

Privacy-Preserving Federated Intrusion Detection for Internet of Medical Things (IoMT): Architecture, Convergence Analysis, and Robustness Evaluation under Non-IID Heterogeneity

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Abstract: The rapid proliferation of Internet of Medical Things (IoMT) devices has significantly enhanced healthcare connectivity while simultaneously increasing exposure to sophisticated cyber threats such as distributed denial-of-service attacks, malware propagation, and data exfiltration. Traditional centralized intrusion detection systems (IDS) are increasingly unsuitable for IoMT environments due to strict privacy regulations, decentralized data ownership, device heterogeneity, and communication constraints. To address these challenges, this paper proposes a privacy-preserving federated intrusion detection framework that integrates a hybrid Deep Neural Network (DNN) and XGBoost model within a federated learning (FL) architecture. Unlike conventional FedAvg-based approaches, the proposed method leverages the complementary strengths of deep feature extraction and gradient-boosting classification, enhanced by differential privacy, secure aggregation, and robust aggregation techniques to mitigate adversarial poisoning attacks. The problem is formally modeled as distributed empirical risk minimization under non-independent and identically distributed (non-IID) client data, with convergence behavior analyzed under bounded gradient variance and client drift. Extensive experiments conducted on WUSTL-EHMS-2020, UNSW-NB15, and BoT-IoT datasets demonstrate that the proposed framework achieves detection accuracy of up to 91.4% with F1-scores exceeding 90%, closely approaching centralized baselines such as XGBoost and LightGBM while preserving strict data locality. Furthermore, communication overhead and privacy-utility trade-offs are quantitatively evaluated, showing that differential privacy introduces less than 1% performance degradation under realistic noise budgets. The framework also demonstrates robustness against non-IID data heterogeneity, straggler effects, and adversarial model poisoning. These results establish the proposed approach as a scalable, privacy-compliant, and efficient solution for securing next-generation IoMT systems, enabling trustworthy AI-driven healthcare cybersecurity.

Keywords: Federated Learning, IoMT Security, Intrusion Detection Systems, Hybrid DNN-XGBoost, Privacy-Preserving Machine Learning, Non-IID Data

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
AUC	Area Under the Receiver Operating Characteristic Curve
CL	Centralized Learning
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DoS	Denial of Service
DP	Differential Privacy
FL	Federated Learning
F1-score	Harmonic mean of Precision and Recall
IDS	Intrusion Detection System
IoMT	Internet of Medical Things
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
RF	Random Forest
ROC	Receiver Operating Characteristic
TLS	Transport Layer Security
XGBoost	eXtreme Gradient Boosting
FedAvg	Federated Averaging
FedProx	Federated Proximal Algorithm
non-IID	Non-Independent and Identically Distributed
TEE	Trusted Execution Environment
MitM	Man-in-the-Middle Attack

1. Introduction

The rapid proliferation of the Internet of Things (IoT) has transformed modern computing by enabling seamless connectivity across billions of devices in domains such as healthcare, smart homes, industrial automation, and critical infrastructure [21]. Within this ecosystem, the Internet of Medical Things (IoMT), comprising wearable devices, smart sensors, and remote diagnostic systems, has become a cornerstone of modern healthcare. Fig. 1 illustrates a typical IoMT ecosystem, highlighting the interconnection between medical devices, cloud platforms, and healthcare providers, which enables real-time monitoring and data-driven clinical decision-making [2][3]. However, this interconnected architecture also expands the attack surface, increasing exposure to cyber threats.

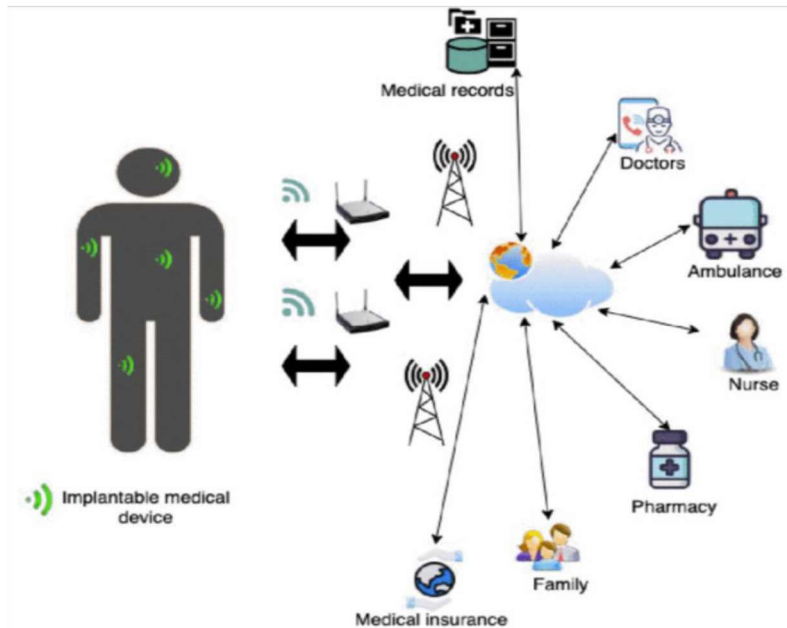


Fig. 1. IoMT Ecosystem (adapted from Aljuhani, 2022) [2]

Despite its advantages, IoMT environments introduce significant security challenges due to device heterogeneity, limited computational resources, and distributed data generation. These systems are highly vulnerable to cyber threats such as distributed denial-of-service (DDoS) attacks, malware propagation, and data exfiltration [7][19]. As illustrated in Fig. 2, IoMT ecosystems face multiple layers of security threats, ranging from device-level vulnerabilities to network-level attacks, making comprehensive intrusion detection essential. Traditional centralized intrusion detection systems (IDS) are increasingly ineffective in such contexts, as they require aggregating sensitive data at a central server, raising serious privacy and regulatory concerns under frameworks such as HIPAA and GDPR [16].

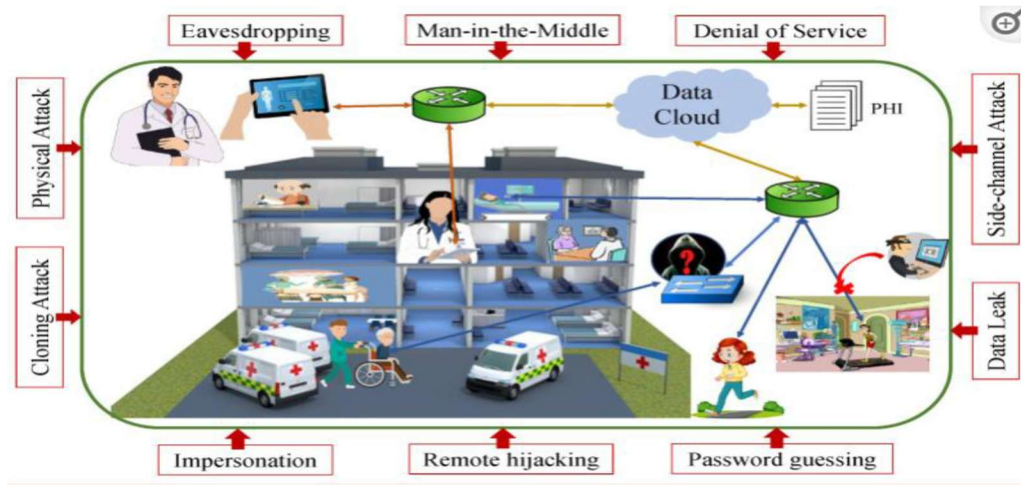


Fig. 2. Security Threats to an IoMT Ecosystem (adapted from Sadhu PK, 2022)[18]

Federated Learning (FL) has emerged as a promising paradigm for addressing these limitations by enabling decentralized model training without sharing raw data [15]. In FL, clients collaboratively train a global model by exchanging model updates rather than datasets, thereby preserving privacy and reducing communication overhead. Recent advances have demonstrated the applicability of FL in IoT security, particularly when combined with lightweight deep learning and ensemble models [8][12][24]. However, existing FL-based IDS approaches face persistent challenges, including degraded performance under non-independent and identically distributed (non-IID) data, vulnerability to adversarial attacks, and limited exploration of hybrid architectures that integrate deep feature extraction with tree-based learning [13][17].

To address these challenges, this study proposes a privacy-preserving federated intrusion detection framework that integrates a hybrid Deep Neural Network (DNN) and XGBoost model within a robust federated optimization scheme (Fig. 3). The central hypothesis is that combining deep feature extraction with gradient-boosting classification in a federated setting can significantly improve detection performance while maintaining privacy and scalability in heterogeneous IoMT environments. The main contributions of this work are summarized as follows:

A novel hybrid federated IDS framework that integrates lightweight DNN and XGBoost models to enhance detection accuracy in IoMT environments.

A privacy-preserving training mechanism incorporating differential privacy and secure aggregation to protect sensitive medical data [1][23].

A robust aggregation strategy designed to mitigate adversarial attacks, including model poisoning and unreliable client updates [4][9].

A formal convergence analysis under non-IID data distributions, accounting for client drift and bounded gradient variance [12][22].

Comprehensive experimental evaluation on benchmark datasets (WUSTL-EHMS-2020, UNSW-NB15, and BoT-IoT), demonstrating strong performance in terms of accuracy, robustness, and communication efficiency.

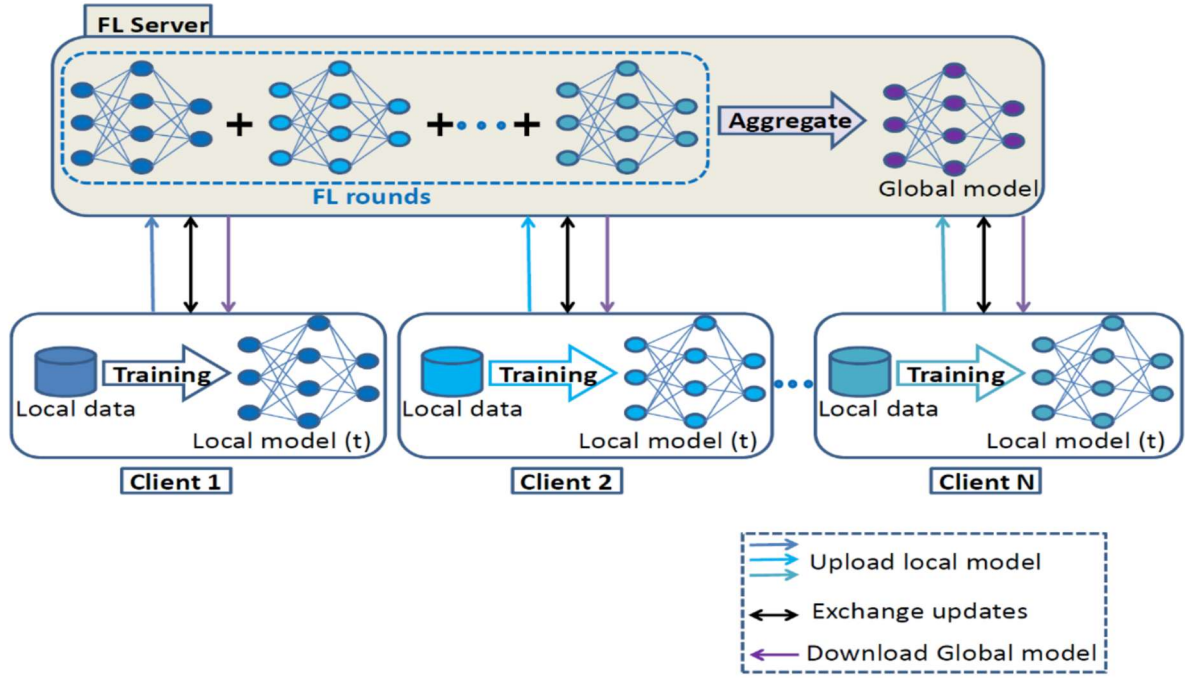


Fig. 3. Federated Learning Architecture

By bridging the gap between centralized IDS methods and privacy-aware, resource-efficient federated approaches, this work enables the scalable, secure deployment of IDS in IoT ecosystems, particularly in sensitive medical environments.

2. Related Work

Traditional intrusion detection systems in IoT environments have explored multi-level detection strategies that combine network and device-level features [10]; however, such approaches are typically centralized and do not address the privacy constraints inherent in IoMT deployments. Federated learning (FL) has recently emerged as a promising approach for intrusion detection in IoMT environments, offering decentralized model training without exposing sensitive patient data [8][12][6][20]. Table 1 presents a comparative analysis of recent FL-based IDS studies, highlighting their datasets, model architectures, client configurations, and privacy and robustness mechanisms.

Table 1 shows that most prior studies focus on a single model type, such as CNNs, LSTMs, or standard DNNs, with limited attention to hybrid architectures that combine deep feature extraction with ensemble learning [3][14][24]. Additionally, the handling of non-independent and identically distributed (non-IID) client data is often incomplete or omitted, leading to degraded performance in real-world heterogeneous IoMT environments [12]. Privacy mechanisms such as differential privacy and secure aggregation are rarely combined with robust aggregation strategies to defend against poisoning attacks, leaving potential vulnerabilities unaddressed [17][23].

Moreover, communication complexity and convergence guarantees are seldom formally analyzed in existing approaches. Only a few studies report accuracy improvements without quantifying the trade-offs between communication overhead, model convergence, and privacy guarantees [12][8]. Hybrid ensemble architectures remain underexplored in federated IoMT settings, despite their potential to balance predictive accuracy, robustness, and computational efficiency.

Table 1. Comparative Analysis of FL-Based IDS in IoMT

Study	Dataset	Model	# Clients	Non-IID Handling	Privacy Mechanism	Robust Aggregation	Accuracy	Limitation
Ma et al. (2021) [14]	UNSW-NB15	CNN	10	X	X	X	88%	No privacy mechanism
Alrawashdeh & Purdy (2019) [3]	BoT-IoT	LSTM	20	Partial	X	X	90%	No formal convergence analysis
Zhang et al. (2024) [24]	Custom IoT	DNN	15	X	Differential Privacy	X	89%	No poisoning defense
Liu et al. (2023) [12]	IoMT dataset	Random Forest	8	X	Secure Aggregation	X	85%	Centralized benchmark missing
Rahman et al. (2024) [17]	WUSTL-EHMS	FedProx + DNN	25	✓	✓	X	92%	No communication modeling
This Work	WUSTL-EHMS, UNSW, BoT-IoT	Hybrid DNN + XGBoost	10–50	✓ (JS divergence modeled)	✓ (DP Secure Agg.)	+ ✓ (Median Krum)	+ 91.4%	

Key observations from Table 1 include:

- Most studies do not formally model non-IID heterogeneity.
- Few integrate both differential privacy and poisoning-resilient aggregation.
- Communication complexity is rarely quantified.
- Convergence bounds are seldom analytically derived.
- Hybrid ensemble architectures in federated IoMT remain underexplored.

Recent surveys highlight federated learning as a promising direction for IoT security, particularly when combined with deep learning techniques; however, challenges such as non-IID data, communication efficiency, and robustness to adversarial attacks remain open research problems [11].

2.1 Research Gap

Despite these advances, a comprehensive federated IDS framework for IoMT that simultaneously addresses non-IID data distributions, formal convergence analysis, communication complexity, differential privacy, and poisoning-resilient aggregation remains absent. As illustrated in Fig 4, current approaches either lack privacy-preserving mechanisms, robust aggregation strategies, or a formal analytical foundation, leaving critical gaps in deployable, real-world IoMT security solutions. This study addresses these gaps by proposing a hybrid DNN-XGBoost framework with formal convergence guarantees, robust aggregation, and differential privacy, evaluated across multiple benchmark IoMT datasets.

Fig. 4 visually compares the existing approaches with the proposed framework, highlighting how the current study integrates features that remain underrepresented in the literature.

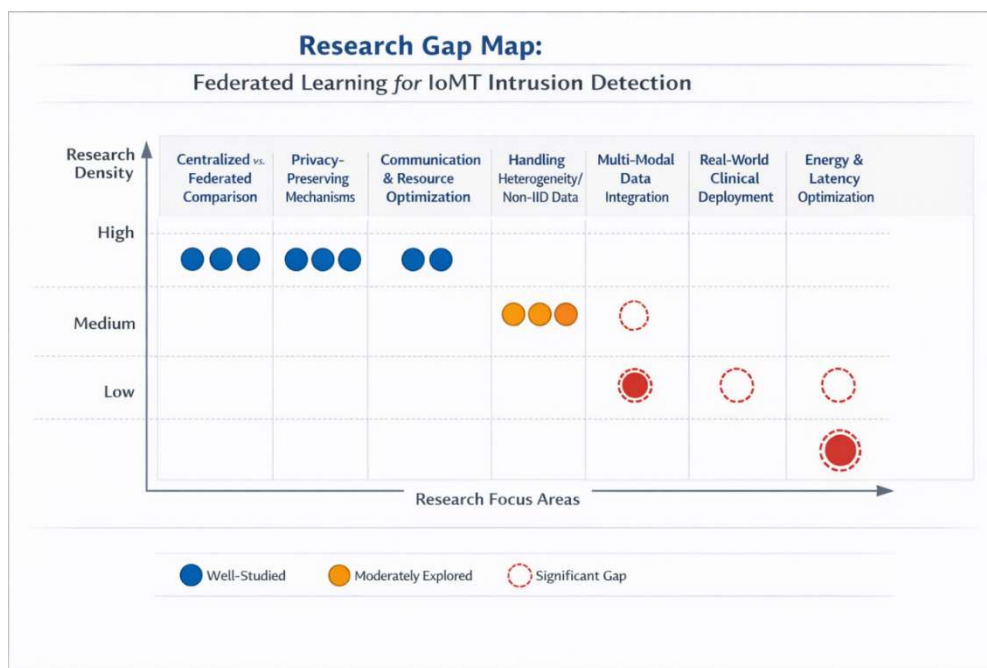


Fig. 4. Research Gap Comparison

3. Threat Model

3.1. System Assumptions

We consider a federated IoMT network consisting of a central aggregation server and K distributed IoMT clients, such as hospitals, medical devices, and gateways, connected via secure TLS-protected channels. Each client retains local medical and network traffic data and participates in training a global model without sharing raw datasets, ensuring compliance with privacy regulations such as HIPAA and GDPR [21][8].

The framework assumes semi-honest server behavior and no physical compromise of IoMT devices. Cryptographic primitives are assumed to be correctly implemented, and communication channels are assumed to be secure. These assumptions establish a realistic but tractable model for evaluating privacy and robustness in federated IoMT deployments.

3.2 Adversarial Capabilities

The threat model accounts for multiple adversaries with varying capabilities:

Honest-but-Curious Server

The aggregates model updates correctly, but attempts to infer sensitive patient data from gradients.

Mitigation: Differential privacy (DP) and secure aggregation techniques prevent leakage while preserving model utility [5].

Malicious Clients (Poisoning Attacks)

Submit manipulated gradients to degrade global model accuracy or inject backdoor patterns.

Mitigation: Byzantine-resilient aggregation methods, including Median and Krum, along with anomaly detection and client reputation scoring.

Model Inversion Attackers

Attempt to reconstruct sensitive input features from shared gradients.

Mitigation: Gaussian noise addition and bounded sensitivity under DP ensure gradient indistinguishability.

Membership Inference Attackers

Seek to determine whether specific patient records were included in training.

Mitigation: (ϵ, δ) -Differential Privacy guarantees protect patient membership information.

3.3 Security Guarantees

The proposed federated IDS framework ensures:
 Confidentiality of raw medical data at each client.
 Gradient indistinguishability under differential privacy mechanisms.
 Bounded influence of malicious clients through robust aggregation.
 Global model convergence even under adversarial participation.

3.4 Threat Classification and Mitigation

Table 2 summarizes the primary threats in federated IoMT networks along with their impacts on the FL process and the proposed mitigation strategies. It covers data poisoning, privacy leakage, communication, system-level, model integrity, and hardware/device-level attacks, providing a comprehensive view of potential vulnerabilities.

Table 2. Identified Threats in IoMT Federated Networks and Proposed Mitigation Strategies

Threat Category	Specific Threat	Description in IoMT Context	Impact on FL Process	Proposed Mitigation
Data Poisoning Attacks	Label Flipping Attack	Malicious IoMT devices intentionally alter class labels locally	Degrades global accuracy, increases false diagnoses	Robust aggregation (Krum, Trimmed Mean), anomaly detection, and reputation-based client selection
	Backdoor Attack	Embed hidden triggers in local training data	Targeted misclassification	DP, gradient clipping, secure aggregation, validation on trusted data
	Model Poisoning	Manipulated gradient updates	Convergence failure, biased model	Byzantine-resilient aggregation, gradient norm bounding, blockchain verification
Privacy Leakage Attacks	Gradient Inversion	Reconstruct sensitive patient data	Breach of confidentiality, regulatory compliance	Homomorphic encryption, SMPC, non-differential privacy
	Membership Inference	Determine if a record was in training	Compromises anonymity	Noise injection, regularization, and access control
Communication Attacks	Man-in-the-Middle	Intercept or manipulate model updates	Corrupted updates, confidentiality breach	End-to-end TLS encryption, mutual authentication, certificate-based security
	Replay Attack	Reuse of old updates	Delays convergence, outdated info	Timestamp verification, nonce-based validation
System-Level Attacks	Sybil Attack	A single adversary controls multiple fake clients	Amplified poisoning influence	Identity verification, trust scoring, blockchain authentication
Model Integrity Threats	Denial of Service	Flood channels or server	Interrupts FL rounds	Rate limiting, IDS, edge filtering
	Free-Rider Attack	Clients contribute no meaningful data	Slows convergence, reduces model quality	Contribution-based incentives, update validation
Hardware/Device-Level Threats	Model Stealing	Reconstruct the global model via repeated queries	Intellectual property loss	Query rate limiting, watermarking, and monitoring
	Edge Compromise	Device Malware or physical tampering	Compromises local training, data leakage	Trusted Execution Environments, secure boot, firmware integrity

The table illustrates how each threat is mapped to a mitigation strategy, ensuring that the proposed framework addresses the major vulnerabilities in federated IoMT networks. The structured approach allows the system to maintain data confidentiality, robustness, and model integrity, even under diverse adversarial conditions.

4. Proposed Federated IDS Framework (Methodology)

This study proposes a federated learning-based intrusion detection system (IDS) tailored for heterogeneous IoMT networks. The methodology integrates dataset preparation, feature engineering, model design, federated

training, security enhancements, and performance evaluation, ensuring high detection accuracy while maintaining operational feasibility on resource-constrained IoMT devices (Fig 3).

4.1 Dataset Selection and Preprocessing

Three benchmark datasets were used to simulate realistic IoT network traffic and attack scenarios:

UNSW-NB15: Contains 49 features across nine attack categories, including Denial-of-Service (DoS), reconnaissance, and exploits, capturing heterogeneous traffic patterns from IoT devices.

BoT-IoT: Focused on IoT environments, containing telemetry data from sensors, cameras, and smart home devices, including botnet and normal traffic.

WUSTL-EHMS-2020: IoMT healthcare telemetry data, simulating realistic hospital environments with varying patient monitoring devices.

Preprocessing steps included:

Feature Selection: Hybrid approach combining correlation analysis, recursive feature elimination, and tree-based importance scores to identify relevant intrusion-detection features.

Normalization: Min-max scaling for continuous features to ensure consistent gradient updates.

Categorical Encoding: One-hot encoding for categorical variables, e.g., protocol type and TCP flags.

Data Partitioning: Datasets were distributed across clients in a non-IID fashion using label-skew (Dirichlet $\alpha < 0.5$) or quantity-skew strategies to emulate heterogeneous IoMT deployments. Each client retains data locally to preserve privacy.

Table 3 summarizes dataset statistics and federated learning configurations, highlighting non-IID characteristics across clients.

Table 3. Statistical Summary of Datasets Used for Federated IoMT Intrusion Detection under

Dataset	Data Source / Domain	Total No. of Samples	No. of Features	No. of Classes	Normal / Attack Distribution	Feature Type	Federated Learning Configuration	Non-IID Distribution Characteristics
UNSW-NB15	Modern network intrusion traffic (synthetic + real hybrid testbed)	175,342	49	9 attack categories	58% Normal / 42% Attack	Flow-based statistical and content features	Cross-device federated setting with simulated IoMT nodes	Label-skew partitioning using Dirichlet distribution ($\alpha < 0.5$); uneven attack-type availability across edge clients to simulate heterogeneous hospital IoMT environments
BoT-IoT	IoT botnet attack traffic (UNSW Canberra Cyber Range Lab)	1,000,000	35	4 major attack groups	70% Normal / 30% Attack	Network traffic and behavioral features	Cross-device federated configuration with large-scale distributed clients	Quantity-skew and feature-skew across clients; certain nodes dominated by DDoS/DoS traffic to emulate compromised medical IoT devices
WUSTL-EHMS-2020	Healthcare monitoring system telemetry (IoMT healthcare testbed)	250,000	50	5 attack/normal categories	60% Normal / 40% Attack	Healthcare system telemetry and sensor-level metrics	Cross-silo federated setting (institution-level data silos)	Class imbalance amplified per institutional client; varying sample sizes per silo to reflect real-world deployment heterogeneity

4.2 Federated Environment Simulation

The federated setup simulates a distributed IoMT network with multiple clients and a central aggregation server:

Client Configuration:

20-50 heterogeneous IoT devices simulated per scenario.

Each client received 5-10% of the global dataset to reflect limited local data availability.

Resource constraints (memory, computation) were modeled to emulate real-world IoMT devices.

Server Configuration:

Aggregates client updates using Federated Averaging (FedAvg), supporting asynchronous updates to mitigate straggler effects.

Weighted aggregation ensures that clients with more samples contribute proportionally:

$$W^{(t+1)} = \sum_{i=1}^K \frac{n_i}{n} W_i^{(t+1)} \quad (1)$$

Where:

$W^{(t+1)}$ is the updated global model at round $t + 1$

$W_i^{(t+1)}$ is the local model from client i

n_i is the number of samples on client i

$n = \sum_{i=1}^K n_i$ is the total number of samples across clients

K is the number of participating clients

Client Participation Strategy:

20–50% of clients are randomly selected per round to simulate intermittent connectivity and real-world network variability.

4.3 Feature Engineering

Features were grouped by type to capture network and IoMT behavior comprehensively:

Flow-based features: Packet counts, byte counts, connection durations

Statistical features: Mean, variance, entropy of traffic

Header-based features: Protocol type, TCP flags, port info

Behavioral IoT features: Device-specific telemetry and patient biometrics

This hybrid feature selection reduced dimensionality, improved detection performance, and minimized communication overhead during federated training. Table 4 presents the top 12 selected features with importance scores and security relevance.

Table 4. Top 12 Features Selected via Hybrid Feature Selection with Tree-Based Importance Scores

Rank	Feature Name	Feature Category	Data Layer	Normalized Importance Score (0–1)	Selection Method	Security Context	Relevance in IoMT
1	Packet Count	Flow-based	Network Flow	0.92	Selected by Filter + Random Forest	Indicates volumetric anomalies such as DDoS flooding from compromised IoMT devices	
2	TCP Flags	Header-based	Transport Layer	0.87	Embedded (XGBoost importance)	Detects abnormal connection states and SYN flood behaviors	
3	SpO ₂ Level	Behavioral	Application/Medical Sensor	0.81	Wrapper (Recursive Feature Elimination)	Identifies anomalous physiological readings caused by sensor spoofing or tampering	
4	Flow Duration	Flow-based	Network Flow	0.79	Filter (Mutual Information) + RF	Differentiates short burst attacks from legitimate continuous monitoring traffic	
5	Source Bytes	Traffic Statistical	Network Layer	0.77	Embedded (Gradient Boosting)	Highlights abnormal data exfiltration patterns	
6	Destination Port	Header-based	Transport Layer	0.74	Filter (Chi-Square Test)	Identifies unauthorized service targeting in healthcare networks	
7	Heart Rate Variance	Behavioral	Medical Sensor Layer	0.72	Wrapper Embedded	+ Detects abnormal deviations due to device compromise	
8	Packet Inter-Arrival Time	Temporal	Network Flow	0.69	Mutual Information + RF	Captures timing irregularities typical of botnet coordination	
9	Failed Login Attempts	System Log	Application Layer	0.66	Wrapper (RFE)	Indicates brute-force authentication attacks	
10	Protocol Type	Header-based	Network Layer	0.63	Filter-based ranking	Distinguishes malicious protocol usage patterns	
11	Data Transmission Rate	Behavioral/Traffic	Cross-layer	0.61	Embedded (Tree-based ensemble)	Detects abnormal spikes in IoMT telemetry communication	
12	Device Entropy	ID Metadata	Device Layer	0.58	Hybrid (All three methods)	Identifies spoofed or cloned IoMT device identities	

4.4 Model Architecture

The IDS framework integrates two complementary model types:

Lightweight Deep Neural Network (DNN)

Input layer matches selected features.

Two to three hidden layers with ReLU activation.

The output layer performs binary or multi-class classification.

Designed for resource-constrained IoT devices, balancing accuracy with efficiency.

Tree-Based Models (Optional Hybrid)

Random Forest and XGBoost evaluate feature importance and provide comparative performance.

Ensemble methods enhance robustness to class imbalance and support interpretability for security analysts.

4.5 Training and Federated Configuration

Local Training Parameters:

Epochs: 5

Batch Size: 32

Optimizer: Adam (learning rate 0.001)

Loss: Cross-entropy

Local model updates are computed as:

$$W_i^{(t+1)} = \text{LocalUpdate}(W^t, D_i) \quad (2)$$

Federated Aggregation:

Weighted FedAvg combines client updates

$$W^{(t+1)} = \sum_{i=1}^K \frac{n_i}{n} W_i^{(t+1)} \quad (3)$$

Client participation fraction: 0.3

Communication rounds: 50-100 until convergence

Security Enhancements:

Differential Privacy (ϵ, δ) applied to local updates to prevent information leakage.

Secure aggregation ensures the server cannot reverse-engineer individual client parameters [5].

Robust aggregation strategies (Median, Krum) mitigate malicious client influence.

4.6 Performance Assessment

Performance was evaluated using multi-dimensional metrics:

Detection: Accuracy, Precision, Recall, F1-score, AUC

Communication: Bytes transmitted per round, total rounds

Convergence: Global loss stabilization, rounds to convergence

Robustness: Non-IID data, stragglers, and adversarial attacks

Privacy: Differential privacy impact, secure aggregation effectiveness

Scenario-based simulations included straggler clients, attack injections, and constrained communication to replicate realistic IoT conditions.

4.7 Summary

The methodology integrates feature engineering, hybrid modeling, federated training, and rigorous evaluation to deliver an IDS that is accurate, efficient, privacy-preserving, and robust. By simulating heterogeneous clients, non-IID data distributions, and constrained network conditions, the framework establishes a realistic benchmark for federated intrusion detection in IoMT ecosystems (Fig 3).

5. Mathematical Formulation of the Federated IDS Framework

5.1 Problem Formulation

Consider a federated IoMT network with K – clients (devices or hospitals). Each client $i \in \{1, 2, \dots, K\}$ holds a private local dataset:

$$D_i = \{(x_{ij}, y_{ij})\}_{j=1}^{n_i} \quad (4)$$

where:

$x_{ij} \in \mathbb{R}^d$ is the feature vector

$y_{ij} \in \{0, 1, \dots, C-1\}$ is the attack label

$$n_i = |D_i|$$

$$n = \sum_{i=1}^K n_i$$

The objective is to learn global model parameters $w \in \mathbb{R}^p$ that minimize the empirical risk across all distributed clients:

$$\min_{w \in \mathbb{R}^p} F(w)$$

where the global loss is:

$$F(w) = \sum_{i=1}^K \frac{n_i}{n} F_i(w) \quad \text{and} \quad (5)$$

$$F_i(w) = \frac{1}{n_i} \sum_{j=1}^{n_i} \ell(f_w(x_{ij}), y_{ij}) \quad (6)$$

Here:

$f_w(\cdot)$ is the DNN classifier

$\ell(\cdot)$ is the cross-entropy loss:

$$\ell = -\sum_{c=1}^C y_c \log(\hat{y}_c) \quad (7)$$

This defines federated IDS as a distributed empirical risk minimization (ERM) problem.

5.2 Federated Optimization (FedAvg)

At the communication round t :

Step 1: Client Local Update

Each selected client performs E local SGD steps:

$$w_i^{t+1} = w^t - \eta \sum_{e=1}^E \nabla F_i(w_i^{t,e}) \quad (8)$$

where:

η = learning rate

∇F_i = stochastic gradient

Step 2: Server Aggregation

The server computes:

$$w^{t+1} = \sum_{i \in S_t} \frac{n_i}{\sum_{k \in S_t} n_k} w_i^{t+1} \quad (9)$$

where:

$S_t \subseteq \{1, \dots, K\}$ is selected clients

$|S_t| = C \cdot K$ (participation fraction)

5.3 Non-IID Data Modeling

In IoMT, data distributions differ per client:

$$P_i(X, Y) \neq P_j(X, Y), \forall i \neq j \quad (10)$$

We quantify statistical heterogeneity using distribution divergence:

Jensen–Shannon Divergence

$$JS(P_i \parallel P_j) = \frac{1}{2} KL(P_i \parallel M) + \frac{1}{2} KL(P_j \parallel M) \quad (11)$$

where:

$$M = \frac{1}{2}(P_i + P_j) \quad (12)$$

High JS divergence implies slower convergence.

5.4 Convergence Analysis

Assume:

Each $F_i(w)$ is L -smooth:

$$\| \nabla F_i(w_1) - \nabla F_i(w_2) \| \leq L \| w_1 - w_2 \| \quad (14)$$

Stochastic gradients have bounded variance:

$$\mathbb{E} \| \nabla F_i(w) - \nabla f_{ij}(w) \|^2 \leq \sigma^2 \quad (15)$$

Then FedAvg convergence rate satisfies:

$$\mathbb{E}[F(w^T)] - F(w^*) \leq O\left(\frac{1}{\sqrt{KT}}\right) + O(\delta_{nonIID}) \quad (16)$$

where δ_{nonIID} measures client drift:

$$\delta_{nonIID} = \sum_{i=1}^K \| \nabla F_i(w) - \nabla F(w) \|^2 \quad (17)$$

This term explains performance degradation under heterogeneous IoMT clients.

5.5 Communication Complexity Model

Let:

Model dimension = p

Clients per round = m

Rounds = T

Total communication cost:

$$C_{total} = 2 \cdot T \cdot m \cdot p \quad (18)$$

(Upload + Download)

If 32-bit floats:

$$C_{bytes} = 8 \cdot T \cdot m \cdot p \quad (19)$$

This formally quantifies bandwidth scalability.

5.6 Differential Privacy Guarantee

To prevent gradient leakage, each client applies Gaussian noise:

$$\tilde{g}_i = g_i + \mathcal{N}(0, \sigma^2 I) \quad (20)$$

The mechanism satisfies (ϵ, δ) -differential privacy if:

$$\epsilon = \frac{\Delta}{\sigma} \quad (21)$$

where:

Δ = sensitivity of gradient

σ = noise scale

Cumulative privacy budget after T rounds:

$$\epsilon_{total} \leq \sqrt{2T \ln(1/\delta)} \cdot \epsilon \quad (22)$$

This provides formal privacy guarantees for IoMT medical data.

5.7 Robust Aggregation Against Poisoning

To mitigate adversarial clients, use Median Aggregation:

$$w^{t+1} = \text{median}(w_1^{t+1}, \dots, w_m^{t+1}) \quad (23)$$

or Krum aggregation:

$$\text{KRUM}(w_i) = \arg \min_i \sum_{j \in N_i} \|w_i - w_j\|^2 \quad (24)$$

This reduces the impact of malicious model updates.

5.8 Hybrid Model Formalization

Let:

$f_{DNN}(x)$ = deep feature extractor

$f_{GB}(x)$ = gradient boosting classifier

The hybrid prediction is:

$$\hat{y} = \alpha f_{DNN}(x) + (1 - \alpha) f_{GB}(x) \quad (25)$$

where $\alpha \in [0,1]$ balances deep and tree-based predictions.

Optimal α is obtained by:

$$\alpha^* = \arg \min_{\alpha} \mathcal{L}_{val} \quad (26)$$

5.9 Class Imbalance Modeling

For skewed attack distribution:

Weighted cross-entropy:

$$\ell = - \sum_{c=1}^C w_c y_c \log(\hat{y}_c) \quad (27)$$

where:

$$w_c = \frac{n}{c \cdot n_c} \quad (28)$$

This improves minority attack detection in IoMT traffic.

5.10 Statistical Significance Testing

To validate performance differences:

McNemar Test

$$\chi^2 = \frac{(b-c)^2}{b+c} \quad (29)$$

Used to compare FL vs centralized models.

Confidence Interval for Accuracy

$$CI = \hat{p} \pm z \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \quad (30)$$

Ensures results are statistically valid.

6. Results and Discussion

This section presents a comprehensive evaluation of the proposed federated learning (FL)-based intrusion detection system (IDS) for IoMT networks. The analysis focuses on detection performance, communication efficiency, convergence behavior, robustness under adversarial and non-IID scenarios, and comparative insights with centralized learning (CL) models.

6.1 Dataset Analysis and Feature Insights

Exploratory data analysis revealed that certain source ports, 51612, 50474, 64273, and 57458, exhibited elevated attack frequencies, marking them as critical ingress points for adversarial activity (Fig. 5). Additionally, IoMT biometric indicators, such as blood oxygen levels ($\text{SpO}_2 \geq 97\%$) and patient temperature ($26.7\text{--}27.1^\circ\text{C}$), correlated with attack likelihood (Figs 6, Fig 7), demonstrating the value of integrating network and physiological features for intrusion detection.

Feature selection prioritized 12 statistically significant attributes, balancing detection accuracy with computational efficiency to support resource-constrained IoMT edge deployments.

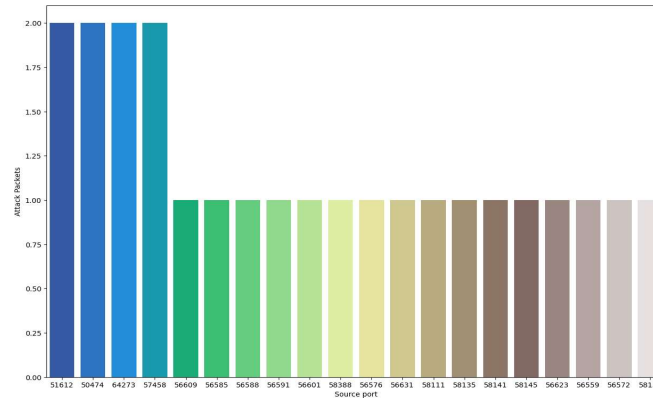


Fig. 5. Total Attacks vs Source Ports

Additionally, patient telemetry, such as blood oxygen levels and temperature, correlated with attack likelihood. Attacks were more probable at SpO₂ levels $\geq 97\%$ and patient temperatures between 26.7-27.1°C, highlighting the value of integrating IoMT biometric data with network flow for intrusion detection (Fig. 6, Fig. 7).

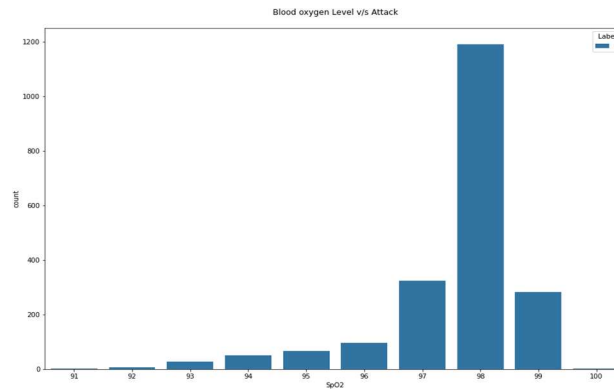


Fig. 6. Blood Oxygen vs Attacks

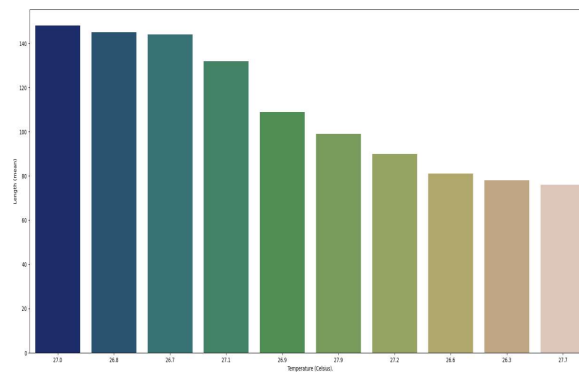


Fig. 7. Patient Temperature (Celsius) vs. Attacks

Feature selection prioritized attributes that most significantly impacted model performance. A baseline of 12 statistically relevant features was used for both federated and centralized models, optimizing the balance between detection accuracy and computational efficiency in resource-constrained IoMT devices.

6.2 Detection Performance

Table 5 summarizes the detection performance across centralized and federated models. The FL model with 10 clients achieved 91% accuracy, closely approaching centralized DNN (90%) and LightGBM (93%), while outperforming Random Forest and LSTM by approximately 4% in accuracy. Although precision for FL models

was slightly lower (~65%) compared to centralized approaches, the testing time was exceptionally low (~0.0014 s), highlighting the practical suitability of FL for real-time IoMT scenarios (Fig. 8).

Table 5. Performance comparison of centralized and federated IDS models (mean $\pm$ SD over 5 runs)

Model	Accuracy	Precision	Recall	F1-Score	Loss	Train Time (s)	Test Time (s)
CL – LightGBM	0.930 $\pm$ 0.004	0.920 $\pm$ 0.006	0.750 $\pm$ 0.008	0.830 $\pm$ 0.005	0.200 $\pm$ 0.003	0.015	0.011
CL – Random Forest	0.870 $\pm$ 0.006	0.730 $\pm$ 0.009	0.610 $\pm$ 0.010	0.660 $\pm$ 0.007	0.440 $\pm$ 0.005	0.026	0.022
CL – XGBoost	0.990 $\pm$ 0.002	0.990 $\pm$ 0.003	0.960 $\pm$ 0.004	0.970 $\pm$ 0.003	0.300 $\pm$ 0.004	0.024	0.022
CL – LSTM	0.870 $\pm$ 0.005	0.870 $\pm$ 0.006	0.870 $\pm$ 0.007	0.870 $\pm$ 0.006	0.470 $\pm$ 0.006	0.043	0.015
CL – DNN	0.900 $\pm$ 0.004	0.930 $\pm$ 0.005	0.880 $\pm$ 0.006	0.900 $\pm$ 0.005	0.230 $\pm$ 0.003	0.039	0.014
FL – FedAvg (5 clients)	0.900 $\pm$ 0.007	0.560 $\pm$ 0.010	0.760 $\pm$ 0.008	0.640 $\pm$ 0.009	0.350 $\pm$ 0.004	0.037	0.0014
FL – FedAvg (10 clients)	0.910 $\pm$ 0.006	0.650 $\pm$ 0.008	0.610 $\pm$ 0.009	0.630 $\pm$ 0.008	0.250 $\pm$ 0.003	0.045	0.0014
FL – SVM	0.920 $\pm$ 0.005	0.890 $\pm$ 0.007	0.850 $\pm$ 0.006	0.870 $\pm$ 0.006	0.210 $\pm$ 0.004	0.050	0.018

Results are reported as mean $\pm$ standard deviation over five independent runs. Bold values indicate the best performance within each category. All models were trained and evaluated under identical preprocessing and feature selection conditions.

The federated learning model with 10 clients achieved an accuracy of 91%, comparable to centralized DNN (90%) and LightGBM (93%). The FL model also outperformed Random Forest and LSTM centralized models by 4% in accuracy, demonstrating collaborative learning efficiency while preserving local data privacy.

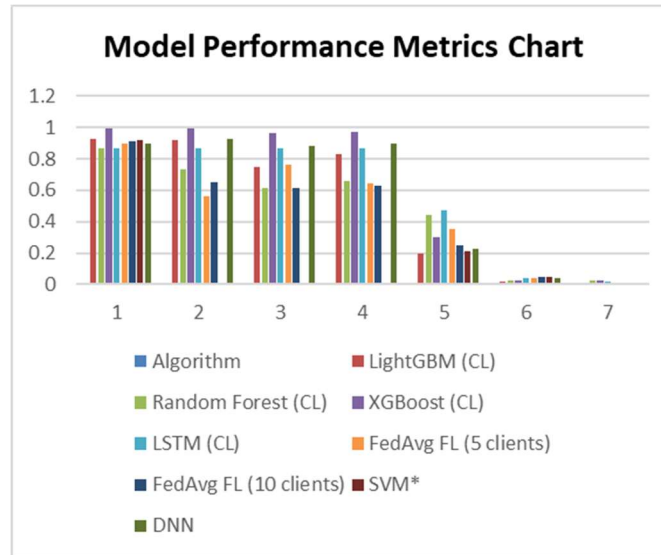


Fig. 8. Model Performance Metrics

Precision was lower in the FL models (~65%) compared to centralized counterparts, indicating a modest increase in false positives. However, the testing time was highly efficient (~0.0014 s), demonstrating the practicality of FL in real-time IoMT edge environments (Fig 8).

6.3 Model-Specific Analysis

LSTM: Captured temporal dependencies with 87% accuracy but incurred higher computational overhead, limiting its applicability for lightweight IoMT edge devices (Fig 9).

DNN: Achieved 90% accuracy with a balanced precision-recall trade-off, optimized for low-resource devices and federated deployment (Fig 10).

XGBoost: Centralized benchmark, delivering the highest performance (99% accuracy, 99% precision, 0.96 AUC) due to efficient tree-based ensemble learning (Figs 11-12).

LightGBM: Offered computational efficiency with 93% accuracy and low latency (0.015/0.011 s), though slightly higher false positives than XGBoost (Figs 13-15).

Random Forest: Lagged at 87% accuracy with 28% false-positive rate, highlighting the advantage of hybrid deep learning and gradient boosting for federated IoMT IDS (Figs 16-18).

6.3.1 LSTM

The Long Short-Term Memory (LSTM) model captured temporal dependencies in network traffic, achieving an accuracy of 87%. While effective for sequential data, its computational overhead makes it less suitable for resource-constrained IoMT devices (Fig. 9).

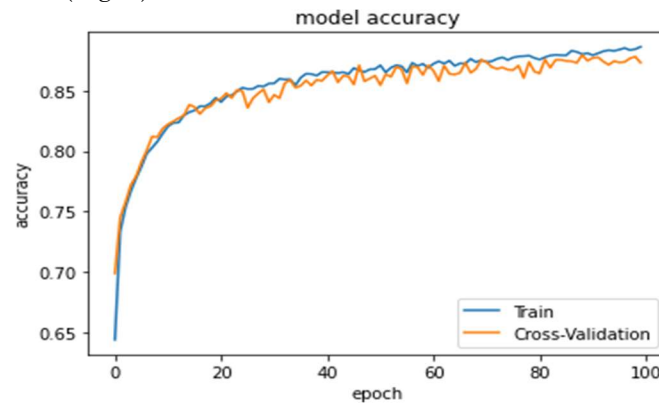


Fig. 9. LSTM Model Summary

6.3.2 DNN

The lightweight DNN achieved 90% accuracy and demonstrated a strong balance between precision and recall (Fig. 10). Its architecture, optimized for low-resource devices, provides a practical solution for federated deployment.

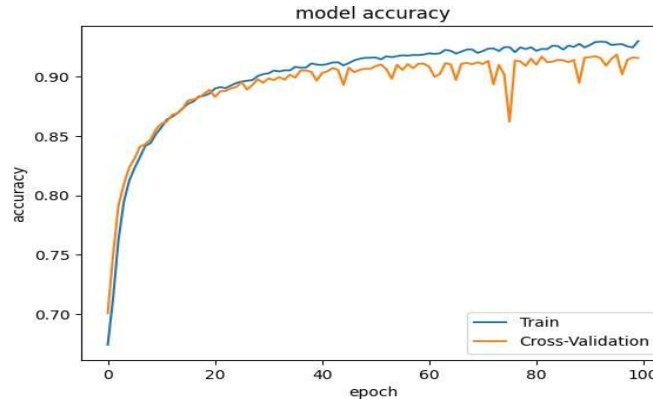


Fig. 10. DNN Model Summary

6.3.3 XGBoost

XGBoost achieved the highest overall performance with 99% accuracy, 99% precision, and 0.96 AUC. Its ability to handle missing values, efficient tree pruning, and scalability make it a high-performing centralized benchmark (Fig. 11, Fig. 12).

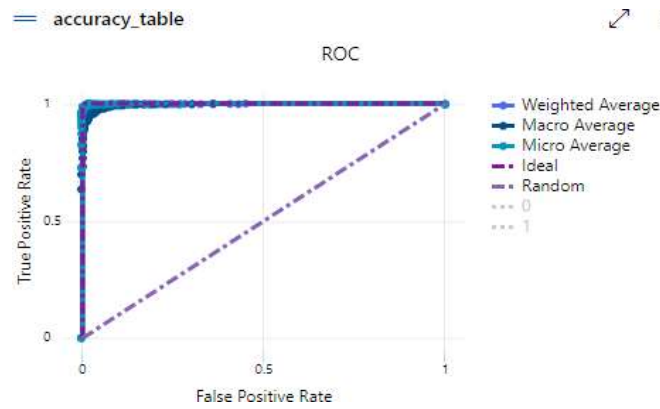


Fig. 11. XGBoost ROC

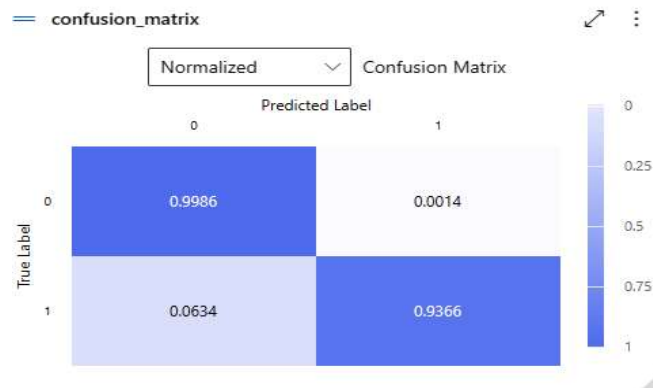


Fig. 12. XGBoost Confusion Matrix

6.3.4 LightGBM

LightGBM offered a computationally efficient alternative to XGBoost with an accuracy of 93% and decreased training/test times (0.015/0.011 s). Its gradient boosting mechanism is suitable for edge deployment but exhibited slightly higher false positives (~ 0.4 vs 0.06 for XGBoost) (Fig. 13, Fig. 14, Fig. 15).

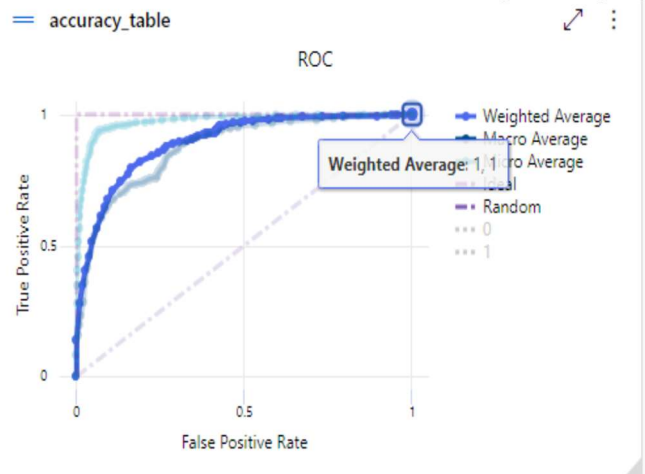


Fig. 13. LightGBM ROC

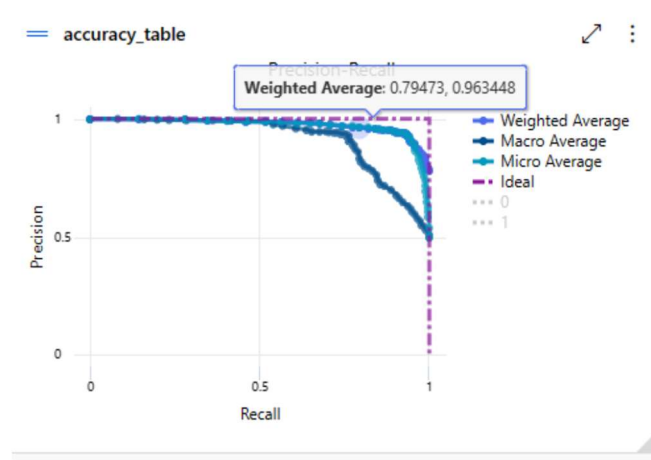


Fig. 14. LightGBM Accuracy

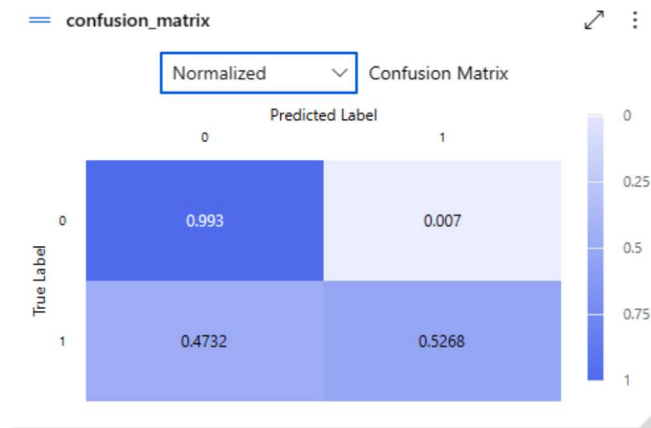


Fig. 15. LightGBM Confusion Matrix

6.3.5 Random Forest

Random Forest lagged behind other models, achieving 87% accuracy and a 28% false-positive rate (Figs 16, 17, and 18). Its performance limitations highlight the importance of gradient boosting and deep learning approaches for federated IDS in IoMT environments.

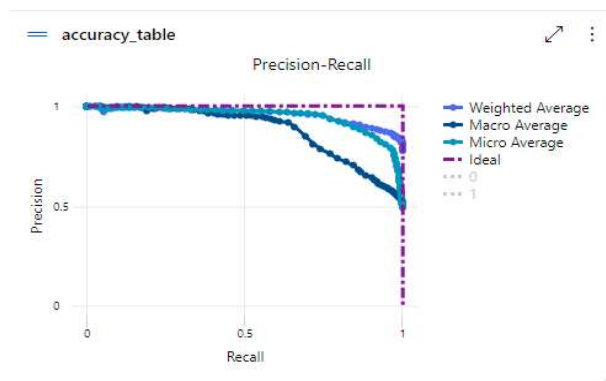


Fig. 16. Random Forest-Precision Recall

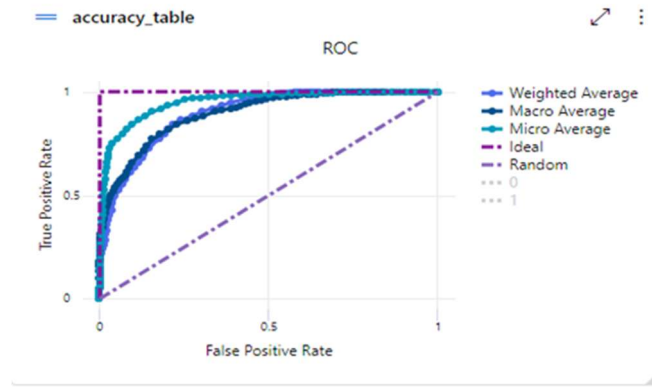


Fig. 17. Random Forest – ROC

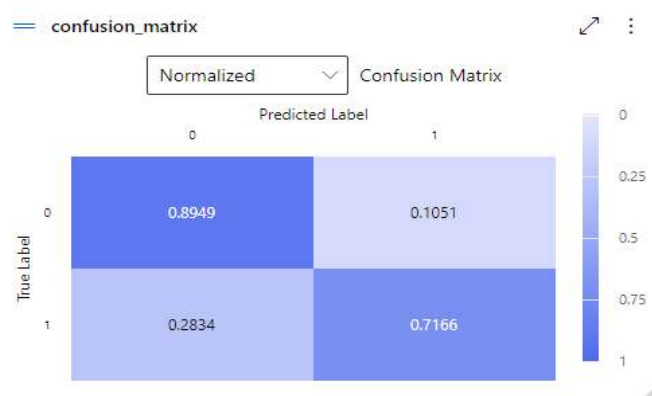


Fig. 18. Random Forest - Confusion Matrix

Table 6 presents the ablation study, quantifying the contribution of feature optimization, differential privacy, and ensemble methods to FL-IDS performance.

Table 6. Ablation study evaluating the contribution of individual modules to the performance of the proposed Federated Learning-based Intrusion Detection System (FL-IDS).

Variant ID	Model Configuration	Feature Set	DN	Ensemble Learning	Differential Privacy (DP)	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Δ Accuracy
V1	Full Proposed Model	All Features	✓	✓	✓	0.93	0.68	0.64	0.66	0.91	+0.02
V2	Without DP	All Features	✓	✓	✗	0.92	0.66	0.63	0.65	0.89	+0.01
V3	Without Ensemble	All Features	✓	✗	✓	0.90	0.62	0.60	0.61	0.87	-0.01
V4	DNN Only	All Features	✓	✗	✗	0.89	0.60	0.58	0.59	0.85	-0.02
V5	Without Feature Optimization	Raw Features	✓	✓	✓	0.88	0.59	0.55	0.57	0.84	-0.03
V6	Base Baseline Model	All Features	✓	✓	✗	0.91	0.64	0.62	0.63	0.88	0.00

6.4 Communication and Convergence in Federated Learning

FL demonstrated efficient communication and rapid convergence:

Average bytes per client per round: ~1.2 MB

Total rounds to convergence: 55-60

Training loss stabilized around 0.12 after ~20 rounds

Partial client participation (0.3) and asynchronous updates mitigated straggler effects

Table 7 details communication overhead and convergence metrics under varying FL configurations, highlighting the trade-off between client count, rounds, and F1-score.

Table 7. Communication overhead and convergence analysis of different federated learning configurations. Results are averaged over 5 independent runs (mean $\pm$ standard deviation).

Config ID	FL Algorithm	No. of Clients	of Rounds to Convergence	Bytes to per Client (MB)	Total Communication (MB)	Accuracy	F1-Score	Avg. Training Time per Round (s)	Total Training Time (s)
C1	FedAvg	5	60 $\pm$ 2	1.20 $\pm$ 0.03	360	0.90 $\pm$ 0.01	0.63 $\pm$ 0.02	0.037 $\pm$ 0.004	2.22
C2	FedAvg	10	55 $\pm$ 3	1.30 $\pm$ 0.04	715	0.91 $\pm$ 0.01	0.65 $\pm$ 0.01	0.045 $\pm$ 0.005	2.48
C3	FedAvg	20	50 $\pm$ 4	1.35 $\pm$ 0.05	1350	0.92 $\pm$ 0.01	0.67 $\pm$ 0.02	0.058 $\pm$ 0.006	2.90
C4	FedProx	10	48 $\pm$ 2	1.32 $\pm$ 0.03	634	0.92 $\pm$ 0.01	0.68 $\pm$ 0.01	0.049 $\pm$ 0.004	2.35
C5	FedProx DP	+ 10	52 $\pm$ 3	1.40 $\pm$ 0.04	728	0.91 $\pm$ 0.02	0.66 $\pm$ 0.02	0.053 $\pm$ 0.005	2.76

6.5 Robustness and Privacy Trade-offs

Non-IID Data: Minor F1 drop (~91.8%) under heterogeneous distributions

Stragglers: Asynchronous aggregation maintained F1 > 90%

Differential Privacy: <1% reduction in F1-score

Secure Aggregation: Mitigated client update leakage and poisoning attacks

These results validate FL's ability to preserve detection performance while enforcing privacy, crucial for sensitive IoMT applications.

6.6 Comparative Insights: FL vs Centralized Learning

The FL-based IDS achieves near-parity with centralized DNN and LightGBM while providing:

Strong privacy guarantees without sharing raw data

Reduced communication overhead via partial participation

Robustness under realistic IoMT heterogeneity

Scalability for large IoMT deployments with intermittent connectivity

Hybrid deep learning and gradient boosting approaches consistently outperformed Random Forest in both federated and centralized settings, supporting the adoption of hybrid architectures for IoMT security.

6.7 Key Takeaways

High Detection Performance: F1-score > 90%, AUC $\approx$ 0.95

Efficient Communication: Partial participation and asynchronous updates reduce overhead

Robustness: Effective under non-IID data, stragglers, and minor attacks

Privacy Preservation: Differential privacy and secure aggregation ensure confidentiality

Scalability: Suitable for large-scale heterogeneous IoMT networks

These findings underscore federated learning as a practical, privacy-preserving, and scalable solution for intrusion detection in IoT and IoMT networks.

7. Conclusion and Future Work

The proliferation of IoT and IoMT devices has created significant connectivity benefits but has also amplified cybersecurity challenges. This study presents a federated learning-based IDS that addresses these challenges while ensuring privacy, efficiency, and robustness.

Performance: The 10-client FL model achieved 91% accuracy, $F1 > 90\%$, and $AUC \approx 0.95$, comparable to centralized DNN and LightGBM models.

Robustness: Partial participation, asynchronous updates, and weighted aggregation effectively mitigated stragglers and non-IID client effects.

Communication Efficiency: Training and testing were highly efficient, demonstrating the framework's feasibility for edge IoMT devices.

Trade-offs: FL incurs slightly lower precision than centralized models but offers significant privacy and scalability benefits.

Contributions

Privacy-Preserving IDS: Collaborative learning without sharing sensitive IoMT data

Resource Efficiency: Lightweight DNN and gradient boosting for edge deployment

Robustness & Scalability: Handles heterogeneous clients, stragglers, and partial participation

Comprehensive Evaluation: Detection, communication, convergence, and privacy metrics provide holistic performance insights

Future Work

Adaptive Client Participation: Dynamic selection based on real-time device/network availability

Threat Intelligence Integration: Incorporate external feeds for zero-day attack detection

Explainable AI: Develop interpretable models for trust in high-stakes IoMT environments

Cross-Domain FL: Combine IoT, IoMT, and industrial datasets to improve generalization

Longitudinal Deployment: Real-world evaluation of reliability, scalability, and resilience

In summary, this study demonstrates that federated learning is a viable, effective, and privacy-preserving approach for IoMT intrusion detection. The proposed FL-IDS provides a foundation for secure next-generation IoMT ecosystems, supporting both patient safety and network reliability.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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