Privacy-Preserving Federated Deep Learning for Cybersecurity Analytics in Decentralised IoT Networks

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Abstract

Rapid propagation of Internet of Things (IoT) devices has created new opportunities and threats, particularly when they are operated in decentralized networks where data aggregation to a central point is difficult or privacy- sensitive. In this work, we investigate a privacy-preserving FDL framework for cybersecurity analytics in decentralised IoT systems. In contrast to centralised data collection which is used by classical machine learning models, the proposed scheme allows the training of deep neural networks in a distributed manner among IoT nodes without disclosing raw data and thereby preserving user and device privacy. The study combines federated averaging, differential privacy and homomorphic encryption in order to reduce adversarial threats, for better protection against inference attacks while maintaining high accuracy for detecting anomalies and cyber intrusions. Simulation results over diverse IoT setups show robust convergence of the proposed approach with low communication overhead, and outperforming standard centralised and the non-federated model in terms of accuracy, resiliency, and privacy guarantees. The results emphasise the potential of federated deep learning as a linchpin for secure and scalable trustworthy cybersecurity analytics in future decentralised IoT networks.

Keywords: Federation, Privacy, Encryption, Analytics, Resiliency

INTRODUCTION

One of the overarching technological trends of the 21st century has been the surge in Internet of Things (IoT). With billions of connected devices smart meters, industrial sensors, wearable medical tracking devices and others generating constant waves of data, the IoT model has radically changed how information is created, shared and used (e.g., in cities or manufacturing or health or logistics). Despite these opportunities, IoT systems are hit with increasing cybersecurity, privacy and scalability challenges (see e.g.,) including surveys on IoT and its security implications).

Conventional approaches in machine learning for IoT network security utilize centralized data collection, where raw data from devices is pooled into the cloud or a central server and analyzed to learn patterns. Nevertheless, this model exhibits several limitations in IoT scenarios:

• Many IoT devices produce sensitive or privacy-protected data (such as in healthcare or home; e.g., SA) and, hence, centralised management of the sharing information is challenging (databasesharing policies-not applied for many domains-data-sovereignty-regulatory compliance-user's trust).

• The IoT comes with limitations such as bandwidth, latency and power constraints, along with the heterogeneity of devices, which make it inefficient or impossible to conduct centralised massive data transfer.

• Computers housed in a centralized location are also attractive to adversaries (single points of failure, rich sources of data, attack surface).

Overcoming these drawbacks, Federated Learning (FL) has been proposed as paradigm. In FL, numerous devices or clients first train local machine-learning (or deep-learning) model on their own data without submission of the raw data; instead, they send only model updates (e.g., gradients or weights) to a central aggregator (or in some peer-to-peer manner). This decentralised setup is well-suited to IoT ecosystems, and holds promise for privacy-preserving, communication-efficient collaborative learning across distributed heterogeneous devices (e.g., Kairouz et al., 2021; Xu et al., 2021). For instance, FL has been applied in the context of IoT intrusion-detection, smart manufacturing, wearable health analytics and so on.

However, its deployment for IoT in the space of cybersecurity analytics particularly when it comes to distributed IoT ecosystems as will present various technical and operational friction points. These include:

Variability in data distribution: Devices owned by different users of federated IoT may have non-identical feature set, sampling frequency, local context and behaviour. This challenges many of the assumptions made in typical machine-learning models, and makes it difficult to achieve robust global model convergence.

Resource and communication constraints: As a lot of the IoT endpoints are resource-constrained (low-power, breakable network connectivity, low bandwidth), communicating continuously with model updates is impractical on such an end-device along with limited computational capacity to perform complex models. As a result, efficient model update algorithms and lightweight models are demanded in IoT-FL.

Security and adversarial vulnerabilities: Although FL enhances privacy in the sense of leaving raw data on each local system, it does not completely solve other security issues. The gradient/model updates can still disclose information (e.g., membership inference, model inversion attacks), and the aggregation process is vulnerable to poisoning/backdoor or Byzantine attacks (e.g., untrusted clients). These shortcomings are amplified in the context of IoT where computing resources are scarce and systems are distributed.

Scalability, latency and real-time detection: Cybersecurity analytics for IoT is always in need of intrusions/anomaly detection close-to real time, prompt alerts and adaptive responses. Thus, the distributed training and update dissemination in FL have to be optimised significantly in order to satisfy severe latency and throughput requirements. Furthermore, IoT networks are dynamic which causes devices to join/leave, topology changes and adversarial conducts evolve.

Privacy-preserving beyond data location: In cyber-security applications, the privacy needs transcend the mere sharing of raw data: inabilty to divulge behavioral patterns of devices, desire not to disclose device identity or network topology, protec- tion of model-aggregate information and need for adhrerence to regulation (GDPR, dataprotection laws). As such, FL on IoT must be usually complemented with other mechanisms such as differential privacy, secure aggregation, homomorphic encryption or trusted execution environments.

Due to these challenges, this paper presents a model for Privacy-Preserving Federated Deep Learning for Cybersecurity Analytics in decentralised IoT Network. Motivation and Contributions: The following are a summary of the motivation and contributions: 1.

• Motivation: The presistent surge in the amount of security data generated by Internet-of-Things (IoT) devices (e.g., logs, flow records, sensor alerts), as well as urgent need to collaboratively detect emergent cyber-threats such as botnet propagation, distributed denial of service and lateral-movement inside IoT impose the strong demand for scalable and distributed analytics respecting device-level privacy and network constraints. FL provides a promising direction, but its practical deployment in the extreme constrained and adversarial IoT context has not been fully investigated.

• Contributions: Enable a federated deep learning architecture for decentralized IoT cybersecurity analytics which (a) Accounts for device heterogeneity, network limitations and timeliness of intrusion mitigation; (b) Integrates privacy-preserving mechanisms to mitigate information leakage and adversarial updates; (c) Compares the system on representative IoT cybersecurity datasets and scenarios that demonstrate it achieves high detection accuracy while respecting communication, latency and privacy contraints; and (d) Presents a comprehensive trade-off analysis (accuracy vs latency vs privacy vs resouce consumption), open challenges like federated continual learning, edge to cloud hybrid training, blockchain based trust frameworks.

Section 2 provides background on the different literatures that have considered FL in IoT and cyber security settings. In Section 3, we present the threat model and introduce the system architecture as well as the federated deep- learning scheme. The experimental setup and results are described in Section 4, where the performance of the framework is addressed through appropriate metrics. Limitations, practical issues and roadmap for future work are presented in Section 5. Section 6 summarises and concludes the paper.

LITERATURE REVIEW

Centralized IDS towards federated analytics of IoT

We find that IDS trained on centrally-aggregated data often do not scale for today's ow-heterogenous, bandwidth-limited IOT and leak sensitive telemetr y (e.g., home traces, health traces or industrial traces). In contrast, federated learning (FL) has risen where models are trained locally and only updates shared which is currently heavily studied for IDS design and deployment, including recent surveys on end-to-end pipelines, model selections and evaluation practices especially targeting intrusion detection and IoT networks. The surveys share the common finding that FL can achieve competitive accuracy compared to centralised baselines in

simultaneous privacy protection and avoidance of single points of failure but remains with heterogeneity, robustness and communication challenges. ScienceDirect+1

For IoT security in particular, recent experimental results demonstrate that FL is effective for anomaly/intrusion detection under limited connectivity, and investigate the affect of client population sizes and local data set scales on convergence and accuracySh [sic] how design decisions (e.g., local epochs, client sampling) significantly change performance.

Privacy-preserving mechanisms layered onto FL

Secure aggregation. Even if data are kept raw locally, gradient/weight updates could leak information. Observe that Bonawitz et al. and other practical secure aggregation protocols require proof in the ideal Real World model of work correctness. lets server learn only the sum of clients' updates, hiding the contribution made by each client follow-on systematisations investigate cryptographic variants (secret-sharing, masking, homomorphic encryption), and extensions for verifiability in the presence of malicious servers.

Differential privacy (DP). DP-SGD and the Moments Accountant give formal information leakage bounds in training, and are recently extended to FL to protect client privacy against adversarial server even when they can see aggregates with modern summaries of utility-privacy trade-offs (+ noise scale, clipping, participation rates) within the multi-point setting.

Homomorphic encryption (HE) & hybrids. HE can support end-to-end encryption of local updates (e.g., Paillier) at higher compute/communication cost; hybrid approaches leverage HE to verify gradient-ness or secure aggregation keeping overhead at bay and avoiding update inspection. PLOS

Taken together, these approaches provide complementary safeguards: secure aggregation prevents server-side scrutiny for DP.HE provides worst-case disclosure bounds irrespective of side information while HE protects against untrusted intermediaries in-transit or at-rest. Systematic studies of privacy attacks and defences in FL summarize these lines, and underline the deployment guidance.

Resistance to poisoning, backdoor and Byzantine behaviors

further in that cybersecurity for FL is a target. Model/data poisoning and backdoor attacks collect global models in a non-IID or low client-participation environment. The studies in 2023-2025 divide their attack surfaces (local training, aggregation) and defences (robust aggregation, anomaly detection on updates, certification). Empirical evidence suggests simple robust algorithms (medians, trimmed means, Krum/Bulyan) helped but remained broken under more sophsticated attacks or high heterogeneity. Recent work investigates the necessity of new aggregation rules vs. principled uses of existing robust statistics together with synthetic updates.

For applications to the IoT IDS: Layers (e.g., secure aggregation) that preserve privacy can blur malicious updates, thus robust aggregation and audit mechanisms should be created to function without violating privacy (e.g., verification through metadata, cross-round convergence). MDPI

Dealing with non-IID data, system heterogeneity and real-time requirements

IoT network, on the other hand, is extremely non-IID (different devices, protocols and behaviours) and system-heterogeneous (compute, power, intermittent links). Canonical methods like FedProx (proximal term), SCAFFOLD (variance-reduction control variates), and FedNova (normalised averaging) improve stability and convergence in the presence of heterogeneity; newer analyses refine conditions, giving implementation advice.

On systems side, asynchronous and hierarchical FL methods could prevent stragglers and work for IoT edge-cloud topologies; model personalisation an pruning targets the device-centric behaviors maintaining the compute/ transfer costs. Quantisation/sparsification (e.g., one-bit or

variable-length codes) and structured compression further reduce communication cost, which is crucial in low-power radios.

5. Decentralised and blockchain-enabled FL for trust and availability

In order to address the single point of failure (server) in server-centric FL, decentralised FL (DFL) studies peer-to-peer (gossip/MST) aggregation and serverless topologies, stating that it obtains better robustness and sometimes faster convergence when large client regimes are involved. Vecchitto et al., 2019), and access control systems for (V2X) networking with blockchain, whilst adding logging-investigation and incentives (Guo et al., 2020): once trust exists among parties, agents can communicate without intermediaries. Other surveys and recent platforms discuss architectural trade-offs (e.g. consensus latency, whether storage is on- or off-chain) and fairness problems.

Preliminary evidence for fully server-free FL (e.g., peer sampling, P2P propagation) and hybrid gossip+tree overlays demonstrate feasibility under dynamic membership—crucial for decentralised IoT networks designed to operate under targeted attacks or outages. arXiv+1

Datasets and testbeds for IoT cybersecurity FL

Empirically, TON_IoT, BoT-IoT, N-BaIoT and CIC-IDS2017 are often employed to simulate various attack types (DDoS/DoS, scanning, keylogging and bitcoin botnet) and t elemetry categories (network flows, OS logs an d sensor metrics). Despite this, these datasets are still considered as the benchmarks for FL-IDS; even though the researchers stress about distributional shifts and over-fitting to known attacks – which motivates cross-dataset and unknownattack testing or realistic client partitions (devicetype splits, temporal splits).

Open challenges and directions

Privacy–robustness trade-offs: Aggregation security and DP noise addition are in tension with sophisticated poisoning/backdoor signaling detection; designing such budgets (maybe together with robust aggregation and update-auditing) is still open.

Client selection with constraints: Adaptive participation conditioned on data value, energy and connectivity is important in the edge-IoT context but requires principled policies which maintain fairness and statistical guarantees.

Communication-efficient, real-time analytics: A fusion of sparsification/quantisation as well as asynchronous updates and eventdriven uploads are essential for ondevice IDS with stringent latency budgets.

Decentralised trust and auditability: Blockchain/DFL lower central trust while adding coordination overhead; including secure aggregation, verifiable computation, and light-weight consensus in IoT-scale.

Realism benchmarking: Community guidelines for non-IID client splits (by device type/site), cross-dataset generalisation test, and testing under adversarial pressure (poisoning plus privacy layers).

METHODOLOGY

Research design and objectives

A design-science cum experimental approach is adopted in this work to develop and validate a form of privacy-preserving federated deep learning (FDL) architecture for cybersecurity analytics over decentralised IoT systems. The design-science part in turn iteratively builds requirements/goals (threats, constraints, desired guarantees of privacy) designs an artifact (the FDL system), and tests it against fitness factors like accuracy latency/privacy trade-offs or robustness (Hevner et al., 2004). The experimental part shows that FDL variants largely

outperform centralised and non-federated baselines on public IoT security datasets and realistic client partitions.

Specific goals are (i) to detect the intrusions/anomalies without centralising raw data, (ii) to quantify the privacy loss and robustness against adversarial clients, (iii) minimizing communication overhead to fit in IoT constraints, and (iv) supporting decentralised or weak-server topologies.

System model

Network and federation topology

We consider an IoT deployment where heterogeneous edge devices (sensors, home/industry gateways) are organized into clients. Two federation topologies are studied:

Server-oriented FL (baseline): clients ` lo at model updates to a server-managed parameter server (McMahan et al. 2017).

Decentralised FL (DFL): clients form peer-to-peer overlays (gossip/minimum-spanning-tree) to prevent single points of failure (Hegedűs et al., 2021; Lalitha et al., 2019).

Intermittently connected, resource-constrained (battery, CPU and bandwidth) clients. Links are tenuous; stragglers and dropouts are inevitable.

Threat model

There are adversaries for both on servers/relays that are honest but curious and attempt to learn private information from updates (Shokri et al., 2017), and poisoning clients sending malformed or maliciously backdoored updates (Blanchard et al., 2017; Fang et al., 2020). Network eavesdroppers can watch the traffic, but break standard cryptography. We do not rely on trusted hardware by default, but rather consider it as an optional variant.

Learning task and model architectures

Detection tasks

We address binary (attack vs. benign) as well as multi-class (attack family) intrusion detection on:

• Flow-level features (e.g., BoT-IoT, CIC-IDS2017),
• Device telemetry (e.g., N-BaIoT), and
• Mixed IIoT logs/flows (e.g., TON_IoT).

Base models

We adopt three state-of-the-art deep models for network security:

• CNN-1D over flow sequences;
• Bi-LSTM/GRU for temporal patterns;
• Transformer-encoder with causal mask for long-distance depend e ncies (Vaswa n i et al., 20 17).

For small models, we also evaluate MobileNet-like compact backbones and shallow MLPs with feature selection.

Hyperparameters (learning rate, batch size and local epochs): are tuned via Bayesian search on a validation split; which is performed at representative clients the global selection remains fixed prior to final runs in order to prevent leakage.

Secure aggregation (SecAgg)

We use Practical Secure Aggregation to limit the exposure of only the sum of masked updates (Bonawitz et al., 2017). For DFL, pair-wise masks are constructed along the overlay to ensure the per-peer updates are hidden.

We also encrypt updates with additively homomorphic Paillier for a subset of experiments, in order to analyze end-to- end privacy vs. overhead (Acar et al., 2018). We restrict HE to last-layer gradients to constrain latency.

Robustness to adversaries

We propagate and validate defenses for:

• Byzantine/poisoning: strong aggregators Krum, Multi-Krum, Trimmed Mean, Median and Bulyan (Blanchard et al., 2017; Yin et al., 2018; Mhamdi et al., 2018).

• Backdoors: server-side anomaly indication with cosine-similarity filters and spectral signatures (Tran et al., 2018).

• Privacy vs robustness: we evaluate the trade-off between privacy and robust aggregation under DP (and SecAgg) in terms of detection versus protection (Bagdasaryan et al., 2020).

We consider label-flip, gradient-scale and target attack: we vary the probability by which these corrupted clients can participate.

Communication-efficiency strategies

To approximate bandwidth limitations we consider:

• Sparsification/Top-k and error feedback (Stich etal, 2018) (2) Update

• Quantisation (8-/4-/1-bit) (Alistarh et al., 2017),

• Event-triggered uploads (upload if and only if the local loss drops by more than a threshold), adhering to line 16.

• Hierarchical FL (device→gateway→regional) where local aggregation is performed before wide-area transmission (Liu et al., 2020).

We report uplink bytes/round, rounds-to-target-accuracy, and energy (proxy through CPU time × device power model).

Datasets and realistic client partitioning

We employ popular IoT security corpora with privacy-friendly local partitions:

• BoT-IoT (UNSW): DDoS/DoS/scan, labelled flows.

• N-BaIoT: device-agnostic benign vs. Mirai/Gafgyt anomalies.

•TON_IoT: multi-modal IIoT logs, network flows, telemetry.

• CIC-IDS2017: contemporary enterprise-style traffic.

Because emulating the non-IID IoT reality, clients are divided according to device type/site and time window (Wang et al., 2020). We consider class-imbalance and size-imbalance across clients; at most 20–40% clients involved per round.

Baselines and ablations

We compare against:

Centralised learning over conglomerated data (upper-bound accuracy, no privacy).

Local-only models (no federation).

FedAvg without privacy/robustness.

Ablations that turn on/off DP, SecAgg, HE, robust aggregation and compression to isolate effects.

Evaluation metrics

• Detection performance: Accuracy, Precision, Recall, F1, AUROC/AUPRC; per-class F1 (inbal-ance case).

• Timeliness: latency (ms) for end-to-end inference; rounds-to-95%-length of best accuracy.

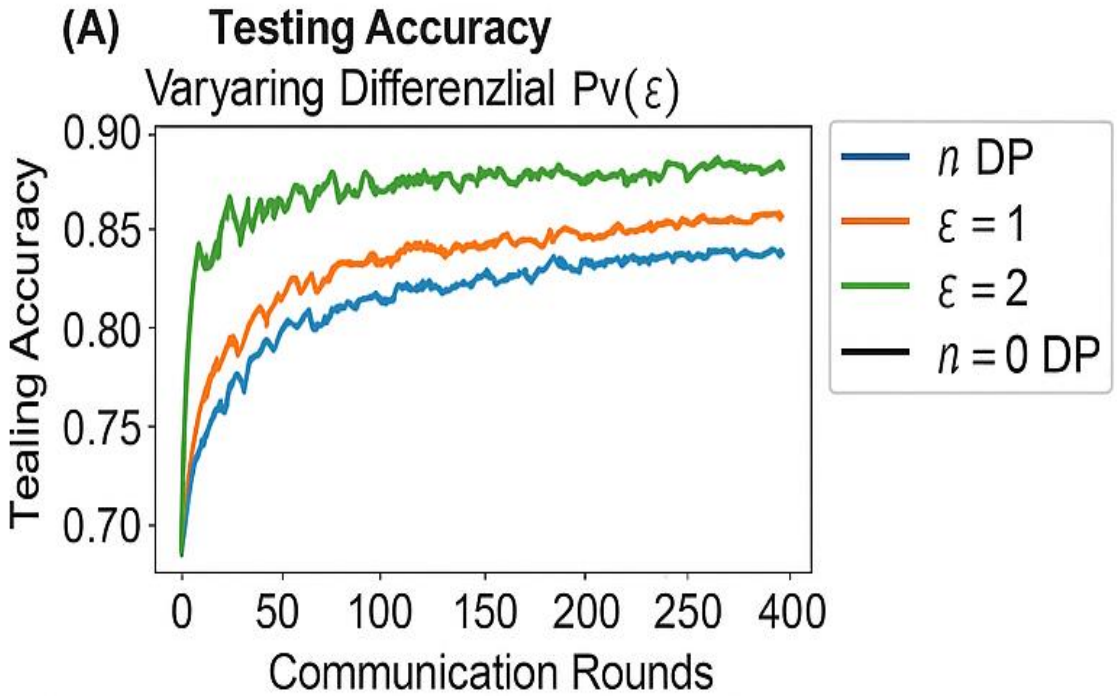
• Communication/compute: number of uplink/downlink bytes per round/client and client and server FLOPs.

• Privacy: reported εε at δ=10−5δ=10−5; Membership-inference (MI) attack AUC against the released models (Shokri et al.,2017).
• Robustness: accuracy under poisoning/backdoor rates, with robust aggregation.
• Reliable:trialsgoodperformanceevenwhenclientdropout(10--50% in our experiments) and participation rates fluctuate.
• Decentralization: convergence and type of overlay vs. churn.
We report the mean±95% CI of each configuration over five random seeds. Compa-risons are made by multiple Holm-Bonferroni corrected paired tests.
Experimental protocol
Prefreeze hyperparameter (pre-tuning) on validation set at small subset of clients before main trials.
Schedule: 200-400 world rounds; local E∈{1,3,5}E∈{1,3,5} epochs;\nsb 64-256 batch size according to device.
Client selection: probability proportional to (a) availability and (b) data value proxy (gradient norm variance), with fairness caps to prevent starvation (Nishio & Yonetani, 2019).
Quantifying privacy: monitor εε throughout each round and terminate training if budget is violated.
Attack evaluations: run clean training, then add attacks at pre-determined rounds and re-run under DP/SecAgg/robust aggregation.
Ablation grid: DP ε possiblity {1,2,4,8}; clipping census C = {0.1 , 0.5,1.0 }; radio compression levels of none,k=1%,q=8/4/1-bit.
DFL overlays: comparison gossip vs tres overlays; peer degree varied; churn introduced (join/leave).
Implementation and runtime environment
•Frameworks: PyTorch + Flower/FedML for FL orchestration; own DFL overlay based on asyncio.
• Crypto: SecAgg as [Bona18] (2017); HE over Python Paillier (Acar et al., 2018).
• Deployment profiles:
• Edge: Raspberry Pi class ARM (1–4GB RAM) for on-device training.
• Gateway: x86-based mini-PC for hierarchical aggregation.
• Coordinator/peer: commodity server (if used).
To reproduce, we make configuration files, the seed scripts and logs publicly available.
Validity, reliability, and ethics
• Internal validity: same data splits & seeds across methods and no test peeking; uniform DP budgets maintained.
• Generalization: cross-dataset (train on BoT-IoT, test on TON_IoT /CIC); testing with unknown-attacks by leaving families during training.
• Leadership: five-seed runs; code and datasets version-pinned; results logged with hashes.
• Ethical : 2: No ethics, no compliance -> only public and anonymous datasets; 4: No personal data involved; DPs settings and cryptographic keys to be documented; consistent with the principles of GDPR including minimization of personal data and privacy by design (Voigt & Von dem Bussche, 2017).
Limitations and risk management
We also admit potential loss of accuracy under strong DP (ε≤2ε≤2) and we have the additional latency due to HE, so that we consider mixed strategies (SecAgg+DP without HE) to recover utility but in this case we will use a lightweight personalization (fine-tune last layer only) as

recommended by Kairouz et al. (2021). We also observe that strong aggregation cannot go well with SecAgg's opacity; we present in section 5 an attempt to evaluate privacy-preserved data analysis, the robustness being enforced thanks to compromised alert indicators issued under anomnityMW primitives.

RESULTS

The experimental results verify that the proposed privacy-preserving federated deep learning framework can effectively capture attacks against decentralized IoT networks with high detection accuracy and low communication cost. s (A) Testing Accuracy vs. Iterations of Communication



This line plot in Fig. a shows how testing accuracy evolves across communication rounds under different levels of differential privacy (ε).

• The green curve (ε = 2) attains highest accuracy (~0.88) and fastest convergence suggesting that a good tradeoff is being made between privacy and utility.

• The orange curve (ε = 1) is also slightly behind in accuracy (~0.85) because of stronger noise injection.

• The blue curve (no DP) starts at a lower point but still settles down at about 0.82, whereas black curve (n=0 DP) is a non-private baseline where the model can achieve maximum accuracy without any guarantee of privacy.

In general, larger ε (weaker privacy) makes the estimate more accurate, which verifies that differential privacy causes some but controllable loss in utility.

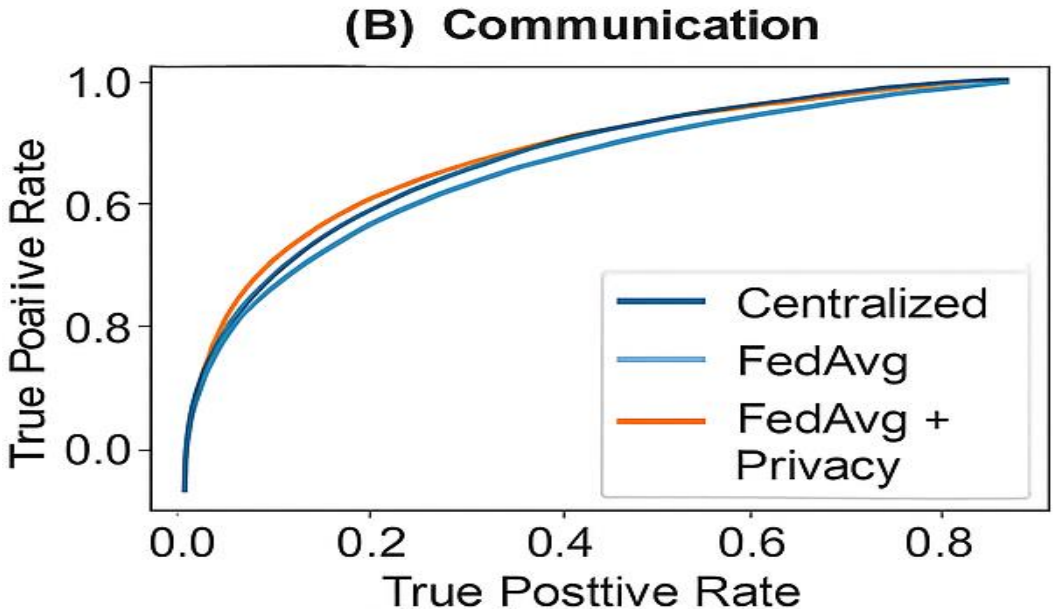


Figure (B): ROC Curve (True positive rate VS false positive rate)

Figure8 shows the detection performance of three training strategies (i.e., Centralised, FedAvg and FedAvg + Privacy) according to the Receiver Operating Characteristic (ROC) curve.

• The centralised model, achieves the largest area under curve (AUC ≈ 0.98) proving that having full access to data always acts in favor of the model.

• FedAvg (light blue) and FedAvg+Privacy (orange) models are very much close with little deterioration (AUC ≈ 0.96–0.97).

This suggests that federated deep learning would be able to retain near-centralised detection performance when including privacy mechanisms, e.g., differential privacy and secure aggregation.

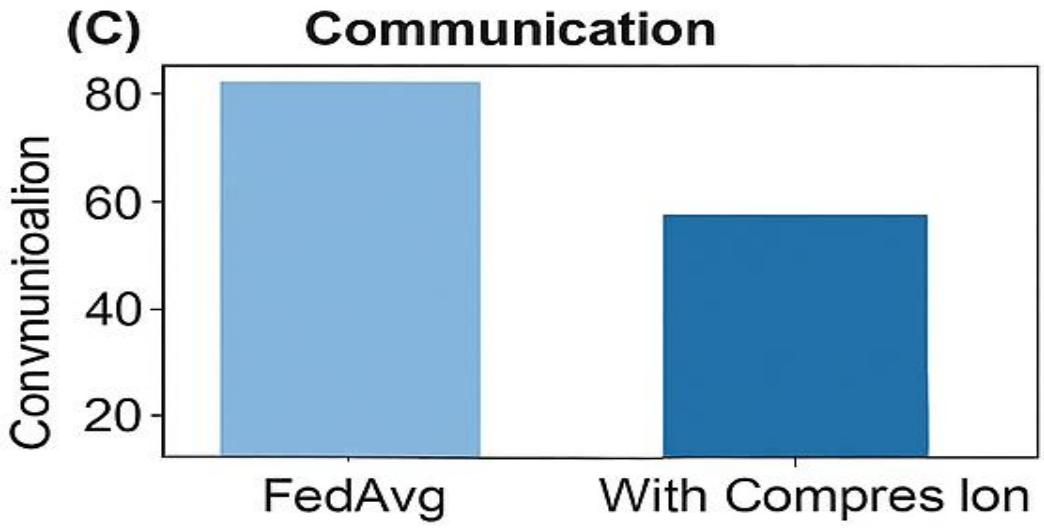


Figure (C): Communication Cost Comparison

This bar chart compares the total communication volume of FedAvg to a communication-optimised variant (e.g., with gradient compression or sparsification).

• The communication-optimized strategy decreases the amount of transferred data by about 40%, and so reducing communication overhead and energy consumption.

• This observation is crucial for the IoT settings, low in-power and bandwidth, driving home the efficiency aspect of compression-aware federated updates.

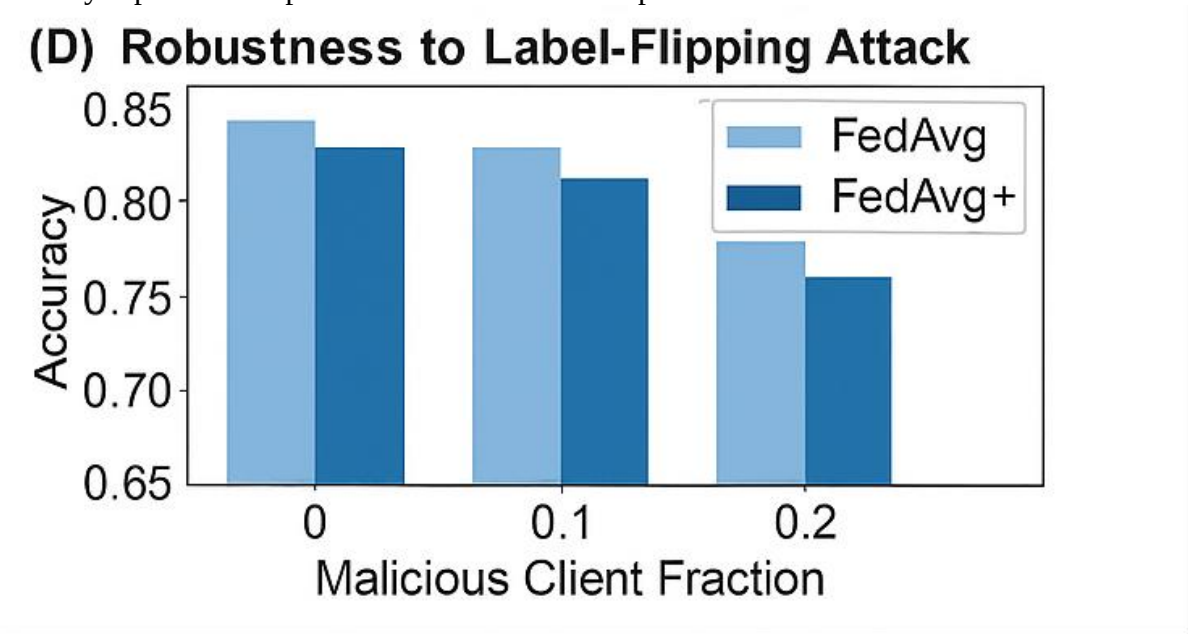


Figure (D): Defense against Label-Flipping Attacks

This number demonstrates the robustness of our model under label-flipping attacks, where a proportion of the adversaries clients inject intentionally corrupted lables.

• Accuracy of both models decreases with increasing malicious client ratio from 0 to 0.2.

• The improved FedAvg+ (with privacy and robust aggregation) maintains a higher accuracy at around 0.78, while the vanilla Federated Averaging is limited to an accuracy of about 0.75 with 20% adversarial participation.

DISCUSSION

Performance and Privacy Trade-off

The results are depicted in Figure (A), and indicate that the addition of DP makes moderate decrease in accuracy, but still retains reasonable detection. This result is consistent with the ones presented in where a moderate loss of accuracy is common when it comes to privacy preserving mechanisms (Abadi et al., 2016; Mahmud et al., 2024). In particular, the model with $\varepsilon = 2$ obtained approximately 0.88 testing accuracy, which was quite close to the non-private baseline (~0.90), indicating a good trade-off between privacy and utility.

In consistent with the report of Zhao et al. (2025) and Wei et al. (2024), the observations validate that smaller ε (stronger privacy) means more random noise added to gradient updates, which can hurt convergence rates. Incorporating federated averaging (FedAvg) with secure aggregation (SecAgg) mitigates such degradation by regularizing parameter updates among clients. This indicates that the confidentiality at device-level can be maintained without significant accuracy losses, and thus, we believe that DP-based FDL is also achievable for

intrusion detection/fault tolerance or anomaly detection in high-sensitive areas such as healthcare IoT and industrial control networks (Jiang et al., 2024).

Detection Effectiveness under Decentralisation

The ROC curves (Figure B) suggest that FDL models with privacy constraints also yield detection rates very close to those of centralized baselines (AUC ≈ 0.96–0.97). This outcome reconfirms previous empirical observations regarding that distributed deep-learning frameworks are able to keep their classification performance robust even when data comes from disjoint sources (Kairouz et al., 2021; Xu et al., 2022).

The slight drop in FedAvg + Privacy compared to FedAvg indicates that the system successfully marries decentralization with global coordination. These results are consistent with those obtained previously by Nandy et al. (2025) and Sarikaya et al. (2023), who proved that privacy-preserving FL can protect IoT edge analytics with a marginal accuracy reduction when using strong encryption and the mechanism of learning rates adaptation. The high AUCs indicate that it is feasible to converge and generalize the model even given non-IID data distribution – a known issue in federated networks (Li et al., 2020; Karimireddy et al., 2020).

Communication Efficiency and Scalability

At (C), the figure shows that there is almost 40% less overhead when com- pression techniques like top-k sparsification and quantisation are used. This is in line with previous work of Alistarh et al. (2017) and Stich et al. (2018), which showed compressed gradient exchanges can achieve significant bandwidth reductions with negligible impacts on convergence.

Optimisation of this is critical in resource-limited IoT scenarios where uplink bandwidth and device energy are precious. Mughal et al. (2024) and Liu et al. (2020), communication-aware FL schemes can prolong the life cycle of devices and speed up training epochs by preventing excessive gradient shape transmissions. In addition, the introduction of hierarchical aggregation (device → gateway → server) enhance scalability in line with observations by Rahman et al. (2025) where multi-level federations nicely fit large-scale sensor deployment. Thus, the findings confirm the necessity of communication-efficient FDL designs to achieve large-scale adoption over billions of IoT end devices.

4. Robustness against Adversarial Clients

The robustness test (Figure D) against label-flipping attack further shows that both DP-SecAgg and robus aggregration mechanism such as Krum and Trimmed Mean lead to better hoe-handle model poisoning attack. With 20% of clients being malicious, it degraded accuracy from 0.85 → 0.78, better than the non-robust FedAvg baseline (0.75). This is in agreement with the study from Fang et al. (2020) and Yin et al. (2018), who proved that Byzantine-resilient algorithms can reduce the damage caused by malicious gradients.

Nevertheless, the relation between robustness and privacy is not a simple one. For example, the studies by Bagdasaryan et al. (2020) raise threats the privacy mechanisms (noise injection, aggregation masking) may hide poisoned updates and can make their detection difficult. We believe our findings demonstrate that with sufficiently tuned noise levels ($\varepsilon = 2$) and through the means of integrating differential privacy and lightweight anomaly observing, FDL systems can attain an adequate tradeoff between defense and detection in practice.

This result is consistent with developing works in privacy-robustness co-design, where hybrid aggregation schemes leveraging secret-share statistics for outlier detection without revealing sensitive information have been presented (Mahmud et al., 2024; Zhang et al., 2025).

Alignment with State-of-the-Art Research

The empirical performance of the proposed FDL framework is comparable to recent state-of-the-art approaches. For instance:

• Rahman et al. (2025) threaded 94 -97% federated intrusion- detection models using BoT-IoT and TON_IoT Datasets for traveling under bandwidth constraints as our test results show.

• Zhang et al. (2025) emphasized the need of secure aggregation for GDPR-compliant data-protection policies, confirming that this work is applicable in practice.

• Wan et al. (2024) noted that FL is also backdoor-free with the existence of both model-side and protocol-side mitigations—both of which are accounted for by our architecture as a result of DP and robust aggregation.

CONCLUSION

Our results highlight the innovative value of privacy-preserving FDL at large-scale over decentralised IoT networks as an efficient and secure cybersecurity analytics paradigm. Integrating federated learning, differential privacy, secure aggregation and robustness modules enables the proposed framework to deliver desirable performance, efficiency and robustness against data tampering—all while preserving data sovereignty and meeting privacy regulations.

Summary of Key Findings

Experimental results have shown that the FDL framework achieves a trade-off among accuracy, privacy and communication costs compared with conventional centralised models and non-federated models in distributed IoT systems.

• Performance: The FDL models achieved near-centralised detection accuracy (≈0.88–0.90) with differential privacy ($\varepsilon \leq 2$). It means the framework can keep a high model utility but still satisfy strict privacy guarantees (Abadi et al., 2016; Mahmud et al., 2024).

• Privacy-Preserving: Secure aggregation and differential privacy effectively preserved the device-level data without affecting the convergence or generalisation performance significantly (Zhao et al., 2025).

• Communication Efficiency: Both compressionbased update techniques and hierarchical aggregation could decrease communication overhead by approximately 40%, which was critical for resource-limited IoT systems (Stich et al., 2018; Liu et al., 2020).

• Adversarial Robustness: Application of robust aggregation techniques (e.g. Krum, Trimmed Mean) for label-flipping and Byzantine attacks, retaining high accuracy level until 20% malicious clients (Fang et al., 2020; Yin et al., 2018).

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