LayerGuard: Poisoning-Resilient Federated Learning via Layer-Wise Similarity Analysis

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Abstract

In recent years, model poisoning attacks have gradually evolved from conventional global parameter manipulations to more stealthy and strategic Targeted Layer Poisoning (TLP) attacks.These attacks achieve high attack success rates by selectively poisoning only a subset of layers. However, most existing defenses rely on evaluation of the entire network and are thus ineffective against TLP attacks, posing new challenges to the security of Federated Learning (FL).In this paper, we propose **LayerGuard**, a comprehensive defense framework featuring dynamic detection and adaptive aggregation to protect FL against advanced model poisoning attacks. Diverging from traditional methods that analyze the entire network collectively, **LayerGuard** performs layer-wise similarity analysis to detect anomalous clients and adaptively identifies layers under attack based on the clustering behavior of malicious updates, facilitating more precise threat detection. Building on this, we introduce a joint weighting mechanism in the aggregation process, which evaluates each client's credibility at the layer level from two complementary informational dimensions: inter-layer and intra-layer, balancing attack mitigation and benign contribution retention. Extensive experiments across various datasets and model architectures demonstrate that **LayerGuard** successfully reduces the average attack success rate of TLP attacks to around 5%. Moreover, when confronted with other advanced model poisoning attacks, **LayerGuard** consistently maintains global model accuracy—even under high poisoning rates and severe non-IID conditions—comparable to that of FedAvg under no-attack settings, marking a significant improvement over existing defenses.

1 Introduction

Background and Problem. Federated Learning (FL) has gained widespread adoption in privacy-sensitive domains such as healthcare[3] and finance[4], due to its ability to enable collaborative model training without sharing raw data[1, 2]. However, the decentralized nature of FL also makes it vulnerable to model poisoning attacks[11–18], where adversaries manipulate a subset of client updates to degrade global model performance, posing a serious threat to the reliability of FL systems. Recently, poisoning strategies have evolved from coarse-grained global parameter perturbations[12–18] to more stealthy and strategic forms of Targeted Layer Poisoning (TLP)[11]—where only specific layers of the model are maliciously altered, effectively bypassing existing defenses that rely on evaluation of the entire network[2, 5–10]. In parallel, more general and disruptive poisoning variants such as advanced untargeted attacks[12–15] have emerged, by exhibiting high similarity to benign updates in gradient space, thereby disguising malicious behavior and subtly interfering with the training process. Existing defense mechanisms[5–10] struggle to detect fine-grained layer-level anomalies, and often misclassify benign clients, ultimately harming the overall performance of the global model. These limitations highlight the urgent need for a more fine-grained and robust defense

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framework capable of resisting TLP and other advanced poisoning strategies while preserving model utility.

Limitations of Previous Works. To defend against model poisoning attacks, researchers have proposed various defenses. These include defenses that leverage cross-client information, such as Krum, Trimmed Mean, Norm Bound, and FLAME[5–8], where the server compares statistical properties across clients—e.g., Euclidean distance, cosine similarity—to identify anomalous updates. Defense methods that utilize global information, such as FLTrust and FLDetector[9, 10], in which the server uses trusted gradients or reference models to determine whether a client behaves abnormally. Although progress has been made, existing defenses still face significant limitations against emerging attack strategies. First, these defenses rely on evaluation of the entire network, which fails to capture TLP attacks where only a subset of model layers is manipulated[11]. As a result, such attacks can bypass detection with minimal effort. Second, under highly non-IID data distributions, current defenses struggle to distinguish malicious updates from genuinely benign ones[26]. In such settings, benign clients may generate statistically deviant updates that are nonetheless critical for model performance. These challenges call for a new defense paradigm that can effectively detect localized anomalies while preserving benign diversity, enabling more robust and fine-grained protection in FL.

Our Work. To address the above limitations, we propose **LayerGuard**, a comprehensive defense framework featuring dynamic detection and adaptive aggregation. Diverging from traditional methods that evaluate client behavior at the whole-model level, **LayerGuard** performs layer-wise similarity analysis to detect anomalous clients and adaptively identifies layers likely to be compromised, based on the clustering behavior of malicious updates. Building on this analysis, we introduce a joint weighting mechanism in the aggregation process that evaluates the credibility of each client across individual layers from two complementary informational dimensions: *user-level weights* analyze inter-layer information, while *layer-specific weights* capture intra-layer behavior. Extensive experiments on diverse datasets and model architectures show that **LayerGuard** reduces the average attack success rate of TLP attacks from approximately 90% to around 5%. When confronted with other advanced model poisoning attacks, **LayerGuard** maintains global model accuracy under high poisoning rates and severe non-IID conditions, comparable to that of FedAvg in no-attack settings.

Contribution. The main contributions are:

(a) We uncover a limitation of existing defenses: their coarse-grained evaluation based on the entire network fails to detect localized anomalies, rendering them ineffective against Targeted Layer Poisoning (TLP) attacks.

(b) We propose **LayerGuard**, a novel defense framework that operates at a finer granularity by analyzing each layer individually to identify anomalous clients and adaptively detect layers under attack.This novel approach facilitates more precise threat detection.

(c) We design a joint weighting mechanism for aggregation, which evaluates each client's credibility at the layer level based on two complementary informational dimensions: inter-layer and intra-layer. This design enables precise suppression of malicious updates while retaining the contribution of benign ones.

(d) We conduct extensive experiments on **LayerGuard** against TLP attacks, other advanced model poisoning attacks, and adaptive attacks.

2 Related Works

2.1 Model Poisoning Attacks

In FL, model poisoning attacks directly manipulate client gradients during training and pose greater threats than data poisoning[18, 13], which relies on altering local training data[19, 20]. Depending on their objectives, these attacks are typically categorized into untargeted attacks[12–15], which aim to degrade overall model performance, and targeted attacks[15–18], such as backdoor insertion[16, 17], which manipulate specific outputs. Untargeted poisoning is a more severe threat to model prediction performance than the targeted one in FL[14]. In this work, we primarily focus on untargeted poisoning attacks. For targeted attacks, we focus on a recently proposed backdoor attack based on TLP[11].

Untargeted Attack. We consider five representative advanced untargeted model poisoning attacks in our evaluation. LIE[12] perturbs the average of benign gradients with calibrated noise to subtly degrade model performance while evading detection. Fang[13] is an optimization-based method that manipulates gradient directions by solving for a global scaling coefficient λ. Min-Sum[14] constrains the sum of squared distances between malicious and benign gradients so that it remains within the maximum squared distance among benign updates, while Min-Max[14] instead limits the maximum distance, effectively camouflaging malicious updates among benign ones. MPAF[15] leverages momentum from historical gradients to craft stealthy and disruptive updates that are harder to detect.

2.2 Targeted Layer Poisoning Attacks

Targeted Layer Poisoning (TLP) attacks achieve high attack success rates by selectively poisoning only a subset of model layers. We refer to the poisoned layers as targeted layers, and the unaltered layers as non-targeted layers. The Layer-wise Poisoning (LP) attack[11], proposed by Zhuang et al., is a backdoor-based TLP attack. It identifies Backdoor Critical (BC) layers using Backdoor Success Rate (BSR) as the evaluation metric, and poisons only these targeted layers. Malicious clients optimize their local models through layer-wise analysis, continuously injecting backdoors across multiple communication rounds. The BC layers are not fixed and may vary from round to round, which increases the stealthiness of the attack while maintaining high BSR. Currently, no effective defense strategy exists to counter this type of attack.

3 Design of LayerGuard

3.1 Design Challenges

Our core idea is inspired by previous research[13, 14] that emphasizes the necessity of a certain degree of similarity among malicious updates in order to significantly compromise FL. However, under more complex and stealthy threat scenarios—such as Targeted Layer Poisoning (TLP) attacks and advanced untargeted attacks—designing defense mechanisms based on this principle presents the following technical challenges:

C1- In contrast to conventional poisoning attacks that target the entire model update, TLP attacks selectively poison specific layers. This raises the question: how can the similarity among malicious updates be effectively quantified when only partial-layer poisoning is involved?

C2- Given that TLP attacks affect only selected layers while leaving others largely benign[11], how can a defense mechanism suppress malicious updates in the targeted layers without disrupting the aggregation of benign updates in the non-targeted layers?

C3- Do benign updates sometimes exhibit high similarity similar to that of malicious ones? How can we ensure that such benign updates are not mistakenly classified as malicious?

C4- How can malicious updates be effectively mitigated while minimizing the impact on benign contributions?

3.2 Overview

To address the aforementioned challenges, we propose a novel and advanced defense mechanism for FL, termed **LayerGuard**. The design motivations and inspirations behind this method are detailed in Appendix A. The overall architecture of **LayerGuard** is depicted in Figure 1. Specifically, the process consists of the following core components:

(1) Anomalous User Identification. Identify highly similar anomalous users per layer based on layer-wise similarity scores(LCSS). **(2) High-Risk Layer Detection.** By examining the distribution of anomalous users across different layers, **LayerGuard** identifies the high-risk layers where malicious activity is primarily concentrated. **(3) User-Level Weight Calculation.** Given the identified high-risk layers, **LayerGuard** assigns a user-level weight to each client. **(4) Layer Update Boundary Definition.** Adaptively establish benign and malicious boundaries for updates on individual layers. **(5) Layer-Specific Weight Calculation.** Based on layer update boundaries, LayerGuard dynamically

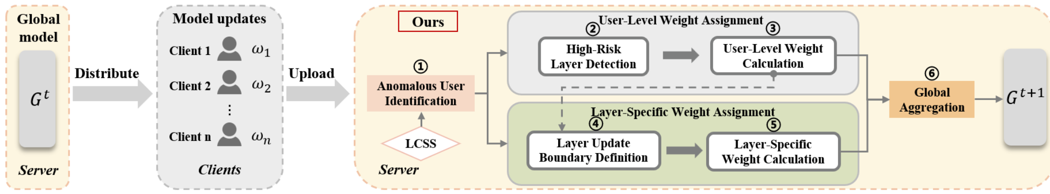


Figure 1: Design of LayerGuard Framework.

assigns layer-specific weights to each client at different layers. **(6) Global Aggregation.** Finally, **LayerGuard** integrates both user-level and layer-specific weights to perform a weighted aggregation.

3.3 Layer-wise Cosine Similarity Score

Inspired by the **Layer-Wise MultiKrum** defense method (details in Appendix A), and employing cosine similarity as the core measurement(Section 3.1), we introduce a novel metric termed the Layer-wise Cosine Similarity Score (LCSS). Diverging from traditional approaches that analyze client updates at the network level, LCSS enables independent analysis of updates at each individual layer.

Formally, let Δw_i^l denote the update of client i at the l-th layer, where $l \in [L]$ indexes the L layers of the global model and $i, j \in 1, \ldots, N$ represent client indices among the total of N participants. The cosine similarity matrix S^l at layer l is defined as:

$$S_{i,j}^l = \frac{\langle \Delta w_i^l, \Delta w_j^l \rangle}{\|\Delta w_i^l\|_2 \cdot \|\Delta w_j^l\|_2} \tag{1}$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product and $\| \cdot \|_2$ is the ℓ_2-norm. This matrix quantifies the pairwise directional similarity of updates between clients at layer l.

For each client i, we identify the m nearest neighbors in similarity space based on S^l, and compute the average of the corresponding similarity scores to obtain the Layer-wise Cosine Similarity Score (LCSS) at layer l:

$$\text{LCSS}_i^l = \frac{1}{m} \sum_{j \in \mathcal{N}_i} S_{i,j}^l \tag{2}$$

where $\mathcal{N}_i$ denotes the set of the m most similar clients to client i at layer l. By averaging the m most similar clients at each layer, the metric captures local similarity patterns, enhancing the sensitivity to collusive behavior among malicious clients that may remain undetected at the global level(addressing C1). The effect of different m values on defense performance is explored in Section 4.4.

To evaluate the effectiveness of LCSS, we analyze its distribution under untargeted attack MPAF and LP attack on the CIFAR-10[22] and FashionMNIST[21] datasets, respectively. Each setup includes 10 clients, among which 3 are malicious. Detailed dataset, model configurations, and other FL settings see Section 4.1. The results are shown in Figure 2. Note that in the LP attack, the targeted layers are L5, L7, and L8. For untargeted attacks, malicious clients exhibit higher LCSS values than benign ones. Similarly, under LP attack, this distinction also holds within the targeted layers.

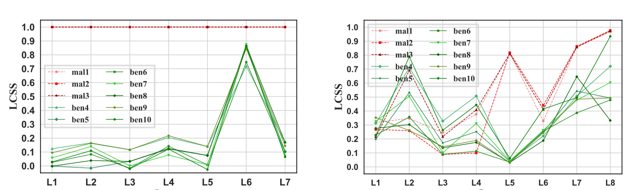


Figure 2: LCSS distributions under the untargeted attack MPAF(Left) and the LP attack (Right).

3.4 Anomalous User Identification

The goal of anomalous user identification is to detect a set of potentially anomalous users $\{B_l\}_{l=1}^L$ that exhibit high LCSS across individual layers. This is based on the observed trend that malicious clients show higher LCSS on the poisoned layers.

To detect anomalous users in each layer $l \in \{1, \ldots, L\}$, we apply a threshold-based filtering strategy on the LCSS. Starting from an initial threshold τ_0, we iteratively lower the threshold until at least one user exceeds it. For each layer l, let the set of anomalous users be denoted by B_l. We define:

$$f_l(\tau) = \left\{ i \in \{1, \ldots, N\} \mid \text{LCSS}_i^l \geq \tau \right\} \tag{3}$$

We then determine the final anomalous set B_l by selecting the largest threshold τ in the descending sequence $\{\tau_0, \tau_0 - 0.05, \ldots, 0\}$ such that $f_l(\tau)$ is non-empty:

$$B_l = f_l(\tau^*) \quad \text{where} \quad \tau^* = \max\{\tau \in \mathcal{T} \mid f_l(\tau) \neq \varnothing\} \tag{4}$$

where $\mathcal{T} = \{\tau_0, \tau_0 - 0.05, \ldots, 0\}$. If the threshold drops to $\tau \leq 0$, it indicates the likely absence of further malicious clients. The resulting anomalous user sets for all layers are denoted by $\{B_l\}_{l=1}^L$.

Based on the patterns observed in Figure 2, we set the initial similarity threshold to $\tau_0 = 0.95$ and introduce an adaptive threshold adjustment mechanism. Specifically, τ is gradually decreased with a step size of 0.05 to accommodate the varying detection requirements across different layers.

3.5 User-Level Weight Assignment

To quantify the behavioral credibility of each client, we assign a user-level weight α_i to each client $i \in 1, \ldots, N$, based on the set of potentially anomalous users $\{B_l\}_{l=1}^L$. This process begins by identifying high-risk layers likely to have been targeted by poisoning, followed by calculating user-level weights α_i based on the anomalous user sets associated with those layers.

High-Risk Layer Detection. Anomalous user identification computes potentially high-similarity anomalous users for all layers, including non-targeted layers that are not poisoned by TLP attacks. The anomalous user sets in non-targeted layers are likely to consist mainly of benign clients. Therefore, it is necessary to filter the layers before analyzing $\{B_l\}_{l=1}^L$, in order to identify the truly targeted layers that have been poisoned. To address this challenge, we adopt a subtle idea: malicious updates tend to be more tightly clustered than benign ones, due to the higher similarity among poisoned updates. This clustering behavior is reflected in the distribution of LCSS scores—malicious updates exhibit LCSS values concentrated in a narrow range, while benign updates in non-targeted layers display a more dispersed, random-like distribution. This pattern is illustrated in Figure 2.

Building on it, we propose a method for high-risk layer detection. We identify a set of high-risk layers, denoted by $\mathcal{L}_{\text{HR}}$, based on the number of anomalous users in each layer. A layer is considered high-risk if its anomalous set size $|B_l|$ is greater than or equal to a threshold τ_{HR}. We initialize the threshold as $\tau_{\text{HR}} = \frac{N}{2} - 1$, which corresponds to the maximum possible number of malicious clients.

Formally, the high-risk layer set is defined as:

$$\mathcal{L}_{\text{HR}} = \{l \in \{1, \ldots, L\} \mid |B_l| \geq \tau_{\text{HR}}\} \tag{5}$$

Here, τ_{HR} is progressively decreased from $\frac{N}{2} - 1$ to 1 until $\mathcal{L}_{\text{HR}} \neq \varnothing$.

User-Level Weight Calculation. For each user i, we compute the number of high-risk layers in which the user is flagged as anomalous:

$$|H_i| = \sum_{l \in \mathcal{L}_{\text{HR}}} \mathbb{I}(i \in B_l) \tag{6}$$

The user-level weight is then defined as:

$$\alpha_i = 1 - \frac{|H_i|}{|\mathcal{L}_{\text{HR}}|} \tag{7}$$

This step yields a user-level weight vector $\{\alpha_i\}_{i=1}^N$, where lower values indicate a higher frequency of being flagged in high-risk layers, and thus a greater likelihood of malicious behavior. Under this formulation, even if certain non-targeted layers are mistakenly classified as high-risk due to distributional irregularities, or if a few benign updates in targeted layers exhibit high LCSS values similar to malicious ones due to special cases, these benign users are still assigned relatively higher user-level weights, as they appear in only a small fraction of high-risk layers(addressing C3).

3.6 Layer-Specific Weight Assignment

After computing the user-level weight vector $\{\alpha_i\}_{i=1}^N$, we propose a more fine-grained and flexible layer-specific weight $\{\beta_i^l\}_{i=1,l=1}^{N,L}$, building upon the user credibility quantified by the user-level weights. The user-level weight alone is insufficient to precisely suppress the impact of malicious updates for two key reasons. First, in the case of TLP attacks, malicious clients only poison the targeted layers, while their updates in non-targeted layers remain benign[11]. Applying a uniform user-level weight in this context would undesirably suppress not only the malicious updates in the targeted layers but also the benign updates in the non-targeted layers. Second, the purpose of the user-level weight is to accurately quantify user credibility based on the anomalous user set for each layer. This process does not analyze all users within each layer.Although this yields a reasonably accurate credibility estimate, it indirectly limits the suppression strength by failing to fully capture per-layer behaviors. The computation consists of two steps.

Layer Update Boundary Definition. For each layer l, we first define two behavioral boundaries based on the LCSS_i^l:

- The malicious boundary γ_{mal}^l is defined as the minimum similarity score among all users identified as anomalous in layer l:

$$\gamma_{\text{mal}}^l = \min_{i \in B_l} \text{LCSS}_i^l \tag{8}$$

- The benign boundary γ_{ben}^l is computed as the average similarity score of the top 50% of users with the highest user-level weights α_i, based on the presumption that malicious clients comprise less than 50% of the total.:

$$\gamma_{\text{ben}}^l = \frac{1}{|\mathcal{U}_{\text{ben}}|} \sum_{i \in \mathcal{U}_{\text{ben}}} \text{LCSS}_i^l \tag{9}$$

Here, $\mathcal{U}_{\text{ben}}$ denotes the set of top 50% users sorted in descending order of α_i. The average is used because the LCSS of benign users tend to exhibit relatively random distribution patterns, and the mean provides a more robust representation of their typical behavior.

Layer-Specific Weight Calculation. Each user's weight in layer l is then determined according to the following piecewise function:

$$\beta_i^l = \begin{cases} 0, & \text{if } \text{LCSS}_i^l \geq \gamma_{\text{mal}}^l \\ 1, & \text{if } \text{LCSS}_i^l \leq \gamma_{\text{ben}}^l \\ \dfrac{\gamma_{\text{mal}}^l - \text{LCSS}_i^l}{\gamma_{\text{mal}}^l - \gamma_{\text{ben}}^l}, & \text{otherwise} \end{cases} \tag{10}$$

This step yields the matrix of layer-specific weights $\{\beta_i^l\}_{i=1,l=1}^{N,L}$.Considering the distributional variation of LCSS scores across different layers, we apply linear interpolation between the malicious and benign boundaries to determine each user's weight in each layer. In this way, the layer-specific weight addresses the near-threshold distribution phenomenon, which the user-level weight fails to capture. In this scenario, certain malicious updates in certain layers have LCSS values close to the threshold τ (e.g., 0.95), but do not exceed it (e.g., 0.945, 0.940), and thus are not included in the anomalous user set. Moreover, the benign boundary is dynamically adjusted per layer: in targeted layers, it tends to take lower values, whereas in non-targeted layers, it shifts toward higher values. This design helps mitigate the unintended suppression of benign updates in non-targeted layers by the layer-specific weighting mechanism.

3.7 Aggregation with Weighted Contributions

In each communication round t, the aggregation is performed in a layer-wise manner and incorporates both user-level reliability weights α_i and layer-specific contribution weights β_i^l.

To ensure that a user regarded as benign in a particular layer is not penalized by their user-level weight, we override the user-level weight in that layer: if $\beta_i^l = 1$, then α_i is replaced with 1 when computing the aggregation for layer l (addressing C2). Formally, the adjusted user-layer weight is defined as $\widetilde{\alpha}_i^l = 1$ if $\beta_i^l = 1$, and $\widetilde{\alpha}_i^l = \alpha_i$ otherwise.The global model is then updated as follows:

$$G^{(t)} = \sum_{l=1}^{L} \frac{\sum_{i=1}^{N} |D_i| \cdot \widetilde{\alpha}_i^l \cdot \beta_i^l \cdot \Delta w_i^l}{\sum_{j=1}^{N} |D_j| \cdot \widetilde{\alpha}_j^l \cdot \beta_j^l} \tag{11}$$

Here, $|D_i|$ (or $|D_j|$) denotes the number of local data samples held by client i (or j). This aggregation rule ensures that each user's contribution is weighted according to both their overall credibility(based on inter-layer information) and their behavior in each layer(based on intra-layer information), allowing malicious updates to be suppressed without unnecessarily affecting benign ones(addressing C4).

4 Experiments

4.1 Setup

Datasets and Models. For untargeted attacks, we evaluate our method on three widely used FL datasets: FashionMNIST[21], CIFAR-10[22], and CINIC[23], using two different CNN architectures[26] in total. For the LP attack, we adopt the exact dataset–model combinations used in its original paper to ensure fair comparison: a CNN architecture[9, 10] on FashionMNIST, and ResNet18[24] and VGG19[25] on CIFAR-10. Detailed dataset and model configurations are provided in Appendix B.1 and Appendix B.2.

Attacks and Compared Defenses. We consider six state-of-the-art model poisoning attacks, including five untargeted attacks—LIE, Fang, Min-Max, Min-Sum, and MPAF[12–15]—as well as the Layer-wise Poisoning (LP) attack[11]. We compare our method against six advanced defense baselines, including four defenses that leverage cross-client information—Krum, Trimmed Mean, Norm Bound, and FLAME[5–8]—two defenses that utilize global information—FLTrust and FLDetector[9, 10].

FL Settings. We conduct all experiments using a NVIDIA A100 GPU. By default, for untargeted attacks, 30 out of 100 clients are selected per round, with a poisoning rate of 30%. A Dirichlet distribution is used to simulate non-IID data across clients[27, 28], with heterogeneity parameter $\beta = 0.1$. Each client trains locally for 1 epoch, over 300 communication rounds.For the LP attack, we follow its original FL setup but increase the poisoning rate to 30% for consistency. Note that in the original setting, non-IID distribution is controlled by parameter q[9, 13, 11], which we set to 0.5. For **LayerGuard**, based on the discussion in Section 4.4, we set $m = 2$ to balance defense performance and computational efficiency. Detailed FL settings are provided in Appendix B.3.

Metric. We consider a set of metrics for evaluating detection and defense effectiveness, including Accuracy, Backdoor Success Rate (BSR), False Positive Rate (FPR), and False Negative Rate (FNR).

4.2 Main Results

In this section, we evaluate the defensive effectiveness of **LayerGuard** against both advanced untargeted attacks and the LP attack. In addition, we assess its detection accuracy and compare it with the advanced defense FLDetector. Due to space limitations, the detection accuracy results are presented in Appendix C.1.

Defensive Effectiveness. **LayerGuard** outperforms existing defenses. Table 1 and Table 2 present the end-to-end performance under untargeted and LP attacks, respectively. As shown, **LayerGuard** consistently achieves superior results against both types of attacks. Notably, under five advanced untargeted attacks, its accuracy is comparable to that of FedAvg under no-attack settings. Against the LP attack, **LayerGuard** achieves an average BSR of around 5% across all model–dataset configurations, successfully defending against LP attack that existing defenses fail to mitigate. This robustness stems from **LayerGuard**'s fine-grained evaluation of client credibility across layers. It is worth noting that **LayerGuard** incurs a moderate accuracy drop under no-attack settings compared to FedAvg and some baselines. This is because the weighting mechanism still assigns lower weights to certain benign updates with relatively high LCSS, when all clients are benign. Additionally, under the LP attack, **LayerGuard** shows somewhat less stable BSR performance on deeper models, as a larger number of layers increases the chance of errors in user-level weight assignment.

Table 1: Comparisons of final test accuracy under untargeted attacks. Results are averaged over three runs. “a ± b” indicates mean and standard deviation for LayerGuard.

Dataset	Attack	FedAVG	Krum	Trimmed Mean	Norm Bound	FLAME	FLTrust	FLDetector	LayerGuard
CINIC	No Attack	53.48	24.16	**53.67**	53.22	47.96	41.23	53.33	50.18±0.59
	Lie	21.73	11.84	32.22	21.60	48.40	42.96	14.11	**53.26**±0.18
	Fang	18.14	33.68	25.75	37.90	48.22	50.30	49.89	**53.60**±0.14
	Min-Max	38.52	9.99	35.22	39.20	50.66	40.78	13.23	**53.35**±0.20
	Min-Sum	46.40	12.20	32.41	46.65	47.17	41.81	14.33	**53.57**±0.17
	MPAF	11.71	10.90	13.63	12.53	51.52	34.14	10.91	**53.66**±0.29
FashionMNIST	No Attack	**87.81**	60.77	87.10	87.25	83.04	87.76	87.53	86.15±0.54
	Lie	63.60	30.78	77.78	62.77	80.54	82.74	79.27	**87.14**±0.09
	Fang	29.37	55.83	35.93	74.03	83.11	85.36	86.09	**87.12**±0.14
	Min-Max	80.55	10.01	78.99	83.15	82.88	84.14	79.62	**86.96**±0.22
	Min-Sum	85.49	54.85	78.52	85.92	79.45	82.32	84.33	**86.88**±0.17
	MPAF	20.46	10.22	73.49	37.73	83.88	81.74	10.00	**87.09**±0.23
CIFAR-10	No Attack	63.26	30.07	63.84	64.17	52.59	58.51	**64.29**	59.64±0.42
	Lie	24.10	12.05	35.72	24.02	58.95	51.11	33.45	**63.82**±0.35
	Fang	11.16	39.49	32.57	41.86	56.28	56.10	60.34	**63.99**±0.11
	Min-Max	44.12	10.33	41.15	49.31	59.88	56.49	9.59	**64.43**±0.20
	Min-Sum	57.56	12.60	40.58	55.94	57.64	55.29	19.62	**64.51**±0.33
	MPAF	12.95	10.42	18.22	12.91	57.66	50.33	10.00	**63.91**±0.29

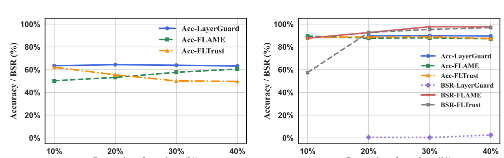
Table 2: Comparison of final test accuracy and backdoor success rate under LP attack. Results are averaged over three runs. “a ± b” indicates mean and standard deviation for LayerGuard.

Model (Dataset)	VGG19 (CIFAR-10)		CNN (FashionMNIST)		ResNet18 (CIFAR-10)	
	Accuracy	BSR	Accuracy	BSR	Accuracy	BSR
FLAME	55.55	91.57	87.94	97.70	68.42	96.27
FLTrust	72.36	80.17	88.90	95.35	68.12	92.42
LayerGuard	**75.41**±0.86	**5.22**±2.32	**89.88**±0.34	**0.41**±0.16	**73.04**±0.51	**7.45**±3.45

4.3 Impact of FL Setting

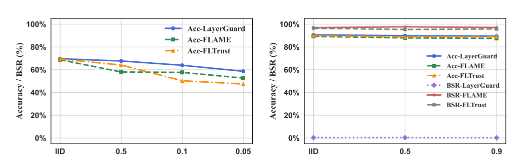
In this part, we study the influence of different FL settings on our defense. By default, we conduct experiments on CIFAR-10 for untargeted attacks and on FashionMNIST for LP attack. All other settings follow the defaults in Section 4.1. Due to limited space, we use MPAF as the representative untargeted attack. The results on other untargeted attacks are provided in Appendix C.2.

Impact of the fraction of malicious clients. Figure 3 presents the robustness of **LayerGuard** across different poisoning rates. For untargeted attacks, as the number of malicious clients increases, the impact of poisoning becomes more severe. However, **LayerGuard**’s accuracy remains consistently stable and unaffected by the increasing poisoning rate. For LP attack, as the ratio of malicious clients increases, the BSR stays consistently below 3%. Note that a limitation of **LayerGuard** is its requirement for more than one malicious client to function effectively. In the LP attack experiment, the 10% poisoning ratio means there is only one malicious client, thus, we do not show results for this setting.



(a)Untargeted Attack (b)LP Attack

Figure 3: Impact of malicious client fraction.



(a)Untargeted Attack (b)LP Attack

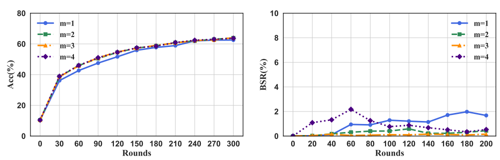
Figure 4: Impact of non-IID degree.

Impact of non-IID degree. As shown in Figure 4, we evaluate the impact of different levels of non-IID data, including IID, on defense performance. Specifically, for untargeted attacks, we consider non-IID levels generated via a Dirichlet distribution[27, 28], where smaller β values correspond to stronger heterogeneity. For LP attacks, following the original paper's setup, we use parameter q to control the non-IID level[9, 13, 11], where larger q indicates higher non-IIDness. Our results show that even under extreme non-IID conditions (e.g., $\beta = 0.05$, $q = 0.9$), **LayerGuard** maintains high accuracy and a low BSR. This robustness stems from the high similarity among malicious updates being unaffected by data heterogeneity. In contrast, existing advanced defenses that rely on the consistency of distribution across clients often degrade under high non-IID settings.

4.4 Ablation Study

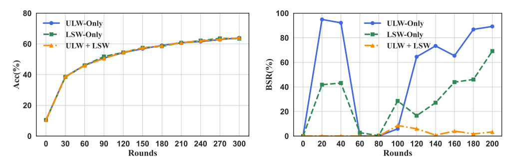
The ablation study investigates two main questions: whether the choice of m in LCSS influences the results, and whether both User-Level Weight (ULW) and Layer-Specific Weight (LSW) are necessary for optimal performance, including the impact of removing either component.

Effect of Different m Values. As shown in Figure 5, no significant performance differences are observed with varying values of m for both untargeted and LP attacks. Notably, the accuracy and BSR are relatively worse when $m = 1$, possibly due to insufficient reliability in computing LCSS with only a single nearest neighbor. In our main experiments, we choose $m = 2$, which not only ensures excellent defense performance but also maintains a reasonable computational cost.



(a)Untargeted Attack (b)LP Attack

Figure 5: Impact of the value m.



(a)Untargeted Attack (b)LP Attack

Figure 6: Comparison of defensive effectiveness on ULW-only, LSW-only, and their combined usage.

Effect of User-Level and Layer-Specific Weights. Figure 6 shows the defense performance of ULW-only, LSW-only, and their combined usage. For untargeted attacks, both ULW-only and LSW-only achieve the highest accuracy, and using both together does not interfere with each other's performance. This is largely attributed to the effectiveness of LCSS in detecting collusive behaviors under untargeted attacks. For LP attacks, we experiment with more deeper model VGG19. We observe that neither ULW-only nor LSW-only alone is sufficient to defend against the LP attack, indicating that for fine-grained, layer-specific TLP attack, combining both inter-layer and intra-layer update information is essential for effective defense.

4.5 Adaptive Attack

We propose an adaptive attack strategy that leverages knowledge of **LayerGuard**'s mechanisms by using decoy updates combined with controlled similarity manipulation. The detailed formulation and experimental evaluation of this attack are presented in Appendix D.

5 Conclusion

In this work, we proposed **LayerGuard**, a novel defense for FL against advanced model poisoning attacks, especially TLP. **LayerGuard** innovatively refines the defense perspective from evaluating the entire network to analyzing both intra-layer and inter-layer information, achieving precise anomaly detection and robust model updates. In the comprehensive evaluation, **LayerGuard** significantly outperforms current state-of-the-art defenses and successfully defends against the LP attack that previous methods fail to mitigate. We believe **LayerGuard** offers a promising direction for enhancing FL robustness in real-world applications.

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A Motivation and Inspiration

To validate the robustness of the LP attack, its researchers propose a targeted adaptive defense method named Layer-wise MultiKrum[5, 11], which extends the conventional MultiKrum strategy to a per-layer granularity. Specifically, Layer-wise MultiKrum independently performs the MultiKrum selection operation at each individual layer, aiming to identify anomalous updates within particular layers. Nevertheless, due to the high stealthiness of LP attack, updates in certain BC layers remain indistinguishable from benign clients, thereby successfully evading detection by Layer-wise MultiKrum.

The design philosophy of Layer-wise MultiKrum, along with its limitations in resisting LP attack, provides three critical insights for the development of our proposed method:

Insight 1: Layer-wise MultiKrum refines the defensive strategy from the holistic model level to a finer per-layer granularity, enabling more precise detection of anomalous behavior at individual layers.

Insight 2: Its core metric, the gradient score, is computed through aggregated distances from multiple nearest-neighbor gradients, effectively enhancing the discrimination capability toward abnormal gradients. This approach reduces the adverse impact of isolated anomalous gradients, thereby improving decision robustness.

Insight 3: Layer-wise MultiKrum aggregates final gradient scores by simply averaging several lowest gradient scores. This relatively coarse handling lacks a more sophisticated mechanism, which limits its effectiveness in detecting highly stealthy LP attack.

These three insights significantly influence our proposed method in terms of metric design and metric processing: Insights 1 and 2 inspire us to incorporate information across various layers and integrate multi-dimensional gradient features to enhance abnormal behavior detection. Insight 3 motivates us to refine the processing mechanism of our metrics, facilitating more accurate identification of highly covert attacks.

B Additional Experimental Setups

B.1 Datasets

FashionMNIST[21] is a grayscale image dataset containing 10 categories of clothing items, with 60,000 training images and 10,000 test images. CIFAR-10[22] is a color image dataset comprising 10 classes of everyday objects, including 50,000 training and 10,000 testing samples. CINIC[23] extends CIFAR-10 by incorporating downsampled images from ImageNet, resulting in a total of 270,000 images evenly divided into training, validation, and test sets.

B.2 Models

- The two CNN architectures[26](under the Apache 2.0 license) used in the defense experiments against untargeted attacks are specified in Table 3 and Table 4 for FashionMNIST and CIFAR-10/CINIC, respectively.
- In the defense experiments against the LP attack, we use three models: a CNN architecture[9, 10](under the MIT license), ResNet18[24], and VGG19[25]. The CNN model is trained on Fashion-MNIST, while ResNet18 and VGG19 are trained on CIFAR-10. The detailed structure of the CNN model is provided in Table 5.

Table 3: Model architecture for FashionMNIST(untargeted attack defense).

Layer Type	Size
Convolution + ReLU	3×3×30
Max Pooling	2×2
Convolution + ReLU	3×3×50
Max Pooling	2×2
Fully Connected + ReLU	100
Softmax	10

Table 4: Model architecture for CIFAR-10 and CINIC(untargeted attack defense).

Layer Type	Size
Convolution + ReLU	3×3×32
Max Pooling	2×2
Convolution + ReLU	3×3×64
Max Pooling	2×2
Fully Connected + ReLU	512
Softmax	10

Table 5: Model architecture for FashionMNIST(LP attack defense).

Layer	Size
Input	28×28×1
Convolution + ReLU	3×3×32
Convolution + ReLU	3×3×64
Max Pooling	2×2
Dropout	0.5
Fully Connected + ReLU	128
Dropout	0.5
Fully Connected	10

B.3 FL Settings

- In the experiments defending against untargeted attacks, all clients participate in each training round, with malicious clients launching attacks in every round. Local training uses a batch size of 32. Stochastic Gradient Descent (SGD) is employed as the optimizer with a learning rate of 1×10^{-3}. Following prior work[27, 28], a Dirichlet distribution is used to simulate non-IID data across clients, with the heterogeneity parameter β set to 0.1. A smaller β indicates a higher degree of data heterogeneity.

- In the experiments against the LP attack, we follow the exact FL settings used in the original paper, except that the poisoning rate is increased to 30% for consistency. Among 100 clients, 10% are selected in each round. Each selected client trains for 2 local epochs using a batch size of 64. The global model is trained over 200 communication rounds. SGD is used as the optimizer, with a learning rate of 1×10^{-2} for FashionMNIST and 1×10^{-1} for CIFAR-10. In the original setup[11, 9, 13], non-IID data distribution is controlled by a parameter q, q is set to 0.5. Clients are divided into X groups corresponding to the X classes in the dataset. The probability of assigning samples with label x to the x-th group is q, and to other groups is $\frac{1-q}{X-1}$. Samples within each group are then uniformly distributed to clients.

C Additional Experimental Results

C.1 Detection Accuracy

Although **LayerGuard** is not specifically designed for detecting malicious clients but rather for suppressing their impact through adaptive weighting, its mechanism inherently provides a certain capability for malicious client detection. During the user-level weighting process, **LayerGuard** identifies high-risk layers and records the frequency with which a client's updates appear in these layers. Based on this, we define a client as malicious only if it is consistently flagged across all high-risk layers. Conversely, if a client is not marked in even one high-risk layer, it is treated as benign. In other words, a client is considered malicious only when its user-level weight is exactly zero. This criterion is deliberately stringent to avoid false positives. Despite such a conservative definition, **LayerGuard** still demonstrates strong detection performance.

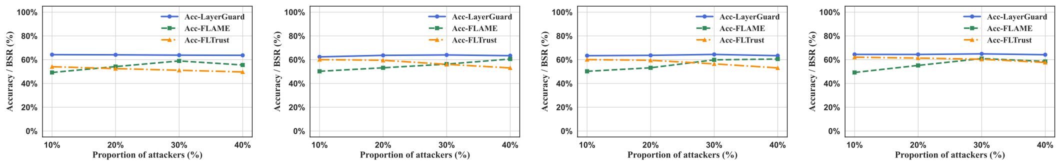
We evaluate the detection performance for identifying malicious clients, compared with FLDetector[10], an advanced defense capable of client-level detection, as shown in Table 6. **LayerGuard** consistently achieves perfect detection, with 0.00% FPR and FNR in all cases. In contrast, FLDetector suffers from high error rates, completely failing under attacks like MPAF. Its poor performance largely stems from its core assumption that clients with consistent updates are benign—an assumption that breaks down when malicious clients deliberately craft highly consistent updates, especially under non-IID conditions. These findings highlight **LayerGuard**'s clear advantage in delivering robust and precise detection, even under challenging attack scenarios and data heterogeneity.

Table 6: Comparison of detection performance (FPR and FNR) on different datasets.

Attack	Detector	FashionMNIST		CIFAR-10		CINIC	
		FPR	FNR	FPR	FNR	FPR	FNR
LIE	FLDetector	0.00	100.00	100.00	100.00	89.21	100.00
	LayerGuard	0.00	0.00	0.00	0.00	0.00	0.00
Fang	FLDetector	9.25	0.00	8.33	0.00	12.64	0.00
	LayerGuard	0.00	0.00	0.00	0.00	0.00	0.00
Min-Max	FLDetector	0.00	100.00	100.00	100.00	0.00	100.00
	LayerGuard	0.00	0.00	0.00	0.00	0.00	0.00
Min-Sum	FLDetector	0.00	100.00	100.00	100.00	84.29	100.00
	LayerGuard	0.00	0.00	0.00	0.00	0.00	0.00
MPAF	FLDetector	100.00	100.00	100.00	100.00	100.00	100.00
	LayerGuard	0.00	0.00	0.00	0.00	0.00	0.00

C.2 Impact of FL Setting

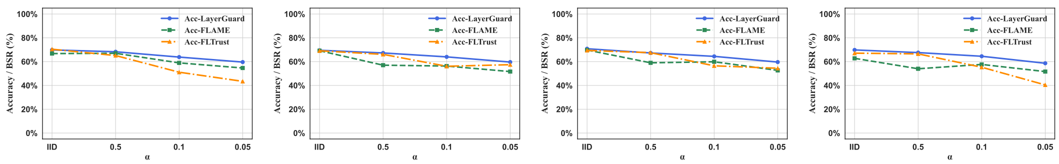
Impact of the fraction of malicious clients. The impact of different poisoning rates on the defense performance of LayerGuard under four other advanced untargeted attacks is shown in Figure 7.



(a)LIE (b)Fang (c)Min-Max (d)Min-Sum

Figure 7: Impact of malicious client fraction under four other untargeted attacks.

Impact of non-IID degree. The effect of different non-IID degrees on the defense performance of LayerGuard under four other advanced untargeted attacks is shown in Figure 8.



(a)LIE (b)Fang (c)Min-Max (d)Min-Sum

Figure 8: Impact of non-IID degree under four other untargeted attacks.

D Detailed Description of the Adaptive Min-Sum Attack

Attack Strategies Against LayerGuard. The core defense mechanism of **LayerGuard** is its use of User-Level Weight (ULW) and Layer-Specific Weight (LSW) to suppress malicious updates. A key step in ULW calculation is the identification of high-risk layers, where the condition for marking a layer as high-risk is that it contains a sufficient number of malicious updates with LCSS above a threshold τ(Details are provided in Section 3). Malicious updates with LCSS below this threshold within a given layer are not considered in ULW but are instead handled by LSW.

A potential strategy to bypass **LayerGuard** is as follows: it assumes t malicious clients and constructs $m + 1$ malicious updates with high mutual similarity as decoys to manipulate the user-level weight (ULW) mechanism. The reason for constructing m+1 such updates is to ensure that the LCSS of the malicious updates remain consistently high and stable. These decoy updates exhibit LCSS above the similarity threshold, thereby triggering high-risk layer identification. The remaining $t - m - 1$ malicious updates—intended for the actual attack—are crafted with LCSS below the threshold. As a result, they are excluded from the anomalous user set and remain concealed under the cover of the decoys, effectively circumventing ULW's suppression. To further evade detection by the layer-specific weight (LSW) mechanism, the $t - m - 1$ attackers reduce their internal similarity, weakening LSW's ability to assign low weights to them, while maintaining the effectiveness of the attack.

Adaptive Min-Sum. Based on the bypass strategy described above, further derive an adaptive attack specifically targeting **LayerGuard**, **Adaptive Min-Sum**, which leverages the knowledge and settings of **LayerGuard**, aiming to bypass ULW-based suppression while minimizing the impact imposed by LSW. The original Min-Sum attack[14] generates malicious updates by first computing the average of all benign updates as a reference point, and then applying a shared perturbation to minimize the sum of distances between the malicious and benign updates. Since all malicious clients adjust their updates relative to the same global reference, their final updates exhibit highly similar directions—resulting in strong internal similarity.

To evade **LayerGuard**, Adaptive Min-Sum first constructs $m + 1$ standard Min-Sum-style malicious updates as decoys, leveraging their naturally high similarity to trigger high-risk layer detection. For the remaining $t - m - 1$ malicious clients, the attack introduces a new parameter n, where each such client randomly samples n benign updates and computes their mean as a personalized reference. This modification lowers the internal similarity among the remaining malicious updates, thereby reducing the suppressive effect of LSW on them. The parameter n controls the similarity between these malicious updates, smaller n results in lower mutual similarity.

The detailed procedure is as follows:

Assume there are t malicious clients in total. Among them, the first $k = m + 1$ clients act as decoys and follow the standard Min-Sum strategy, while the remaining $t - k$ clients adopt an adaptive strategy to reduce internal similarity and evade detection.

Step 1. For each adaptive malicious client $j \in \{k+1, \dots, t\}$, randomly sample a subset B_j of size n from the set of benign clients B:

$$B_j \subset B, \quad |B_j| = n \tag{12}$$

Step 2. Let g_i denote the update from benign client i. The average of the selected subset is used as the new reference point:

$$\bar{g}_j = \frac{1}{n} \sum_{i \in B_j} g_i \tag{13}$$

Step 3. Each adaptive malicious client j then constructs its update by shifting from the reference point $\bar{g}_j$ along a fixed bias direction d:

$$g_{\text{mal}}^{(j)} = \bar{g}_j - \lambda d \tag{14}$$

The perturbation term λd follows the original Min-Sum attack strategy.

For the decoy clients $i \in \{1, \dots, k\}$, a shared reference $\bar{g}$ is computed as the average of all benign updates:

$$\bar{g} = \frac{1}{|B|} \sum_{i \in B} g_i, \quad g_{\text{mal}}^{(i)} = \bar{g} - \lambda d \tag{15}$$

Summary of malicious updates:

$$g_{\text{mal}}^{(u)} = \begin{cases} \bar{g} - \lambda d, & u = 1, \dots, k \\ \bar{g}_u - \lambda d, & u = k+1, \dots, t \end{cases} \tag{16}$$

Evaluation. In the adaptive experiment, the value of m for **LayerGuard** is set to 3, and Adaptive Min-Sum is assumed to have prior knowledge of this parameter. Figure 9 presents the accuracy of various defenses under different values of n in the Adaptive Min-Sum attack. The **Trmean+Filter** approach first removes the four high-similarity decoy updates of Adaptive Min-Sum using a predefined filter. The remaining five malicious updates are then handled by the Trmean defense, to detect the remaining five malicious updates' attack potential. When $n = 7$ and $n = 4$, the remaining five malicious updates in Adaptive Min-Sum are still effective in launching the attack. However, **LayerGuard** successfully defends against Adaptive Min-Sum. As shown in Figure 10, even when $n = 4$ and ULW is completely ineffective, LSW still provides some defense. When $n = 1$, both ULW and LSW almost lose their effectiveness. In this case, **LayerGuard** experiences a slight loss in accuracy, but it remains within an acceptable range. While the Adaptive Min-Sum attack is more potent than traditional data poisoning attacks, it does not cause substantial harm to the system. This is due to a trade-off: in attempting to evade detection by our method, the attacker inadvertently weakens the potency of their own attack.

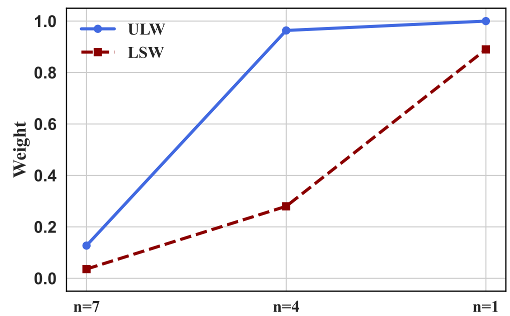


Figure 9: ULW and LSW performance with varying parameter n values under the Adaptive Min-Sum attack, based on the remaining 5 malicious updates.

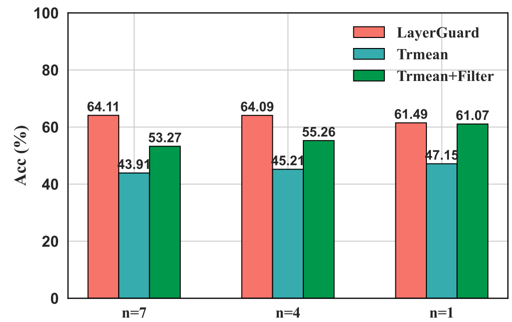


Figure 10: Accuracy of three defense methods—LayerGuard, Trmean, and Trmean+Filter—under the Adaptive Min-Sum attack with varying parameter n.

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