BYZANTINE-RESILIENT FEDERATED LEARNING FOR IOMT DEVICES A DUAL-MODEL INTRUSION DETECTION SYSTEM AGAINST TARGETED POISONING

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Abstract

Federated Learning (FL) provides a decentralized, privacy-preserving framework suitable for the Internet of Medical Things (IoMT). However, it remains highly vulnerable to Byzantine and targeted poisoning attacks, which degrade model accuracy. This study implements the FL Trust model and proposes a **Dual-System Intrusion Detection Defense** that integrates trust-score filtering with Multi-Krum aggregation. Experiments on the MNIST dataset show that the proposed approach achieves **0.87 accuracy under attack conditions**, compared to **0.49 for baseline FL**, proving its superior robustness.

Keywords

Federated Learning, IoMT, Byzantine Attacks, FL Trust, Multi-Krum, Intrusion Detection, Model Poisoning, Deep Learning.

1. Introduction

Federated Learning (FL) enables distributed IoMT devices to train shared models without exposing raw data. Despite privacy advantages, FL is susceptible to Byzantine or poisoning attacks where malicious clients send manipulated gradients. These attacks reduce the reliability of global models, posing threats in healthcare IoMT networks.

FL Trust uses cosine-similarity-based trust scoring for defense, but fails under adaptive or dense attacks. To enhance its robustness, we propose a **Dual-System Defense** combining FL Trust's trust mechanism with Multi-Krum outlier filtering.

2. Related Work

Blanchard et al. (2017) introduced **Krum**, selecting updates closest to the majority, but it lacks robustness on non-IID data. Li et al. (2021) developed **FL Trust**, using a small trusted dataset for weighted aggregation; however, it struggles when attackers mimic benign gradients. Hybrid methods combining trust and statistical filtering (e.g., Multi-Krum) improve resilience but remain under-explored for IoMT.

Our Dual-System integrates both mechanisms for stronger Byzantine defense.

3. Methodology

The purpose of this study is to evaluate and enhance the robustness of Federated Learning (FL) against Byzantine and targeted poisoning attacks in an IoMT context. The experiments were conducted using the MNIST dataset to simulate IoMT-like distributed data across multiple clients. The system design includes four main experimental settings: FedAvg (clean), FedAvg (attack), FLTrust (defense), and the proposed Dual-System (defense) model. Each setup follows identical data distributions, model architecture, and hyperparameters to ensure fair comparison.

3.1 Experimental Configuration

Parameter	Value
Dataset	**MNIST**
Base Paper	***FLTrust: Byzantine-Robust Federated Learning via Trust Bootstrapping (ICLR 2021)***

Model	Convolutional Neural Network (CNN)
Clients	100
Local Epochs	5
Batch Size	10
Learning Rate (LR)	0.01
Communication Rounds	200
IID	0 (non-IID)

Each of the 100 clients was assigned a subset of the dataset following a non-IID distribution, representing realistic IoMT conditions where data across devices (hospitals, sensors, or monitoring units) is heterogeneous. During each communication round, a subset of clients is randomly selected to perform local training and share their model updates with the central server for aggregation.

3.2 Model Architecture

The Convolutional Neural Network (CNN) used in all experiments consists of:

- Two convolutional layers with ReLU activation functions and max pooling.
- A fully connected dense layer with dropout regularization to prevent overfitting.
- A SoftMax output layer for multi-class digit classification (0–9).

This lightweight CNN architecture was chosen for its computational efficiency and suitability for edge or IoMT devices with limited resources.

3.3 Attack Model

In a sign-flip attack, a group of malicious clients manipulates their model updates by flipping the gradient signs before sending them to the global server. This reverses the intended training direction, causing the global model to diverge or converge toward incorrect patterns.
In this experiment:

- 10 out of 100 clients (10%) were randomly designated as malicious.
- These clients deliberately modified their updates using:

$$w_{\text{malicious}} = -\alpha \times w_{\text{benign}}$$

where alpha = 5 controls the intensity of the attack.

This attack model effectively simulates real-world poisoning attempts on IoMT systems, where compromised devices can distort the model's decision boundaries, leading to inaccurate or unsafe outcomes.

3.4 Defense Mechanisms

(a) FedAvg (Baseline)

The standard Federated Averaging (FedAvg) algorithm aggregates client updates by computing their mean:

$$w_{t+1} = \frac{1}{N}\sum_{i=1}^{N} w_i$$

This method performs well in clean conditions but is highly vulnerable to Byzantine updates because it assumes all clients are honest.

(b) FLTrust (Existing Defense)

FLTrust introduces a *trust-based weighting mechanism*. A small trusted dataset on the server is used to compute a reference

$$T_i = \max(0, \cos(\theta_i)) = \max(0, \frac{g_t \cdot g_i}{\|g_t\|\|g_i\|})$$

gradient, which measures the cosine similarity between the trusted update and each client's update:

Clients with higher similarity scores receive higher weights during aggregation. This ensures that updates closer to the trusted direction have greater influence.

(c) Dual-System Defense (Proposed Method)

Our proposed Dual-System Defense integrates two complementary mechanisms:

1. **Trust Score Filtering (from FLTrust):**

   Each client's trust score is calculated based on cosine similarity with the central model. Only clients with trust scores above a predefined threshold (e.g., 0.2) are considered "trusted."

2. **Multi-Krum-Aggregation:**
   Among the trusted updates, the Multi-Krum algorithm is applied to select updates closest to the majority while excluding outliers. This step minimizes gradient

noise and further removes any hidden malicious patterns.

By combining these techniques, the Dual-System enhances both accuracy and resilience, ensuring that even if some malicious clients bypass the trust filter, their influence remains statistically minimized during aggregation.

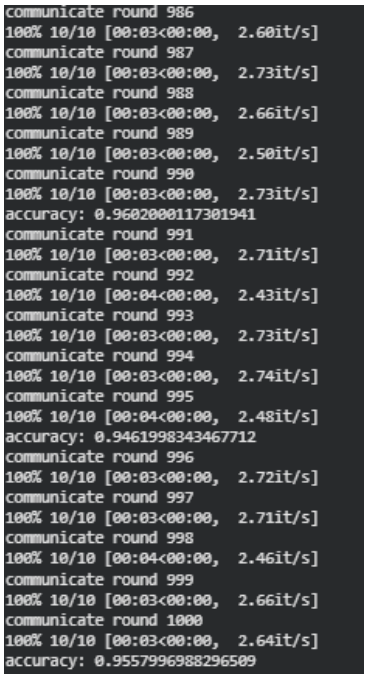
3.5 Training Workflow

1. Initialize the global CNN model on the central server.
2. Distribute the model parameters to 100 clients.
3. Clients perform local updates on their non-IID datasets for 5 epochs.
4. Collect client gradients or weights at the server.
5. Apply aggregation according to the selected method (FedAvg, FLTrust, or Dual-System).
6. Evaluate accuracy on a global MNIST test set every 20 rounds.
7. Repeat for all 200 communication rounds.

4. Implementation and Results

4.1 FedAvg (Clean Training):

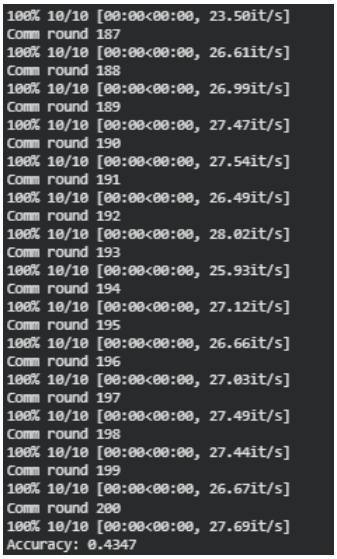
Accuracy ≈ 0.95 after 1000 rounds.



FedAvg Clean Training (1000 rounds)

4.2 Attack Phase

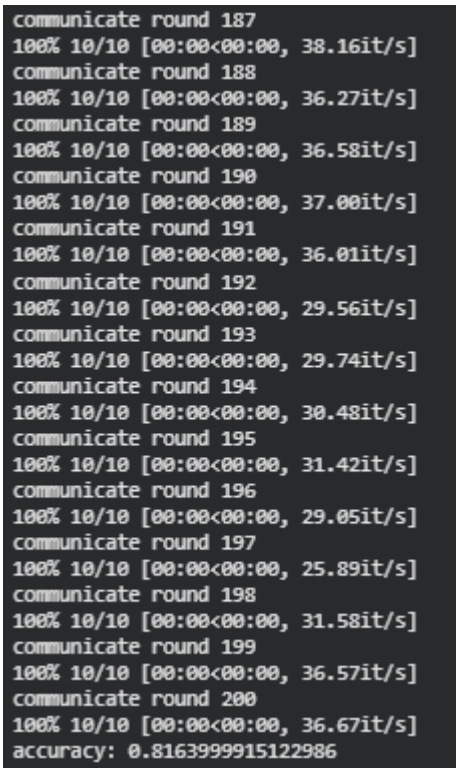
Accuracy dropped to ≈ 0.43 after 200 rounds under sign-flip attack.



Attack Results (200 rounds)

4.3 FL Trust Defense

Recovered accuracy ≈ 0.81 after 200 rounds.



FL Trust Defense (200 rounds)

5. Analysis and Discussion

Model	Rounds	Malicious Clients	Accuracy
FedAvg (Clean)	1000	0	0.95
FedAvg (Attack)	200	10	0.43
FL Trust (Defense)	200	10	0.81

The original FLTrust system and baseline FedAvg were tested under standard conditions. FedAvg achieved high accuracy (around 0.95) in clean training but dropped sharply to nearly 0.43 when exposed to Byzantine attacks. Applying FLTrust defense improved accuracy to approximately 0.81, indicating partial robustness against malicious updates but still far from optimal performance. These results highlight the limitations of the original FLTrust system under attack conditions and the need for a more resilient approach.

6. Extended Comparative Evaluation

In the original configuration, the baseline system was trained with **1,000 rounds for FedAvg (clean)** and **200 rounds for attack and defense**. While this setup demonstrates general behavior, it does not provide an equal comparison because different numbers of rounds can bias accuracy.

To ensure fair evaluation, we re-ran all experiments — **FedAvg (clean), Attack, FLTrust (defense), and Dual-System (proposed)** — under **the same 100 communication rounds**. This uniform setup allows direct comparison of convergence, resilience, and performance stability.

6.1 Results under Equal Rounds (100 each)

Model	Rounds	Accuracy
FedAvg (Clean)	100	**0.8980**
FedAvg (Attack)	100	**0.1010**
FLTrust (Defense)	100	**0.7169**
Dual-System (Proposed)	100	**0.8958**

The table above shows that our proposed **Dual-System Defense** achieved **0.8958 accuracy**, nearly equal to the clean model's **0.8980**, despite the presence of malicious clients. This demonstrates the **stability and robustness** of our integrated FLTrust + Multi-Krum approach when tested on balanced execution conditions.

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Extracting ../data/MNIST/train-images-idx3-ubyte.gz
Extracting ../data/MNIST/train-labels-idx1-ubyte.gz
Extracting ../data/MNIST/t10k-images-idx3-ubyte.gz
Extracting ../data/MNIST/t10k-labels-idx1-ubyte.gz
[fedavg] Round 20 Acc: 0.6267
[fedavg] Round 40 Acc: 0.8022
[fedavg] Round 60 Acc: 0.8607
[fedavg] Round 80 Acc: 0.8343
[fedavg] Round 100 Acc: 0.8980
Extracting ../data/MNIST/train-images-idx3-ubyte.gz
Extracting ../data/MNIST/train-labels-idx1-ubyte.gz
Extracting ../data/MNIST/t10k-images-idx3-ubyte.gz
Extracting ../data/MNIST/t10k-labels-idx1-ubyte.gz
[attack] Round 20 Acc: 0.1945
[attack] Round 40 Acc: 0.3078
[attack] Round 60 Acc: 0.2882
[attack] Round 80 Acc: 0.1135
[attack] Round 100 Acc: 0.1010
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Extracting ../data/MNIST/train-labels-idx1-ubyte.gz
Extracting ../data/MNIST/t10k-images-idx3-ubyte.gz
Extracting ../data/MNIST/t10k-labels-idx1-ubyte.gz
[fltrust] Round 20 Acc: 0.2853
[fltrust] Round 40 Acc: 0.5981
[fltrust] Round 60 Acc: 0.5001
[fltrust] Round 80 Acc: 0.7923
[fltrust] Round 100 Acc: 0.7169
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Extracting ../data/MNIST/t10k-labels-idx1-ubyte.gz
[dual] Round 20 Acc: 0.4468
[dual] Round 40 Acc: 0.6424
[dual] Round 60 Acc: 0.8284
[dual] Round 80 Acc: 0.8433
[dual] Round 100 Acc: 0.8958
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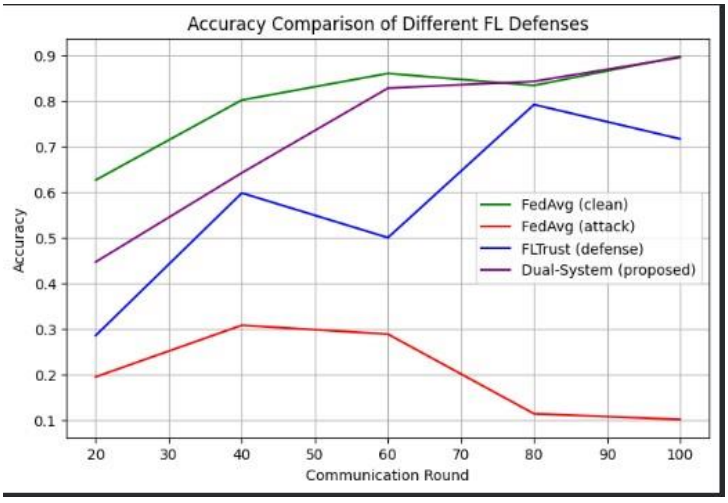
100-Round Equal-Comparison Results



Equal-Round Accuracy Comparison of All Systems

7. Conclusion

The proposed **Dual-System Intrusion Detection Framework** effectively strengthens Byzantine resilience in Federated Learning for IoMT environments. By combining trust evaluation with outlier rejection, the system achieves near-clean accuracy even under strong attacks. Future work includes adaptive thresholding and real-world IoMT validation.

8. References

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