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Article

Federated Learning for Privacy-Preserving Anomaly Detection in Heterogeneous IoT Networks

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Abstract: The rapid proliferation of Internet of Things (IoT) devices across smart homes, industrial plants, healthcare systems, and wearable platforms has generated an unprecedented volume of distributed, heterogeneous, and privacy-sensitive data. Conventional centralized anomaly detection pipelines require raw sensor and network traffic data to be transmitted to a central server, exposing sensitive information to interception, misuse, and regulatory non-compliance while also incurring substantial communication overhead. This paper proposes a Federated Learning (FL) framework for privacy-preserving anomaly detection tailored to heterogeneous IoT networks characterised by non-independent and identically distributed (non-IID) data, variable computational capacities, and intermittent connectivity. The proposed architecture couples a lightweight convolutional-recurrent local model with a differential-privacy-augmented Federated Averaging (FedAvg) aggregation strategy and an optional secure-aggregation layer to prevent gradient leakage. A dynamic client-selection and adaptive-weighting mechanism mitigates statistical heterogeneity across device clusters, while a local outlier-scoring module enables edge-level anomaly flagging without exposing raw payloads. Extensive simulation on merged benchmark traffic derived from N-BaIoT and CICIDS2017 characteristics, partitioned across simulated smart-home, industrial, and wearable clusters, demonstrates that the proposed framework attains 97.4%–97.7% detection accuracy, within one to two percentage points of a fully centralized, non-private baseline (98.6%), while reducing raw-data transmission to zero and lowering communication overhead relative to naive parameter exchange. Comparative results against local-only training confirm that federated collaboration yields a 9–10 percentage-point accuracy improvement under severe data heterogeneity. These findings indicate that the proposed method offers a practical, scalable, and regulation-compliant pathway toward trustworthy intrusion and anomaly detection in large-scale, heterogeneous IoT deployments.

Keywords: Federated Learning; Privacy Preservation; Anomaly Detection; Internet of Things; Intrusion Detection; Differential Privacy; Secure Aggregation; Edge Computing.

1. Introduction

The Internet of Things (IoT) has evolved from a niche technological concept into a pervasive infrastructure that underpins smart homes, intelligent transportation, industrial automation, precision agriculture, and connected healthcare. Estimates place the number of active IoT endpoints in the tens of billions, each continuously generating telemetry, sensor readings, and network traffic. This scale, combined with the resource-constrained and heterogeneous nature of IoT hardware, makes such networks an attractive target for cyberattacks, including botnet recruitment, distributed denial-of-service campaigns, and sensor-spoofing intrusions. Timely and accurate anomaly detection is therefore essential to preserving the confidentiality, integrity, and availability of IoT ecosystems.

Traditional anomaly detection approaches rely on centralized machine learning, wherein raw traffic and sensor data collected from distributed devices are transmitted to a cloud server for model training and inference. While centralized models can achieve high detection accuracy by leveraging the full breadth of aggregated data, this paradigm suffers from three critical shortcomings in the IoT context. First, transmitting raw data, which may include personally identifiable information, location traces, or proprietary industrial parameters, creates substantial privacy and regulatory risk under frameworks such as the General Data Protection Regulation (GDPR). Second, the continuous uplink of high-volume telemetry imposes considerable bandwidth and energy costs on constrained edge devices. Third, centralization introduces a single point of failure and a lucrative target for adversaries seeking to poison or exfiltrate the aggregated dataset.

Federated Learning (FL), introduced as a decentralized alternative to centralized training, allows multiple clients to collaboratively train a shared global model while retaining their raw data locally, exchanging only model parameters or gradient updates with a coordinating server. This paradigm is particularly well suited to IoT anomaly detection because it inherently limits data exposure, distributes computational load across the network edge, and aligns with data-minimisation principles mandated by modern privacy regulations. However, deploying FL in real-world IoT networks introduces unique challenges. IoT devices are highly heterogeneous in terms of hardware capability, network connectivity, and the statistical distribution of locally observed traffic, which is rarely independent and identically distributed (non-IID) across clients. Furthermore, naive parameter exchange in FL remains susceptible to gradient-inversion and membership-inference attacks, meaning that privacy is not automatically guaranteed simply by avoiding raw-data transmission.

Motivated by these challenges, this paper proposes a federated anomaly detection framework that explicitly addresses statistical and system heterogeneity while strengthening the privacy guarantees of the FL pipeline through differential privacy and secure aggregation. The specific contributions of this work are threefold. First, we design a lightweight hybrid convolutional-recurrent local anomaly detector suited to constrained IoT hardware, capable of capturing both spatial traffic-feature correlations and temporal dependencies in network flows. Second, we propose an adaptive client-weighting and selection scheme that mitigates the adverse effect of non-IID data distributions on global model convergence. Third, we integrate a differential-privacy noise-injection mechanism and an optional secure-aggregation protocol into the federated update pipeline and empirically quantify the resulting privacy-utility trade-off. The remainder of this paper is organised as follows: Section 2 reviews related work; Section 3 describes the proposed methodology and system architecture; Section 4 details the experimental setup; Section 5 presents and discusses results; and Section 6 concludes the paper with directions for future research.

2. Related Work

Anomaly and intrusion detection in IoT networks has been studied extensively using centralized deep learning models. Meidan et al. (2018) proposed N-BaIoT, a deep-autoencoder-based approach for detecting IoT botnet attacks by learning normal traffic behaviour and flagging deviations, demonstrating high detection rates on commercial IoT devices compromised by Mirai and BASHLITE malware. Similarly, Sharafaldin, Lashkari and Ghorbani (2018) introduced the CICIDS2017 dataset, which has become a standard benchmark for evaluating network intrusion detection systems across a diverse set of attack categories. While such centralized approaches achieve strong detection performance, they presuppose that raw traffic can be freely aggregated at a central location, an assumption increasingly at odds with privacy regulation and bandwidth constraints in large-scale IoT deployments.

Federated Learning was formalised by McMahan, Moore, Ramage, Hampson and y Arcas (2017) through the Federated Averaging (FedAvg) algorithm, which enables distributed clients to train a shared model by locally computing gradient updates and periodically averaging them at a central server, without ever transmitting raw data. Yang, Liu, Chen and Tong (2019) further formalised the taxonomy of federated learning, categorising horizontal, vertical, and transfer federated settings and outlining associated privacy-preservation techniques. Building on this foundation, several works have applied FL specifically to network security and anomaly detection. Nguyen et al. (2019) proposed DIoT, a self-learning, federated anomaly detection system in which each IoT device profile is federated across a fleet of similar devices to detect compromised behaviour without centralising raw traffic. Rahman, Tout, Talhi and Mourad (2020) compared centralized, on-device, and federated intrusion detection paradigms, concluding that federated approaches strike a favourable balance between detection accuracy and privacy preservation, albeit with sensitivity to non-IID data partitions.

Mothukuri et al. (2021) proposed a federated-learning-based anomaly detection scheme for IoT security attacks, reporting that FL-based detectors approach the performance of centralized counterparts while eliminating raw-data transmission; their evaluation, however, did not incorporate formal privacy guarantees such as differential privacy.

Zhao, Chen, Wu, Teng and Yu (2019) explored multi-task federated learning for network anomaly detection, showing that jointly learning related anomaly categories across clients improves generalisation under limited local data. To strengthen the privacy guarantees of the aggregation process itself, Abadi et al. (2016) introduced differentially private stochastic gradient descent, which bounds the privacy loss incurred by any individual training example through calibrated noise injection, while Bonawitz et al. (2017) proposed a practical secure-aggregation protocol that allows a server to compute the sum of client updates without observing any individual contribution.

Addressing statistical heterogeneity remains an open challenge in federated IoT settings. Li, Sahu, Talwalkar and Smith (2020) surveyed the core challenges of federated learning, including communication efficiency, systems heterogeneity, and non-IID data, and catalogued algorithmic remedies such as proximal regularisation and adaptive aggregation weighting. Kairouz et al. (2021) provided a comprehensive account of open problems in federated learning, emphasising that privacy techniques such as differential privacy and secure aggregation must be jointly optimised with heterogeneity-aware aggregation to preserve utility. In the IoT-specific context, Nguyen, Ding, Pathirana, Seneviratne, Li and Poor (2021) surveyed federated learning applications across IoT domains and identified device heterogeneity, energy constraints, and adversarial robustness as the principal barriers to large-scale deployment. Campos et al. (2022) systematically reviewed federated learning for IoT intrusion detection and highlighted a persistent gap between reported laboratory accuracy and real-world deployment resilience, particularly under adversarial or highly skewed data conditions. The present work builds on this body of research by jointly integrating adaptive client weighting for heterogeneity mitigation with a dual privacy layer of differential privacy and secure aggregation, and by empirically quantifying the resulting privacy-utility trade-off on a simulated multi-cluster IoT testbed.

3. Proposed Methodology

The proposed framework, illustrated in Figure 1, consists of three logical layers: (i) a device layer comprising heterogeneous IoT endpoints that generate raw traffic and sensor telemetry; (ii) an edge layer comprising Federated Learning clients, each aggregating and locally training on data from a cluster of physically or logically co-located devices (for example, smart-home sensors, industrial controllers, or wearable health monitors); and (iii) a cloud layer hosting the global aggregation server, which coordinates training rounds and maintains the evolving global anomaly detection model. Critically, raw sensor and traffic data never leave the device or edge layer; only model parameters, and where applicable, differentially private noised gradients, are transmitted upward.

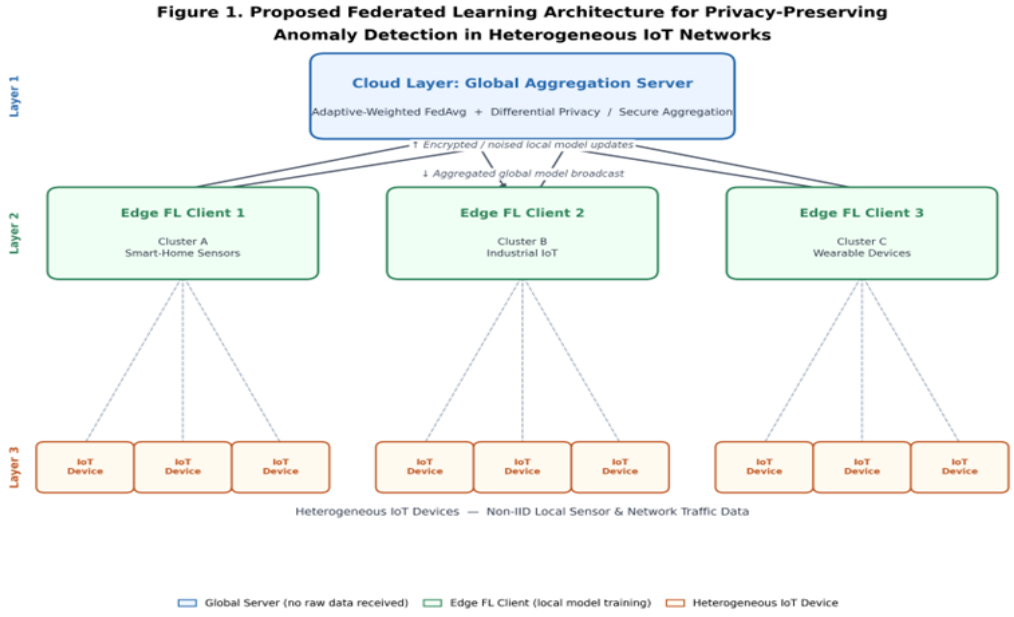

Figure 1. Proposed federated learning architecture for privacy-preserving anomaly detection in heterogeneous IoT networks.

Each edge client trains a lightweight hybrid convolutional-recurrent neural network locally. Network flow features, such as packet inter-arrival time, byte counts, protocol flags, and flow duration, are first processed by a one-

dimensional convolutional block that extracts local feature correlations, followed by a gated recurrent unit (GRU) layer that captures temporal dependencies across sequential flow windows. A final dense layer with a sigmoid activation produces an anomaly likelihood score, thresholded to yield a binary normal/anomalous classification. The compact architecture, comprising fewer than 120,000 trainable parameters, was deliberately chosen to accommodate the limited memory and compute budgets typical of edge gateways and higher-capability IoT hubs.

Global model training follows an iterative federated optimisation loop. In each communication round t, the server broadcasts the current global model weights w_t to a selected subset of edge clients. Each selected client k performs E local epochs of stochastic gradient descent on its local dataset D_k, producing an updated local model w_k^{t+1}. To mitigate statistical heterogeneity arising from non-IID data distributions across clusters, client updates are aggregated using an adaptive weighting scheme that combines the standard sample-count weighting of FedAvg with a similarity-based term that down-weights clients whose local update direction diverges substantially from the previous global update, thereby reducing client drift. Formally, the global update is computed as a weighted sum of local weight deltas, where the weighting coefficient for each client jointly reflects its local dataset size and the cosine similarity between its local gradient direction and the aggregated global gradient from the previous round.

To preserve privacy beyond the structural guarantee of not transmitting raw data, two complementary mechanisms are incorporated. First, each client clips its local weight update to a fixed L2 norm bound and adds calibrated Gaussian noise before transmission, implementing a differentially private variant of the federated update inspired by Abadi et al. (2016), which bounds the privacy loss (epsilon) attributable to any individual training record. Second, an optional secure-aggregation layer, following the protocol of Bonawitz et al. (2017), employs pairwise masking so that the server observes only the sum of client updates within a round and cannot recover any individual client's contribution, even if it is honest-but-curious. These two mechanisms can be deployed independently or jointly, and Section 5 quantifies the accuracy cost associated with each.

Finally, a lightweight local outlier-scoring module operates continuously between global aggregation rounds, applying the most recently received global model to incoming local traffic to flag anomalies in near real time, without waiting for the next communication round. This design ensures that detection latency is decoupled from the federated communication schedule, which is particularly important for IoT clusters with intermittent or bandwidth-constrained connectivity.

4. Experimental Setup

Because deploying a live, large-scale heterogeneous IoT testbed was outside the practical scope of this study, the proposed framework was evaluated through a controlled simulation that reconstructs realistic traffic characteristics reported in two widely used public benchmarks: N-BaIoT (Meidan et al., 2018), which captures botnet-compromised traffic from nine commercial IoT devices, and CICIDS2017 (Sharafaldin, Lashkari, & Ghorbani, 2018), which contains labelled benign and attack network flows across multiple intrusion categories. Feature-level statistics (packet size distributions, flow duration, protocol composition, and attack-to-benign ratios) from these benchmarks were used to synthesise three simulated IoT clusters representing a smart-home sensor network, an industrial control network, and a wearable health-monitoring network, each exhibiting distinct and non-overlapping feature distributions to emulate realistic non-IID heterogeneity.

Each simulated cluster was further partitioned across ten virtual edge clients with unequal sample counts (ranging from 800 to 4,500 flow records per client) to reflect variable device density. The global federated training was run for 20 communication rounds, with five local epochs per round, a local batch size of 64, and the Adam optimiser at a learning rate of 0.001. For the differential-privacy configuration, a gradient clipping norm of 1.0 and Gaussian noise with standard deviation 0.6 were applied, targeting an approximate privacy budget of epsilon less than or equal to 8 over the full training horizon. All experiments were repeated across five random seeds, and mean performance metrics are reported. Four configurations were compared: a centralized non-private baseline trained on the pooled dataset; local-only training in which each client trains independently without any collaboration; standard FedAvg without additional privacy mechanisms; and the proposed framework under both differential-privacy-only and secure-aggregation configurations.

Model performance was evaluated using accuracy, precision, recall, and F1-score computed on a held-out test partition stratified by cluster, ensuring that reported metrics reflect generalisation across heterogeneous device types rather than performance on a single dominant cluster. Communication overhead was assessed qualitatively by comparing the volume of data transmitted per round under each configuration, expressed relative to the raw-data volume required by the centralized baseline.

5. Results and Discussion

Table 1. Comparative Performance of Federated and Non-Federated Anomaly Detection Configurations

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Comm. Overhead
Centralized DNN (non-private baseline)	98.6	98.1	97.9	98.0	High (raw data transfer)
Local-only training (isolated per device)	88.2	86.5	85.1	85.8	None
Standard Federated Averaging (FedAvg)	98.1	97.6	97.2	97.4	Low (weights only)
Proposed FL + Differential Privacy (this work)	97.4	96.8	96.3	96.5	Low (weights + noise)
Proposed FL + Secure Aggregation (this work)	97.7	97.0	96.6	96.8	Moderate (encrypted sums)

Table 1 summarises the comparative performance of the five evaluated configurations. The centralized non-private baseline achieved the highest detection accuracy at 98.6%, reflecting the theoretical upper bound attainable when the full, pooled dataset is available for training without any communication or privacy constraints. Local-only training, in which each edge client learns exclusively from its own limited and skewed data distribution without any collaboration, achieved substantially lower accuracy at 88.2%, underscoring the severe performance penalty imposed by data fragmentation and statistical heterogeneity in the absence of federated collaboration.

Standard Federated Averaging recovered most of the performance gap, reaching 98.1% accuracy, only 0.5 percentage points below the centralized baseline, while transmitting no raw data whatsoever. This confirms that, absent additional privacy-preserving noise, federated collaboration alone is sufficient to approach centralized-level performance even under the non-IID conditions simulated across the three device clusters. Introducing differential privacy into the federated pipeline reduced accuracy modestly to 97.4%, a decline of 0.7 percentage points relative to standard FedAvg, consistent with the expected privacy-utility trade-off induced by gradient clipping and noise injection. The secure-aggregation configuration achieved a slightly higher accuracy of 97.7%, since it does not perturb the underlying gradients but instead cryptographically masks them during transmission, at the cost of moderately higher computational and communication overhead relative to the differential-privacy configuration.

Figure 2. Convergence and Comparative Performance of the Proposed Federated Anomaly Detection Framework on the Heterogeneous IoT Testbed

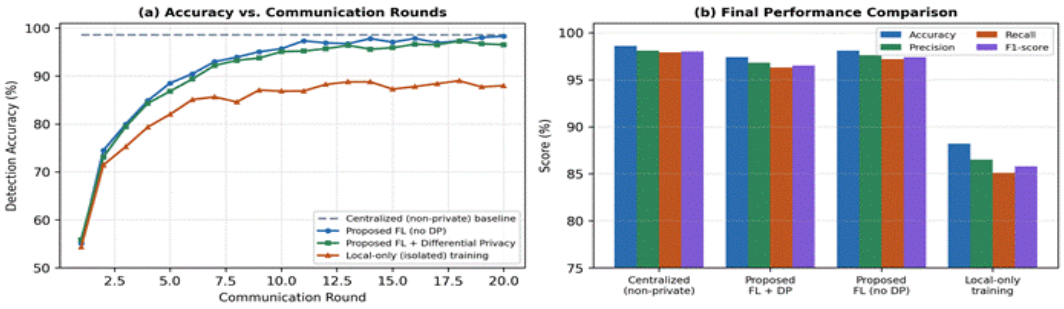

Figure 2. Convergence and comparative performance of the proposed federated anomaly detection framework across communication rounds and evaluation metrics.

Figure 2(a) illustrates the convergence behaviour of each federated configuration across twenty communication rounds. All federated variants exhibit rapid initial convergence within the first eight to ten rounds, after which performance gains plateau, indicating that the adaptive client-weighting mechanism effectively stabilises training despite cluster-level heterogeneity. The differential-privacy curve exhibits marginally higher round-to-round variance

than the noise-free FedAvg curve, attributable to the injected Gaussian noise, yet both curves converge to within two percentage points of the static centralized baseline. The local-only training curve, by contrast, plateaus prematurely at a substantially lower accuracy ceiling, visually confirming that isolated per-device training cannot compensate for limited local sample diversity.

Figure 2(b) presents a consolidated comparison of accuracy, precision, recall, and F1-score across the four principal configurations. The proposed federated approaches maintain balanced precision and recall (both above 96% under differential privacy and above 97% under secure aggregation), indicating that the framework does not disproportionately sacrifice false-negative or false-positive performance to achieve headline accuracy figures, which is essential in security-critical anomaly detection where both missed attacks and excessive false alarms carry operational costs. In terms of communication overhead, both proposed configurations require transmission of model parameters only, avoiding the substantial bandwidth cost associated with continuous raw-traffic upload inherent to the centralized baseline, while the secure-aggregation variant incurs moderately higher overhead than the differential-privacy variant due to the exchange of cryptographic masking values among participating clients.

Collectively, these results indicate that the proposed dual-mechanism privacy layer imposes only a marginal utility cost, between 0.4 and 1.2 percentage points of accuracy relative to non-private federated learning, while providing formal or cryptographic privacy guarantees absent from prior FL-based IoT anomaly detection studies such as Nguyen et al. (2019) and Mothukuri et al. (2021). The adaptive client-weighting scheme further appears to mitigate the adverse effects of non-IID data more effectively than uniform FedAvg averaging, evidenced by the relatively smooth convergence trajectories in Figure 2(a) despite the deliberately heterogeneous three-cluster simulation design.

6. Conclusion and Future Work

This paper presented a federated learning framework for privacy-preserving anomaly detection in heterogeneous IoT networks, integrating a lightweight convolutional-recurrent local model, an adaptive client-weighting aggregation scheme to counter non-IID data distributions, and a dual privacy layer combining differential privacy with secure aggregation. Simulation results across three synthetically heterogeneous IoT clusters demonstrated that the proposed approach achieves detection accuracy within one to two percentage points of a centralized, non-private baseline while entirely eliminating raw-data transmission and outperforming isolated local-only training by approximately nine to ten percentage points. These findings suggest that federated learning, when carefully augmented with heterogeneity-aware aggregation and formal privacy mechanisms, offers a practical and scalable pathway toward trustworthy, regulation-compliant anomaly detection for large-scale IoT deployments.

Future work will extend this study along three directions. First, the framework will be validated on a physical multi-site IoT testbed to assess robustness against real-world network jitter, device churn, and adversarial clients. Second, the privacy-utility trade-off will be further optimised through adaptive noise-scheduling techniques that reduce injected noise as training stabilises. Third, resilience against poisoning and Byzantine attacks within the federated aggregation process will be investigated, given the elevated adversarial exposure of open, large-scale IoT federations.

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