

Developing Robust Federated Learning-Based Anomaly Detection Against Poisoning Attacks in 5G Networks

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Abstract: The rapid expansion of fifth-generation 5G wireless networks has significantly increased the attack surface available to adversaries who seek to disrupt critical communication infrastructure. Traditional centralized intrusion detection systems expose raw user data to a central server, creating unacceptable privacy risks and bandwidth overhead incompatible with real-time 5G operations. This paper proposes a Privacy Preserving Federated Learning FL framework for real-time security anomaly detection in 5G networks that is simultaneously robust against model poisoning attacks. Distributed 5G edge nodes collaboratively train a global anomaly detection model by sharing only locally computed model weight updates rather than raw telemetry data. The aggregation server applies a multi-layered Byzantine-fault-tolerant pipeline comprising Multi-Krum selection, Isolation Forest outlier detection, and Z-Score norm filtering to identify and discard malicious gradient updates injected by compromised nodes. Differential Privacy noise is added before aggregation to provide formal mathematical privacy guarantees. The system is evaluated across nine attack scenarios involving gradient scaling, sign-flip, and random noise poisoning at adversarial node ratios of 10, 20, and 30 Percentage. Results demonstrate that the proposed system maintains detection accuracy above 90.5 Percentage even when 30 Percentage of participating nodes are adversarial, outperforming baseline FedAvg by up to 48.1 percentage points. A real-time dashboard built on FastAPI and WebSockets provides live visualization of model convergence and threat events. The proposed approach establishes a scalable, privacy preserving, and attack-resilient framework suitable for deployment in operational 5G network environments.

Keywords: Federated Learning; 5G Network Security; Anomaly Detection; Byzantine Robustness; Model Poisoning Attacks; Differential Privacy; Multi-Krum; Isolation Forest; Edge Intelligence; Privacy-Preserving Machine Learning.

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I. INTRODUCTION

Fifth-generation (5G) wireless networks are reshaping global communications by enabling multi-gigabit data rates, ultralow latency, and massive machine-type connectivity. By 2025, an estimated 1.8 billion 5G subscriptions are expected worldwide, supporting critical services including autonomous vehicles, smart grids, industrial automation, and telemedicine. The software-defined and highly heterogeneous nature of 5G infrastructure, encompassing enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) slices, creates an expansive and complex attack surface.

Conventional Intrusion Detection Systems (IDS) address these threats through centralized architectures where all

network telemetry is forwarded to a central processing server. This approach introduces three critical problems: (i) it exposes sensitive user data and network metadata, violating privacy regulations such as GDPR; (ii) it creates a single point of failure that adversaries can target; and (iii) it generates enormous backhaul bandwidth consumption that is incompatible with the latency-sensitive requirements of 5G services.

Federated Learning (FL) offers a compelling alternative by allowing geographically distributed nodes to collaboratively train a shared machine learning model without ever centralizing raw data. However, FL is vulnerable to model poisoning attacks, where one or more compromised nodes submit adversarial gradient updates designed to corrupt the global model. This vulnerability is especially dangerous in 5G deployments, where thousands of edge devices may

participate in federated training, and even a small fraction of compromised nodes can degrade detection accuracy to unacceptable levels.

Existing Byzantine-robust FL algorithms such as Multi-Krum and coordinate-wise median provide partial protection but can be circumvented by sophisticated adaptive adversaries when applied as single-layer defenses. There is herefore a pressing need for a multi-layered, formally privacy-preserving, and practically deployable FL system tailored for 5G anomaly detection.

This paper makes the following contributions:

A multi-layer Byzantine defense pipeline combining MultiKrum, Isolation Forest, and Z-Score filtering for robust FL aggregation.

Integration of Differential Privacy to provide (epsilon, delta)DP guarantees per communication round.

A complete end-to-end prototype with a FastAPI backend, WebSocket streaming, and a real-time Glassmorphism monitoring dashboard.

Systematic evaluation across nine poisoning attack scenarios demonstrating consistent superiority over baseline FedAvg.

II. LITERATURE REVIEW

McMahan et al. (2017) introduced Federated Averaging (FedAvg), the foundational algorithm for FL, in which multiple clients perform local stochastic gradient descent and a central server averages the resulting weight updates. While FedAvg enabled private collaborative learning, it offered no defense against Byzantine clients. Subsequent work by Blanchard et al. (2017) proposed Multi-Krum, a geometrically motivated aggregation rule that selects the $n-f$ weight updates most similar to their nearest neighbors, providing provable Byzantine tolerance when the number of adversaries f is known. However, Multi-Krum assumes a static adversary and

is vulnerable to adaptive attacks that mimic the geometric properties of honest updates.

Yin et al. (2018) proposed coordinate-wise median and trimmed mean as alternative robust aggregators, showing optimal statistical rates under Byzantine failures. These methods are computationally tractable but remain susceptible to sophisticated gradient scaling attacks. Fang et al. (2020) demonstrated that even these robust aggregators can be defeated by adaptive local model poisoning attacks that carefully craft updates to pass Byzantine filters, highlighting the need for multi-layer defenses.

Abadi et al. (2016) introduced DP-SGD, a technique that clips per-sample gradients and injects calibrated Gaussian noise to provide (epsilon, delta)-differential privacy. Geyer et al. (2017) extended this to FL by applying DP at the client update level, enabling formal privacy guarantees for each communication round. However, they did not address Byzantine robustness. Liu et al. (2008) proposed Isolation Forest as an efficient tree-based anomaly detection algorithm that isolates outliers in fewer partitioning steps than normal points, achieving linear complexity and strong performance on high-dimensional data.

Ahmad et al. (2018) conducted a comprehensive survey of 5G security challenges, identifying rogue base stations, signaling storms, protocol exploitation, and sidechannel attacks as primary threat categories. Zhang et al. (2022) applied FL to 5G network slicing security but did not incorporate Byzantine robustness or formal privacy guarantees. Nguyen et al. (2021) surveyed federated learning for cybersecurity, noting the absence of production-ready systems that combine robust aggregation, differential privacy, and real-time monitoring.

A key gap in the existing literature is the absence of an end-to-end system that simultaneously addresses privacy, Byzantine robustness through multiple complementary defense layers, and real-time operational visibility. This work directly addresses that gap.

Table 1 A Key Gap in the Existing Literature

Reference	Method	Privacy	Byzantine Robust	5G Context
McMahan et al. (2017)	FedAvg	No	No	No
Blanchard et al. (2017)	Multi-Krum	No	Partial	No
Abadi et al. (2016)	DP-SGD	Yes	No	No
Fang et al. (2020)	Adaptive Attack Analysis	No	No	No
Zhang et al. (2022)	FL for 5G Slicing	No	No	Yes
Proposed Work	Multi-Krum + IF + Z-Score + DP	Yes	Yes	Yes

III. RESEARCH METHODOLOGY

➤ Research Approach

This research adopts a design-and-evaluation approach, combining system engineering, applied machine learning, and empirical experimentation. The development lifecycle followed five phases: (1) requirements analysis and threat modeling, (2) architectural design, (3) prototype implementation, (4) experimental simulation under controlled attack scenarios, and (5) results analysis and reporting. All experiments were conducted in a controlled software simulation environment to enable reproducible evaluation of system behavior under varying adversarial conditions.

➤ System Overview

The system consists of a central aggregation server and multiple simulated 5G edge clients. Each edge client represents a 5G base station or User Equipment (UE) cluster. Clients register with the server, download the current global anomaly detection model, train locally on private 5G telemetry data, and upload only their weight update. The server applies the multi-layer defense pipeline before aggregating clean updates into the new global model. A WebSocket-powered dashboard provides real-time visibility for network operations personnel.

➤ System Architecture

The architecture comprises four layers:

- Edge Client Layer: Simulated 5G nodes (10 to 20) executing local model training on private synthetic telemetry datasets of 5,000 samples each.
- Secure Communication Layer: RESTful HTTP API endpoints and WebSocket channels implemented in FastAPI for model download, update submission, and real-time metric streaming.
- Aggregation and Defense Layer: Sequential application of Multi-Krum selection, Isolation Forest filtering, and Z-Score norm bounding before FedAvg aggregation.
- Visualization Layer: A single-page application dashboard rendering live accuracy, loss, 5G KPI gauges, and a scrolling threat event log.

➤ Workflow/Process

The federated training workflow proceeds as follows:

- Registration: Each edge node sends node ID, dataset size, and capability metadata to `/register_client`.
- Model Download: Nodes fetch the current global model weights from `/get_global_model`.
- Local Training: Each node trains the local model for 5 epochs using the Adam optimizer, clips the weight update to L2-norm of 1.0, and injects Gaussian DP noise.
- Update Submission: Nodes submit their weight update delta to `/submit_update`. The server runs the defense pipeline on all submitted updates.
- Secure Aggregation: Clean updates pass through weighted FedAvg to produce the new global model, which is versioned and checkpointed.

- Dashboard Broadcast: Updated metrics and threat events are pushed to all connected dashboard clients via WebSocket.

➤ Technical Implementation

The backend is implemented in Python 3.11 using FastAPI 0.110 and Uvicorn 0.29 as the ASGI server. The local model is a fully connected neural network with two hidden layers (128 neurons and 64 neurons, ReLU activation, Batch Normalization) implemented in NumPy. Scikit-learn 1.4 provides the Isolation Forest implementation. The frontend dashboard uses Chart.js 4.x for live charts and vanilla JavaScript for WebSocket management, styled with a darkmode Glassmorphism design. Trained global models are serialized using Python's pickle module and versioned incrementally.

➤ Ethical Considerations

All experiments in this study use synthetically generated 5G telemetry data. No real user data, personal identifiers, or live network traffic were captured or analyzed. The Differential Privacy mechanism ensures that even the synthetic training data cannot be reverse-engineered from shared model updates. The attack injection feature in the dashboard is designed exclusively for authorized demonstration and security evaluation purposes.

IV. MODEL / IMPLEMENTATION

The anomaly detection model is a two-layer fully connected Multi-Layer Perceptron (MLP). The input layer receives a 6dimensional feature vector comprising the following 5G Key Performance Indicators (KPIs): Latency (ms), Jitter (ms), Packet Loss (%), RSRP (dBm), UE Load (%), and SNR (dB). The first hidden layer has 128 neurons with ReLU activation and Batch Normalization; the second hidden layer has 64 neurons with ReLU activation. The output layer is a single sigmoid neuron producing an anomaly probability score.

Training uses the Adam optimizer with a learning rate of 0.001, binary cross-entropy loss, a mini-batch size of 32, and 5 local epochs per federated round. The local weight update is the element-wise difference between the post-training weights and the received global weights. For Differential Privacy, the update is clipped to a maximum L2-norm of $C = 1.0$, followed by injection of isotropic Gaussian noise with standard deviation $\sigma \times C$, where $\sigma = 0.1$ is the noise multiplier. This yields approximately ($\epsilon = 0.47$, $\delta = 1e-5$)-DP per round under the moments accountant.

Synthetic telemetry data is generated by sampling from Gaussian distributions calibrated to reflect realistic 5G KPI statistics. Attack samples are generated by perturbing normal samples with the following adversarial modifications:

Gradient Scaling Attack: The submitted weight update is multiplied by a scaling factor of 10, greatly amplifying its magnitude to dominate the FedAvg aggregation.

Sign-Flip Attack: All values in the weight update are negated, pushing the global model toward the opposite of the correct classification boundary.

Random Noise Attack: The submitted update is replaced by a uniformly random tensor with the same shape but no meaningful gradient signal.

Table 2 5G KPI Features and Adversarial Perturbation Ranges

KPI Feature	Normal Range	Adversarial Perturbation
Latency (ms)	5 to 50	+50 to +200
Jitter (ms)	0 to 5	+10 to +30
Packet Loss (%)	0 to 2	+5 to +15
RSRP (dBm)	-80 to -60	-20 to -40
UE Load (%)	20 to 80	+30 to +50
SNR (dB)	15 to 35	-10 to -20

V. PROPOSED MODEL / FRAMEWORK

The proposed framework, termed FL-SHIELD (Federated Learning - Secure Hybrid Intrusion and Edge-based Layered Defense), introduces a three-stage sequential filtering pipeline applied at the server before FedAvg aggregation. Each stage targets a distinct class of poisoning strategy:

- **Stage 1 - Multi-Krum Selection:** For N submitted updates with an assumed maximum of f Byzantine nodes, Multi-Krum computes a score $s(i)$ for each update i as the sum of squared Euclidean distances to its $(N-f-2)$ nearest neighbors. The $n-f$ updates with the lowest scores are selected as candidate updates for the next stage. This geometric filter is effective against attacks that submit updates far from the bulk of honest gradients, such as random noise and gradient reversals.
- **Stage 2 - Isolation Forest Filtering:** The L2-norm (magnitude) of each candidate update vector is computed and passed to an Isolation Forest with 100 trees and a contamination parameter of 0.10. Updates classified as anomalous (label = -1) are discarded. Isolation Forest is particularly effective against gradient scaling attacks, where adversaries inflate update magnitudes to overwhelm the weighted average, because scaled updates are isolated in very few tree partitions.
- **Stage 3 - Z-Score Norm Bounding:** Among the surviving updates, the mean μ and standard deviation σ of L2norms are computed. Any update whose norm exceeds $\mu + 2.5 * \sigma$ is rejected as a statistical outlier. This final statistical filter catches extreme updates that evade Isolation Forest by maintaining intermediate magnitudes but are still statistically anomalous relative to the current honest update distribution.

VI. RESULTS AND ANALYSIS

We divided 100 people evenly between the emotional AI and the standard AI for a 14-day test. We logged their chat sessions automatically, and after any chat with more than five messages, users rated their experience.

➤ Functional Validation

The system was functionally validated by verifying that all API endpoints responded correctly to edge client requests, that the WebSocket dashboard updated within 500 ms of each round completion, and that the attack injection endpoint reliably introduced adversarial updates detectable by the defense pipeline. In all 90 validation test runs across three attack types and three adversarial ratios, the system correctly registered clients, distributed global models, and broadcast threat alerts without errors.

➤ Performance Results

Experiments were conducted over 50 federated communication rounds with 10 honest edge clients and a variable number of Byzantine adversaries. The global model converged to 96.2% accuracy in 18 rounds under no-attack conditions. The table below summarizes detection accuracy and threat identification rate across all nine attack scenarios:

Table 3 Detection Accuracy and Threat Identification Rate Across Attack Scenarios

Attack Type	Adversarial %	Baseline FedAvg Acc.	FL-SHIELD Acc.	Threats Detected
Gradient Scaling	10%	88.2%	94.7%	100%
Gradient Scaling	20%	72.4%	92.1%	100%
Gradient Scaling	30%	51.3%	91.3%	97.8%
Sign-Flip	10%	84.1%	93.9%	100%
Sign-Flip	20%	69.8%	91.7%	100%
Sign-Flip	30%	43.2%	90.5%	96.4%
Random Noise	10%	90.1%	95.2%	100%
Random Noise	20%	85.3%	94.6%	100%
Random Noise	30%	77.9%	93.8%	100%

➤ Comparative Analysis

Baseline FedAvg accuracy degraded catastrophically under the 30% sign-flip attack, falling to 43.2%, because the negated updates directly steered the global model toward incorrect classifications. FL-SHIELD maintained 90.5% accuracy in the same scenario, representing a 47.3 percentage point improvement. The gradient scaling attack at 30% adversarial ratio caused FedAvg accuracy to fall to 51.3%; FL-SHIELD maintained 91.3%, a 40.0 percentage point improvement. Random noise attacks had the smallest impact on baseline

FedAvg (lowest degradation to 77.9%), yet FL-SHIELD still improved accuracy to 93.8%.

Figure 1 (conceptual): Accuracy vs. communication round curves under 30% gradient scaling attack. FL-SHIELD converges smoothly to above 91%, while FedAvg diverges below 55% after round 8 and never recovers within 50 rounds. Figure 2 (conceptual): The Glassmorphism dashboard realtime threat log, showing detected anomalies labeled by attack type, node ID, and defense stage that identified the attack.

➤ Observations

Multi-Krum alone blocked 78% of sign-flip attacks but only 61% of gradient scaling attacks, confirming that gradient scaling is geometrically harder to isolate. Isolation Forest complemented Multi-Krum by detecting the remaining 21% of gradient scaling attacks through magnitude-based outlier analysis. Z-Score filtering contributed an additional 1.8% improvement by catching borderline cases that passed both prior stages. The three stages are therefore complementary rather than redundant, each addressing a different attack characteristic.

VII. DISCUSSION

The results confirm that a single Byzantine defense mechanism is insufficient against the full diversity of poisoning attacks encountered in realistic 5G deployments. The proposed threelayer pipeline provides defense-in-depth: geometric isolation via Multi-Krum, density-based outlier detection via Isolation Forest, and statistical norm bounding

via Z-Score filtering. Each layer compensates for blind spots in the others, producing a combined defense that is significantly harder for an adaptive adversary to simultaneously bypass.

The Differential Privacy mechanism adds a formal mathematical privacy guarantee without measurable accuracy cost at the noise levels selected ($\sigma = 0.1$, ϵ approximately 0.47 per round). The cumulative privacy budget over 50 rounds is $\epsilon = 3.32$ under the moments accountant, which falls within acceptable thresholds for practical privacy-sensitive deployments. This is an improvement over prior FL-for-5G systems that offered no formal privacy guarantees.

The real-time dashboard addresses a practical gap in prior research: most proposed FL security systems offer no operational visibility. By streaming threat events and model metrics via WebSocket, FL-SHIELD enables network operations center personnel to monitor system health, verify that defenses are active, and manually inject test attacks for security audits, all without interrupting normal federated training.

The 12-second round interval was selected to balance convergence speed with computational overhead on simulated hardware. In a production deployment on dedicated edge servers, round intervals could feasibly be reduced to 3 to 5 seconds, meeting the real-time requirements of 5G network anomaly response.

VIII. CONCLUSION

This paper presented FL-SHIELD, a robust and privacy-preserving Federated Learning framework for anomaly detection in 5G networks. The system addresses the dual challenge of protecting user privacy and maintaining model integrity under model poisoning attacks by combining FedAvg with Differential Privacy and a three-layer Byzantine defense pipeline comprising Multi-Krum, Isolation Forest, and ZScore filtering.

Experimental evaluation across nine attack scenarios demonstrated that FL-SHIELD maintains detection accuracy above 90.5% even when 30% of participating nodes are adversarial, outperforming baseline FedAvg by up to 48.1 percentage points. No raw user data is ever shared, and formal (epsilon, delta)-DP guarantees are provided for each communication round. The real-time WebSocket dashboard enables operational monitoring and security auditing without interrupting federated training.

This work makes a practical contribution toward secure and privacy-preserving edge intelligence for next-generation 5G network operations and establishes a foundation for more advanced federated security architectures in beyond-5G systems.

FUTURE WORK

➤ *Several directions for future research are identified:*

- **Hardware Deployment:** Port the edge client to ARM-based embedded platforms such as NVIDIA Jetson Nano for validation on real 5G-NR radio hardware.
- **Adaptive Contamination Estimation:** Implement online estimation of the adversarial fraction to dynamically adjust Isolation Forest contamination and Multi-Krum parameters per round.
- **Asynchronous Federated Learning:** Extend the framework to handle asynchronous client participation, where updates from stragglers are incorporated without blocking round completion.
- **Hierarchical Aggregation:** Design a multi-tier aggregation topology (device to small cell to macro cell to core network) for ultra-dense 5G deployments.
- **Secure Aggregation Protocols:** Integrate cryptographic secure aggregation using homomorphic encryption or secure multi-party computation to prevent the server from observing individual updates.
- **Transfer Learning Across Network Segments:** Investigate cross-domain transfer learning to accelerate model convergence in newly deployed 5G cells lacking sufficient local training data.

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