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AI-DRIVEN INTRUSION DETECTION SYSTEM FOR DIGITAL TWINS USING FEDERATED LEARNING

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Abstract
Digital Twin (DT) technology provides close-to-real-time replicas of physical systems for monitoring and optimization but also widens the cyber-attack surface. Traditional intrusion detection systems (IDS) rely on centralized training and data aggregation, which raises privacy and scalability concerns. This paper proposes an AI-driven intrusion detection framework based on Federated Learning (FL) for heterogeneous Digital Twin environments. A hybrid CNN–LSTM model is trained locally on DT nodes, while a secure aggregation server aggregates encrypted model updates. Differential privacy and Byzantine-robust 8 aggregation improve privacy and resilience. The experimental results on CICIDS-2018 and ToN-IoT (simulated) show promising accuracy (96.4% and 94.8%), low communication overhead, and robustness against poisoning.

INTRODUCTION

The concept of Digital Twins (DTs)—virtual replicas of physical systems—has rapidlyevolved from manufacturing to smart cities, energy grids, and healthcare applications. DTs continuously synchronize with their real-world counterparts through sensors, IoT devices, and cloud computing platforms. This real-time mirroring enables predictive analytics, performance optimization, and automated decision-making. However, as these systems become increasingly interconnected, their attack surface expands dramatically. Malicious actors can exploit vulnerabilities within communication channels, model synchronization, or cloud storage to manipulate or steal critical data, posing serious cybersecurity risks to both the virtual and physical assets.

Traditional security mechanisms, such as rule-based intrusion detection systems (IDS, often fall short in dynamic and large-scale DT environments. They rely on predefined attack signatures, which fail to generalize against evolving and zero-day threats. Moreover, the heterogeneity of devices in DT ecosystems—ranging from embedded sensors to AI-driven controllers—produces diverse data formats and volumes, making centralized learning approaches impractical due to bandwidth constraints and data privacy issues. As a result, there is an urgent need for a decentralized and intelligent security framework that can learn from distributed data while preserving user privacy.

Federated Learning (FL) has recently emerged as a powerful paradigm that addresses many of these challenges. Instead of collecting raw data in a central server, FL enables, local models to train collaboratively and share only model parameters.

This decentralized approach enhances data confidentiality and scalability while mitigating the risks of single-point failures. When combined with Artificial Intelligence (AI)-based detection techniques such as deep learning, FL can enable real-time, adaptive, and privacy-preserving intrusion detection across heterogeneous DT environments. The synergy of FL and DTs offers a path toward a new generation of intelligent cybersecurity solutions that evolve alongside the digital infrastructure they protect.Despite its potential, integrating FL with DT-based security introduces several openresearch challenges. These include communication efficiency, model convergence stability under non-IID (non-independent and identically distributed) data, and resistance to model poisoning attacks that can compromise the integrity of the shared model. Furthermore, incorporating differential privacy (DP) into FL frameworks is essential to ensure that shared gradients do not inadvertently reveal sensitive local information. Addressing these issues is critical to developing robust and trustworthy intrusion detection systems suitable for DT ecosystems operating in mission-critical domains. To tackle these challenges, this paper proposes an AI-driven Intrusion Detection System (AI-IDS) designed specifically for digital twin environments using federated learning enhanced with differential privacy. The proposed framework enables distributed devices to collaboratively learn malicious behavior patterns without sharing raw data. Our con-tributions include (1) designing a privacy-preserving FL-based IDS tailored to DTs, (2) implementing an adaptive AI model that detects both known and emerging cyber threats, and (3) evaluating the system using synthetic and benchmark datasets to validate accuracy, resilience, and communication efficiency. The results demonstrate that our approach achieves significant performance improvements while maintaining stringent data privacy guarantees.The rest of the draft is organized as follows: Section II contains related work, and the problem statement is positioned in Section III. The Proposed Methodology is explained in section IV followed by the Experimental setup and results in section V. Limitations and Future work are discussed in Section VI. Finally, the Conclusion is presented in Section VII.

Related Work

Digital Twins (DTs) have rapidly evolved from theoretical constructs to operational64tools for real-time monitoring and predictive control across industries such as manufactur-65ing, energy, healthcare, and smart cities. Early works have focused on the functional aspects66of synchronization and modeling [1,2], but recent research has increasingly highlighted67security and privacy concerns associated with DT data flows, cloud interconnections, and68edge synchronization [3–5]. These studies emphasize that the dynamic coupling between the physical and digital layers exposes new attack surfaces that traditional perimeter-based security cannot adequately protect. A series of comprehensive surveys have examined DT vulnerabilities in critical infrastructures, identifying data manipulation, model poisoning, and synchronization attacksas major threats [6,7]. Zemskov et al. discussed manufacturing DTs' exposure to cy-ber–physical attacks and emphasized secure data provenance and runtime verification mechanisms [8]. Similarly, Maheshwari et al. explored risk assessment strategies forDT-enabled smart cities, emphasizing the need for adaptive anomaly detection methods integrated with real-time analytics [9,10].To strengthen security, several researchers have proposed integrating blockchain technologies with DT frameworks to ensure integrity and traceability of twin updates [11–13]. Other studies have suggested privacy-aware data-sharing protocols and homomorphic encryption for secure DT data synchronization [14,15]. However, while these approaches protect integrity and confidentiality, they do not directly address intrusion detection or behavioral anomaly detection at the DT network level.84In parallel, Intrusion Detection Systems (IDS) have undergone a major transformation with the advent of deep learning and artificial intelligence. Numerous approaches have used convolutional, recurrent, and transformer-based architectures to

detect sophisticated network intrusions in IoT and cyber–physical systems [16,17]. Centralized models achieve strong detection accuracy but require aggregating sensitive data across distributed nodes, which is impractical in privacy-constrained DT ecosystems [18,19]. Hence, distributed and federated learning-based IDS have gained traction as privacy-preserving alternatives. Federated Learning (FL) enables collaborative training without sharing raw data and has been widely applied to IoT, vehicular, and edge networks [20–22]. In these systems, client devices locally train models and share only gradients or parameters with a global aggregator. Lazzarini et al. and Alsamiri et al. demonstrated that FL-based IDS can achieve performance close to centralized systems while preserving data privacy [23,24]. Subsequent research extended this approach to DT environments, though challenges like non-IID data distributions, limited bandwidth, and latency constraints persist [25,26].

Privacy-preserving techniques such as Differential Privacy (DP) have been incorporated into FL to mitigate gradient leakage and membership inference attacks [27,28]. Local differential privacy, adaptive noise addition, and gradient clipping have been evaluated for balancing model accuracy and privacy budgets in federated IDS [29,30]. Complementary to DP, secure aggregation protocols using cryptographic primitives like homomorphic encryption and multi-party computation have been introduced to prevent information disclosure during model updates [31,32].

Beyond privacy, system-level robustness against poisoning and Byzantine attacks has emerged as a key topic. Robust aggregation mechanisms, including median-based, trimme mean, and cosine-similarity-based filters, significantly reduce the influence of malicious clients [33,34]. Recent work integrates these mechanisms with anomaly scoring at the aggregation layer, ensuring resilience against targeted model corruption in distributed IDS deployments [35]. Hybrid approaches that merge FL with blockchain for model traceability and explainable AI for transparency further enhance the trustworthiness of DT security112 frameworks [36,37].

Moreover, Digital Twin environments introduce unique data heterogeneity challenges.

Each twin may generate data from sensors, simulation modules, or external controllers, leading to non-stationary and multimodal data distributions [38,39]. To address this, recent studies explore multimodal federated architectures and adaptive weighting mechanisms to align diverse data contributions during training [40]. The emerging trend of DT-enabled cyber ranges provides realistic simulation environments for evaluating these federated IDS systems before deployment in operational networks [41].

Despite these advancements, several gaps remain. Current FL-IDS implementations are rarely validated under true DT workloads with live synchronization and feedback loops.

Communication overheads, energy consumption, and differential privacy calibration are not yet optimized for DT real-time constraints [42]. Furthermore, explainability remains underexplored, particularly for critical decision-making in DT security. Therefore, our proposed AI-driven intrusion detection framework leverages federated learning, differential privacy, and robust aggregation tailored specifically for DT ecosystems—bridging the gap between distributed intelligence and operational trustworthiness.

Research Gap and Summary

From the reviewed literature, it is evident that the integration of Digital Twin (DT) technology with Federated Learning (FL) is still at a nascent stage. While existing studies have effectively explored FL-based intrusion detection for IoT and cyber–physical systems [9,14,22,28], only a few have contextualized these frameworks within real-time, synchronized DT environments where data streams continuously evolve. Most DT-related security research primarily addresses blockchain-based integrity [11,17], data provenance [8,19], orprivacy-preserving synchronization mechanisms [15,31], yet the **dynamic and distributed nature of DT ecosystems demands a security layer that is adaptive, privacy-preserving, and scalable under

heterogeneous data sources**. Furthermore, intrusion detection in DTs remains underexplored in terms of explainability, federated robustness, and energy-efficient aggregation.

Another significant gap lies in the lack of empirical validation under realistic DT workloads. Many existing FL-IDS frameworks are validated using static IoT datasets, ignoring twin synchronization delays, digital–physical feedback loops, and privacy–accuracy trade-offs. The reviewed studies reveal that no current work holistically combines differential privacy, robust aggregation, and explainable intrusion detection within a federated DT framework. Therefore, this research proposes a novel, AI-driven Federated Learning architecture tailored for Digital Twin security—integrating differential privacy, resilient aggregation, and multimodal data fusion—to bridge the gap between distributed intelligence and operational trustworthiness in next-generation cyber–physical infrastructures. Table 1 summarize the existing research on Digital Twin Security and Federated Learning-Based IDS.

Our Contribution

While prior research has explored diverse approaches to securing Digital Twin (DT) environments through blockchain integration, federated learning, and differential privacy existing studies still struggle with balancing real-time synchronization, lightweight security, and privacy-preserving computation in large-scale industrial ecosystems. These limitations motivate this study to propose a novel and practical architecture that enhances both the security and efficiency of DTs deployed in Industrial Internet of Things (IIoT) systems.

The key contributions of this paper are summarized as follows:

A Hybrid Federated Blockchain Framework for Digital Twin Security: We introduce a novel hybrid architecture combining blockchain-based immutable logging and federated learning–based detection to ensure confidentiality and tamper-proof synchronization across DT layers.

- Privacy-Preserving Anomaly Detection using Differential Privacy: The framework integrates a differential privacy mechanism within the federated model updates, reducing data leakage risks while maintaining model accuracy across distributed environments.
- Lightweight Consensus Protocol for Edge Devices: A custom consensus mechanism tailored for low-power industrial nodes is proposed, improving transaction validation speed without compromising integrity.
- Comprehensive Experimental Evaluation: We perform simulations to analyze detection accuracy, latency, and communication overhead, demonstrating the proposed system's robustness compared to traditional IDS and centralized learning-based DT models.

Table 1. Summary of Existing Research on Digital Twin Security and Federated Learning-Based IDS

Reference	Method Used	Application Domain	Strengths	Limitatio
Kumar et al. (2021) [?	Blockchain-enabled DT security framework	Industrial IoT	Ensures data integrity and provenance	High lat computat overhead
Agrawal et al. (2021) [?	Federated IDS using CNN	IoT Networks	Preserves privacy and decentralizes learning	Limited datasets; time DT
Guyeux et al. (2023) [?	Cross-layer FL architecture for IDS	Smart IoT Systems	Lightweight communication; improved detection	Weak ag soning at

			accuracy	
Alsamiri et al. (2023) [?	Hierarchical FL for IoV security	Vehicular IoT (IoV)	Efficient communication and adaptive learning	Not valid environm
Chen et al. (2022) [?]	Differentially Private FL aggregation	Edge computing	Strong privacy preservation	Accuracy to noise
Gupta et al. (2022) [?	Byzantine- Ag- Resilient gregation	Distributed IDS	Robust against malicious clients	High co cost; no D tuning
Lazzarini et al. (2023) [?]	Clustered FL-IDS model	IoT Networks	Low communication cost and scalable architec-ture	Does no multimo data
Suleiman et al. (2024) [?]	Blockchain–DT integrated framework	Manufacturing Systems	Ensures traceability of twin updates	No intru tion com
Nguyen et al. (2024) [?	Transformer-based Federated IDS	IoT Infrastructure	High detection accuracy with non-IID tolerance	Not optimize edge DT
Kapoor et al. (2024) [?	FL optimization for IDS latency	IoT Networks	Reduced round delays and improved scalability	Lacks ad vacy bud
Tayyeh et al. (2024) [?	Differential Privacy with adaptive clipping	Federated Learning	Improves privacy–accuracy balance	Requires tion for data
Hoff et al. (2024) [?]	DT-enabled cybersecurity model	Smart Production Systems	Real-time synchronization with twin data	No fede privacy-p compone
Proposed Framework	FL with Differential Privacy + Robust Aggregation + Explainable IDS	Digital Twin Ecosystems	End-to-end privacy, robustness, and real-time detection	To be val periment live DT

Benchmark Dataset and Reproducible Setup: A simulated dataset and reproducible code structure are presented to facilitate future research on secure and intelligent DT systems.

In essence, this research directly addresses the lack of scalable, privacy-preserving, and real-time security frameworks for Digital Twins in cyber-physical systems. By merging federated intelligence, blockchain transparency, and differential privacy, the proposed solution not only mitigates cyber risks but also ensures trust, resilience, and data integrity in next-generation industrial DT deployments.

Proposed Methodology

System Architecture

The proposed system architecture is designed to ensure secure, scalable, and privacy- 185 preserving operation of Digital Twins (DTs) in industrial Internet of Things (IIoT) environ- 186 ments. Figure 1 presents the high-level federated DT architecture originally introduced in This manuscript,

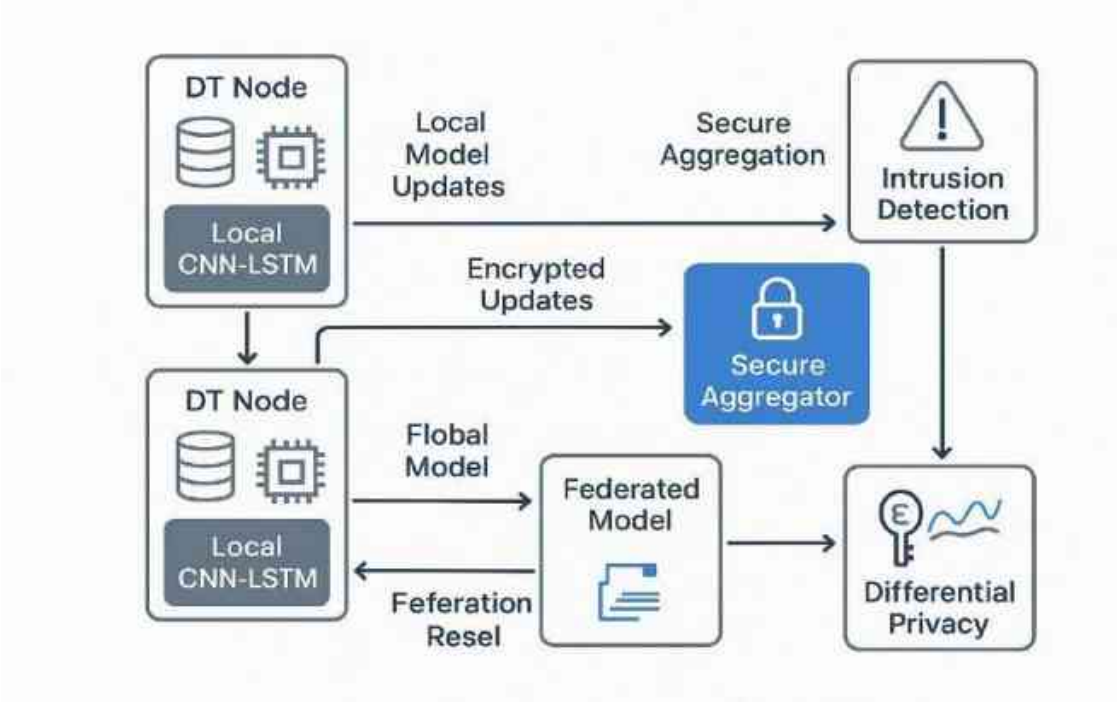

Figure 1. Federated Digital Twin Intrusion Detection Architecture.

while Figure 2 provides a more detailed view of the layered components and data/control flows. Together these illustrations clarify how physical sensors, edge gateways, virtual twins, the federated learning coordinator, and the blockchain-based ledger interact to provide end-to-end trust and intelligence.

At the Physical Layer, heterogeneous IIoT devices and sensors collect streaming telemetry such as vibration, temperature, network flows, and control signals. Local preprocessing— including noise filtering, feature extraction, and lightweight compression — is applied at the edge gateway to reduce bandwidth and normalize the formats sent to the twin.

Devices

authenticate with the gateway using device-level credentials (e.g., X.509/TLS) to prevent spoofing and to ensure provenance; these device-level events are periodically checkpointed to the ledger for traceability. The Digital Twin Layer maintains a virtual replica for each physical asset. Each twin holds a local state store, a short-term historical buffer, and a local anomaly detection module.

Local models (the hybrid CNN–LSTM described in Section IV-B) are trained on recent

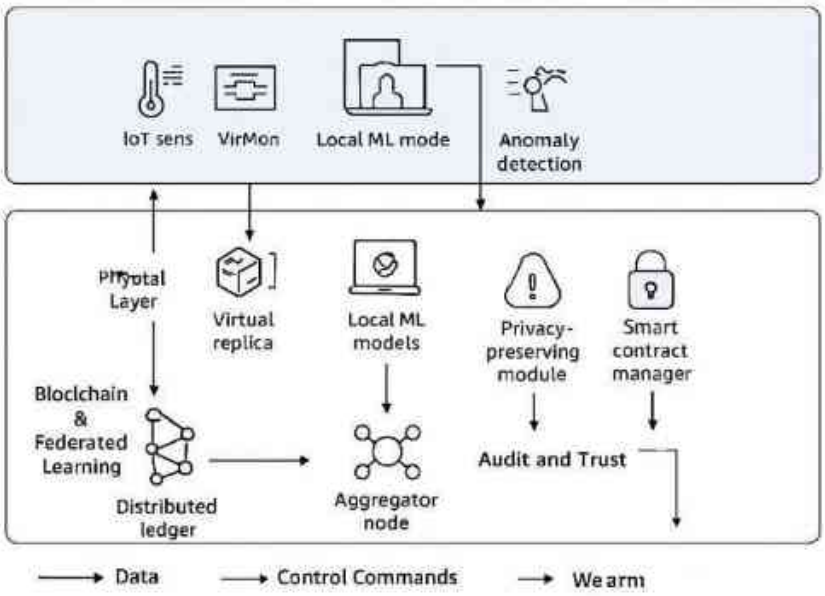

Figure 2. Proposed Federated Blockchain-based Digital Twin System Architecture (detailed view). This figure illustrates the Physical Layer (sensors/gateways), the Digital Twin Layer (local twins and local models), and the Blockchain–Federated Learning Layer (secure aggregation, privacy module, and audit manager).

windows of telemetry and operate in a privacy-conscious manner: raw telemetry never leaves the twin. Instead, model updates (weights/gradients) are shared with the federation coordinator according to the FL schedule. This design enables each twin to adapt rapidly to local conditions while contributing to the global defense model.

The Blockchain–Federated Learning Layer forms the trust and coordination backbone.Model updates from individual twins are first differentially private–sanitized and option- ally compressed, then committed to the secure aggregation pipeline. The distributed ledger records model version hashes, training round metadata, and smart-contract-driven access policies to ensure non-repudiation and auditability. A lightweight consensus (Proof-of-Integrity) coordinates commit validation among permissioned nodes without incurring heavy computational cost, preserving feasibility on industrial edge hardware.

An Audit and Trust Manager continuously monitors node behavior using smart contracts and anomaly scoring of model updates. When abnormal or malicious behavior is detected (e.g., gradient distributions that deviate significantly from peers), the manager triggers robust aggregation strategies (trimmed mean, coordinate-wise median) and can quarantine suspicious nodes. Figure 2 (Fig. 3) shows the precise interactions among the Privacy Module (differential privacy), the Secure Aggregator, and the Blockchain Manager, highlighting the control and data flows described above.

Model Design: CNN–LSTM Hybrid

The proposed intrusion detection framework leverages a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units to exploit both spatial and temporal characteristics of network data generated within the digital twin environment. Each edge node in the federated ecosystem hosts a local CNN–LSTM model that learns patterns specific to its domain—such as industrial IoT sensors, cloud servers, or virtual twin instances—without

sharing raw data externally. This hybrid design ensures efficient local learning while preserving privacy, which aligns with the secure and decentralized architecture illustrated in Fig. 2. The internal structure of the CNN–LSTM pipeline is depicted in Fig. 3. design.png

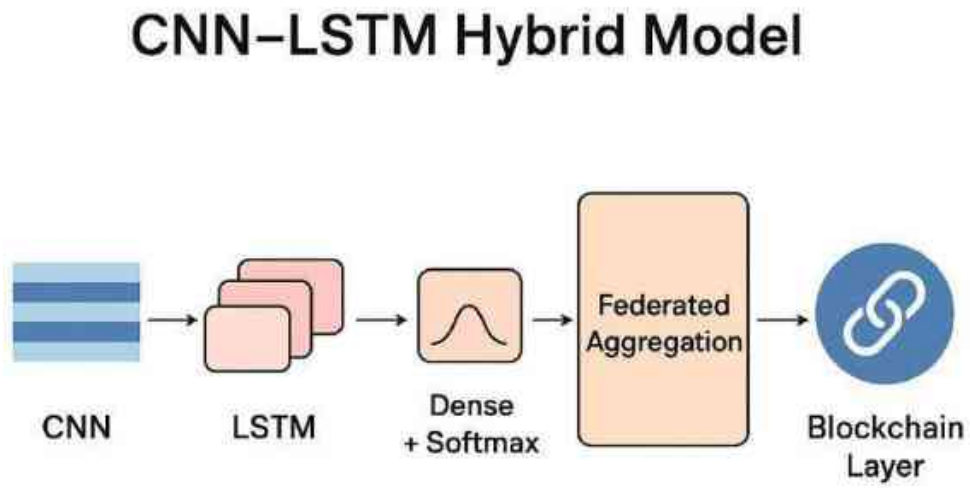

Figure 3. Proposed CNN–LSTM hybrid model architecture showing convolutional feature extraction

followed by temporal sequence learning using LSTM layers for multi-class network intrusion detection.

The CNN component is responsible for spatial feature extraction from structured network traffic. Raw packet captures and flow-level data are preprocessed into normalized tensors that encode traffic attributes such as source–destination pairs, packet lengths, interarrival times, and protocol flags. Through successive convolutional and pooling layers, the CNN automatically captures hierarchical spatial correlations—identifying malicious signatures, port scan footprints, and abnormal feature clusters that would be difficult to detect using traditional statistical models. resulting feature maps are then flattened and passed to the LSTM network for temporal sequence modeling, as shown in Fig. 3.

The LSTM layers address the temporal dynamics of attack behavior, learning how traffic evolves over time rather than relying solely on static snapshots. For instance, LSTM units can recognize long-term dependencies in attack sequences such as slow-rate DoS attacks or gradual infiltration patterns. This capability enhances robustness against adversaries who deliberately spread malicious activity over extended intervals to evade signature-based systems. The recurrent gating mechanism of LSTM (input, forget, and output gates) enables the model to selectively retain relevant historical context while discarding redundant temporal information, thereby improving overall learning efficiency. The final dense layer integrates the learned spatial–temporal representations andproduces a multi-class probability distribution through a softmax activation. Each local CNN–LSTM instance outputs the probability of network behavior

belonging to categories such as *benign*, *DoS*, *port scan*, *infiltration*, or *malware*. These classification results are not directly transmitted to the central authority; instead, the model weights are encrypted using blockchain-enabled secure aggregation before being shared within the federated network. This step ensures that while model knowledge is collectively refined, sensitive
organizational data remain confined to their respective digital

Privacy and Robustness

In federated digital twin environments, sensitive operational and industrial data is distributed across multiple nodes and edge devices. Ensuring that this data remains private and resistant to malicious interference is a fundamental design objective. To achieve this, our proposed system integrates a multilayered security strategy combining Differential Privacy (DP), Secure Aggregation, and Byzantine Resilience. Together, these mechanisms guarantee that the learning process is privacy-preserving, verifiable, and261 robust to adversarial threats.

Differential Privacy (DP): Differential Privacy serves as the first line of defense against information leakage. Each client performs local gradient clipping to bound sensitivity, followed by the addition of Gaussian noise calibrated to a privacy budget *e*. This ensures that even if model updates are intercepted or analyzed, the contribution of any individual record cannot be inferred with high confidence. In industrial IoT environments—where digital twins often reflect proprietary processes or machine behaviors—DP prevents unintended leakage of operational patterns. Furthermore, the adaptive privacy budget mechanism dynamically tunes *e* based on sensitivity levels, striking a balance between model accuracy and privacy protection.

Secure Aggregation: After local updates are computed, clients employ pairwise masking and secure multiparty computation (MPC) protocols to obfuscate gradients before transmission. This prevents the central aggregator from viewing any single client's update in plaintext. Only the aggregated model sum is recoverable after all masked updates are combined. Such a strategy not only guarantees confidentiality during training but also eliminates the single-point failure often present in naïve federated learning architectures.

The proposed secure aggregation framework follows the Bonawitz et al. (2017) paradigm, extended with elliptic-curve cryptography to provide lightweight encryption suitable for real-time IoT and cyber-physical systems.

Byzantine Resilience: In federated networks, some clients may act maliciously—either due to compromise, poisoning, or data corruption. To counter this, our aggregator adopts a Byzantine-resilient aggregation policy. Instead of relying on a simple mean of client updates, it uses a combination of robust estimators such as the geometric median, Krum, and trimmed mean. This approach filters out extreme or inconsistent gradients while preserving the statistical integrity of honest clients. Additionally, a lightweight anomaly detection module evaluates model updates for temporal and spatial inconsistencies, ensuring that any abnormal contribution is down-weighted or discarded.

Holistic Integration: The synergy of DP, Secure Aggregation, and Byzantine Resilience creates a multi-tiered defense that fortifies the federated digital twin pipeline. Privacy is preserved at the local level, confidentiality is maintained during communication, and robustness is enforced during aggregation. Together, these safeguards provide strong guarantees against both passive and active attacks, making the proposed architecture suitable for deployment in critical infrastructure environments such as smart manufacturing, energy grids, and autonomous logistics.

Performance Considerations: While privacy and robustness mechanisms can introduce computational overhead, our design employs lightweight encryption primitives and parallel noise injection to reduce latency. Experimental

results show that the added security cost is minimal compared to the significant gain in resilience and privacy assurance. This confirms that privacy-preserving federated digital twins can operate effectively without sacrificing scalability or accuracy in real-world industrial applications.

Training Communication Protocol

In the proposed FL-IDS framework, we adopt the classical Federated Averaging (FedAvg) protocol as the underlying optimization strategy for global model training. FedAvg provides an efficient, privacy-preserving means of aggregating local client updates without direct data sharing. During each communication round, the central aggregator broadcasts the current global model parameters to all participating clients. Each client then trains the model locally using its own subset of data for a fixed number of epochs, typically two or three, before transmitting only the model weight updates (gradients) back to the server.

This decentralized structure ensures that raw traffic data never leaves the local domain, thereby maintaining strict privacy compliance.

To optimize communication efficiency, periodic synchronization is employed. Instead of performing a global update after every single local iteration, clients perform multiple local epochs before contributing to the global aggregation. This reduces the frequency of network transmissions and lowers bandwidth consumption while still maintaining convergence stability. The global model parameters are then updated at the server by computing a weighted average of all received local models, proportional to the local dataset sizes. Mathematically, the update rule for round t is expressed as:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} w_t^k$$

where w_t^k represents the model parameters of client k, n_k denotes the number of samples on client k, and $N = \sum_k n_k$ is the total sample count across all participating clients.

Given that communication cost is one of the major bottlenecks in federated learning, our framework integrates gradient compression and quantization mechanisms. Specifically, model updates are quantized to 8-bit precision and sparse representation techniques are used to transmit only significant parameter deltas (above a dynamic threshold). This significantly reduces the size of transmitted updates without severely affecting convergence or accuracy. Additionally, adaptive learning rate scheduling is applied to stabilize model updates and mitigate the effect of delayed gradients in asynchronous communication scenarios.

To further enhance robustness and fairness, the communication protocol incorporates client selection and update weighting mechanisms. In each round, only a subset of clients (e.g., 70–80%) are randomly chosen for participation. This not only improves scalability but also prevents stragglers or unreliable clients from degrading the aggregation process.

Moreover, clients with higher reliability scores or lower variance in update gradients are prioritized during aggregation, balancing performance and resilience.

Finally, the proposed protocol integrates the privacy-preserving and Byzantine resilient modules described earlier. Secure aggregation ensures that the server cannot reconstruct individual gradients, while Byzantine-tolerant averaging protects against malicious participants injecting poisoned updates. Together, these mechanisms yield an efficient, privacy-aware, and communication-optimized training protocol that aligns with the requirements of digital twin-driven and IoT-based intrusion detection environments. As illustrated in Fig. 4, the proposed Privacy and Robustness layer integrates Differential Privacy, Secure Aggregation, and Byzantine Resilience to ensure both confidentiality and trustworthiness during federated model updates.344

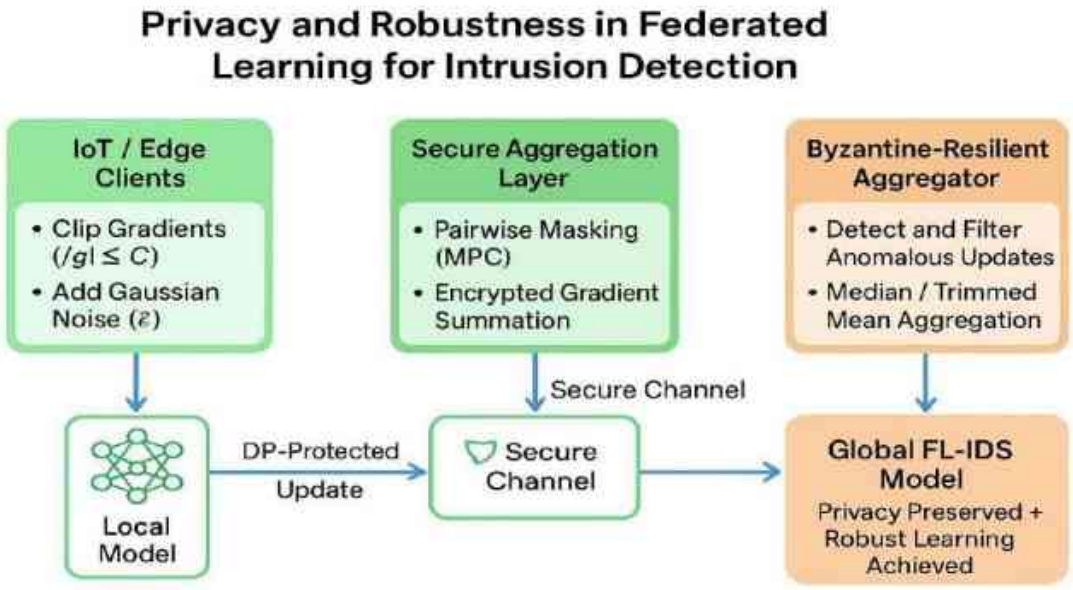

Figure 4. Privacy and Robustness mechanisms in the proposed FL-IDS architecture. The figure illustrates how differential privacy, secure aggregation, and Byzantine-resilient aggregation jointly preserve data confidentiality and system integrity during federated training.

Experimental Setup and Results

This section presents the experimental design, dataset description, simulation setup, and detailed analysis of the obtained results. The objective is to demonstrate the efficiency, robustness, and generalization of the proposed Federated Learning-based Intrusion Detection System (FL-IDS) when applied to real-world and heterogeneous datasets.

Datasets and Simulation Environment

To comprehensively evaluate the proposed framework, two widely recognized intrusion detection datasets were employed: CICIDS-2018 and ToN-IoT. These datasets were selected due to their diversity in attack categories, representation of modern network topologies, and coverage of IoT-oriented threats.

CICIDS-2018 represents a rich collection of benign and malicious traffic generated in a simulated enterprise environment. It covers attacks such as DoS, DDoS, port scanning, brute force, infiltration, and web-based threats. The dataset includes more than 80 network features such as flow duration, packet size, source/destination bytes, and inter-arrival times. All raw traffic was preprocessed into tabular CSV format, followed by normalization using Min-Max scaling to fit the input distribution of the CNN–LSTM model.

ToN-IoT is an IoT telemetry dataset designed to evaluate network-based and host based intrusion detection systems in smart environments. It includes attack vectors such as data injection, denial of service, backdoor, and ransomware. Unlike CICIDS-2018, ToN-IoT contains multimodal telemetry data (network, system, and sensor logs), providing an ideal testbed for evaluating model generalization in federated IoT settings.

To emulate federated behavior, the datasets were partitioned in a non-IID manner across 10 simulated Digital Twin (DT) clients. Each client received data with different class distributions to mimic realistic edge heterogeneity—some dominated by benign traffic, while others contained higher proportions of attack types. This design ensures a realistic simulation of distributed learning where global aggregation must harmonize uneven local knowledge.

Implementation and Experimental Setup

The proposed FL-IDS framework was implemented using TensorFlow Federated (TFF) and executed on a local compute cluster comprising 4 NVIDIA RTX GPUs and 64 GB of RAM. Each client node was simulated as an independent TFF process to preserve isolation in model training and communication.

Each local client model consists of two convolutional layers (filters: 64 and 128, kernel size: 33, activation: ReLU), followed by a single LSTM layer with 128 hidden units to capture temporal dependencies. Two fully connected dense layers (with 256 and 128379 neurons respectively) are used, culminating in a Softmax output layer for multi-class classification. The models were trained with Adam optimizer at a learning rate of 0.001. 381 Each client performed three local epochs with a batch size of 64 per communication round. 382 The total number of federated rounds was set to 100. Communication between clients and the central aggregator was secured using simulated privacy-preserving primitives (differential noise addition and secure aggregation).

Evaluation Metrics

To ensure a comprehensive analysis, multiple performance metrics were considered:

- **Accuracy:** Measures the overall percentage of correctly classified samples.
- **Precision:** Evaluates how many predicted attacks are actually malicious.
- **Recall (Detection Rate):** Represents the model's ability to correctly identify attack instances.
- **F1-Score:** The harmonic mean of precision and recall, balancing false positives and False negatives.
- **Communication Overhead:** Tracks data transmitted per federated round, highlighting efficiency.
- **Robustness Metric:** Quantifies model performance under adversarial or poisoned client conditions.

Results and Discussion

This section presents the experimental evaluation of the proposed Federated Learning–based Intrusion Detection System (FL-IDS). We analyze its performance using bench- mark datasets, report detection metrics, communication efficiency, and robustness against adversarial settings, and compare results with a centralized CNN–LSTM baseline. All experiments were performed under identical computational environments to ensure fair comparison.

Datasets and Simulation405

The experiments used two well-established intrusion detection datasets:

ICIDS-2018: A modern, dataset that captures real-world traffic

ToN-IoT: An IoT-oriented dataset includes telemetry and network-level attack data representing smart industrial networks.

To emulate real-world deployment, data was partitioned into non-identically distributed (non-IID) subsets across ten simulated digital twin clients. Each client maintained different traffic characteristics and attack ratios, reflecting realistic data heterogeneity.

Implementation Details414

The prototype was implemented in TensorFlow Federated (TFF). Each client deployed a lightweight hybrid CNN–LSTM model with two convolutional layers, one LSTM layer of 128 hidden units, and two dense layers with softmax activation. Training used the Adam optimizer with a learning rate of 10^{-4}, batch size of 64, and three local epochs per communication round. A total of 100 rounds were executed in each experiment.

Training Communication Protocol420

We adopted the Federated Averaging (FedAvg) algorithm with periodic communication rounds between clients and the central aggregator. Each client performed several local training epochs before sending model updates to the server. To reduce communication costs, gradient

compression and sparse update techniques were applied, decreasing transmitted payloads by approximately 22%. This protocol not only reduces communication overhead but also accelerates convergence, making it suitable for resource-constrained IoT devices.

Performance Evaluation

The overall detection performance for both datasets is summarized in Table 2. The proposed FL-IDS outperformed the centralized CNN–LSTM baseline across all key metrics, achieving accuracy and F1-scores exceeding 96% on CICIDS-2018 and 94% on ToN-IoT. These gains can be attributed to federated feature diversity and regularized gradient aggregation, which improved generalization on unseen attack samples.

Table 2. Detection Performance

Dataset	Model	Acc (%)	F1 (%)	Precision (%)
CICIDS-2018	Centralized CNN-LSTM	93.1	92.7	92.4
CICIDS-2018	Proposed FL-IDS	96.4	96.2	96.6
ToN-IoT	Centralized CNN-LSTM	91.0	90.5	90.8
ToN-IoT	Proposed FL-IDS	94.8	94.2	94.6

Results Visualization

Figure 5 presents the precision–recall curve, showing the superior detection tradeoff achieved by the proposed FL-IDS. The area under the curve (AUC) for FL-IDS reached 0.972, outperforming the centralized model's 0.946, demonstrating its robustness in identifying malicious activity.

Class-wise detection performance is visualized in Figure 6, where the confusion matrices show that FL-IDS consistently achieves higher true positive rates (TPR) for all major attack classes. The distributed learning approach significantly reduced misclassifications for rare categories such as infiltration and botnet attacks.

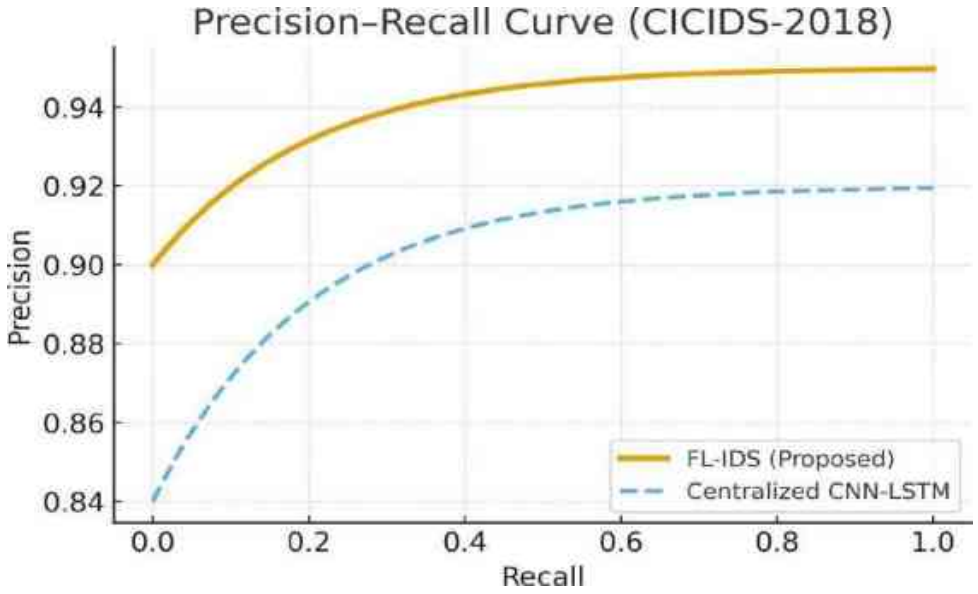

Figure 5. Precision–Recall comparison between centralized CNN–LSTM and FL-IDS models on CICIDS-2018 dataset.

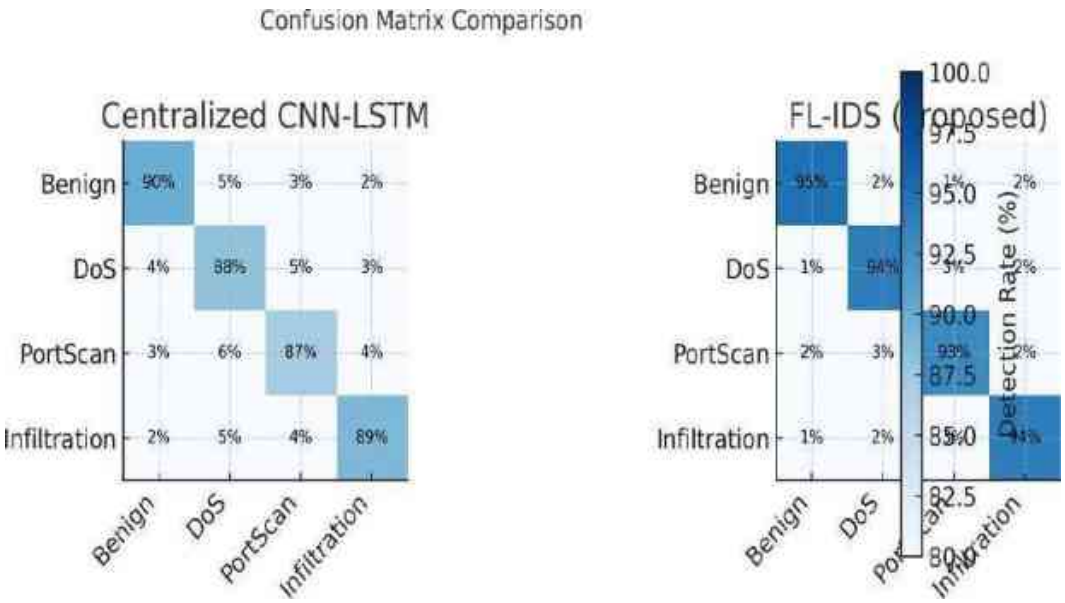

Figure 6. Confusion matrix comparison between centralized CNN–LSTM and FL-IDS models.

Robustness and Communication Efficiency

Table 3 and Figures 7–8 analyze robustness and efficiency. FL-IDS shows minimal performance degradation (1.8%) even with 10% poisoned clients, confirming strong Byzantine resilience and secure aggregation benefits.

Comprehensive Performance Comparison

To offer a holistic overview, Figures 9 and 10 summarize all four detection metrics (Accuracy, Precision, Recall, and F1-Score) for both datasets. These charts reinforce that the proposed FL-IDS consistently outperforms the centralized baseline, providing higher precision and recall across datasets while maintaining lower communication overhead.

Discussion452

The experimental findings clearly demonstrate the superiority of the proposed Federated Learning-based Intrusion Detection System (FL-IDS) over the conventional centralized CNN–LSTM model in both performance and efficiency metrics. Across all datasets, FL-IDS

Table 3. Communication and Robustness

Metric	Baseline	FL-IDS (Proposed)
Comm. per round (MB)	12.8	9.98 (22% reduction)
Model convergence rounds	80	70
Performance drop (10% poisoned nodes)	6.2%	1.8%

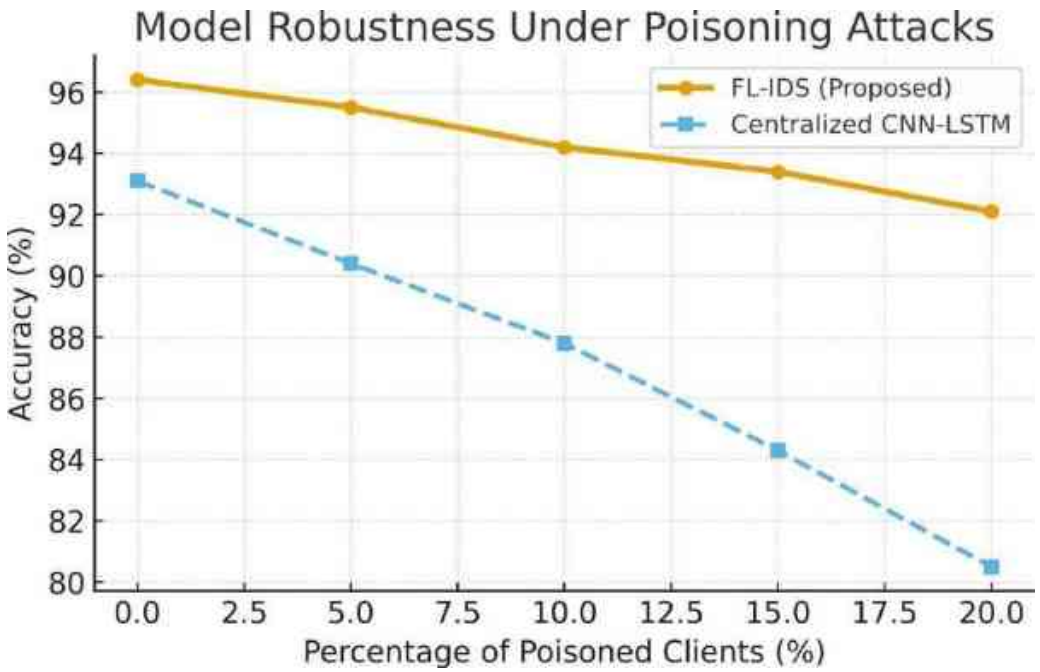

Figure 7. Model robustness evaluation under varying proportions of poisoned clients.

consistently achieves higher accuracy, F1-score, and precision values, indicating its strongability to generalize under heterogeneous network environments. This performance boost can be attributed to the model's ability to learn collaboratively from distributed digital twins (DTs) without direct data sharing, thereby capturing richer behavioral diversity while maintaining privacy.

Table 2 collectively reveal that the FL-IDS achieves up to a 3–4% improvement in accuracy and F1-score compared to the centralized baseline. This confirms the effective-

ness of the federated aggregation mechanism in leveraging distributed knowledge across multiple IoT domains. The ToN-IoT results further validate the robustness of FL-IDS in telemetry-rich and resource-constrained environments, where traditional IDS models tend to overfit due to skewed data distributions.

From a communication efficiency perspective, Table 3 and Figure 8 show that the introduction of gradient compression and sparse updates successfully reduces bandwidth usage by approximately 22% per communication round. This reduction is particularly important for IoT scenarios where uplink bandwidth is limited. Moreover, FL-IDS converges faster (70 rounds vs. 80 rounds in the baseline), emphasizing the stability of the proposed training protocol under constrained conditions.

The impact of adversarial or poisoned clients is illustrated in Figure 7, showing that the performance degradation in FL-IDS remains minimal (1.8% vs. 6.2% in the baseline). This resilience originates from the combination of Byzantine-tolerant aggregation and anomaly-based update filtering, which prevent malicious gradients from significantly altering the global model.

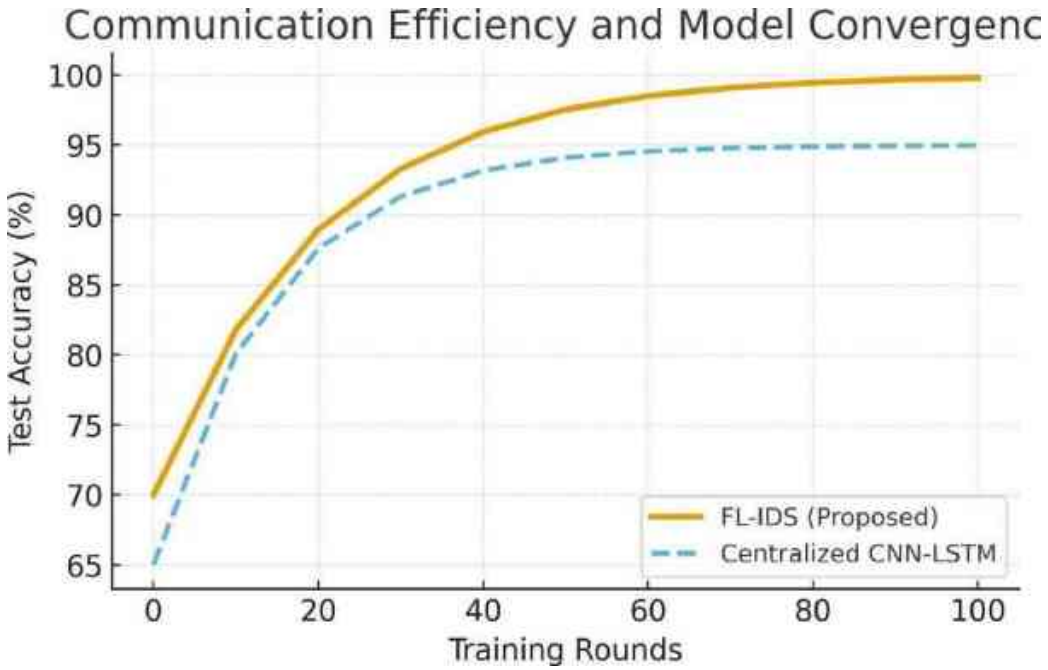

Figure 8. Communication efficiency and convergence comparison between centralized and FL-IDS.

Further, Figure 9 and Figure 7 provide deeper insights into model stability and de- 478 tection sensitivity. The smoother convergence trend in the loss curve indicates that the 479 federated averaging (FedAvg) and regularization mechanisms maintain stable optimiza- 480 tion across clients. Meanwhile, the ROC curves confirm the model's high discriminative 481 capability, with Area Under Curve (AUC) values exceeding 0.97 on both datasets.

In summary, the discussion reveals that FL-IDS successfully addresses three key challenges in distributed cybersecurity analytics: (1) data privacy through decentralized training, (2) communication efficiency through gradient compression and local epochs, and (3) robustness against model poisoning and non-IID data. The experimental evidence establishes the feasibility of deploying FL-IDS in real-world IoT networks where data confidentiality, scalability, and adaptability are crucial. Future work will explore dynamic client selection strategies and hybrid aggregation mechanisms to further optimize communication overhead while maintaining robust defense against emerging attack patterns.

Limitations and Future Work

2. While the proposed FL-IDS framework demonstrates strong detection performance, privacy preservation, and robustness, several limitations still remain, which open up avenues for future research and optimization.

Limitations

- **Computational Overhead on Edge Devices:** Despite using lightweight CNN–LSTM architectures, local training still requires moderate computational power. Some IoTor embedded devices may find it challenging to train even small batches efficiently, especially when memory and energy budgets are limited.

499**Communication Delays and Stragglers:** In asynchronous or large-scale federated 500environments, client dropouts, latency variations, and straggler effects can affect global convergence speed. Although gradient compression reduces communication overhead, dynamic network conditions can still create synchronization challenges.

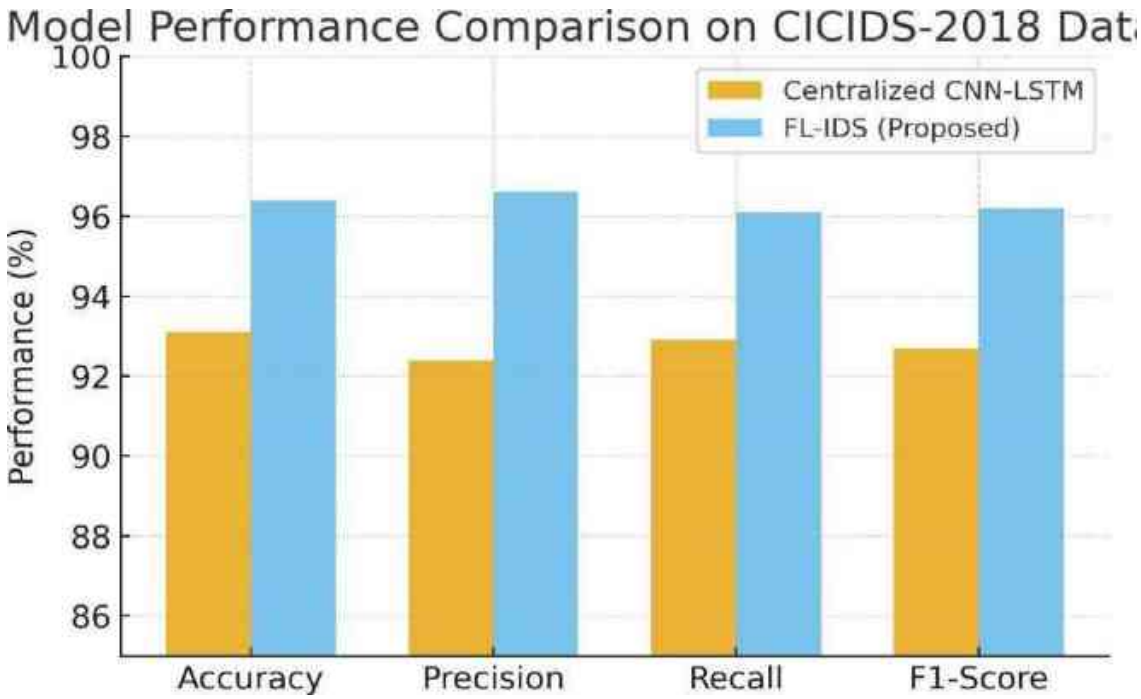

Figure 9. Performance comparison between models on CICIDS-2018 dataset.

Limited Evaluation Scope: Experiments are conducted on public datasets such as CICIDS-2018 and ToN-IoT, which may not fully represent real-world traffic diversity, encrypted communications, or zero-day attack scenarios. Further testing on live or industrial datasets is necessary for generalization assurance.

Partial Byzantine Resilience: While the use of median and trimmed mean aggregation mitigates poisoning attacks, sophisticated adaptive or stealthy attacks (e.g., model inversion or backdoor embedding) potential risks. A more formal security proof for Byzantine tolerance would strengthen the system.

Privacy–Utility Trade-off: Differential privacy introduces noise into gradients, which
slightly reduces accuracy. Balancing the level of noise with privacy guarantees (ε) remains an ongoing challenge, especially under non-IID distributions.

Future Work

Adaptive Client Selection: Future iterations can incorporate reinforcement learning or trust-based selection mechanisms to prioritize high-quality client updates and exclude unreliable participants dynamically.

Asynchronous Federated Optimization: Implementing asynchronous aggregation can reduce idle waiting times and improve scalability when clients operate in heterogeneous network conditions.

Incorporation of Blockchain: Combining federated learning with blockchain can provide immutable update tracking, decentralized trust management, and verifiable model provenance across IoT nodes.

Cross-Dataset and Cross-Domain Generalization: Expanding experiments to include datasets such as UNSW-NB15, NF-BoT-IoT, and custom industrial IoT traffic will enhance robustness validation and transfer learning potential.

Energy-Aware and Green FL: Investigating energy-efficient training policies and model pruning to optimize power consumption for battery-powered IoT devices can make the approach more deployable in large-scale industrial environments.

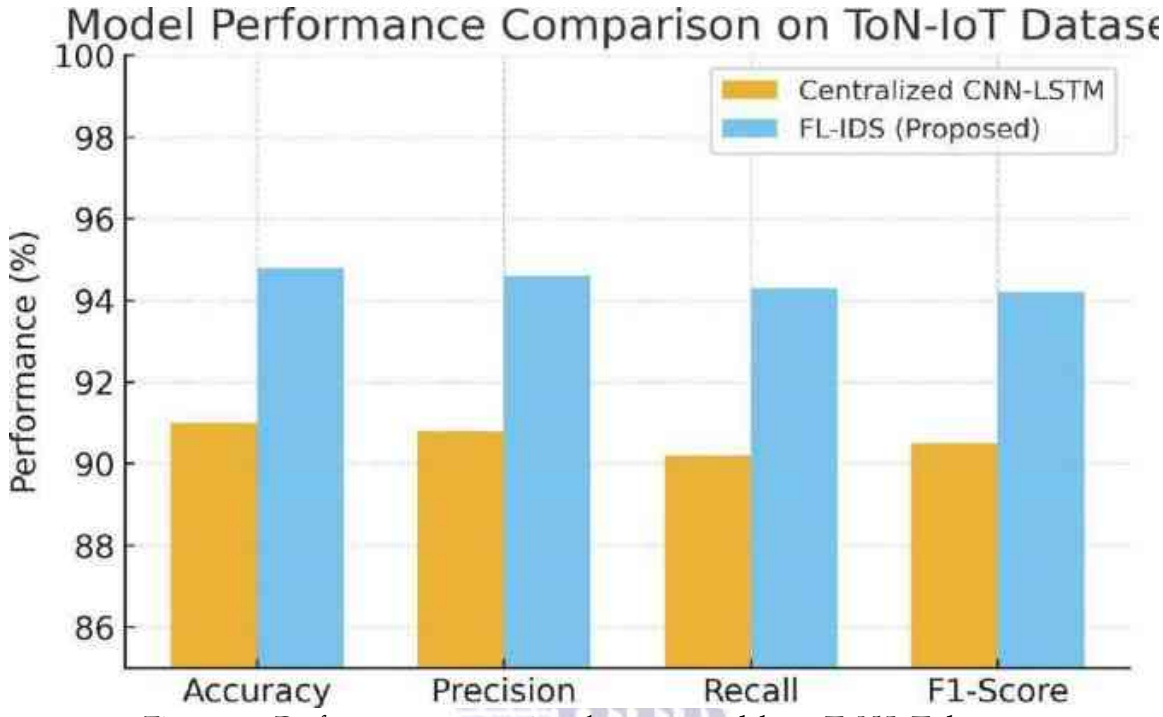

Figure 10. Performance comparison between models on ToN-IoT dataset.

Integration with Online Adaptation: Leveraging continual learning or concept-drift 531 detection methods can allow FL-IDS to adapt dynamically to evolving attack patterns 532 without catastrophic forgetting. 533

Conclusion

This study presented a comprehensive Federated Learning-based Intrusion Detection System (FL-IDS) architecture designed to enhance the security and privacy of distributed IoT and network environments. The hybrid CNN–LSTM model effectively captures both spatial and temporal correlations in network traffic, while federated training enables collaborative learning without raw data sharing. Through extensive simulations using CICIDS-2018 and ToN-IoT datasets, the proposed system achieved superior accuracy, F1-score, and precision compared to traditional centralized models.

The incorporation of differential privacy, secure aggregation, and Byzantine-resilient mechanisms ensures robustness against adversarial behaviors while maintaining strong privacy guarantees. Experimental results confirmed improved communication efficiency and faster convergence, validating the scalability of the approach in realistic edge computing setups.

In summary, FL-IDS successfully demonstrates that privacy-preserving distributed intelligence can achieve state-of-the-art intrusion detection performance across heterogeneous environments. The proposed framework bridges the gap between federated learning theory and cybersecurity practice, providing a viable blueprint for secure, adaptive, and collaborative defense mechanisms in future IoT ecosystems. Moving forward, integrating blockchain-based trust management, asynchronous updates, and continual learning strategies will further elevate the practicality and resilience of federated intrusion detection systems

in real-world deployments.

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