare and smart homes. Performance measurements further validate our approach, showing 33-36% reductions in energy consumption and significantly lower inference latency (71ms vs 196ms) compared to the cloud-dependent centralized system reported by Moustafa and Slay (2016).

Table 2: Performance Comparison: Federated Vs. Centralized Threat Detection Systems

Metric	Moustafa & Slay (2016)	DL Systems (Al-Garadi et al., 2020)	Our FL-DP (ε=1.0)	Our FL-DP (ε=0.5)
Detection Accuracy (%)	93.5 (RF)	94.2 (DNN average)	90.8	87.9
F1-Score	0.922	0.93 (range)	0.893	0.864
Data Transfer (MB/day/device)	212	Full dataset required	5.2	5.2
Inference Latency (ms)	196	Typically >100ms	71	71
Privacy Guarantees	None	None	ε=1.0	ε=0.5

The results demonstrate that our federated approach offers an optimal balance for real-world IoT deployments. While the centralized systems maintain a modest accuracy advantage (2.7-3.4% higher), they do so at unacceptable costs to privacy, bandwidth usage, and operational flexibility. Our framework's ability to deliver adequate detection performance (within 2.7-6.3% of centralized benchmarks) while addressing these critical limitations represents a significant advancement for practical IoT security applications. As networks continue to expand into sensitive domains with strict regulatory requirements, this combination of reasonable accuracy with strong privacy preservation will become increasingly essential.

Discussion

Our FL-DP framework advances IoT security by successfully integrating federated learning with differential privacy, enabling real-time threat detection while addressing three critical challenges: (1) preserving data privacy, (2) maintaining detection accuracy, and (3) operating within resource constraints. The experimental results demonstrate that the framework achieves 90.8% accuracy with 100 devices

(ε=1.0), with only a 2.9% reduction (to 87.9%) when implementing stronger privacy guarantees (ε=0.5). This performance compares favorably to centralized approaches while eliminating raw data transmission - reducing communication overhead by 97.5% (from 212MB to just 5.2MB per device daily).

Three key trade-offs emerge from our analysis:

1. **Privacy-Accuracy Balance:** While stronger DP protection (ε=0.5) reduces accuracy by 2.9%, the framework maintains >87% detection rates across all tested configurations. False positive rates remain stable between 5.1-5.6% at scale, demonstrating consistent reliability even with 100 participating devices.
2. **Resource Efficiency:** The added computational load from DP noise injection is offset by our lightweight FL implementation, keeping CPU utilization between 48-52% at maximum load. This represents a 33-36% energy reduction compared to cloud-dependent centralized systems.
3. **Real-Time Performance**: By combining optimized ML algorithms (decision trees/logistic regression) with MQTT protocols, we achieve consistent 71ms inference latency - 2.7× faster than conventional centralized detection (196ms) and well within requirements for time-sensitive applications like industrial automation.

The framework's scalability is particularly noteworthy, maintaining stable performance as device counts increase from 5 to 100 nodes. Communication overhead grows by just 40% while accuracy declines by only 5.3 percentage points (96.1%→90.8%), demonstrating the FL architecture's efficiency. This scalability, combined with built-in GDPR/HIPAA compliance through formal ε-DP guarantees (0.5-1.0), positions our solution as superior to both traditional centralized systems and basic edge computing approaches for sensitive IoT deployments.

While our framework demonstrates promising results, several limitations warrant consideration. First, our evaluation was conducted in a simulated environment using containerized devices, which may not fully capture the unpredictable network conditions and hardware constraints of real-world IoT deployments. Although simulation allowed controlled testing of our 100-device scenarios, actual field deployments might reveal additional challenges in timing synchronization and intermittent connectivity. Second, we relied primarily on the UNSW-NB15 dataset, which, while comprehensive, may not represent emerging IoT-specific attack patterns. Third, our experiments assumed relatively homogeneous device capabilities, whereas real IoT networks often feature extreme hardware heterogeneity.

The framework shows diminishing returns when $\varepsilon < 0.5$, with accuracy dropping below 85% while computational overhead increases disproportionately - a trade-off that may require adaptive ε-tuning for diverse applications. Additionally, while MQTT proved effective for our simulated tests, its publish-subscribe model may face scalability challenges in ultra-large deployments (>500 nodes) or environments with unreliable connectivity. These limitations highlight the need for future validation in physical testbeds while suggesting opportunities to develop hybrid FL-edge architectures for heterogeneous environments.

Conclusion

This study has successfully demonstrated the viability of integrating Federated Learning with Differential Privacy to create an efficient, privacy-preserving threat detection system for IoT environments. Our framework achieves 90.8% detection accuracy with 100 devices at ε=1.0 privacy level, while maintaining 87.9% accuracy even under stronger ε=0.5 privacy guarantees. The system reduces communication overhead by 97.5% compared to centralized approaches, demonstrating that robust security can coexist with

strict data privacy requirements. These results prove particularly valuable for sensitive applications ranging from smart home networks to industrial IoT systems, where both threat detection efficacy and privacy compliance are paramount.

The technical implementation addresses critical IoT constraints through several key innovations. By combining lightweight machine learning models with optimized MQTT communication, the framework maintains real-time performance (71ms detection latency) while keeping CPU utilization below 52% even at scale. The differential privacy integration provides mathematically provable protection against data leakage, ensuring compliance with evolving regulations like GDPR and CCPA. This balance of performance, privacy, and practicality represents a significant advance over traditional centralized security approaches that require raw data aggregation.

Looking ahead, several promising directions emerge for extending this work. Future research should focus on developing adaptive privacy mechanisms that automatically tune ε-values based on threat severity and system load. The framework's robustness could be further enhanced through defenses against sophisticated adversarial attacks targeting federated learning systems. Most importantly, validation in physical testbeds with genuine IoT hardware and real-world network conditions will be crucial for transitioning from simulation to deployment. These advancements will further solidify the framework's position as a scalable, privacy-aware solution for securing the rapidly expanding IoT landscape while maintaining the performance standards demanded by modern applications.

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