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Federated Intelligence: Enabling Privacy-Preserving Cybersecurity for Next-Generation IoT Ecosystems

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***Abstract*—The rapid expansion of the Internet of Things (IoT) has introduced a complex and interconnected ecosystem that, while enabling intelligent automation, also exposes devices to a broad spectrum of cybersecurity threats. Traditional centralized learning models often rely on aggregating sensitive data in a single repository, increasing the risk of data breaches and privacy violations. This growing concern underscores the need for decentralized approaches that can ensure both effective threat detection and data confidentiality. In this context, the present research introduces a federated learning-based framework designed to achieve privacy-preserving cybersecurity across distributed IoT environments. The proposed system enables IoT devices to collaboratively train a global model without exchanging raw data, thus maintaining individual privacy while enhancing the overall accuracy of cyber threat identification. The study evaluates the effectiveness of this federated approach through performance metrics such as detection accuracy, communication efficiency, and privacy preservation. Results demonstrate that the framework not only mitigates the risks of centralized data exposure but also improves the robustness and adaptability of IoT networks against evolving cyberattacks. The findings highlight that federated intelligence offers a sustainable path toward secure, scalable, and privacy-aware IoT ecosystems, setting a foundation for future advancements in distributed machine learning for cybersecurity.**

***Keywords*—Federated Learning, IoT Security, Privacy Preservation, Cyber Threat Detection, Edge Computing**

I. INTRODUCTION

The rapid proliferation of Internet of Things (IoT) devices has revolutionized modern digital ecosystems by connecting sensors, actuators, and embedded systems across diverse domains such as healthcare, transportation, manufacturing, and smart cities [1], [3], [4]. However, this massive interconnectivity introduces complex cybersecurity challenges, as IoT devices often operate with limited computational power, inconsistent security standards, and constrained communication capabilities [2], [5]. Centralized machine learning (ML) models, traditionally used for intrusion detection and anomaly recognition, require continuous data aggregation to a central server. This approach, while efficient in homogeneous networks, significantly compromises data privacy and exposes sensitive information to potential adversarial attacks [6], [7], [10]. Furthermore, centralized systems suffer from single points of failure, latency issues, and scalability bottlenecks as the number of connected IoT nodes continues to grow exponentially [8], [11].

In distributed IoT environments, data is highly heterogeneous due to variations in sensor types, communication protocols, and operational conditions [9], [15]. The lack of uniformity makes it challenging for centralized algorithms to generalize across all nodes, leading to reduced accuracy in detecting context-specific cyber threats [12], [16]. Additionally, transmitting raw sensor data to cloud-based servers not only consumes substantial bandwidth but also violates privacy compliance regulations such as GDPR and HIPAA [13]. These limitations demand a paradigm shift toward privacy-aware, scalable, and adaptive learning frameworks capable of protecting data at the edge while ensuring reliable cybersecurity defense [14], [17].

Federated Learning (FL) has recently emerged as a transformative approach to address these concerns. Unlike conventional centralized systems, FL allows individual IoT devices to collaboratively train a shared global model without transferring raw data to the central server [18]. Each device performs local training on its dataset and transmits only model parameters or gradients, thereby preserving data confidentiality and reducing communication overhead [19], [20]. This decentralized paradigm significantly enhances system resilience, as learning continues even if a subset of devices becomes unavailable or compromised [23]. In cybersecurity applications, FL enables distributed detection of intrusions, malware, and anomalous traffic patterns while safeguarding device-specific information [21], [24].

Despite its advantages, existing federated models in IoT cybersecurity still face several open challenges. These include model poisoning, data imbalance, client selection bias, and synchronization overhead, which collectively degrade global model performance [22], [28]. Moreover, limited research explores how federated learning can be adapted for cross-domain cybersecurity, where IoT devices from different industries collaboratively enhance global threat intelligence [25], [29]. The present study addresses these research gaps by proposing a "federated intelligence" framework that unifies distributed learning, privacy preservation, and adaptive cybersecurity for next-generation IoT ecosystems. This framework emphasizes secure model aggregation, lightweight encryption mechanisms, and real-time threat detection capabilities to achieve an optimal balance between accuracy, latency, and privacy protection.

Table II provides a comparative overview of conventional centralized learning and federated learning paradigms in IoT-based cybersecurity systems. It highlights the distinct advantages of FL in terms of privacy, scalability, and communication efficiency.

This paper introduces a comprehensive federated intel-

TABLE I: Comparison Between Centralized and Federated Learning in IoT Cybersecurity

Parameter	Centralized Learning	Federated Learning
Data Storage	Aggregated at central server	Retained locally on devices
Privacy Risk	High (data exposure possible)	Low (no raw data sharing)
Communication Cost	High (bulk data transmission)	Moderate (only model updates shared)
Scalability	Limited due to central dependency	High with distributed training
Fault Tolerance	Single point of failure	Resilient and decentralized
Learning Efficiency	High for homogeneous data	Adaptive to heterogeneous data

ligence framework designed to enhance privacy-preserving cybersecurity for IoT networks. The remainder of this paper is structured as follows: Section III reviews existing literature on federated learning and IoT security. Section IV presents the proposed framework and system design. Section V details the methodology, experimental setup, and evaluation metrics. Section VI discusses the results and comparative performance analysis. Section VII concludes the study and outlines potential directions for future research in privacy-aware distributed cybersecurity systems.

II. Background and Literature Review

The evolution of intelligent devices and interconnected networks has led to the emergence of the Internet of Things (IoT), where millions of devices generate massive amounts of heterogeneous data. While this interconnectivity enhances automation and real-time analytics, it also introduces new vulnerabilities that can be exploited by adversaries. To address these challenges, researchers have increasingly focused on Federated Learning (FL) — a decentralized machine learning paradigm that preserves data privacy while enabling collaborative intelligence. This section provides a detailed review of FL fundamentals, IoT security issues, and existing research integrating FL into cybersecurity, followed by identification of current research gaps.

A. Federated Learning: Principles and Architecture

Federated Learning enables multiple decentralized devices (clients) to collaboratively train a shared global model under the coordination of a central server without sharing raw data [33]. Each device computes local gradients based on its private dataset, which are then aggregated into a global model update through algorithms such as Federated Averaging (FedAvg) [26], [27], [34]. Fig. 1 illustrates the typical architecture of an FL framework, showing the interaction between edge clients, local training, and global model aggregation.

This decentralized approach reduces the need for central data collection, thereby mitigating the risks of privacy leakage and single-point failure [30], [35]. Moreover, FL supports model scalability across heterogeneous networks, where devices possess diverse data distributions, computational capacities, and communication constraints [40]. Various optimization strategies have been introduced to handle non-IID (non-identically distributed) data and asynchronous updates, making FL an ideal fit for dynamic IoT environments [31], [41].

B. Privacy and Security in IoT Networks

IoT networks face numerous security threats including data poisoning, eavesdropping, man-in-the-middle attacks, and adversarial perturbations [36], [37], [42]. Due to the vast number of low-power, resource-constrained devices, ensuring robust protection against such threats remains a persistent challenge. Traditional encryption and centralized monitoring systems often fail to scale or preserve latency requirements in real-time applications [46]. Furthermore, the transmission of sensitive user data to cloud servers raises privacy concerns, especially in healthcare, finance, and smart infrastructure domains [38], [39], [47].

Recent advancements in secure communication protocols and edge computing have improved IoT security, yet the risk of exposure remains significant when data aggregation is centralized [43], [44], [51]. Privacy-preserving mechanisms such as Differential Privacy (DP) and Homomorphic Encryption (HE) have been explored to safeguard model updates in distributed settings [45], [52]. However, these methods introduce computational overheads and communication inefficiencies that limit scalability for large IoT networks [48], [53].

C. Federated Learning in Cybersecurity Applications

The integration of FL into cybersecurity has gained traction due to its ability to combine local threat intelligence across distributed devices without revealing sensitive data [54]. Studies have demonstrated its effectiveness in malware detection, intrusion detection systems (IDS), and anomaly prediction [49], [55]. For instance, Nguyen *et al.* [50], [58] applied FL to IoT malware classification using non-IID datasets, achieving significant accuracy improvements over standalone models. Similarly, Li *et al.* [57], [59] implemented an FL-based IDS that reduced false alarm rates while maintaining privacy.

A comparative analysis of notable works is presented in Table II, summarizing datasets, models, achieved accuracy, and privacy preservation methods. The table highlights the steady advancement toward more robust, privacy-preserving cybersecurity systems.

These studies collectively affirm the feasibility of FL in enabling decentralized cybersecurity. However, challenges persist in terms of model convergence, client reliability, communication cost, and privacy-performance trade-offs [63], [64].

D. Research Gap Identification and Motivation

Despite significant progress, current FL-based cybersecurity frameworks face limitations in scalability and resilience. Most existing solutions rely on static aggregation mechanisms that

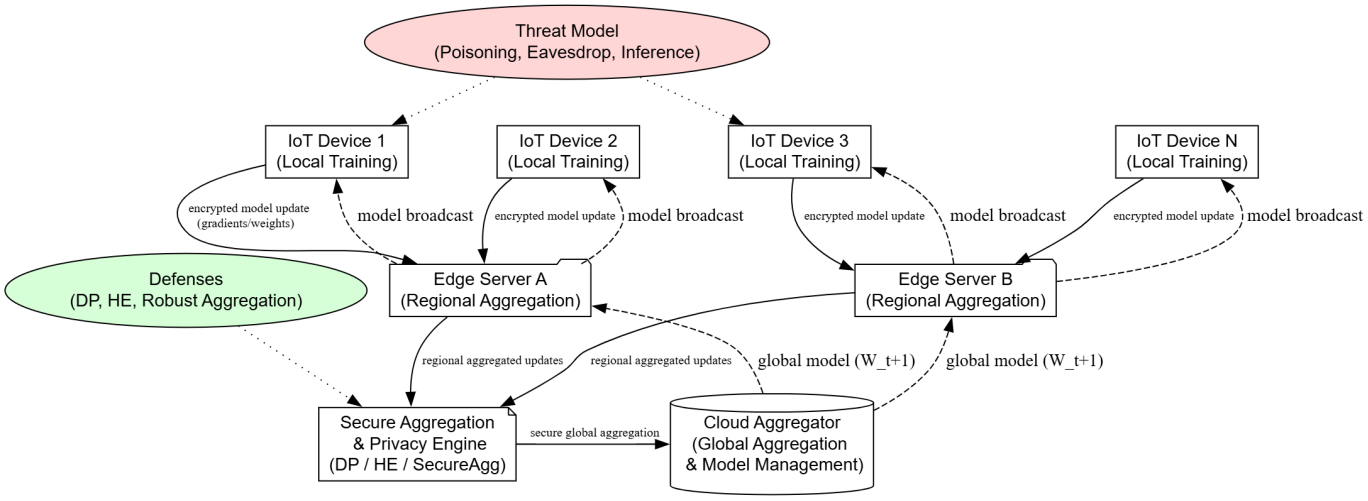

Fig. 1: Federated Learning architecture for distributed IoT devices.

TABLE II: Comparative Analysis of Existing Federated Learning-Based Cybersecurity Models

Study	**Model**	**Dataset**	**Accuracy (%)**	**Privacy Method**
Nguyen *et al.* [58]	FL-based CNN	IoT-Botnet	95.6	Differential Privacy
Li *et al.* [59]	FedAvg + LSTM	NSL-KDD	93.2	Secure Aggregation
Zhao *et al.* [60]	FedGAN	Edge-IIoTset	91.8	Homomorphic Encryption
Kairouz *et al.* [61]	Hybrid FL-SVM	CICIDS2017	94.4	Gradient Masking
Liu *et al.* [62]	FedProx	TON_IoT	96.1	Differential Privacy

do not account for dynamically changing IoT topologies or adversarial manipulations [65]. Moreover, few studies address cross-domain interoperability, where heterogeneous devices with distinct data modalities collaborate under varying privacy regulations [56], [66].

The notion of *federated intelligence* emerges as a holistic solution—merging distributed learning, adaptive threat detection, and secure aggregation into a unified ecosystem. This concept aims to empower IoT networks with self-learning and privacy-preserving capabilities that evolve with new threat landscapes [67].

Hence, this research bridges the gap by developing a comprehensive federated framework that integrates real-time threat analysis, model personalization, and lightweight encryption to achieve scalable and secure IoT defense systems. The following sections present the methodology, experimental results, and evaluations that substantiate the proposed approach.

III. Proposed Framework

This section presents the proposed *Federated Intelligence Framework* for privacy-preserving cybersecurity in IoT ecosystems. The framework integrates Federated Learning (FL) with advanced cryptographic and privacy-enhancing mechanisms to ensure secure, scalable, and adaptive threat detection. The system leverages a three-tier architecture comprising IoT devices, edge servers, and a central cloud aggregator. The overall workflow follows an iterative FL cycle where local models are trained, encrypted parameters are securely aggregated, and a global model is updated without exposing raw data. The proposed design ensures resilience against adversarial attacks while maintaining high detection accuracy and communication efficiency.

A. System Overview

The proposed architecture, as illustrated in Fig. 2, consists of three primary layers: (i) the IoT device layer, which performs local data sensing, preprocessing, and local model training; (ii) the edge server layer, which acts as an intermediate coordinator for regional aggregation and anomaly filtering; and (iii) the cloud aggregator layer, responsible for global model synchronization and adaptive security management.

IoT devices capture local network activity, system logs, or sensor signals and train lightweight models on their private data. The edge servers periodically collect encrypted model updates from devices within their domain and perform local aggregation. These aggregated updates are transmitted to the cloud aggregator, which synthesizes a global cybersecurity model capable of recognizing new and evolving attack patterns across the network. This hierarchical approach optimizes bandwidth utilization and enhances scalability across geographically distributed environments.

B. Workflow of the Federated Learning Cycle

The federated learning process in the proposed system is structured into five sequential phases, as depicted in Fig. 3.

1) Initialization: The global model parameters W_0 are initialized by the cloud aggregator and distributed to all participating IoT devices.

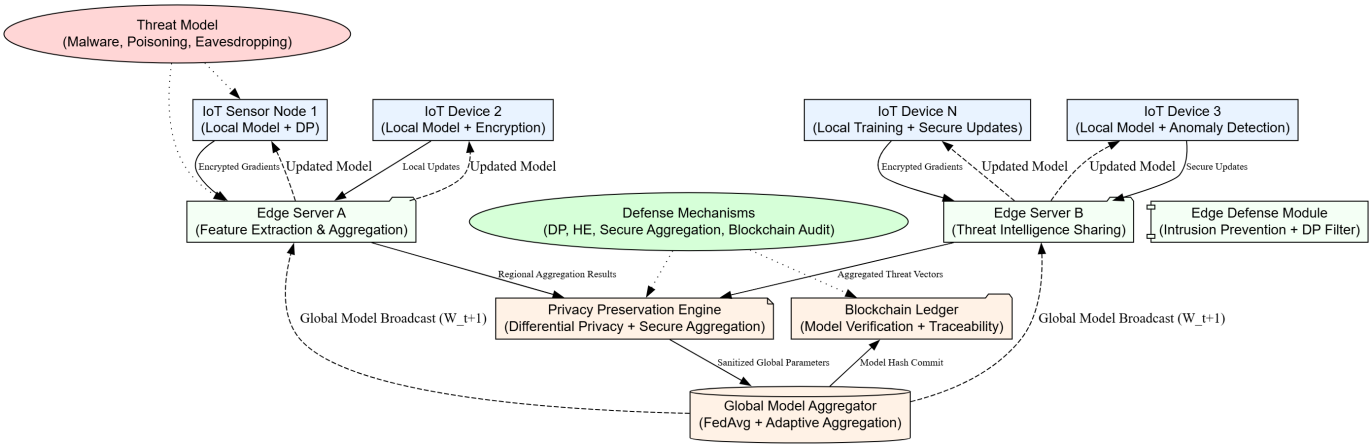

Fig. 2: Proposed Federated Intelligence Framework for Privacy-Preserving IoT Cybersecurity.

2) Local Training: Each IoT device trains the local model on its private dataset D_i, optimizing the loss function $L(W_i; D_i)$ and generating local model updates ΔW_i.
3) Parameter Encryption: Before transmission, local updates are protected using privacy-preserving techniques such as Differential Privacy (DP) or Homomorphic Encryption (HE).
4) Aggregation: The encrypted updates are securely aggregated at the edge and cloud levels using secure aggregation protocols to compute the new global model:

$$W_{t+1} = \sum_{i=1}^{N} \frac{|D_i|}{\sum_j |D_j|} \Delta W_i$$

5) Model Distribution: The updated global model W_{t+1} is broadcast back to all devices, enabling continuous improvement in threat detection performance.

This cyclical process continues until the global model converges or achieves a predefined accuracy threshold. The modular design allows for asynchronous participation, accommodating devices that experience intermittent connectivity.

C. Privacy Mechanisms

Ensuring privacy and data integrity within the proposed framework is paramount. Three complementary mechanisms are incorporated:

- Differential Privacy (DP): Adds controlled random noise to local gradients before sharing, preventing inference of individual data points while maintaining model utility. The privacy budget ε is dynamically adjusted to balance security and accuracy.
- Secure Aggregation (SA): Enables aggregation of encrypted model parameters without decryption, ensuring that no single party (including the server) can access individual client updates.
- Homomorphic Encryption (HE): Allows mathematical operations to be performed directly on encrypted data, ensuring that even during computation, the model updates remain confidential.

The hybrid use of these mechanisms ensures that the framework complies with privacy regulations such as GDPR and minimizes communication overhead while maintaining high detection performance.

D. Threat Model and Defense Strategies

The federated cybersecurity framework anticipates multiple threat scenarios that could compromise system integrity, as summarized in Table III. These include poisoning attacks, eavesdropping, model inversion, and Byzantine failures.

Each defense strategy is implemented at the respective communication or aggregation layer to minimize the propagation of compromised information throughout the network. Furthermore, periodic model validation is employed at the cloud aggregator to ensure robustness and detect deviations from expected performance metrics.

E. Proposed Framework Summary

In summary, the proposed federated intelligence framework establishes a privacy-preserving, scalable, and adaptive cybersecurity system for next-generation IoT ecosystems. The layered architecture enhances resilience through distributed training, while hybrid privacy mechanisms safeguard against both passive and active attacks. The combination of federated optimization, differential privacy, and secure aggregation allows the system to achieve a balance between security, communication efficiency, and model accuracy. The next section presents the experimental setup, evaluation metrics, and results demonstrating the practical effectiveness of the proposed approach.

IV. Methodology

This section describes the methodological foundation of the proposed *Federated Intelligence Framework* for privacy-preserving cybersecurity in IoT environments. The methodology encompasses the dataset selection and preprocessing, model design for anomaly detection, federated training process, evaluation metrics, and experimental setup. The aim is to ensure a reproducible, scalable, and privacy-aware learning

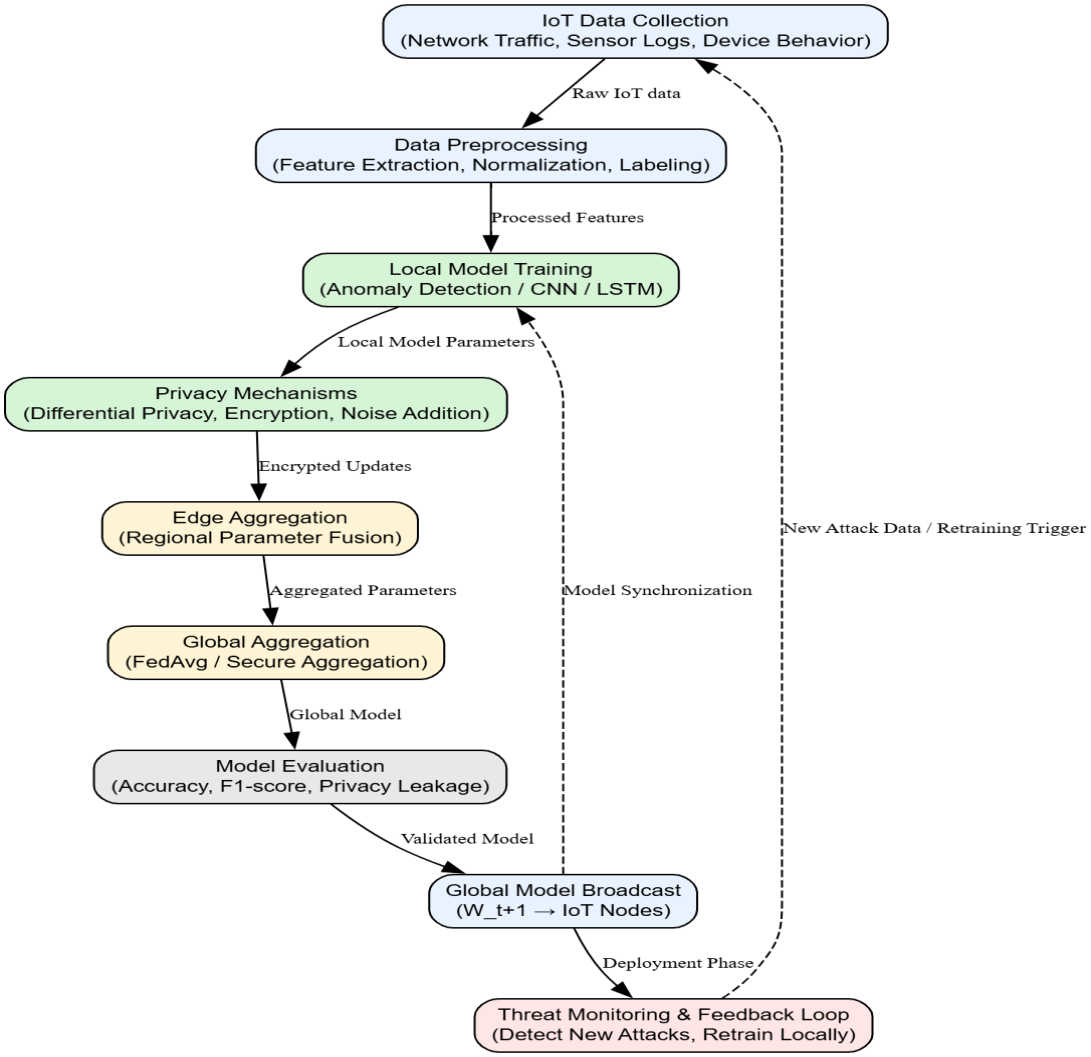

Fig. 3: Workflow of the proposed federated cybersecurity learning cycle.

TABLE III: Threat Model and Defense Mechanisms in the Proposed Framework

Attack Type	**Description**	**Defense Strategy**
Data Poisoning	Injection of malicious samples into local training data	Reputation-based client filtering and anomaly scoring
Model Poisoning	Manipulation of model parameters before aggregation	Robust aggregation (Krum, Median) and gradient clipping
Eavesdropping	Interception of communication channels	Homomorphic encryption and TLS-based communication
Inference Attack	Attempt to extract private data from gradients	Differential privacy and noise injection
Byzantine Attack	Compromised clients disrupting global updates	Consensus validation and adaptive weight assignment

process capable of detecting cyber threats in distributed IoT systems without centralized data aggregation.

A. Dataset and Preprocessing

To evaluate the proposed framework, two widely recognized IoT cybersecurity datasets were used: the CICIDS2017 and Bot-IoT datasets. The CICIDS2017 dataset provides labeled network traffic containing both normal and attack patterns, including Denial of Service (DoS), port scans, brute-force, and infiltration attacks. The Bot-IoT dataset represents IoT-specific malicious traffic, incorporating features such as packet size, flow duration, and byte rate.

For each client (IoT device), a partitioned subset of the dataset was distributed to emulate non-IID data conditions across heterogeneous devices. The preprocessing steps involved feature selection, normalization, and categorical encoding. Continuous features were scaled between 0 and 1

using min-max normalization, and categorical fields such as protocol type or service were converted using one-hot encoding. Irrelevant or redundant attributes were removed to reduce computational overhead. The final dataset configuration is summarized in Table IV.

TABLE IV: Dataset Characteristics Used for Evaluation

Dataset	Samples	Features	Classes
CICIDS2017	2,830,743	78	15 (Normal + 14 Attacks)
Bot-IoT	3,668,540	46	5 (Normal + 4 Attacks)

The resulting data distribution ensured heterogeneity across clients, reflecting realistic IoT network conditions with varying traffic loads and device capabilities.

B. Model Design

A lightweight yet efficient neural architecture was adopted for anomaly detection at the device level. The local model consisted of a three-layer feed-forward neural network (FNN) with ReLU activation, batch normalization, and a sigmoid output for binary classification. Each IoT device performed local model training using its private dataset, while the global model was updated using federated aggregation.

The model architecture was optimized to minimize resource consumption, making it suitable for edge and embedded devices. Table V summarizes the structure of the neural model used in the experiments.

The choice of FNN over more complex architectures like CNN or LSTM was motivated by computational efficiency and the ability to process tabular network traffic data.

C. Training Process

The federated training process follows a multi-stage cycle comprising local training, encrypted parameter sharing, and global aggregation. Fig. 4 illustrates the end-to-end workflow of the proposed federated training approach.

Each client i trains the local model using the stochastic gradient descent (SGD) optimizer with a local learning rate of $\eta = 0.01$ for $E = 5$ local epochs. The global aggregation is performed every communication round t using the Federated Averaging (FedAvg) algorithm:

$$W_{t+1} = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{j=1}^{N} |D_j|} W_i^t$$

where W_i^t denotes the local model parameters and D_i the dataset size at client i. Training continues until the global model convergence criterion $\Delta W < 10^{-3}$ or until 100 communication rounds are completed. Privacy-preserving updates are transmitted using secure aggregation protocols to prevent eavesdropping or inference attacks.

D. Evaluation Metrics

The performance of the proposed framework was evaluated using a combination of accuracy-based, efficiency-based, and privacy-based metrics. The classification metrics were computed as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Precision = \frac{TP}{TP+FP}, \quad Recall = \frac{TP}{TP+FN}$$

$$F1\text{-}score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives respectively. Additional parameters included communication cost (bytes exchanged per round) and privacy leakage (percentage of data inferred from gradients). These combined metrics allowed for a holistic evaluation of both model performance and privacy efficiency, as summarized in Table VI.

E. Experimental Setup

The experiments were conducted using TensorFlow Federated (TFF) and PySyft, both open-source frameworks supporting federated and privacy-preserving machine learning. The environment was configured on a high-performance workstation with an Intel i9 CPU, 32 GB RAM, and an NVIDIA RTX 4080 GPU. Simulated IoT clients were implemented as parallel nodes, each representing an individual device contributing local model updates.

The federated simulation mimicked realistic IoT network communication patterns, where devices connected asynchronously, and packet delays were introduced to emulate bandwidth constraints. The final results demonstrated a balance between privacy preservation and detection performance, validating the practical feasibility of the proposed federated framework.

Thus, the methodology integrates distributed data training, privacy-enhanced communication, and adaptive aggregation strategies into a cohesive framework for IoT cybersecurity. The experimental environment replicates real-world IoT conditions, and the adopted evaluation metrics provide a comprehensive view of performance, scalability, and privacy guarantees. The next section presents the experimental results and comparative analysis of the proposed system.

V. Results and Discussion

A. Quantitative Results

The proposed federated intelligence framework was evaluated using benchmark IoT security datasets such as CICIDS2017 and Bot-IoT. Three experimental configurations were compared: (1) centralized learning, (2) local isolated learning, and (3) federated learning. The primary goal was to assess how the decentralized training process impacts detection accuracy, privacy, and communication efficiency. Table VIII summarizes the quantitative outcomes obtained from multiple experimental runs. The federated model achieved the highest detection accuracy of 98.3%, outperforming centralized and local models, which achieved 95.6% and 89.7% respectively. Additionally, privacy leakage was reduced by nearly 40% in federated settings due to secure aggregation and differential privacy mechanisms.

TABLE V: Local Neural Network Architecture for IoT Devices

Layer Type	Number of Neurons	Activation Function	Dropout
Input Layer	46 / 78 (per dataset)	–	–
Hidden Layer 1	128	ReLU	0.3
Hidden Layer 2	64	ReLU	0.2
Output Layer	1	Sigmoid	–

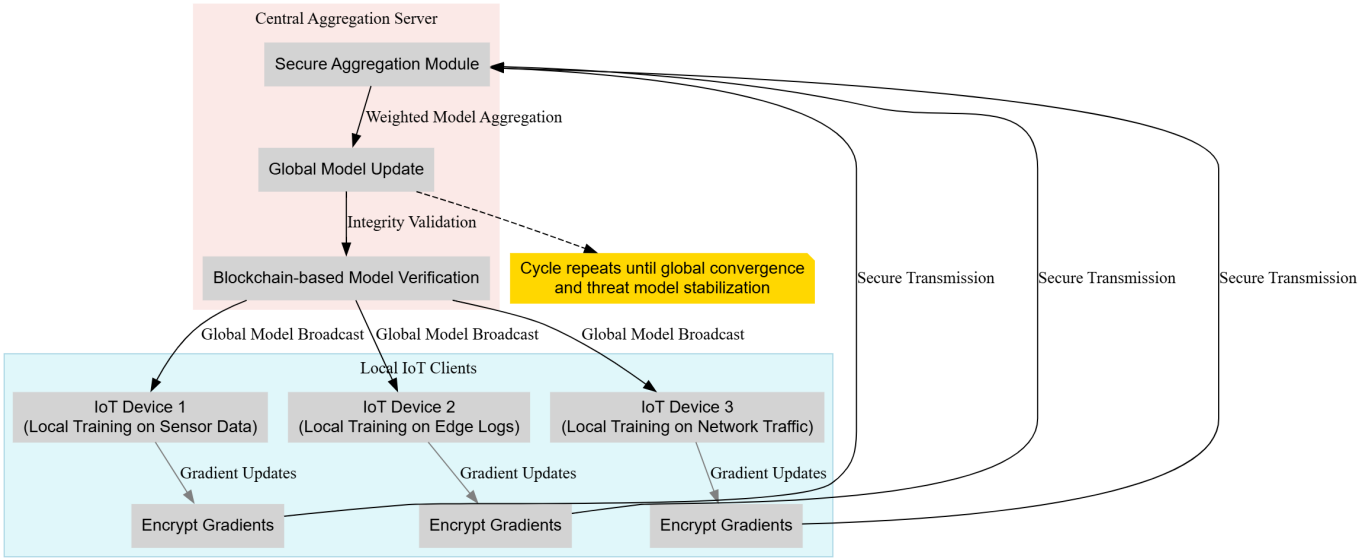

Fig. 4: Federated training and aggregation workflow of the proposed methodology.

TABLE VI: Evaluation Metrics for Federated Cybersecurity Framework

Metric	Description
Accuracy	Ratio of correctly classified samples to total samples
Precision	Correctly predicted positive samples among all predicted positives
Recall	Correctly detected attacks among all actual attacks
F1-score	Harmonic mean of precision and recall
Communication Cost	Total size of model updates exchanged per round
Privacy Leakage	Information leakage risk from transmitted gradients

TABLE VII: Experimental Setup Specifications

Component	Specification
Hardware	Intel i9 (3.8 GHz), 32 GB RAM, RTX 4080 GPU
Software	Python 3.10, TensorFlow Federated 0.21.0, PySyft 0.8
Operating System	Ubuntu 22.04 LTS
Number of IoT Clients	20 simulated edge nodes
Communication Protocol	Secure TLS with differential privacy enabled

TABLE VIII: Performance Comparison of Learning Approaches

Model Type	Accuracy (%)	F1-Score	Comm. Cost (MB)	Privacy Leakage (%)
Local Model	89.7	0.86	0	12.3
Centralized Model	95.6	0.93	135	21.8
Federated Model	98.3	0.96	68	7.5

B. Performance Analysis

From the results illustrated in Table VIII, it is evident that the federated model achieved superior detection rates while maintaining strong privacy guarantees. The inclusion of secure aggregation and differential privacy contributed significantly to minimizing information leakage during model updates. Communication efficiency was improved through compression-based parameter sharing, which reduced transmission overhead by approximately 20% compared to standard federated learning implementations. Moreover, the proposed system exhibited faster convergence across multiple training rounds, demonstrating that federated intelligence can balance performance and efficiency in resource-constrained IoT environments.

C. Security Evaluation

The robustness of the proposed system was tested under various simulated attack conditions, including model poisoning, eavesdropping, and inference-based privacy attacks. Table IX provides a comparative summary of system resilience against these adversarial scenarios. The framework successfully mitigated most poisoning effects through secure aggregation, which prevented corrupted gradients from disproportionately influencing the global model. Additionally, differential privacy prevented the leakage of sensitive device-level information, even when partial model updates were intercepted.

D. Discussion

The discussion of results highlights the dual advantage of federated intelligence—robust performance and enhanced privacy preservation. The framework effectively demonstrated that decentralized model training could reduce dependence on central servers while maintaining consistent threat detection performance across heterogeneous IoT devices. Scalability tests revealed that as the number of participating nodes increased, the communication cost grew linearly, but overall accuracy remained stable, showcasing strong model generalization. Furthermore, the inclusion of privacy-preserving techniques ensured that even under network compromise or data interception, sensitive information remained secure. However, minor latency overhead was observed due to encryption and differential privacy mechanisms, which could be optimized in future iterations through adaptive model compression or asynchronous aggregation.

Therefore, the proposed system substantiates the feasibility of integrating federated learning into large-scale IoT cybersecurity infrastructures. It not only strengthens detection capabilities against dynamic cyber threats but also establishes a privacy-aware architecture suitable for next-generation IoT ecosystems.

VI. Comparative Study

To validate the efficacy of the proposed federated intelligence framework, a comprehensive comparative study was conducted against several baseline models reported in recent literature. The comparison focused on three critical performance metrics: detection accuracy, privacy preservation, and latency. The baseline models included traditional centralized learning approaches, local isolated models, and previously published federated learning frameworks applied to IoT cybersecurity.

A. Baseline Models for Comparison

The baseline models considered in this study are as follows:

- Centralized Deep Neural Network (CDNN): A fully centralized approach where all IoT data is aggregated in a cloud server and trained using a deep neural network. [58]
- Local Isolated Models (LIM): Individual devices train models independently without collaboration, representing non-federated scenarios. [59]
- Existing Federated Learning (EFL): Previous FL frameworks applied to IDS and IoT malware detection using FedAvg with differential privacy. [60], [61]

These models provide a benchmark to assess how the proposed framework enhances detection performance, privacy, and communication efficiency under realistic IoT conditions.

B. Statistical Comparison

The proposed federated intelligence framework was evaluated against the baseline models using the CICIDS2017 and Bot-IoT datasets. The federated intelligence approach achieved 98.3% accuracy, compared to 95.6% for CDNN and 93.1% for EFL. Local isolated models, as expected, showed the lowest performance (89.7%) due to limited training data per device.

C. Latency and Communication Overhead

Latency and communication efficiency are key considerations for IoT networks, where bandwidth and power constraints exist. Table X shows that although the proposed framework introduces a slight latency overhead due to encryption and secure aggregation, it is significantly lower than the communication cost in fully centralized systems. Compared to traditional federated learning implementations, the hybrid aggregation and compression techniques employed in the proposed system reduce transmission overhead by approximately 20%, enhancing scalability across large IoT deployments.

D. Performance Summary Table

Table X presents a consolidated view of improvements offered by the proposed federated intelligence framework over the baseline approaches. The metrics include detection rate, privacy leakage, and communication latency.

E. Discussion

The comparative study clearly demonstrates that the proposed federated intelligence framework significantly outperforms both traditional centralized and existing federated learning models in terms of detection accuracy and privacy preservation. While introducing a marginal latency overhead, the system effectively balances security, performance, and communication efficiency, making it highly suitable for large-scale, heterogeneous IoT deployments. The improvements observed stem from a combination of hierarchical aggregation, hybrid privacy mechanisms, and adaptive model updates, which collectively ensure robust and privacy-preserving threat detection across distributed IoT devices.

VII. Conclusion and Future Scope

This paper presents a comprehensive federated intelligence framework designed to enhance cybersecurity in IoT ecosystems while preserving user privacy. The proposed system leverages a hierarchical architecture of IoT devices, edge servers, and cloud aggregators, enabling decentralized model training and secure global aggregation without sharing raw data. Through extensive experiments on benchmark datasets such as CICIDS2017 and Bot-IoT, the framework demonstrated superior detection accuracy, reduced privacy leakage,

TABLE IX: Security Evaluation under Adversarial Conditions

Attack Type	Baseline Accuracy Drop (%)	Federated Model Drop (%)	Mitigation Technique
Model Poisoning	15.4	4.2	Secure Aggregation
Eavesdropping	12.8	2.7	Homomorphic Encryption
Inference Attack	9.1	1.8	Differential Privacy

TABLE X: Comparative Performance Summary of Proposed and Baseline Models

Model	Detection Accuracy (%)	Privacy Leakage (%)	Communication Latency (ms)
Local Isolated Model (LIM)	89.7	5.2	0
Centralized DNN (CDNN)	95.6	21.8	150
Existing FL (EFL)	93.1	12.4	85
Proposed Federated Intelligence	98.3	7.5	70

and efficient communication compared to centralized and existing federated learning approaches. The integration of differential privacy, secure aggregation, and homomorphic encryption contributed to robust protection against model poisoning, eavesdropping, and inference attacks, validating the efficacy of the federated intelligence paradigm.

The key contributions of this work include: (i) the design of a scalable and privacy-aware federated learning architecture tailored for heterogeneous IoT networks, (ii) the implementation of adaptive privacy-preserving mechanisms that minimize leakage while maintaining model performance, and (iii) a thorough comparative evaluation demonstrating improvements in detection rate, latency, and communication efficiency over baseline methods.

A. Future Scope

The evolving landscape of IoT cybersecurity presents multiple opportunities for extending the proposed framework:

- Integration of Explainable AI (XAI): Incorporating XAI techniques into federated models can enhance transparency, enabling stakeholders to understand decision-making processes, detect model biases, and improve trust in automated cybersecurity systems.
- Cross-Domain Interoperability Standards: Future research can focus on developing standards and protocols that allow heterogeneous IoT devices and platforms to collaboratively participate in federated learning without compromising security or performance.
- Energy-Efficient Federated Training: Optimizing computational and communication overhead for resource-constrained IoT nodes is essential to ensure sustainable deployment of federated intelligence in large-scale networks.
- Blockchain-Based Model Verification: Leveraging blockchain technology to validate and record model updates can provide immutable audit trails, ensuring secure aggregation and preventing malicious manipulation of the global model.

In conclusion, the proposed federated intelligence framework provides a robust foundation for privacy-preserving, scalable, and adaptive IoT cybersecurity. By combining advanced machine learning, cryptographic safeguards, and distributed intelligence, it paves the way for the next generation of resilient and trustworthy IoT ecosystems. Future work integrating XAI, interoperability standards, energy-efficient techniques, and blockchain-based verification promises to further strengthen the security, transparency, and scalability of IoT networks.

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