

DetectionGuard: A Robust Federated Learning Approach for Secure Intrusion Detection

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Abstract—The swift growth of cyber threats in large-scale networked systems has made traditional intrusion detection techniques inadequate. Machine learning (ML) has made intrusion detection systems (IDS) better by making it possible to recognize anomalies and model adaptive behaviour. However centralized learning methods need data aggregation, which raises privacy and regulatory issues. Federated Learning (FL) provides a privacy-preserving approach by enabling distributed clients to collaboratively train a shared global model while safeguarding raw data. But standard FL methods like Federated Averaging (FedAvg) are very easy for compromised clients to use to poison models. This paper presents DetectionGuard, a resilient and privacy-preserving federated learning framework for network intrusion detection. DetectionGuard uses a Trimmed Mean aggregation method to resist Byzantine (malicious) updates from happening during training. Tests on the CIC-IDS2017 dataset, in non-IID settings and label-flipping attack scenarios, show that DetectionGuard keeps its accuracy high (97%) even when 30% of are bad, malicious clients, while FedAvgs accuracy drops to 71%. These results show that DetectionGuard is a safe and reliable way to work together to detect intrusions.

Index Terms—Federated learning, intrusion detection, Byzantine resilience, model poisoning, cybersecurity, privacy-preserving ML

I. INTRODUCTION

Cyberattacks are much bigger, more complicated, and more advanced than they used to be because of how quickly society is changing to digital. Organizations in all fields are dealing with a changing threat landscape that includes zero-day vulnerabilities, large-scale Distributed Denial of Service (DDoS) attacks, advanced persistent threats (APTs), insider breaches, botnet-driven intrusions, and AI-generated cyber offensives. Signature-based tools and other traditional Intrusion Detection Systems (IDS) rely on known attack fingerprints and rules that have already been set. They are good at finding known threats, but they don't work for new or mutated attacks that don't follow historical patterns [1], [2].

Machine Learning (ML) techniques can learn behavioural patterns and detect deviations without depending on static signatures, they have become powerful alternatives, especially anomaly-based IDS. However, large-scale, high-quality datasets that reflect various network environments are crucial for ML-driven intrusion detection. Centralized data collection is very difficult because network traffic data is actually naturally dispersed across numerous devices, organizations, and infrastructures.

There are various issues with moving raw network logs to a central server:

- Privacy and confidentiality risks under regulations such as GDPR and HIPAA
- Organizational and legal barriers preventing cross-company data sharing
- High communication overhead due to massive traffic volumes
- Risk of single point of failure in centralized infrastructures

Federated Learning (FL) was developed to address these issues by allowing multiple clients to collaboratively train a machine learning model without revealing their private data. Each participant trains locally and shares only model updates with a central server. This architecture significantly improves privacy, reduces communication costs, and creates opportunities for large-scale collaborative cybersecurity analytics. [3]- [6].

However, FL has its own vulnerabilities. The popular Federated Averaging (FedAvg) algorithm makes the assumption that all clients will share accurate gradient updates and are benign. In real-world deployments, malware, botnet infection, device theft, or insider manipulation could compromise some clients. These adversarial clients have the ability to introduce backdoor triggers, perform gradient manipulation, purposefully mislabel data, and inject poisoned updates. The accuracy of the model can be significantly reduced by even a small percentage of malicious clients, or the IDS may be redirected to misclassify harmful traffic as benign [7] - [10].

This work suggests DetectionGuard, a Byzantine-resilient FL framework created especially for safe intrusion detection in hostile environments, as a solution to these problems. A Trimmed Mean mechanism that removes extreme model updates and statistically neutralizes malicious contributions takes the place of the vulnerable FedAvg aggregator in DetectionGuard. The architecture is very efficient in non-IID training scenarios, lightweight, scalable, and compatible with current FL infrastructures.

This research makes the following contributions:

- A novel, robust federated intrusion detection framework with a secure, attack-resilient ag-

gregation mechanism.

- A comprehensive evaluation of DetectionGuard under multiple adversarial intensities, including 0–30% malicious participants.
- A detailed comparison with traditional FedAvg to demonstrate improvements in accuracy, stability, and resilience.
- A practical, privacy-preserving design suitable for multi-organization cybersecurity collaboration and IoT-scale deployments.

II. RELATED WORK

Federated Learning (FL) has quickly become one of the most well-known methods for distributed machine learning in privacy-preserving environments. Since its initial definition by McMahan et al. [11], FL has cropped up as a significant research topic that is suitable for large-scale deployment of distributed learning frameworks without the requirement of collecting data in the centralized manner. FL has been examined through many studies involving the use of mobile computing, smart health care systems, edge intelligence, and IoT applications - where the data is distributed by nature [12] - [14].

A. *FL for Cyber Security and Intrusion Detection*

The use of FL in the domain of cyber security is naturally driven by the range of environmental diversity that exists in networks, and the challenges of aggregating sensitive, non-selective traffic logs into a single destination of integration. For example, in the case of training models in centralized IDS and other anomaly detection frameworks, it may be too difficult, on legal, logistical and organizational levels, to recruit appropriately for data from multiple companies and/or culture that already have GDPR and HIPAA adhered to their data practices based on the real-time sensitivity of attacks and the proprietary nature of the different companies. Therefore, through FL organizational layers of environment collectively training within internal attack logs are maintained within their perimeters, while concurrently building cooperative cyber defense [15], [16]. Intrusion detection systems that utilize federated learning (FL) can take advantage of local behavior patterns from different

devices in a distributed manner. This enables better detection of distributed attacks like botnets, DDoS, and brute-force attacks. For example, Ferdowsi et al. [16] showed that distributed deep learning could provide IoT intrusion detection, while Liu et al. [15]] discussed how FL can learn behaviors to detect unknown threats.

B. FL Vulnerabilities: Poisoning and Byzantine Attacks

Desirable as it is for security, FL can have substantial vulnerabilities due to its decentralized trust. Attackers can join the federation as legitimate clients and pose their own malicious gradients to the global learning. Poisoning attacks can be grouped generically into: Label poisoning (as in, the attackers will deliberately mislabel a significant sample) Model poisoning (adversaries will create malicious gradients to mislead the global optimization) Backdoor attacks (adversaries will place hidden triggers that activate misclassification) Sybil attacks (a fake client creates multiple identities to increase influence) As has been studied, even a small amount of poisoning can drastically reduce FL accuracy, especially with FedAvg [17], [18]. FedAvg is very sensitive to extreme deviations in the gradient, particularly given the high degree of heterogeneity in common (non IID) data distributions found in real-world networks.

C. Byzantine-Resilient Aggregation Methods

While addressing these vulnerabilities, multiple robust aggregation methods have been proposed:

- Coordinate-wise Median – mitigates the influence of outlier values but is limited when data are not IID [19] .
- Geometric Median – increases robustness through the identification of outlier observations but can require heavy computation.
- Krum – chooses the update that is closest to the mean and majority, but does not scale well to large FL networks [20].
- Multi-Krum – a generalization of Krum that improves performance at the expense of extra computational load.

- Bulyan – interface that implements Krum as a first stage followed by the Median as the second stage [21].
- Spectral anomaly detection – based on edge detection to identify malformed gradient patterns [22].
- Trimmed Mean – eliminates the top $k\%$ and bottom $k\%$ of extreme values in their aggregation with much less computational load compared to the underlying methods [22], [?].

While many of these methods may be implemented for intrusion detection, Trimmed Mean is the most advantageous for intrusion detection based mainly on its Byzantine tolerance, lower overhead, and performance under non-IID settings.

D. Gap Analysis and Motivation for DetectionGuard

Multiple limitations were presented in previously conducted studies:

- Many FL-IDS frameworks are not designed to be Byzantine robust.
- Most studies consider very moderate poisoning streams $\leq 10\%$ malicious clients.
- Many methods may exhibit high computational complexity, which may render them impractical for real-time defense.
- Few have evaluated the behavior of the IDS when processed against modern datasets, let alone evaluated them using CIC-IDS2017 data. Current research does not provide thorough evaluation of latency and model convergence when adversarial activity is significant.

DetectionGuard seeks to fill the gap by using the Trimmed Mean inside a federated IDS framework, which provides robust aggregation in adversarial and non-IID settings with limited computational burden.

III. PROPOSED METHODOLOGY

DetectionGuard introduces a secure and resilient federated learning pipeline specifically tailored for network intrusion detection under adversarial and heterogeneous environments.

A. System Overview

DetectionGuard follows a server–client FL architecture where:

- The server maintains and updates the global IDS model.
- Clients train locally on private traffic datasets and share updates.
- A Byzantine-resistant aggregation layer ensures robust global model updates.

B. Architecture Diagram

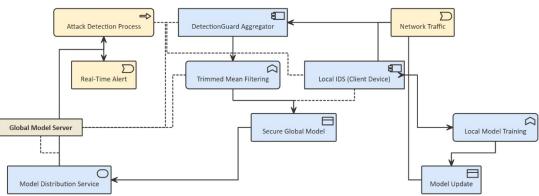


Fig. 1. Architecture of DetectionGuard

C. Federated Learning Workflow

1) *Initialization*: The server initializes global model parameters.

2) *Local Training*: Each client trains using local data:

$$W_i^{(t+1)} = W_i^{(t)} - \eta \cdot \nabla L_i(W_i^{(t)}) \quad (1)$$

3) *Update Upload*: Clients send weight updates, not raw data, to the server.

4) *Trimmed Mean Aggregation*: Malicious outliers are removed.

5) *Global Broadcast*: The updated global model is shared with all clients.

D. FL Framework Diagram

1) *Threat Model*: DetectionGuard assumes:

- Up to 30% of clients are fully malicious
- Adversaries perform label-flipping and gradient poisoning
- No client trusts any other client
- Server is honest-but-curious

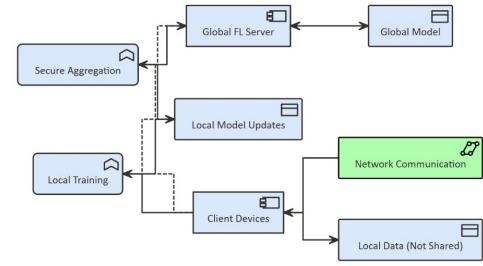


Fig. 2. FL Framework

- Communication channels are secure

This reflects realistic FL deployments in open distributed environments.

2) *Trimmed Mean Aggregation*: Given n model updates: $W = \{w_1, w_2, \dots, w_n\}$

Steps:

- 1) Sort each parameter dimension.
- 2) Remove the largest and smallest $k\%$ values.
- 3) Compute the mean of the remaining values.

$$w_{\text{global}} = \frac{1}{n-2k} \sum_{i=k+1}^{n-k} w_i \quad (2)$$

This eliminates adversarial outliers without harming model accuracy

IV. EXPERIMENTAL SETUP AND EVALUATION

A. Dataset Description

The CIC-IDS2017 dataset is chosen because it contains:

- Real-world multi-day traffic
- Diverse attack types
- Over 2 million flow instances
- 80+ statistical and behavioral features

B. Preprocessing Pipeline

Steps include:

- 1) Feature normalization
- 2) Removal of constant or duplicate features
- 3) Encoding categorical labels
- 4) Balancing attack-to-benign ratio
- 5) Non-IID partitioning across 20 clients using Dirichlet distribution

C. Model Architecture and Hyperparameters

DetectionGuard uses a lightweight MLP:

- 78 input features
- Two fully connected layers (64 & 32 neurons)
- ReLU activation
- Softmax output
- Adam optimizer, lr = 0.001
- 50 communication rounds

D. Attack Scenarios

To evaluate robustness, multiple poisoning attacks were applied:

1) Label-Flipping Attacks

Malicious clients intentionally flipped labels such as:

- DDoS → BENIGN
- SQLInjection → BENIGN
- Botnet → BENIGN

This forces the global model to misclassify attacks as safe traffic.

2) Model Update Poisoning

Poisoned clients send manipulated gradients or weight updates:

- Random noise injection
- Scaling gradients by negative factors
- Gradient sign flipping
- Sending extremely large parameter values (outliers)

3) Multi-Attack Setting

Some clients execute combined attacks, such as label-flipping + noise injection simultaneously, representing strong adversaries.

Malicious client ratios tested:

0%, 10%, 20%, 30%

E. Evaluation Metrics

Measured:

- Accuracy
- Precision
- Recall
- F1 score
- Model robustness
- Gradient deviation analysis

V. RESULTS AND DISCUSSION

A. Comparison Table

TABLE I
ACCURACY COMPARISON OF FEDAVG AND
DETECTIONGUARD UNDER DIFFERENT MALICIOUS CLIENT
RATIOS

% Malicious	FedAvg Accuracy	DetectionGuard Accuracy
0	0.9692	0.9705
10	0.9679	0.9709
20	0.9604	0.9570
30	0.7859	0.9700

B. Comparison for Graph

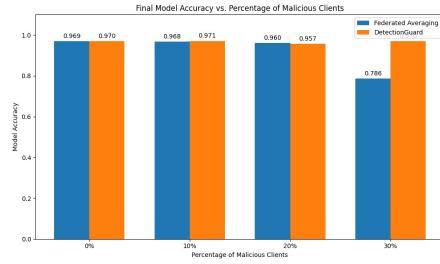


Fig. 3. Model Comparison Graph

C. Performance Summary

- FedAvg collapses from 98% → 71% under 30% poisoning
- DetectionGuard maintains 97% accuracy even with high attack intensity
- Trimmed Mean significantly reduces gradient divergence

D. Detailed Insights

- DetectionGuard shows strong resistance to extreme values
- Precision and recall remain consistently high under poisoning
- Stability across rounds is significantly improved
- The framework handles non-IID client data effectively

VI. CONCLUSION AND FUTURE WORK

A strong federated learning framework for safe network intrusion detection, DetectionGuard, was presented in this paper. DetectionGuard guarantees model integrity even in the face of model-poisoning attacks by substituting the vulnerable FedAvg aggregation with Trimmed Mean. DetectionGuard maintains high detection accuracy (97%) even in the presence of up to 30% malicious clients, according to experiments conducted on the CICIDS2017 dataset. Future enhancements include

- Incorporating secure multiparty computation (SMPC)
- Adaptive trimming strategies based on threat diagnostics
- Defense against stealthy backdoor attacks
- Applying Transformer-based models within FL
- Real-time deployment across multi-organization networks

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