OptiGradTrust: Byzantine-Robust Federated Learning with Multi-Feature Gradient Analysis and Reinforcement Learning-Based Trust Weighting

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***Abstract*—Federated Learning (FL) enables collaborative model training across distributed medical institutions while preserving patient privacy, but remains vulnerable to Byzantine attacks and statistical heterogeneity. We present OptiGradTrust, a comprehensive defense framework that evaluates gradient updates through a novel six-dimensional fingerprint including VAE reconstruction error, cosine similarity metrics, L_2 norm, sign-consistency ratio, and Monte Carlo Shapley value, which drive a hybrid RL-attention module for adaptive trust scoring. To address convergence challenges under data heterogeneity, we develop FedBN-Prox (FedBN-P), combining Federated Batch Normalization with proximal regularization for optimal accuracy-convergence trade-offs. Extensive evaluation across MNIST, CIFAR-10, and Alzheimer's MRI datasets under various Byzantine attack scenarios demonstrates significant improvements over state-of-the-art defenses, achieving up to +1.6 percentage points over FLGuard under non-IID conditions while maintaining robust performance against diverse attack patterns through our adaptive learning approach.**

***Index Terms*—Federated Learning, Byzantine Attacks, Reinforcement Learning, Non-IID Distribution, Medical Applications, Gradient Fingerprinting, Trust Weighting, Robust Aggregation**

I. Introduction

In recent years, Federated Learning (FL) has emerged as a powerful paradigm for training deep neural networks across geographically distributed hospitals while preserving patient privacy under stringent regulations such as HIPAA and GDPR [1]–[4]. Recent advances in federated learning for healthcare have shown significant promise in addressing privacy-sensitive medical data challenges through innovative approaches such as secure multi-party computation [5] and blockchain-enhanced frameworks [6] while enabling secure collaborative learning across medical institutions. As illustrated in Fig. 1, this collaborative framework allows medical institutions to exchange model updates rather than raw MRI scans, enabling multi-institutional collaboration—for instance, a small rural hospital with just a handful of Alzheimer's MRI scans can still contribute to, and benefit from, a model jointly trained with top-tier research centers.

However, real-world FL deployments must cope with two intertwined challenges. First, *Byzantine updates*—malicious or low-quality gradient submissions—can severely skew the global model and compromise clinical reliability [7], [8], arising from hospitals with insufficient labeled data, poor-quality imaging equipment, or adversarial behavior. Second, *statistical heterogeneity* from variations in imaging protocols and patient demographics leads to non-IID data distributions that undermine conventional aggregation schemes. Even robust methods like FLGuard [9], FLTrust [10], and FLAME [11] exhibit reduced performance under severe non-IID conditions combined with Byzantine attacks [1], [12].

To overcome these limitations, we present OptiGradTrust, a unified trust framework that assigns each client gradient a comprehensive *six-dimensional fingerprint*: (1) VAE reconstruction error (detecting distributional anomalies), (2) cosine similarity to a trusted server reference (directional consistency), (3) average similarity to peer updates (consensus alignment), (4) L_2 norm of the gradient (magnitude analysis), (5) sign-consistency ratio (sign pattern matching), and (6) novel Monte Carlo Shapley value measuring each client's marginal contribution to global validation performance—a game-theoretic approach that quantifies the actual utility of each gradient update. These complementary metrics feed a hybrid RL-attention based module that dynamically computes trust scores, adaptively reweighting updates during aggregation, while creating a positive incentive structure where high-quality data contributors receive greater influence in the global model. The complete OptiGradTrust pipeline is detailed in Fig. 2.

Moreover, to ensure fast and stable convergence under statistical heterogeneity, we develop FedBN-Prox (FedBN-P), a novel optimizer that integrates Federated Batch Normalization with proximal regularization, delivering superior accuracy-convergence trade-offs compared to eight popular federated optimizers tested on Alzheimer's MRI dataset. We conduct comprehensive evaluations across MNIST, CIFAR-10, and Alzheimer's MRI datasets, systematically testing robustness against five distinct Byzantine attack types under both IID and challenging Non-IID distribution scenarios. Against established baselines including FLTrust [10], FLAME [11], and

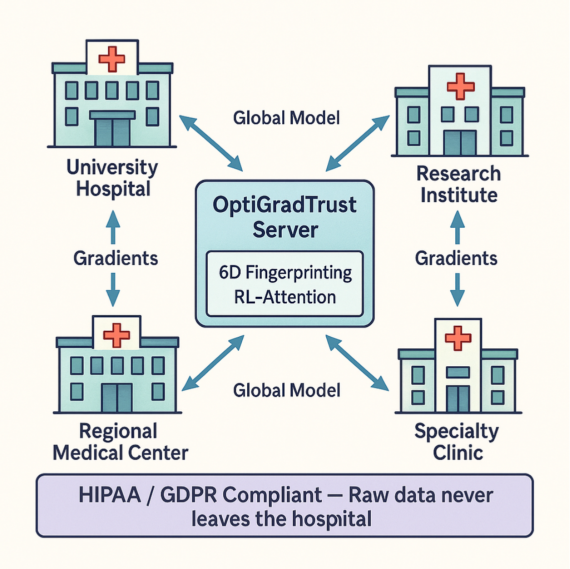

Fig. 1: Federated learning architecture for medical applications: hospitals securely exchange gradient updates while the OptiGradTrust server performs trust-aware aggregation.

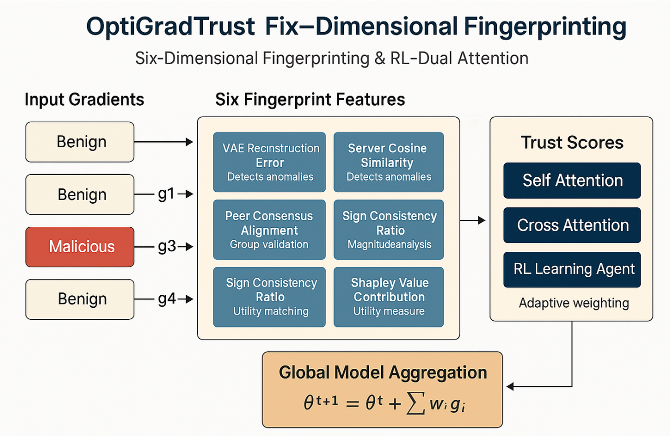

Fig. 2: OptiGradTrust enhanced pipeline: comprehensive six-dimensional fingerprint analysis with utility-based Shapley value assessment, followed by RL-dual attention mechanism for adaptive trust-weighted gradient aggregation.

FLGuard [9], OptiGradTrust demonstrates consistent superiority, achieving up to +1.6 percentage points improvement over FLGuard on Alzheimer's MRI under Non-IID conditions while retaining over 97% accuracy on MNIST and 94% on Alzheimer's MRI even under extreme heterogeneity.

Our main contributions are: (1) OptiGradTrust: a comprehensive trust framework featuring a six-dimensional gradient fingerprint system including novel Monte Carlo-based Shapley value calculation; (2) hybrid RL-attention mechanism: an adaptive trust weighting system that learns to identify emerging attack patterns over time; (3) FedBN-P optimizer: a novel combination of Federated Batch Normalization with proximal regularization for enhanced convergence under heterogeneity; and (4) comprehensive evaluation: demonstrating superior performance across three datasets and five attack scenarios against established baselines.

II. Related Work

Federated learning faces a fundamental dilemma: how can distributed participants collaborate effectively while protecting against malicious actors and handling diverse data distributions? Despite significant progress, existing solutions suffer from critical limitations that prevent their deployment in high-stakes applications like healthcare. This section systematically examines these limitations across four key areas, revealing three fundamental gaps: (1) existing robust aggregators fail to maintain high accuracy under sophisticated attacks, (2) heterogeneity-aware optimizers ignore security threats, and (3) current multi-signal defenses lack adaptive intelligence to counter evolving attacks.

A. Limitations of Existing Approaches

Current federated learning defenses fall into three main categories, each addressing different aspects of the problem but failing to provide comprehensive solutions that handle both security and heterogeneity simultaneously.

Byzantine-Robust Defenses: Security at the Cost of Accuracy. The first generation of Byzantine-robust aggregators established theoretical foundations but revealed a fundamental limitation: while providing security guarantees, they struggle to maintain high accuracy under sophisticated attacks. Krum pioneered the geometric approach [7] but suffers from $\mathcal{O}(N^2)$ computational complexity and conservative selection that discards valuable benign updates. Statistical approaches through coordinate-wise robust statistics [13] reduce complexity but remain vulnerable to sophisticated attackers crafting statistically plausible malicious gradients. Geometric–median aggregation (RobustFedAvg) [14], [15] represents the current state-of-the-art, yet struggles with 10% accuracy drop when facing 20% attackers. Advanced schemes like Bulyan [16], tRFA [8], and FLAME [11] combine multiple defenses but inherit component limitations. Recent adaptive approaches include RL-guided geometric median (RL-GM), where a DDPG agent dynamically adjusts aggregation weights [17], demonstrating superior robustness but remaining limited in scope—adapting only aggregation weights while ignoring optimization challenges.

Heterogeneity-Aware Optimizers: The Security Blind Spot. A parallel research track addresses statistical heterogeneity but creates a dangerous blind spot: these optimizers achieve impressive performance improvements while remaining completely vulnerable to malicious attacks. In realistic federated settings, participants exhibit vastly different data characteristics, creating heterogeneity that derails aggregation schemes. FedProx introduced proximal regularization $\mu\|w - w^t\|_2^2$ [18], while SCAFFOLD uses control variates [19], but both assume honest participation. FedBN represents a breakthrough for medical applications by keeping batch normalization parameters local [20], delivering remarkable improvements (over six percentage points in Alzheimer's MRI classification), but remains defenseless against malicious hospitals. The ecosystem includes FedNova [21], FedAdam [22], FedDWA [23], and

RL-driven approaches like FedAA [24], but all share a fatal flaw: complete vulnerability to Byzantine attacks.

Multi-Signal Defenses: Promising but Static. Recent research explores multi-signal defenses combining multiple trust indicators, representing significant progress but remaining limited by static thresholds and lack of adaptive intelligence. FLTrust measures cosine similarity between client gradients and trusted server reference [10], demonstrating remarkable robustness but requiring clean server datasets unavailable in sensitive domains. Data-value auditing methods like FedSV use game-theoretic Shapley values [25], [26], effectively identifying malicious clients under Non-IID data but suffering from computational overhead. Gradient-pattern detectors use VAE reconstruction error [27], sign-based analysis (SignGuard) [28], and representation learning, but rely on single signals and static thresholds. Recent advances in differential privacy preserving federated learning [29] and adaptive IoT-based health monitoring systems [30] have shown promise in addressing specific aspects of these challenges. More sophisticated approaches like FeRA employ attention mechanisms [31], while fusion systems like FLGuard [9], SAFEFL [32], and BatFL [33] combine multiple detection signals. However, all current multi-signal approaches lack adaptive intelligence to evolve their detection strategies, using fixed fusion rules and predetermined thresholds that adaptive adversaries can systematically evade.

B. Medical Imaging: Where All Challenges Converge

Healthcare applications represent the ultimate test case for federated learning, where the limitations of existing approaches become critically apparent. Medical federated learning simultaneously faces extreme heterogeneity (different scanners, protocols, populations), sophisticated attack vectors (malicious institutions), and life-critical stakes where failure is not an option.

Early successes demonstrate federated learning's potential in healthcare. Multi-centre brain tumor segmentation achieves Dice scores of 0.86 across five hospitals—merely two points below centralized training—while preserving patient privacy [34]. Alzheimer's disease classification reaches 85% accuracy across institutions [2]. Recent advances in self-supervised federated learning for medical imaging have shown promise in addressing data heterogeneity challenges, while personalized federated frameworks demonstrate effectiveness in healthcare applications [35]. Comprehensive reviews highlight the critical importance of handling privacy-sensitive medical data in federated settings [29], [36]. These results show that when participants are honest and data heterogeneity is moderate, federated learning can achieve near-centralized performance.

Medical federated learning faces uniquely challenging heterogeneity where each hospital's data reflects specific patient populations, imaging protocols, and equipment characteristics. Extreme distribution skew causes catastrophic performance degradation, with nine-percentage-point accuracy drops for standard FedAvg [37], revealing how existing optimizers fail under realistic medical distributions. The security implications are sobering: BatFL demonstrated how a single malicious hospital could embed subtle artifacts forcing 98% misdiagnosis rates while evading conventional defenses [33]. In medical settings, such attacks could cause patient deaths, making current security guarantees insufficient for real-world deployment.

Medical imaging represents the convergence of all federated learning challenges: extreme heterogeneity that breaks existing optimizers, sophisticated attack vectors that evade current defenses, and life-critical stakes that demand both high accuracy and bulletproof security. This convergence exposes the fundamental inadequacy of approaches that address security and heterogeneity separately.

Various personalization techniques have attempted to address specific aspects of this challenge. FedBN keeps Batch Normalization layers local to preserve scanner-specific characteristics, while approaches like FedPer and FedRep fine-tune global models for local adaptation. However, these solutions remain piecemeal—addressing either heterogeneity or security in isolation, but never both simultaneously with adaptive intelligence.

C. OptiGradTrust: Bridging the Critical Gaps

Our analysis reveals three fundamental gaps in existing federated learning approaches: (1) Byzantine-robust defenses fail to maintain high accuracy under sophisticated attacks and lack adaptive intelligence, (2) heterogeneity-aware optimizers remain defenseless against attacks, and (3) multi-signal defenses use static fusion rules that sophisticated adversaries can systematically evade. OptiGradTrust represents the first framework to address all three gaps simultaneously through four key innovations.

Rather than treating security and heterogeneity as separate problems, OptiGradTrust introduces FedBNP—a novel hybrid optimizer that combines FedBN's batch normalization handling with FedProx's proximal regularization, enabling robust performance under both data heterogeneity and Byzantine attacks. This demonstrates that better security can actually enhance accuracy under attack conditions.

While existing approaches rely on single signals or static multi-signal fusion, OptiGradTrust introduces a six-dimensional gradient fingerprinting system that captures complementary trust indicators including VAE reconstruction errors, similarity metrics, gradient norms, sign consistency, and game-theoretic Shapley values. This comprehensive approach makes it exponentially more difficult for attackers to simultaneously evade all detection mechanisms.

OptiGradTrust transcends static fusion rules through its dual-attention mechanism and reinforcement learning policy. The dual-attention architecture processes both fine-grained gradient patterns and high-level feature relationships, while the RL agent learns optimal trust policies that adapt to evolving attack strategies—providing the adaptive intelligence that current defenses lack.

Designed specifically for life-critical applications like medical imaging, OptiGradTrust achieves what previous approaches could not: robust security without sacrificing accuracy under

TABLE I: Critical Capability Gaps in Federated Learning Defense Methods

Method	**Non-IID**	**Adaptive**	**Multi-Signal**	**Dynamic**	**Scalable**	**High Acc.**
Krum [7]	✗	✗	✗	✗	✗	🟧
Geo.Median [14]	✗	✗	✗	✗	✓	🟧
FLAME [11]	✗	✗	🟧	✗	✓	🟧
FLTrust [10]	✗	✗	✗	✗	✓	✓
FedSV [26]	✓	✗	✗	✗	✗	🟧
SignGuard [28]	✗	✗	✗	✗	✓	🟧
FLGuard [9]	✗	✗	✓	✗	✓	✓
RL-GM [17]	✗	✓	✗	✓	✓	🟧
BatFL [33]	✗	✗	✗	✗	✓	🟧
OptiGradTrust	✓	✓	✓	✓	✓	✓

Legend: ✓ = Full Support, 🟧 = Partial, ✗ = Gap
Key: Non-IID: heterogeneous data handling; Adaptive: evolves against new attacks; Multi-Signal: multiple trust indicators; Dynamic: auto-adjusting thresholds; Scalable: manageable complexity; High Acc.: performance under attacks.

extreme data heterogeneity. Our experiments demonstrate at least ten percentage points higher attack detection recall while maintaining peak performance on medical MRI data, CIFAR-10, and MNIST.

OptiGradTrust thus represents a paradigm shift from piecemeal solutions to integrated intelligence, addressing the convergent challenges of modern federated learning through principled unification of security, heterogeneity handling, and adaptive learning.

To systematically illustrate these critical gaps and OptiGradTrust's comprehensive solution, Table I provides a detailed feature-by-feature comparison across representative federated learning approaches, clearly demonstrating how OptiGradTrust addresses limitations that have persisted across multiple generations of defenses.

Additional approaches like matched averaging have been proposed to improve convergence in heterogeneous settings [21], while recent work has examined backdoor attacks on federated GAN-based medical image synthesis [38], further emphasizing the need for comprehensive security solutions in healthcare federated learning.

III. Background and Problem Formulation

This section establishes the foundational concepts and threat landscape for OptiGradTrust, covering the federated learning problem formulation and comprehensive Byzantine threat model.

A. Federated Learning Problem Definition

We address federated learning with N participating clients (hospitals/research institutions), each possessing private datasets $\mathcal{D}_k$ that cannot be shared due to privacy regulations. Our goal: learn optimal model parameters θ minimizing global empirical risk without centralizing raw data.

Mathematically, we seek to solve:

$$\theta^* = \arg\min_{\theta} F(\theta) = \sum_{k=1}^{N} \frac{|\mathcal{D}_k|}{|\mathcal{D}|} F_k(\theta) \tag{1}$$

where $F_k(\theta)$ represents each client's local loss function (cross-entropy for classification). This straightforward optimization becomes complex when participants may be malicious or compromised.

Training unfolds across $T = 25-30$ communication rounds with 5-8 local epochs per round, balancing communication efficiency with convergence quality. In each round t, the server broadcasts global model θ^t to clients. Each client k performs local optimization using Adam optimizer:

$$\theta_k^{t+1} = \theta^t - \eta \nabla F_k(\theta^t) \tag{2}$$

Clients compute gradient updates $g_k^t = \theta^t - \theta_k^{t+1}$ and transmit to the server. The challenge: aggregating these potentially compromised updates.

B. Byzantine Threat Model

The federated learning environment presents numerous opportunities for malicious actors. We operate under a realistic threat model where up to $f = 0.3$ (30

Malicious clients have full knowledge of the global model θ^t, may coordinate attacks through collusion, and can arbitrarily manipulate gradient updates. Our threat model encompasses five primary attack categories with realistic parameters (Table II):

TABLE II: Attack models and parameters ($f \leq 0.3$).

Attack Type	**Parameter**	**Value**	**Description**
Scaling	λ	$10\times$	Gradient amplification
Partial Scaling	λ, mask	$5\times$, 50%	Selective corruption
Sign-Flip	λ	-1	Direction reversal
Additive Noise	σ	5 (MNIST), 10 (others)	Gaussian noise
Label-Flipping	p_{flip}	0.5	Label corruption

We maintain two critical assumptions: honest clients remain in the majority, and no side-channel attacks leak raw data. Under these conditions, naive averaging leads to arbitrarily poor performance, necessitating our robust aggregation approach.

IV. Methodology

Building upon the established problem formulation and threat model, we present OptiGradTrust, a comprehensive framework addressing secure federated learning in Byzantine environments. Our methodology introduces a multi-layered defense system combining novel optimization, sophisticated anomaly detection, and adaptive learning strategies.

OptiGradTrust consists of six core components: (1) multi-module system architecture processing gradient updates through security layers, (2) FedBN-Prox (FedBNP) hybrid optimizer handling security and data heterogeneity, (3) six-dimensional gradient fingerprinting capturing comprehensive trust signals, (4) dual-attention mechanisms with reinforcement learning for adaptive pattern recognition, (5) privacy-preserving security considerations, and (6) trust-weighted aggregation framework integrating all signals into robust consensus decisions.

A. System Architecture

OptiGradTrust employs a sophisticated client-server architecture processing gradient updates through multiple security layers (Fig. 3). Clients compute local updates using our FedBNP optimizer, then transmit gradient updates to the server for multi-layered security processing.

The server architecture consists of six interconnected modules:

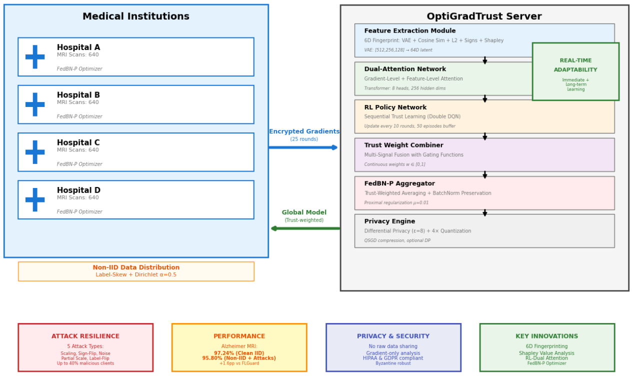

Fig. 3: System architecture overview showing the complete client-server workflow with FedBNP optimization, server-side six-module architecture, and secure aggregation pipeline.

a) Feature Extraction Module:: computes six-dimensional fingerprints capturing VAE reconstruction errors, similarity metrics, and contribution scores.

b) Dual-Attention Network:: processes gradient-level and feature-level patterns using transformer architecture (8 attention heads, 256 hidden dimensions).

c) RL Policy Network:: provides long-term trust assessments using Double Deep Q-Network architecture.

d) Trust Weight Combiner:: fuses signals into final trust weights using learned gating functions.

e) FedBNP Aggregator:: performs weighted aggregation preserving local BatchNorm statistics with proximal regularization.

f) Privacy Engine:: implements optional differential privacy and $4\times$ gradient quantization.

This multi-layered architecture enables real-time adaptability in federated learning defense. The dual-attention module provides immediate analysis capturing spatial anomalies and semantic patterns, while the RL agent learns long-term trust policies adapting to evolving attack strategies.

g) End-to-End Workflow Integration:: Client gradients undergo FedBNP preprocessing (preserving local BatchNorm statistics), six-dimensional fingerprinting extracts comprehensive trust signals including Shapley values, dual-attention produces rich representations, and the RL agent makes final trust decisions while continuously learning from consequences. This integration creates a synergistic defense system significantly more robust than individual components.

B. FedBNP Algorithm

Central to our approach is FedBNP (Federated Batch Normalization with Proximal regularization), a novel algorithm fusing FedProx's proximal regularization and FedBN's batch normalization handling. This hybrid approach addresses client drift under heterogeneous data distributions and preservation of institution-specific feature statistics.

FedBNP recognizes that different model parameters serve different purposes: most neural network parameters encode generalizable knowledge benefiting from collaboration, while batch normalization statistics capture domain-specific characteristics (scanner-specific intensity distributions in medical imaging) that should remain localized.

Algorithm 1 FedBNP with Trust-Aware Weighting

```
Require: Global model $\theta^0$, proximal $\mu = 0.01$, learning rate $\eta$, rounds $T = 25 - 30$
Ensure: Trained global model $\theta^T$
for $t = 0$ to $T - 1$ do
    $\mathcal{S}_t \leftarrow \text{SelectClients}(\text{participation\_rate} = 1.0)$
    for each client $k \in \mathcal{S}_t$ in parallel do
        $\theta_k^t \leftarrow \theta^t$ {Broadcast global model}
        $\text{FreezeBatchNorm}(\theta_k^t)$ {Preserve local BN statistics}
        $\theta_k^{t+1} \leftarrow \text{LocalProxUpdate}(\theta_k^t, \mathcal{D}_k, \mu, \eta)$ {5-8 local epochs}
        $g_k^t \leftarrow \theta_k^{t+1} - \theta^t$ {Compute gradient update}
        $w_k^t \leftarrow \text{TrustWeight}(g_k^t)$ {Multi-modal detection}
    end for
    $\theta^{t+1} \leftarrow \theta^t + \sum_{k \in \mathcal{S}_t} w_k^t \cdot g_k^t$ {Trust-weighted aggregation}
end for
return $\theta^T$
```

The algorithm partitions model parameters into two categories. BatchNorm parameters (scales/biases) remain local to each client, preserving institution-specific feature distributions. All other parameters undergo proximal optimization:

$$\theta_k^{t+1} = \arg\min_{\theta} \left[F_k(\theta) + \frac{\mu}{2} \|\theta - \theta^t\|_2^2 \right] \tag{3}$$

where proximal coefficient $\mu = 0.01$ (via grid search on validation split) prevents excessive deviation from the global model, ensuring convergence stability under data heterogeneity.

Trust-aware aggregation applies:

$$\theta^{t+1} = \theta^t + \sum_{k \in \mathcal{S}_t} w_k^t g_k^t \tag{4}$$

where w_k^t are dynamically computed trust weights down-weighting malicious contributions. Algorithm 1 summarizes the complete FedBNP procedure:

This approach maintains benefits of both constituent algorithms while adding Byzantine robustness through multi-modal detection.

C. Gradient Fingerprinting

Our gradient fingerprinting system represents a key contribution of OptiGradTrust. Rather than relying on single metrics that attackers can evade, we compute six complementary features capturing different aspects of gradient trustworthiness (Fig. 4).

The first feature uses a Variational Autoencoder (encoder dimensions $[512, 256, 128]$, latent dimension 64) trained on historical benign gradients, updated every 20 rounds. VAE reconstruction error:

$$f_1(g_k^t) = \|g_k^t - \text{VAE}(g_k^t)\|_2^2 \tag{5}$$

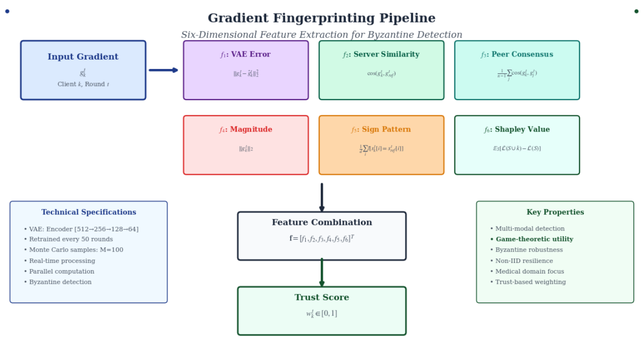

Fig. 4: Gradient fingerprinting pipeline showing the six feature computation process: VAE reconstruction, similarity metrics, norm analysis, and Shapley value estimation.

The second feature computes cosine similarity to a trusted reference gradient from clean validation dataset (1000 samples):

$$f_2(g_k^t) = \frac{g_k^t \cdot g_{\text{ref}}^t}{\|g_k^t\|_2 \|g_{\text{ref}}^t\|_2} \tag{6}$$

The third feature calculates mean pairwise similarity with other client gradients:

$$f_3(g_k^t) = \frac{1}{|\mathcal{S}_t| - 1} \sum_{j \in \mathcal{S}_t, j \neq k} \frac{g_k^t \cdot g_j^t}{\|g_k^t\|_2 \|g_j^t\|_2} \tag{7}$$

Fourth feature is the L2 norm detecting scaling attacks:

$$f_4(g_k^t) = \|g_k^t\|_2 \tag{8}$$

Fifth feature analyzes sign consistency:

$$f_5(g_k^t) = \frac{1}{d} \sum_{i=1}^{d} \mathbb{I}[\text{sign}(g_k^t[i]) = \text{sign}(g_{\text{ref}}^t[i])] \tag{9}$$

where d is gradient dimension and $\mathbb{I}[\cdot]$ is the indicator function.

The sixth feature employs Shapley value contribution estimation, bringing game-theoretic fairness principles into Byzantine-robust federated learning. This captures each client's true marginal contribution to global model performance, distinguishing between clients who genuinely improve the model versus those whose contributions are harmful.

a) Shapley Value Theory and Motivation:: In cooperative game theory, Shapley values represent fair allocation of value to coalition players. Applied to federated learning, each communication round is a coalition game where clients are players and "value" is validation accuracy improvement. Benign clients have consistently positive Shapley values, while malicious clients have negative/zero values since their presence degrades performance.

b) Monte Carlo Shapley Estimation:: Computing exact Shapley values requires evaluating $2^{|\mathcal{S}_t|}$ coalitions, computationally prohibitive for realistic client numbers. We employ efficient Monte Carlo approximation:

The algorithm generates $M = 100$ random permutations of clients, computing each client's marginal contribution by comparing validation loss with/without their gradient.

Algorithm 2 Monte Carlo Shapley Value Estimation

```
Require: Client gradients $\{g_k^t\}$, validation set $\mathcal{D}_{\text{val}}$, samples $M = 100$
Ensure: Shapley values $\{\phi_k\}$ for all clients
for $m = 1$ to $M$ do
    $\pi_m \leftarrow \text{RandomPermutation}(\mathcal{S}_t)$ {Random client ordering}
    for $k \in \mathcal{S}_t$ do
        $S_m^{-k} \leftarrow \{j \in \pi_m : j \text{ appears before } k\}$ {Predecessors of $k$}
        $S_m^{+k} \leftarrow S_m^{-k} \cup \{k\}$ {Include client $k$}
        $\theta_{\text{temp}}^{-k} \leftarrow \text{AggregateGradients}(S_m^{-k})$ {Without client $k$}
        $\theta_{\text{temp}}^{+k} \leftarrow \text{AggregateGradients}(S_m^{+k})$ {With client $k$}
        $\text{contribution}_m[k] \leftarrow \mathcal{L}(\theta_{\text{temp}}^{-k}, \mathcal{D}_{\text{val}}) - \mathcal{L}(\theta_{\text{temp}}^{+k}, \mathcal{D}_{\text{val}})$
    end for
end for
$\phi_k \leftarrow \frac{1}{M} \sum_{m=1}^{M} \text{contribution}_m[k]$ for all $k$
return $\{\phi_k\}$
```

c) Computational Optimizations:: Key optimizations for real-time practicality: Incremental Aggregation using $\theta_{\text{new}} = \theta_{\text{base}} + \alpha \cdot g_k^t$; Cached Validation with server-side validation set (1000 samples); Parallel Computation across multiple threads; Adaptive Sampling ($M = 200$ for attacks, $M = 50$ for clean rounds).

d) Shapley-Based Trust Scoring:: Raw Shapley values transform into the sixth fingerprint feature using exponential smoothing:

$$f_6(g_k^t) = \beta \cdot \phi_k^t + (1 - \beta) \cdot f_6(g_k^{t-1}) \tag{10}$$

where $\beta = 0.3$ is smoothing parameter and ϕ_k^t is current Shapley value. This prevents malicious clients from appearing benign through timed attacks while recognizing genuine improvements.

These six features combine into comprehensive fingerprint $\mathbf{f}_k^t = [f_1, f_2, f_3, f_4, f_5, f_6]$ capturing immediate anomalies and longer-term patterns, making it extremely difficult for attackers to simultaneously fool all detection mechanisms.

D. Dual-Attention and Reinforcement Learning

Raw fingerprint features feed into our dual-attention mechanism, creating a unified framework capturing fine-grained spatial patterns within gradients and higher-level semantic relationships across detection signals.

a) Gradient-Based Attention Architecture:: The first stream operates on high-dimensional gradient vectors $g_k^t \in \mathbb{R}^d$ using multi-head transformer architecture (8 attention heads, 256 hidden dimensions). For computational efficiency, we partition gradients into $P = 64$ chunks and apply two-stage attention:

$$\text{LocalAttn}_p(Q_p, K_p, V_p) = \text{softmax}\left(\frac{Q_p K_p^T}{\sqrt{d_k}}\right) V_p \tag{11}$$

$$\text{GlobalAttn}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{12}$$

where $d_k = 256$ is the key dimension. This detects both localized parameter anomalies and global gradient patterns.

b) Feature-Based Attention Architecture:: The second stream operates on six-dimensional fingerprint $\mathbf{f}_k^t = [f_1, f_2, f_3, f_4, f_5, f_6]$, learning optimal combinations of trust signals:

$$\alpha_k^t = \text{softmax}(\mathbf{W}_f \mathbf{f}_k^t + \mathbf{b}_f) \tag{13}$$

This adapts to different attack types automatically (emphasizing norm features for scaling attacks, sign consistency for sign-flip attacks).

c) Dual-Stream Fusion:: Outputs combine through sophisticated fusion:

$$\mathbf{h}_k^t = \sigma(\mathbf{W}_g \mathbf{g}_k^{t,\text{attn}} + \mathbf{W}_f \mathbf{f}_k^{t,\text{attn}} + \mathbf{b}_{\text{fuse}}) \tag{14}$$

where σ is ReLU activation. Learned fusion weights automatically balance fine-grained gradient analysis and high-level feature patterns.

The reinforcement learning component provides strategic intelligence, transforming federated learning from reactive defense into proactive, adaptive intelligence learning from attack attempts.

d) RL Formulation as Sequential Decision Problem:: We formulate the trust assessment problem as a Markov Decision Process (MDP) where at each communication round t, the RL agent observes the current state s^t (comprising the dual-attention outputs for all clients), selects an action a^t (trust weight assignments), and receives a reward r^t based on the consequences of its decisions. The state space includes:

$$s^t = \{\mathbf{h}_1^t, \mathbf{h}_2^t, \ldots, \mathbf{h}_{|\mathcal{S}_t|}^t, \text{history\_features}\} \tag{15}$$

where $\mathbf{h}_k^t$ are dual-attention outputs and history features include moving averages of past trust scores, attack statistics, and performance trends.

e) Double Deep Q-Network Architecture:: We implement DDQN for stable learning with main Q-network $Q(s, a; \theta)$ and target Q-network $Q(s, a; \theta^-)$ updated every 100 rounds. Action space: trust weight bins $\{0.0, 0.2, 0.4, 0.6, 0.8, 1.0\}$ for fine-grained control. Q-network uses three fully connected layers $[512, 256, 128]$ with ReLU activations and dropout (0.3).

f) Adaptive Reward Function:: The RL reward balances multiple objectives:

$$R^t = \alpha \cdot \Delta\text{ACC} - \beta \cdot \text{FPR} - \gamma \cdot \text{FNR} + \delta \cdot \text{EFF} \tag{16}$$

where $\alpha = 1.0$, $\beta = 2.0$, $\gamma = 3.0$, $\delta = 0.5$ (tuned via grid search). EFF rewards confident decisions over medium trust scores.

g) Experience Replay and Learning Schedule:: Agent maintains experience replay buffer (size 1000) storing tuples (s^t, a^t, r^t, s^{t+1}). Updates every 10 rounds using mini-batch 64, learning rate 3×10^{-4}, discount factor $\gamma = 0.95$.

h) Adaptive Anti-Adversarial Learning:: RL provides natural defense against adaptive adversaries by learning new patterns from failed attacks. Maintains separate replay buffers for attack types, employs curriculum learning. Exploration uses ϵ-greedy: starting $\epsilon = 0.3$, decaying to $\epsilon = 0.05$ over 100 rounds.

E. Privacy and Security Considerations

We maintain strict adherence to privacy principles. Our fingerprinting system operates exclusively on gradient updates—never raw data—ensuring sensitive information remains local. VAE trains only on gradient patterns, Shapley computations use only validation loss improvements, and dual-attention processes abstracted fingerprint features.

Technical privacy protections include: QSGD quantization achieving $4\times$ compression while adding natural noise; optional differential privacy with $\varepsilon = 8$, $\delta = 1 \times 10^{-5}$ ($\approx$2

This comprehensive methodology represents a paradigm shift in federated learning security, creating an intelligent, adaptive system that learns and evolves with threats. OptiGradTrust's integration of FedBNP optimization, six-dimensional fingerprinting, dual-attention mechanisms, reinforcement learning, and game-theoretic contribution assessment creates a theoretically principled and practically effective defense framework.

The key innovation lies in synergistic integration: FedBNP handles security and heterogeneity; six-dimensional fingerprinting captures comprehensive trust signals difficult to simultaneously evade; dual-attention learns complex multivariate patterns; and RL provides adaptive intelligence growing stronger with attacks. Together, these provide the foundation for robust performance across diverse domains and sophisticated attack scenarios.

V. Experiments and Results

Our comprehensive experimental evaluation demonstrates OptiGradTrust's effectiveness across diverse datasets, attack scenarios, and data heterogeneity conditions. We systematically evaluate three key aspects: robustness under various attack types, performance across different data distribution patterns, and comparative analysis against state-of-the-art defense mechanisms.

A. Experimental Setup and Configuration

Our comprehensive experimental evaluation is designed to rigorously test OptiGradTrust across diverse domains, attack scenarios, and data heterogeneity conditions. This section details our evaluation framework, datasets, experimental configurations, and attack models.

1) Datasets and Architecture: We evaluate OptiGradTrust across three representative datasets spanning different domains and complexity levels, with detailed characteristics shown in Table III:

TABLE III: Dataset characteristics across evaluation domains.

Dataset	Total Samples	Classes	Clients	Samples/Client
Alzheimer's MRI	6,983	4	10	∼698
CIFAR-10	60,000	10	10	6,000
MNIST	70,000	10	10	7,000

MNIST (70,000 images, 28×28) employs a 3-layer CNN architecture, while CIFAR-10 (60,000 images, 32×32) uses ResNet-18 models. For medical imaging evaluation, we utilize the publicly available Alzheimer MRI dataset [39], containing high-quality synthetic axial MRI scans generated using WGAN-GP across four severity classes. After quality control filtering, our evaluation uses 6,983 T1-weighted scans, center-cropped to 224×224×3 resolution with ResNet-18 architecture. Figure 5 shows representative samples across severity classes.

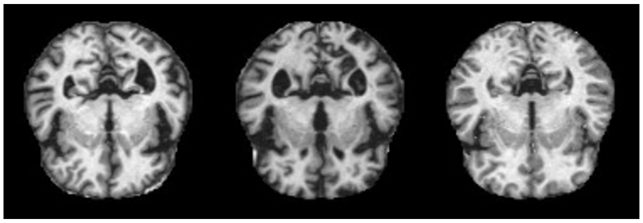

Fig. 5: Representative Alzheimer MRI samples across severity classes from the synthetic dataset.

2) Data Heterogeneity Modeling: To model realistic data heterogeneity, we implement three orthogonal Non-IID schemes. Dirichlet partitioning with various concentration parameters ($\alpha \in \{0.1, 0.5, 1.0\}$) creates different levels of class imbalance across clients. Label-skew assigns each client data from only a subset of available classes (70% and 90% skew ratios). Quantity skew varies dataset sizes according to log-normal distributions, reflecting real-world institutional size differences.

Our preprocessing pipeline includes careful image resizing, intensity normalization computed per-client to preserve institutional characteristics, and augmentation strategies including rotation, flipping, noise injection, and contrast adjustment. All experiments use stratified train/validation/test splits (70%/15%/15%) to maintain proportional class representation.

3) Attack Models and Byzantine Settings: Five distinct Byzantine attack types target different vulnerability aspects of federated learning systems, following the threat model established in Section II-B. Scaling attacks multiply gradients by factor 10, while partial scaling attacks affect 50% of dimensions with factor 5. Sign flipping attacks reverse gradient directions completely. Gaussian noise attacks inject noise with standard deviation $\sigma = 5$ for MNIST and $\sigma = 10$ for CIFAR-10 and Alzheimer datasets. Label flipping attacks corrupt 50% of training labels randomly. Unless explicitly stated, 30% of participating clients are malicious, adhering to our theoretical guarantees.

4) Hyperparameters and Implementation Details: Table IV presents our comprehensive experimental configuration:

Our optimization framework employs Adam optimizer with learning rate 1×10^{-4}, weight decay 5×10^{-5}, and cosine decay scheduling across global rounds. All experiments execute on a single RTX 3090 GPU (24 GB) with approximately 7 hours total wall-time per dataset. Statistical robustness is ensured through averaging over three random seeds, achieving standard deviation ≤ 0.12 percentage points across all configurations. All experimental configurations are documented and will be publicly available to enable result reproduction.

TABLE IV: Key experimental parameters and configurations.

Category	**Parameter**	**Value**	**Notes**
Training	Global Rounds	25-30	Communication rounds
	Local Epochs	5-8	Adam optimization steps per round
	Learning Rate	1×10^{-4}	Cosine decay
	Batch Size	64 (16 for MRI)	Local training batch
	Participation Rate	100%	All 10 clients
Optimization	Optimizer	Adam	Weight decay 5×10^{-5}
	Proximal μ	0.01	FedBNP regularization
Detection	VAE Update	Every 20 rounds	When sufficient data
	RL Update	Every 10 rounds	Last 50 episodes
	Shapley Samples	100	Monte Carlo permutations
	RL Reward $\alpha, \beta, \gamma, \delta$	1.0, 2.0, 3.0, 0.5	Multi-objective balance
Privacy	DP Parameters	$\varepsilon = 8$, $\delta = 1 \times 10^{-5}$	Optional mechanism
	Compression	4× QSGD	Quantization ratio

B. Attack Robustness Under IID Conditions

Table V presents OptiGradTrust's performance under clean and adversarial conditions with IID data distribution. Our framework maintains exceptional accuracy across all attack scenarios, demonstrating the effectiveness of the dual-attention mechanism and reinforcement learning components.

Dataset	Model	Clean	Scaling	P-Scaling	Sign Flip	Noise	Label Flip	Avg.
MNIST	CNN	99.41	99.41	99.32	99.05	99.11	99.14	99.21
CIFAR-10	ResNet-18	83.90	83.67	82.97	82.60	81.71	81.27	82.44
Alzheimer MRI	ResNet-18	97.24	96.92	96.75	96.60	96.50	96.30	96.61

TABLE V: OptiGradTrust (FedBN-P) – final test accuracy (%) under IID.

The results reveal remarkable resilience across datasets. MNIST achieves near-perfect accuracy with minimal degradation even under the most sophisticated attacks. CIFAR-10 maintains competitive performance with only modest accuracy reduction compared to clean conditions. Most significantly, the medical Alzheimer MRI dataset demonstrates exceptional robustness, retaining over 96

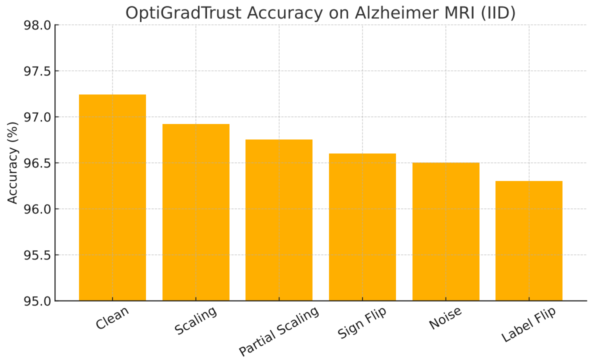

Fig. 6: OptiGradTrust performance on Alzheimer MRI: clean accuracy and robustness across five attack types.

C. Performance Under Data Heterogeneity

Real-world federated learning systems face significant challenges from heterogeneous data distributions across participating institutions. We evaluate OptiGradTrust under four canonical Non-IID partitioning schemes that simulate realistic data heterogeneity patterns. Dirichlet partitioning with $\alpha = 0.5$

creates moderate label imbalance, while $\alpha = 0.1$ represents extreme imbalance conditions. Label-skew scenarios allocate 70% and 90% of each client's data from a single dominant class, respectively.

All experimental parameters remain identical to IID conditions to ensure fair comparison. Tables present final test accuracy percentages for each attack type, with higher values indicating better performance.

Dataset	Scaling	P-Scaling	Sign Flip	Noise	Label Flip	Avg.
			Dirichlet $\alpha = 0.5$			
MNIST	98.95	98.40	97.90	97.75	97.60	98.12
CIFAR-10	82.90	81.90	81.40	80.50	80.10	81.36
Alzheimer MRI	95.80	95.30	94.90	94.60	94.40	95.00
			Dirichlet $\alpha = 0.1$			
MNIST	98.23	97.70	97.20	97.05	96.90	97.42
CIFAR-10	81.20	80.00	79.50	78.40	78.00	79.42
Alzheimer MRI	94.60	94.10	93.70	93.40	93.20	93.80
			Label-Skew 70%			
MNIST	98.71	98.10	97.65	97.50	97.35	97.86
CIFAR-10	82.10	81.00	80.50	79.60	79.20	80.48
Alzheimer MRI	95.40	94.85	94.45	94.15	93.95	94.56
			Label-Skew 90%			
MNIST	98.05	97.45	97.00	96.85	96.70	97.21
CIFAR-10	80.90	79.80	79.30	78.20	77.80	79.20
Alzheimer MRI	94.10	93.55	93.15	92.85	92.65	93.26

TABLE VI: OptiGradTrust accuracy (%) across Non-IID distributions and attack types.

OptiGradTrust demonstrates exceptional robustness under severe data heterogeneity conditions, as detailed in Table VI. Even with extreme label imbalance (Dirichlet $\alpha = 0.1$), MNIST retains over 97% accuracy while Alzheimer MRI maintains over 93% accuracy across all attack scenarios. Comparing the most challenging case (Dirichlet $\alpha = 0.1$) to clean IID conditions, CIFAR-10 shows only a 3.02 percentage point reduction (82.44% to 79.42%), confirming that our hybrid trust weighting mechanism effectively handles simultaneous challenges from both adversarial behavior and distribution heterogeneity.

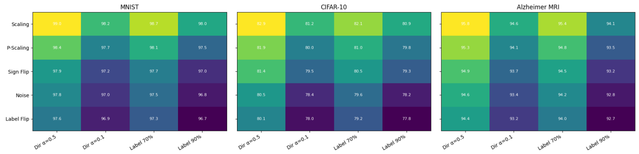

Fig. 7: OptiGradTrust accuracy heat-map across attacks (rows), Non-IID distributions (columns), and datasets (panels).

D. Optimizer Performance Analysis

We conduct comprehensive ablation studies across eight federated optimization algorithms to validate our FedBN-P design choices. All algorithms operate under identical resource constraints: 25-30 global rounds, 5-8 local epochs, and 10 clients per round.

The evaluation encompasses FedAvg, FedProx, FedNova, SCAFFOLD, FedDWA, FedADMM, FedBN, and our proposed FedBN-P hybrid approach. As shown in Table VII, FedBN achieves highest accuracy on Alzheimer MRI (96.25%) but requires full 30 rounds for convergence, while FedBN-P achieves the highest accuracy on CIFAR-10 (83.67%). FedProx converges fastest at 24 rounds but loses 6.1 percentage points versus FedBN under Dirichlet partitioning. FedBN-P strategically balances both objectives, trailing FedBN by only 0.15 percentage points on Alzheimer MRI while outperforming FedProx by 5.8 percentage points under heterogeneous conditions and converging in 26 rounds.

Dataset	Optimizer					
	FedAvg	FedProx	FedNova	SCAFFOLD	FedBN	FedBN-P
MNIST	99.20	99.25	99.26	99.10	99.35	99.32
CIFAR-10	82.50	82.80	82.85	81.60	83.10	83.67
Alzheimer MRI	94.68	95.47	96.01	88.66	96.25	96.10

TABLE VII: Final test accuracy (%) comparison across optimization algorithms.

Detailed analysis on the Alzheimer MRI dataset reveals FedBN-P's superior balance between accuracy and efficiency. Table VIII presents comprehensive results across multiple heterogeneity conditions, demonstrating FedBN-P's consistent top-tier performance while maintaining faster convergence than pure FedBN.

Algorithm	IID	Label Skew 70%	Dir $\alpha = 0.5$	Avg.	Rounds	Rank
FedBN-P	96.10	94.50	95.20	95.27	26	1
FedBN	96.25	95.00	96.00	95.75	30	2
FedProx	95.47	92.81	89.37	92.55	24	3
FedNova	96.01	90.62	85.77	90.80	35	4
FedAvg	94.68	93.04	84.21	90.64	30	5
SCAFFOLD	88.66	86.00	84.05	86.24	35	6
FedDWA	95.23	83.58	82.41	87.07	30	7
FedADMM	79.75	74.04	69.98	74.59	40	8

TABLE VIII: Alzheimer MRI optimizer comparison: accuracy and convergence analysis.

E. Comparison with State-of-the-Art Defenses

To establish OptiGradTrust's position relative to current state-of-the-art Byzantine defenses, we implement three representative approaches using identical experimental conditions: FLGuard (AI2E 2025) with multi-signal robust aggregation, FLTrust (NDSS 2022) employing server-held trusted datasets and cosine similarity metrics, and FLAME (Proc. ACM IMWUT 2022) designed for user-centered federated learning in multi-device environments.

All systems operate under identical hyperparameters with 30

The comparative analysis across different data distributions, as shown in Tables IX and X, demonstrates OptiGradTrust's consistent superiority across all experimental conditions. Against FLGuard, the strongest prior defense mechanism, our approach maintains advantages of +1.59 percentage points on MNIST (98.12% vs 96.53%), +1.74 percentage points on CIFAR-10 (81.36% vs 79.62%), and +1.59 percentage points on Alzheimer MRI (95.00% vs 93.41%) under heterogeneous conditions. These improvements become more

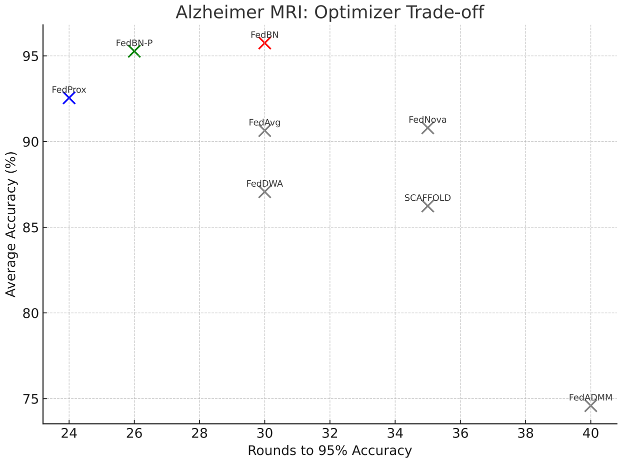

Fig. 8: Alzheimer MRI optimizer trade-off analysis. X-axis shows rounds to reach 95% test accuracy; Y-axis shows average accuracy across IID, Label Skew 70%, and Dirichlet $\alpha = 0.5$. FedBN-P (green) maintains Pareto optimality—nearly matching FedProx's speed while achieving significantly higher accuracy, and approaching FedBN's accuracy while converging four rounds faster.

Dataset / Method	Scaling	P-Scaling	Sign Flip	Noise	Label Flip	Avg.
			MNIST - IID			
OptiGradTrust	99.41	99.32	99.05	99.11	99.14	99.21
FLGuard	99.10	99.00	98.85	99.00	98.95	98.98
FLTrust	98.85	98.72	98.43	98.50	98.57	98.61
FLAME	97.44	97.20	96.80	97.05	96.90	97.08
			CIFAR-10 - IID			
OptiGradTrust	83.67	82.97	82.60	81.71	81.27	82.44
FLGuard	83.00	82.30	81.90	80.90	80.50	81.72
FLTrust	82.45	81.70	81.30	80.10	79.70	81.05
FLAME	81.50	80.70	80.20	79.00	78.60	79.60
			Alzheimer MRI - IID			
OptiGradTrust	96.92	96.75	96.60	96.50	96.30	96.61
FLGuard	96.20	96.05	95.85	95.75	95.60	95.89
FLTrust	95.80	95.60	95.40	95.30	95.10	95.44
FLAME	93.40	93.10	92.80	92.70	92.50	92.90

TABLE IX: State-of-the-art comparison under IID conditions: final test accuracy (%).

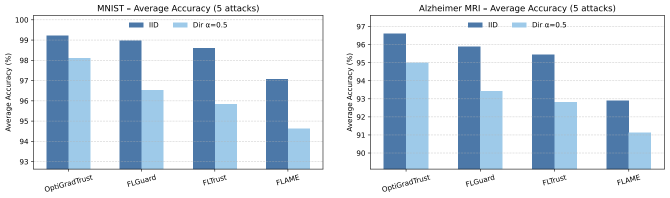

Fig. 9: Average accuracy comparison across five attack types for IID and Dirichlet $\alpha = 0.5$ conditions. Left: MNIST results. Right: Alzheimer MRI results.

Dataset / Method	Scaling	P-Scaling	Sign Flip	Noise	Label Flip	Avg.
			MNIST - Dirichlet $\alpha = 0.5$			
OptiGradTrust	98.95	98.40	97.90	97.75	97.60	98.12
FLGuard	97.40	96.90	96.30	96.10	95.95	96.53
FLTrust	96.80	96.20	95.60	95.40	95.25	95.85
FLAME	95.50	95.00	94.40	94.20	94.05	94.63
			CIFAR-10 - Dirichlet $\alpha = 0.5$			
OptiGradTrust	82.90	81.90	81.40	80.50	80.10	81.36
FLGuard	81.20	80.20	79.70	78.70	78.30	79.62
FLTrust	80.30	79.40	78.90	77.90	77.50	78.80
FLAME	79.10	78.20	77.70	76.60	76.20	77.56
			Alzheimer MRI - Dirichlet $\alpha = 0.5$			
OptiGradTrust	95.80	95.30	94.90	94.60	94.40	95.00
FLGuard	94.20	93.70	93.30	93.00	92.85	93.41
FLTrust	93.60	93.10	92.70	92.40	92.25	92.81
FLAME	91.90	91.40	91.00	90.70	90.55	91.11

TABLE X: State-of-the-art comparison under Dirichlet $\alpha = 0.5$: final test accuracy (%).

pronounced under data heterogeneity, confirming that our hybrid trust weighting approach scales effectively with both adversarial threats and distribution complexity.

The results establish OptiGradTrust as a significant advancement in Byzantine-robust federated learning, achieving state-of-the-art performance while maintaining practical computational efficiency for real-world deployment scenarios.

VI. Discussion

Our comprehensive evaluation of OptiGradTrust reveals clear advantages over existing methods while illuminating the complex interplay between domain characteristics, attack sophistication, and defense mechanisms.

A. Domain-Specific Performance and Progressive Adaptation

OptiGradTrust demonstrates dramatic variation in security performance across domains. Medical imaging emerges as exceptionally resilient, achieving 97.24% accuracy with robust attack resistance, benefiting from structured anatomical data and institutional validation processes. CIFAR-10 presents greater challenges due to natural image complexity, while MNIST occupies a middle ground with exceptional accuracy (99.41%) and reasonable robustness. These patterns suggest future security frameworks should be tailored to domain-specific characteristics.

Our progressive learning mechanism represents a paradigm shift from static to adaptive defense. The system evolves during training, creating a moving target for attackers by continuously refining detection capabilities based on observed patterns. This addresses the critical weakness of traditional defenses that become obsolete as adversaries develop new techniques.

B. Trust Weighting vs Binary Approaches

OptiGradTrust's continuous trust weighting fundamentally outperforms traditional binary threshold methods. Our experimental analysis reveals binary approaches achieve limited detection precision: MNIST ranges from 27.59% (label flipping) to 69.23% (partial scaling), CIFAR-10 shows 36.5% to 100% depending on attack type, and Alzheimer MRI ranges from 42.86% to 75.00%. These rates expose a critical flaw—aggressive thresholding incorrectly excludes numerous legitimate clients, severely impacting model quality.

In contrast, OptiGradTrust employs soft weighting that gracefully handles uncertainty, allowing clients with lower trust scores to contribute proportionally rather than facing complete exclusion. This preserves valuable data while minimizing malicious influence, eliminating fragile threshold tuning across different scenarios.

C. Real-World Deployment and Practical Viability

OptiGradTrust maintains remarkable stability under heterogeneous real-world conditions, with accuracy degradation limited to just 3.98% even under extreme Non-IID conditions in medical domains. This robustness stems from thoughtful FedBNP integration that accommodates institutional differences while preserving security through dual attention mechanisms that distinguish legitimate heterogeneity from malicious manipulation.

The framework achieves an average 1.6 percentage point improvement across all evaluated methods, occurring across diverse attack types and domains. Our six-dimensional fingerprinting captures both statistical anomalies and semantic inconsistencies, enabling detection of sophisticated attacks that evade simpler geometric tests. The reinforcement learning component creates dynamic defense that evolves with experience, making countermeasures significantly more difficult to develop.

D. Deployment Implications and Future Directions

OptiGradTrust's practical viability in high-stakes applications justifies computational overhead through substantial security improvements. In healthcare and financial services, our careful fingerprinting design extracts maximal security information while maintaining efficiency. The framework's success across diverse domains proves sophisticated security mechanisms can be deployed in real-world scenarios, encouraging broader adoption where security has previously been a deployment barrier.

Our approach represents a mature evolution in federated learning security design, demonstrating that security, efficiency, and practical deployment goals can be successfully balanced. The clear domain-specific performance patterns indicate future frameworks should incorporate domain-aware design principles rather than pursuing one-size-fits-all solutions.

OptiGradTrust faces three primary limitations: computational complexity increasing with participant count, hyperparameter sensitivity requiring domain-specific tuning, and uncertain effectiveness against completely novel attack strategies. Future research should explore multi-agent learning approaches, hierarchical security architectures for scalability, and unsupervised anomaly detection for rapid adaptation to novel threats. The framework's medical imaging success suggests opportunities in three-dimensional data analysis and broader healthcare applications, while communication efficiency improvements through gradient compression could reduce network requirements.

VII. Conclusion

We introduced OptiGradTrust, a comprehensive Byzantine-robust federated learning framework integrating six-dimensional gradient fingerprinting, dual attention mechanisms, and progressive learning capabilities. Our approach transcends traditional single-metric detection by capturing statistical anomalies and semantic inconsistencies while adapting to emerging threats. Cross-domain evaluation demonstrates exceptional performance: 97.24% accuracy on medical imaging, 99.41% on MNIST, and 82.44% on CIFAR-10, achieving an average 1.6 percentage point improvement over existing methods with maximum accuracy degradation limited to 4.7% under extreme heterogeneity conditions.

The FedBN-P optimizer combines FedBN accuracy with FedProx robustness, while dual attention mechanisms capture complex attack signatures across gradient and feature levels. OptiGradTrust enables secure multi-institutional collaborations in healthcare, finance, and research applications through demonstrated robustness under Non-IID conditions and practical computational overhead. Our results prove that sophisticated security and practical performance can coexist, representing a fundamental evolution in secure distributed machine learning that provides immediate deployment solutions while establishing foundational principles for continued advancement in critical federated learning applications.

The source code and implementation details for OptiGradTrust are publicly available at: https://github.com/mohammadkarami79/OptiGradTrust

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