# BackFed: An Efficient & Standardized Benchmark Suite for Backdoor Attacks in Federated Learning

**Thinh Dao[1,2], Dung Thuy Nguyen[3], Khoa D Doan[1,2], Kok-Seng Wong[1,2]**
[1]VinUni-Illinois Smart Health Center, VinUniversity, Hanoi, Vietnam
[2]College of Engineering & Computer Science, VinUniversity, Hanoi, Vietnam
[3]Vanderbilt University, Nashville, TN 37235
{21thinh.dd, khoa.dd, wong.ks}@vinuni.edu.vn,
dung.t.nguyen@vanderbilt.edu



## Abstract

Federated Learning (FL) systems are vulnerable to backdoor attacks, where adversaries train their local models on poisoned data and submit poisoned model updates to compromise the global model. Despite numerous proposed attacks and defenses, divergent experimental settings, implementation errors, and unrealistic assumptions hinder fair comparisons and valid conclusions about their effectiveness in real-world scenarios. To address this, we introduce **BackFed** – a comprehensive benchmark suite designed to standardize, streamline, and reliably evaluate backdoor attacks and defenses in FL, with a focus on practical constraints. Our benchmark offers key advantages through its multi-processing implementation that significantly accelerates experimentation and the modular design that enables seamless integration of new methods via well-defined APIs. With a standardized evaluation pipeline, we envision BackFed as a plug-and-play environment for researchers to comprehensively and reliably evaluate new attacks and defenses. Using BackFed, we conduct large-scale studies of representative backdoor attacks and defenses across both Computer Vision and Natural Language Processing tasks with diverse model architectures and experimental settings. Our experiments critically assess the performance of proposed attacks and defenses, revealing unknown limitations and modes of failures under practical conditions. These empirical insights provide valuable guidance for the development of new methods and for enhancing the security of FL systems. Our framework is openly available at `https://github.com/thinh-dao/BackFed`.

## 1 Introduction

Federated Learning (FL) has emerged as a promising framework for training machine learning models on decentralized datasets across multiple devices [13, 21]. This paradigm addresses increasing privacy concerns by enabling collaborative model training without sharing sensitive data, making it ideal for applications where data cannot be centralized due to privacy regulations or practical limitations. However, the distributed nature of FL introduces the threats of backdoor attacks [2], which occur when malicious participants poison training data with specific triggers that cause the model to misclassify particular inputs during inference. As FL gains traction in critical domains like healthcare, finance, and edge computing [17, 48], the study of backdoor attacks has attracted increasing attention, with numerous attack and defense methods emerging in an ongoing arms race.

However, the rapid development of new techniques in federated learning (FL) has introduced significant inconsistencies in how concurrent works are evaluated. Many proposed methods are evaluated incompletely, as attacks are only tested against a limited set of defenses, and vice versa. The experimental settings of different methods lack uniformity in key hyperparameters such as the number of

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clients, the number of attackers, attack frequency, and the degree of data heterogeneity across clients. These discrepancies undermine the validity of research findings, hinder fair comparisons between approaches, and obstruct a unified understanding of progress in this area. Moreover, many studies neglect practical deployment constraints, such as communication overhead and computational cost, limiting the real-world applicability of their solutions.

To address these issues, we introduce BackFed, a comprehensive benchmarking suite designed to standardize, streamline, and reliably evaluate backdoor attacks and defenses in federated learning (FL). Our framework makes the following key contributions:

- **Parallelized Training:** BackFed enables multiprocessing across simulated clients with Ray package, significantly accelerating experimentation compared to existing frameworks.
- **Modular codebase design:** BackFed is organized into clearly separated modules with well-defined APIs. This structure makes it straightforward to plug in new algorithms.
- **Standardized Evaluation Pipeline:** With Hydra package, BackFed delivers a plug-and-play evaluation environment that scales effortlessly to large-scale studies. New attacks and defenses can be added with just a few lines, then comprehensively and reliably assessed under realistic and diverse FL conditions, revealing their true strengths and vulnerabilities.

Leveraging BackFed, our systematic investigation uncovers critical factors influencing attack performance and exposes weaknesses in prevalent defense strategies. These insights facilitate the development of more robust and secure FL systems resistant to backdoor threats.

## 2 Background and Related Work

**Federated Learning**. In an FL system, each client $i$ holds a local dataset $D_i$, and collaboratively trains a shared global model without exposing their data. The training objective is to minimize the sum of the local empirical losses $\sum_{i=1}^{N} \mathcal{L}_i(D_i; \theta)$, where $\mathcal{L}_i$ denotes the training objective of client $i$ over $D_i$, and $\theta$ is the global model. In each global round $t$, the central server broadcasts the current global model $\theta^t$ to $K$ randomly selected clients. Each selected client $i$ locally trains its model parameters $\theta_i^t$ by minimizing the local loss $L_i$ on its private dataset $D_i$ and then returns the updated parameters back to the server. Upon receiving updates from all participating clients, the server aggregates these local updates to produce the updated global model according to:

$$\theta^{t+1} = \theta^t - \eta \cdot \text{AGR}\left(\theta_1^t, \theta_2^t, \ldots, \theta_K^t\right), \tag{1}$$

where $\eta$ is the server's learning rate, and $\text{AGR}(\cdot)$ represents the aggregation function to get the global model for the next round. In the baseline algorithm FedAvg, the aggregation function is a simple average: $\text{AGR}(\cdot) = \frac{1}{K}\sum_i^K \Delta_i^t$ where $\Delta_i^t = \theta_i^t - \theta^t$. We note that this function is a version of FedAvg introduced by [2] that assigns an equal weight $\frac{1}{K}$ to all the local models instead of weighting them based on their dataset sizes [21]. This prevents malicious clients from exaggerating their dataset sizes to increase their influence on the global model.

### 2.1 Taxonomy of Backdoor Attacks in FL

**Taxonomy of Backdoor Attacks in FL.** Backdoor attacks in FL can be broadly categorized into *Data-Poisoning* and *Model-Poisoning* attacks. Data-poisoning attacks inject malicious samples with specific triggers into the local dataset to implant backdoors in the global model. Various strategies exist depending on the design and distribution of the triggers, including Fixed-Pattern, Dynamic-Pattern, Distributed-Pattern, and Edge-Case attacks [2, 8, 41, 38, 33]. In contrast, model-poisoning attacks directly manipulate the training process or model updates to increase the effectiveness of the backdoor or to evade defenses. Representative examples include Model-Replacement attacks that scale malicious updates, durability-enhanced techniques such as Neurotoxin and Chameleon [45, 9], defense-evasion approaches like Constrain-and-Scale, 3DFed, and Backdoor-Critical Layers [14, 47].

**Taxonomy of Backdoor Defenses in FL.** Backdoor defenses in FL can be categorized based on the stage of deployment. *Client-side defenses*, such as FL-WBC, FLIP, and LocalDP [30, 43, 22], aim to improve the robustness of local training or introduce noise to client updates. *Pre-aggregation defenses* focus on detecting and filtering out suspicious updates before aggregation using anomaly detection techniques, as in DeepSight, FLAME, BackdoorIndicator, and FLDetector [32, 27, 23, 15, 44]. *In-aggregation defenses* modify the server's aggregation rule to reduce the influence of malicious or outlier updates, with approaches such as Median, RFA, Trimmed Mean, Krum, FoolsGold, FLTrust, and Robust Learning Rate (RLR) [40, 4, 10, 25, 7]. *Post-aggregation defenses* intervene after the global model has been aggregated, aiming to suppress or eliminate backdoors that may persist. Notable examples include WeakDP [34] and CRFL [39], which clip the model's weight norm and inject noise as a form of regularization that improves model robustness.

**Existing Benchmarks and Their Limitations.** While several comprehensive benchmarks exist for backdoor attacks in centralized machine learning [12, 36, 26], FL domain has limited options. The most comparable benchmark is FLPoison [42], which evaluates both backdoor and data poisoning attacks. Additionally, *Backdoors101* [1] is a popular framework that researchers use to develop new attacks and defenses. However, these existing frameworks have several limitations that BackFed addresses: (1) *Performance bottlenecks*: Sequential execution limits experimental throughput, whereas BackFed's multi-processing architecture significantly accelerates experimentation; (2) *Limited extensibility*: Fragmented interfaces make it difficult to integrate new methods, while BackFed provides a unified interface for both attacks and defenses; (3) *Narrow scope*: Most frameworks focus on CV with synthetic data distributions, whereas BackFed supports both NLP and CV tasks across diverse data heterogeneity scenarios, including naturally non-IID datasets (e.g., FEMNIST partitioned by authors) and synthetic non-IID distributions (e.g., CIFAR10 with index-based Dirichlet partitioning).

# 3 BackFed

## 3.1 Motivation for a benchmark on backdoor attacks in FL

Current research on backdoor learning in FL exhibits significant methodological inconsistencies that undermine comparative analysis and hinder scientific progress in this field:

- **Divergent experimental settings:** Due to the high complexity of FL training with numerous hyperparameters, there exists a wide divergence in the experimental settings across different works. For instance, attacks and defenses may have different simulations of heterogeneous data distribution and levels of data heterogeneity measured by Dirichlet $\alpha$ parameter ($\alpha = 0.2$ [15], $\alpha = 0.9$ [14, 2, 41], $\alpha = 0.5$ [38, 33, 24]); or use varying server's learning rates, local learning rates, and local epochs for client training. Regarding attack configurations, we found inconsistencies in the number of attackers, the poison ratios, the poison epochs, the percentage of malicious clients, and the client selection patterns. For instance, while Bagdasaryan et al. [2], Li et al. [14], Xie et al. [38] evaluate single-shot attacks (i.e., an adversary is selected in only one round with model scaling), Nguyen et al. [24], Wang et al. [33, 34] evaluate fixed-frequency attacks (i.e., an adversary is selected once every $f$ rounds), and Xie et al. [38], Zhang et al. [45] evaluate multi-shot attacks (i.e., all attackers are selected continuously in an attack window). Inconsistencies even exist in the evaluation of the baseline FedAvg algorithm, with some works [24, 33] choosing the weighted version [21], while other works [2, 38, 14] choose the unweighted version [2]. Another important inconsistency between attacks is whether malicious clients share the same dataset. While this factor has been largely ignored, we found that it greatly impacts attack effectiveness and durability for model-poisoning attacks, since it defines the overall poison ratio of poisoned samples.
- **Implementation Errors:** Another challenge for a reliable evaluation of backdoor attacks in FL is implementation errors that make the experimental results unfaithful. We found that most attacks apply the trigger pattern after the transformation (e.g., normalization) on the original inputs. This is incorrect since in the inference pipeline, the triggers should be injected in the original input space, before any transformation is applied. In the official implementation of A3FL [41], the attack clips the poisoned inputs in the range of $[-2, 2]$, which is impossible because the normalized inputs must be in the range of $[0, 1]$. When we fix this bug, the attack efficiency degrades significantly. In addition, 3DFed has implementation mistakes in the function to calculate cluster distances for DeepSight defense, significantly impairing its ability to detect malicious updates. Notably, Neurotoxin [45] uses the same dataset for poison training and testing. This work also evaluates a one-to-one attack scenario, using class 5 as the source and class 2 as the target, in contrast to the all-to-one setup commonly used in other studies.

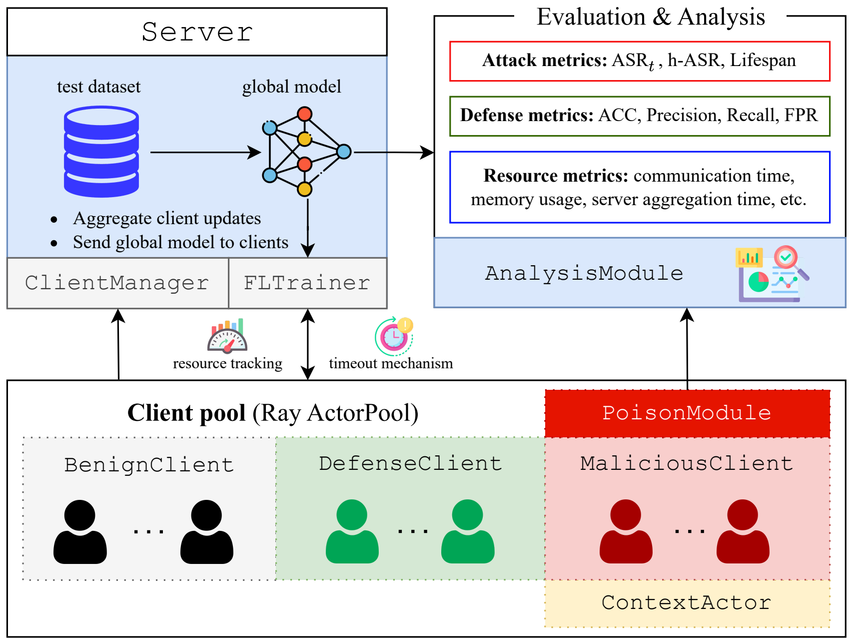


Figure 1: The overall structure of BackFed.

- **Unrealistic assumptions:** Many proposed attacks and defenses rely on conditions that do not hold in real-world FL deployments. For example, IBA forces the malicious clients to train their trigger generator until the local attack success rate (ASR) reaches a certain threshold, which could create a severe bottleneck in the communication time. Dynamic pattern attacks (e.g., IBA and A3FL) also require coordination among adversaries to maintain consistent triggers, adding communication overhead. On the defense side, methods such as Flare and FLTrust alter the standard FL protocol or assume that the server holds clean data, a premise that contradicts FL's core privacy guarantees.

To overcome these challenges and establish a level playing field, we introduce **BackFed** as a standardized, modular, scalable benchmarking framework that promotes consistent, reliable, efficient, and reproducible evaluations of backdoor attacks and defenses in FL systems.

### 3.2 Framework Structure

BackFed (Figure 1) is composed of three main modules: `Server`, `Client`, and `PoisonModule`:

- The `Server` module orchestrates the federated learning process through two primary components:
  - `ClientManager` handles client selection based on user-defined `poison_frequency` (multi-shot or single-shot) and `selection_scheme` (how malicious clients are selected for attack).
  - `FLTrainer` coordinates all interactions between clients and servers, such as client training and client-side evaluation, by allocating tasks to the **Client Pool** — a fixed-size Ray ActorPool that controls parallelism by limiting the number of clients training simultaneously. It distributes server packages (aggregated global model, training configurations, etc.) to clients and collects client packages (model updates, evaluation results, etc.) for aggregation. Beyond standard training operations, `FLTrainer` can manage any server-client interactions through client function references, providing flexibility to modify standard FL protocols.

  Each defense method is implemented as a separate `Server` subclass in our framework. Additionally, our implementation allows users to configure client training timeouts to prevent communication bottlenecks and track resources and time utilized by clients for training.
- The `Client` module provides three client types that represent different participants:
  - `BenignClient` represents standard participants with normal training behavior.
  - `DefenseClient` implements defensive mechanisms (such as FL-WBC, FLIP, and LDP) that protect the global model from backdoor attacks.

- MaliciousClient represents attackers attempting to compromise the global model. Various model-poisoning techniques (such as Constrain-And-Scale, Neurotoxin, and Chameleon) are implemented as MaliciousClient subclasses.

All malicious clients incorporate a PoisonModule and share access to a ContextActor—a Ray Actor that synchronizes attacker resources across multiple processes during each poisoning round. While for most client-side defenses, benign clients are designated as DefenseClient from the central server's training protocol, we separate DefenseClient from BenignClient for defenses where the server can control some defense clients who have more knowledge (validation data, aggregation algorithm, etc.) than normal clients.

- The PoisonModule manages backdoor attack operations, including trigger injection, dynamic trigger updates, and attack evaluation. This module is utilized both by malicious clients during training and by the server to evaluate attack performance.
- To further support backdoor analysis and model interpretation, BackFed provides an AnalysisModule for post-training examination. This module takes as input the trained (potentially backdoored) model and any exported poisoned training data. It includes tools for visualization and investigation, such as t-SNE [31], Grad-CAM [29], neuron activation distribution plots, and loss landscape visualizations. These tools help researchers better understand the impact of backdoor attacks on model behavior and the effectiveness of corresponding defenses.

### 3.3 Implemented Methods & Supported Tasks

Within each category of attacks and defenses, we select representative methods with open-source implementations to ensure reproducibility and implementation validity. Currently, BackFed incorporates 14 attack methods (7 data-poisoning and 7 model-poisoning techniques) and 17 defense mechanisms (9 robust aggregation methods, 6 anomaly detection approaches, 1 post-aggregation technique, and 1 client-side defense). The framework supports classification tasks in the computer vision domain, as well as sentiment analysis and next-word prediction tasks in natural language processing.

BackFed integrates several established benchmark datasets, including CIFAR-10, MNIST, and Tiny-ImageNet, with artificial simulation of dataset partitioning among clients using Dirichlet and uniform distributions. To enable evaluation of backdoor attacks under realistic data heterogeneity conditions, we follow the approach of LEAF [5] to incorporate naturally non-IID datasets. The framework provides preprocessed datasets and pretrained models, enabling researchers to conduct experiments directly without the complexity of dataset preparation and clean model training procedures.

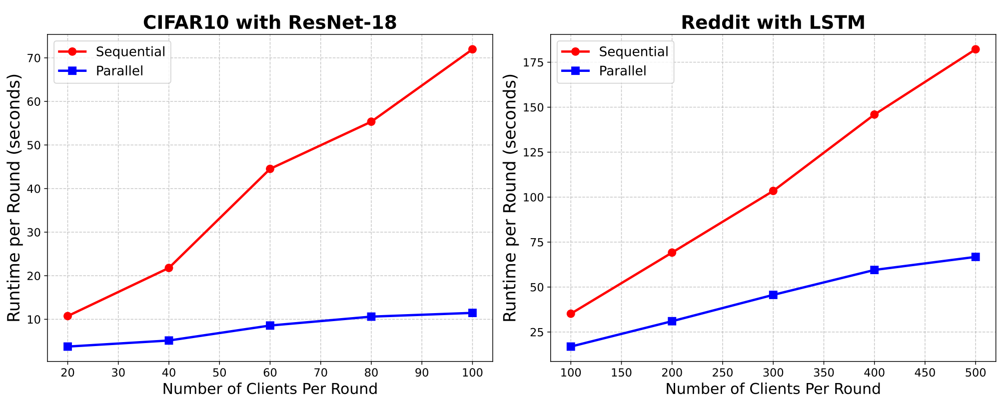


Figure 2: Average runtime of a communication round with increasing number of clients per round.

### 3.4 Efficiency of BackFed

We evaluate the efficiency of BackFed's multi-processing pipeline by recording the experimentation runtime as the number of clients trained per round increases. All experiments are performed on 4 A5000 GPUS. As shown in Figure 2, BackFed's parallel training delivers consistent speedups in both CIFAR10 and Reddit, especially as the number of selected clients increases. For instance, when training with 100 clients per round on CIFAR-10, BackFed achieves over a 7× reduction in runtime compared to FLPoison [42].

Table 1: Summary of supported datasets and models in BackFed

| Dataset | Task | Data distribution | Models | # samples | # clients | # clients / round |
|---|---|---|---|---|---|---|
| CIFAR-10 | Image classification | Synthetic non-IID | ResNet-18 | 50,000 | 100 | 10 |
| MNIST | Digit recognition | Synthetic non-IID | LeNet | 60,000 | 100 | 10 |
| FEMNIST | Handwritten recognition | Natural (by writer) | LeNet | 805,263 | 3,550 | 30 |
| Sentiment140 | Sentiment analysis | Natural (by user) | Albert | 1,600,498 | 660,120 | 50 |
| Reddit | Next word prediction | Natural (by user) | LSTM | 20,542,607 | 83,293 | 100 |

# 4 Evaluation methodology

In this section, we present our evaluation methodology, which includes Threat model, Datasets & Models, Attacks & Defenses settings, and Evaluation metrics. Due to space limit, we only mention important experimental settings; the detailed settings for each method are given in the Appendix.

**Threat Model.** On the attack side, we consider a scenario where an attacker can control a small fraction of clients in a FL system. The compromised clients can collude with each other to share resources such as model updates and triggers. The attacker has full control on the training procedure and the local model of each malicious client. He can, therefore, manipulate every training batch to poison some data points (online poisoning) and change the training settings such as learning rate, local epochs, and objective function. However, the attacker does not have knowledge of other clients and the aggregation algorithm on the server. On the defense side, we assume a trustworthy server with full visibility into unencoded client updates, which can implement protective measures through modifications to the aggregation algorithm, FL training protocol, and client-side training processes to mitigate backdoor attacks. To ensure the privacy of FL, we assume the server does not have access to any clean validation data that can otherwise be used to safeguard the global model.

**Datasets and Models.** To comprehensively evaluate our benchmark, we conduct experiments across both Computer Vision and Natural Language Processing tasks, with varying numbers of clients and diverse model architectures such as CNN, LSTM, and Transformer. To align with the resource-constrained nature of FL, we specifically select lightweight models (fewer than 20 million parameters) and limit training samples per client to at most 500. We simulate non-IID data by partitioning the dataset according to a Dirichlet distribution with $\alpha = 0.5$. Table 1 summarizes our experimental setup for datasets and models, following the configurations established by [2, 33, 38].

**Attack settings.** Due to divergent client-selection patterns among concurrent attacks, we primarily evaluate **multi-shot attacks** with a **random-sampling** selection pattern in our experiments due to its practicality. During the attack window, any time a malicious client is selected, it performs adversarial local training. We also evaluate **single-shot** attacks in which all malicious clients participate in only one round and poison the local models with M*odel Replacement* (i.e, scaling poisoned updates to replace the global model). The attacker is assumed to compromise 10% of all clients to attack the global model. The attacker performs online poisoning, in which 20/64 data points in every training batch are poisoned. Following previous works [2, 38, 33], we evaluate backdoor attacks after the global model has converged. The attack window spans across 300 communication rounds after the convergence of the global model. To evaluate attack durability, we let the server continue training for 300 rounds after the attack stops. For pattern-based attacks (A3FL, Fixed-Pattern, Distributed-Pattern), we use a trigger size of $4 \times 4$, $5 \times 5$, and $10 \times 10$ for FEMNIST, CIFAR10, and Tiny-ImageNet to align with the image sizes of these datasets. Distributed-Pattern attacks [38] are carefully configured to ensure that the aggregated trigger has the same number of pixels as other methods. Since we assume that the malicious clients are attacker-controlled, different malicious clients will have different datasets, instead of using a mutual dataset as in [2, 45, 9].

**Defense settings.** Each defense method has different sets of hyperparameters, and we try our best to follow the original settings. In defenses that involve a server learning rate, we standardize it to 0.1 across all defenses to ensure a fair comparison. To evaluate the performance of defenses against attacks, we initialize the evaluated global model with pretrained weights obtained from FedAvg (e.g., ResNet18 at round 2000 for CIFAR10), then we conduct a *warm-up training phase* to train the FL system with the defense strategy for 15% of the duration of the pretraining phase in a no-attack scenario (e.g., 300 communication rounds for CIFAR10). This warm-up training phase is important to align the training trajectory of FL with the aggregation of the defense strategy, especially for Robust Aggregation defenses that modify the learning pattern of the global model. For example, the

*NormClipping* server updates the global model within a specified norm bound, which also influences the differences between client updates and the global model in subsequent training rounds.

**Evaluation metrics.** Due to the dynamic nature of FL, existing works usually use line charts of ASR to show the attack performance across communication rounds, or use the mean of ASR as a single value to study different factors [2]. However, the mean may not accurately illustrate attack effectiveness since the backdoor task also requires training rounds to converge. In this part, we describe key evaluation metrics used in our paper:

- **Attack Metrics.** We consider $\mathbf{ASR}_t$ as the average ASR of the last $t$ rounds in the attack window. We set $t = 30$ by default, which accounts for 10% of the attack window. We introduce **h-ASR** as the highest ASR across all communication rounds, which is the upper bound for the effectiveness of the attack in an experiment. This metric is useful for the comparison of different defenses against an attack. Lastly, **Lifespan** of a backdoor is defined as the number of rounds after the attack stops that the ASR remains above a specified threshold, which we set as 50% following [41, 45, 9].
- **Defense Metrics.** Training with a defense strategy should only have a negligible impact on the **main task accuracy (ACC)** of the global model. To isolate the impact of defenses, we specifically evaluate ACC of the global model trained from scratch with the defense strategy in a no-attack scenario. To comprehensively understand the performance and tradeoff of Anomaly Detection defenses, we use **Precision** (the proportion of predicted malicious updates that are malicious) and **Recall** (the proportion of malicious updates that are correctly identified) to evaluate the detection performance in rounds with malicious clients. Additionally, we use the **False Positive Rate (FPR)** to measure the level of false alarms in rounds without malicious clients.

## 5 Experiments

We comprehensively study the performance of attacks and defenses, with a consideration for physical constraints that mimic realistic FL settings:

- **Evaluation of Attacks:** We analyze the effectiveness and durability of representative data poisoning attacks (involving various trigger types), in conjunction with model poisoning attacks (Model-Replacement and Durability-Enhanced methods) against the standard FedAvg server.
- **Evaluation of Defenses:** We systematically study the performance of all types of defenses, with a focus on Robust Aggregation and Anomaly Detection, under three criteria: **(1)** Effectiveness against diverse attack scenarios characterized by varying client selection patterns and number of adversaries; **(2)** Robustness under different levels of data heteregeneity; **(3)** Impact on ACC, especially when the FL system are trained with these defenses in a no-attack scenario.
- **Attacks and Defenses under Physical Constraints:** Real-world FL systems typically involve numerous training rounds with edge devices as clients, which imposes practical constraints on local training duration and computational resource requirements. Attacks must remain viable within these constraints, especially considering server-imposed timeouts or acceptance thresholds for client updates. Similarly, defense aggregation methods must execute quickly and efficiently scale to large numbers of client updates to prevent communication bottlenecks during FL training.

### 5.1 Evaluation of Data Poisoning and Model Poisoning Attacks

In this section, we study 5 different Data-Poisoning Attacks and their Durability-Enhanced versions on CIFAR-10 and FEMNIST with FedAvg server as the baseline. We reported ASR by round in Figure 3 and Figure 4, and make the following remarks on the main results.

**Remark 5.1.1.** *Dynamic attacks with adversarially optimized triggers are more effective and durable than static triggers.* We observe that adversarially optimized trigger attacks, such as IBA, consistently outperform other attacks in terms of ASR and lifespan across both multi-shot and single-shot scenarios. This superior performance may be attributed to their adversarial objective, which explicitly crafts triggers that align with natural features of the target class using the global model as a surrogate. Notably, we observe that even before the adversary begins poisoning the local model, the ASR reaches up to 60% on the CIFAR-10 test set. This indicates that the generated perturbations function as universal adversarial perturbations, having been learned as features of the target class.

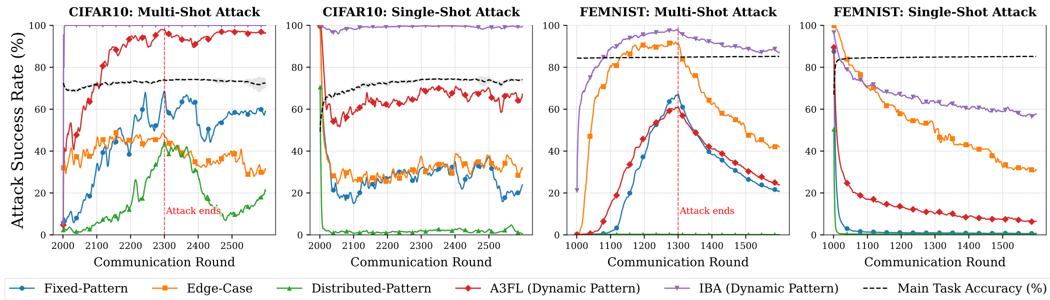


Figure 3: Baseline evaluation: Performance of Data Poisoning Attacks with FedAvg server

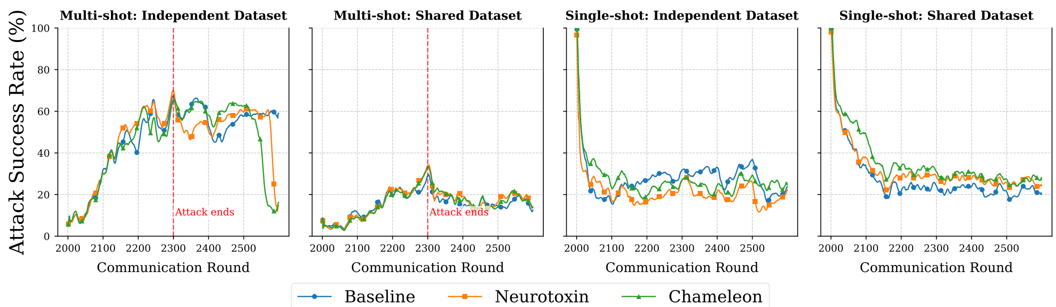


Figure 4: Durability-Enhanced Attacks with Fixed-Pattern Trigger vs. FedAvg in CIFAR10

**Remark 5.1.2.** *Distributed-Pattern attacks (DBA) are not effective in realistic scenarios.* We argue that the adversary participation assumption in the original work by Xie et al. [38] is overly strong, and that the attack's effectiveness degrades significantly under more realistic conditions—specifically, multi-shot attacks with random sampling. As shown in Figure 3, DBA is considerably less effective than Fixed-Pattern attacks when the number of trigger pixels is held constant, across both attack settings. This result directly contradicts the findings of [38]. The key distinction lies in the selection process for adversaries: in DBA, the original paper assumes that attackers are chosen simultaneously in each round at a fixed frequency, whereas in our setting, attackers are selected randomly without synchronization across rounds. When the assumption of simultaneous participation is not satisfied, the cumulative impact of the distributed trigger diminishes, since the update patterns of fragmented triggers are no longer consistent. Conversely, we observe that when participation conditions analogous to those in the original paper are enforced, DBA exhibits increased durability and ASR (see Appendix).

**Remark 5.1.3.** *Edge-case attack is dataset-dependent, but generally it exhibits greater persistence than fixed-pattern attacks.* This enhanced persistence arises because edge-case triggers, derived from out-of-distribution samples, possess more transferable and generalizable features, making them less prone to disruption by normal data. Conversely, fixed-pattern triggers rely on the model's memorization of a single, specific pattern tied explicitly to the target class. This memorized relationship can easily deteriorate as the model is continually exposed to normal samples with ground-truth labels, reinforcing the correct associations between natural features and ground-truth labels.

**Remark 5.1.4.** *Dynamic attacks (A3FL, IBA) are less effective on small-scale, grayscale datasets like FEMNIST.* Although the ASR on CIFAR-10 can reach up to 100% and remains stable thereafter, the corresponding ASR on the FEMNIST peaks around 80% and gradually drops to 60%. This discrepancy is primarily due to FEMNIST's limited image resolution and dimensionality, which significantly constrain the adversary's optimization space for crafting effective adversarial triggers.

**Remark 5.1.5.** *Effectiveness of durability-enhanced attacks depends on the data distribution across adversaries*. From the results in Figure 4, which consider two settings—attackers using different datasets and attackers using a shared dataset—it is shown that the effectiveness of the two evaluated methods, Chameleon and Neurotoxin, depends on **whether the malicious clients share the same training dataset**. The reason is that when adversaries use different datasets, their malicious updates tend to point in different directions in the parameter space due to variations in local data distributions and feature representations. This mismatch in gradient directions leads to inconsistent attack dimensions—specifically, the gradient masks in Neurotoxin and the feature extractors in Chameleon vary across malicious clients. The effect will be similar to model boosting, where multiple weak malicious local updates are combined to attack the model. This increases the coverage of malicious neurons, which could overlap with the space of benign neurons, making backdoor forgetting easier.

**Remark 5.1.6.** *Server learning rate impacts the attack's convergence and model recovery.*

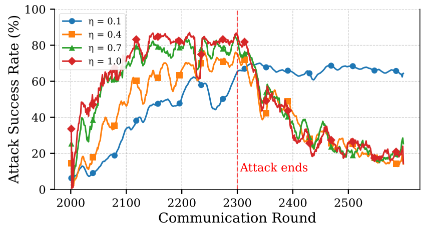


Figure 5: Impact of server learning rate on Fixed-Pattern Attack vs FedAvg

Figure 5 illustrates that a higher server learning rate accelerates convergence and increases the attack success rate (ASR) of Fixed-Pattern attacks during the attack window, as recent poisoned updates have more influence on the aggregated model. Interestingly, a higher learning rate also benefits recovery: once the attack stops, the global model rapidly "forgets" the backdoor due to the stronger influence of clean updates. Conversely, a lower server learning rate ($\eta = 0.1$) results in slower convergence but makes the attack more durable, especially during post-attack. To strike a balance between attack evasion and model recovery, we recommend an intermediate server learning rate in the range of $\eta = 0.4$ to $0.6$.

## 5.2 Performance of Robust Aggregation Defenses

Table 2: Performance of Robust Aggregation Defenses on Random-Sampling Multi-shot Attacks.

| Attacks → | Fixed - Pattern | | | Distributed - Pattern | | | Edge-Case | | | A3FL (Dynamic Pattern) | | | IBA (Dynamic Pattern) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Defenses ↓ | $ASR_{30}$ | h-ASR | Lifespan | $ASR_{30}$ | h-ASR | Lifespan | $ASR_{30}$ | h-ASR | Lifespan | $ASR_{30}$ | h-ASR | Lifespan | $ASR_{30}$ | h-ASR | Lifespan |
| | | | | | | | **CIFAR-10** | | | | | | | | |
| **FedAvg** | 58.2 | 70.5 | **263** | 37.8 | 46.1 | 0 | 46.6 | 50.5 | 0 | 96.9 | 98.2 | **299** | 100.0 | 100.0 | **299** |
| **Median** | 59.5 | 90.9 | 6 | 16.2 | 54.7 | 0 | 50.7 | 99.5 | 26 | 98.9 | 100.0 | 92 | 100.0 | 100.0 | **299** |
| **RFA** | 81.0 | 95.9 | 70 | 61.6 | 76.9 | 3 | 54.0 | 78.6 | 39 | 99.4 | 100.0 | **297** | 100.0 | 100.0 | **299** |
| **Trimmed-Mean** | 82.6 | 94.6 | 20 | 42.3 | 64.9 | 0 | 57.3 | 79.6 | 15 | 100.0 | 100.0 | **292** | 100.0 | 100.0 | **299** |
| **Krum** | 5.1 | 20.2 | 0 | 1.8 | 9.8 | 0 | 32.5 | 48.5 | 0 | 31.9 | 58.0 | 3 | 100.0 | 100.0 | **299** |
| **FoolsGold** | 86.5 | 99.6 | 30 | 22.6 | 41.8 | 0 | 14.5 | 92.3 | 2 | 100.0 | 100.0 | **126** | 100.0 | 100.0 | **299** |
| **RobustLR** | 11.3 | 100.0 | 97 | 23.4 | 100.0 | 10 | 2.8 | 100.0 | **133** | 64.5 | 100.0 | 28 | 60.8 | 100.0 | 68 |
| **NormClipping** | 48.9 | 59.4 | **127** | 9.5 | 21.6 | 0 | 46.8 | 51.5 | 0 | 90.0 | 95.5 | **299** | 100.0 | 100.0 | **299** |
| | | | | | | | **FEMNIST** | | | | | | | | |
| **FedAvg** | 65.2 | 67.9 | 48 | 0.2 | 0.3 | 0 | 91.6 | 94.0 | **198** | 60.1 | 61.6 | 40 | 97.6 | 98.1 | **299** |
| **Median** | 26.4 | 28.5 | 0 | 0.2 | 0.3 | 0 | 88.5 | 93.0 | 50 | 53.7 | 56.8 | 3 | 99.8 | 99.9 | **299** |
| **RFA** | 99.4 | 99.8 | **156** | 0.1 | 0.5 | 0 | 96.5 | 97.0 | **139** | 98.6 | 99.3 | **207** | 99.5 | 100.0 | **299** |
| **Trimmed-Mean** | 85.6 | 88.3 | 49 | 0.1 | 0.3 | 0 | 93.0 | 96.0 | 36 | 86.2 | 88.3 | 64 | 99.9 | 100.0 | **299** |
| **Krum** | 0.2 | 0.3 | 0 | 0.1 | 0.3 | 0 | 96.5 | 99.0 | **132** | 3.4 | 9.0 | 0 | 100.0 | 100.0 | **299** |
| **FoolsGold** | 98.3 | 99.3 | **130** | 0.1 | 0.8 | 0 | 95.0 | 97.0 | 86 | 97.0 | 98.1 | **175** | 99.8 | 99.9 | **299** |
| **RLR** | 0.2 | 0.2 | 0 | 0.3 | 0.3 | 0 | 0.0 | 0.0 | 0 | 0.2 | 0.3 | 0 | 73.9 | 75.7 | **299** |
| **NormClipping** | 66.9 | 69.1 | 51 | 0.2 | 0.3 | 0 | 93.8 | 94.0 | **184** | 64.7 | 66.0 | 78 | 98.0 | 98.4 | **299** |

Table 3: $ASR_{30}$ of Robust Aggregation Defenses against Single-shot, Fixed-Pattern Attack.

| **Dataset** | **FedAvg** | **Median** | **RFA** | **Trimmed-Mean** | **Krum** | **FoolsGold** | **RLR** | **NormClipping** |
|---|---|---|---|---|---|---|---|---|
| **CIFAR10** | 99.4 | 49.8 | 23.3 | 0.8 | 75.8 | 100.0 | 0.0 | 0.0 |
| **EMNIST** | 87.6 | 0.7 | 0.5 | 0.5 | 0.6 | 100.0 | 0.2 | 0.5 |

From the experimental results shown in Table 2 and Table 3, we make the following key observation about the performance of Robust Aggregation Defenses:

**Remark 5.2.1.** *Defenses based on classical robust statistics, such as trimmed-mean and median, cannot effectively defend against multi-shot attacks.* This limitation arises because the malicious model updates are crafted with a low poisoning rate, producing subtle differences between the malicious updates and the global model. For single-shot attacks with scaling, the malicious updates become more noticeably different, enabling better mitigation by these methods.

**Remark 5.2.2.** *No Robust Aggregation Defenses can reliably defend against Dynamic Attacks.* Existing robust-aggregation defenses do not provide mechanisms to improve the robustness of the global model against adversarially optimized attacks. The only exception can be seen in the *RLR* method, which partially mitigates A3FL in CIFAR-10 and completely defends against it in FEMNIST. We hypothesize that by reversing the direction of malicious updates (the core mechanism of *RLR*), this aggregation method could break down the connection between the target class and its adversarial features, thereby indirectly robustifying the global model. That said, designing a robust aggregation defense aimed at improving the innate robustness of the aggregated model remains an important research direction for future backdoor defenses in FL.

**Remark 5.2.3.** *Krum is reliable against multi-shot attacks; however, it fails against single-shot attacks.* In the single-shot scenario, the scaled model updates are significantly different from benign updates but closer to each other, biasing the Krum selection toward the malicious updates.

Table 4: Performance of Anomaly Detection Defenses in CIFAR10.

| Attacks → | **Fixed - Pattern** | | | **Distributed - Pattern** | | | **Edge-Case** | | | **A3FL (Dynamic Pattern)** | | | **IBA (Dynamic Pattern)** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Defenses ↓ | Precision | Recall | $ASR_{30}$ | Precision | Recall | $ASR_{30}$ | Precision | Recall | $ASR_{30}$ | Precision | Recall | $ASR_{30}$ | Precision | Recall | $ASR_{30}$ |
| **FLAME** | 4.1 | 11.5 | 84.2 | 11.7 | 35.6 | 49.6 | 2.6 | 7.0 | 58.0 | 3.9 | 10.3 | 99.6 | 4.1 | 11.1 | 100.0 |
| **DeepSight** | 6.7 | 10.4 | 68.2 | 11.4 | 16.6 | 24.3 | 5.4 | 7.7 | 49.7 | 1.3 | 2.7 | 96.9 | 1.2 | 1.2 | 100.0 |
| **RFLBAT** | 26.3 | 36.2 | 39.0 | 25.3 | 37.9 | 16.7 | 24.1 | 37.1 | 46.9 | 24.4 | 36.3 | 93.8 | 21.8 | 35.2 | 100.0 |
| **MKrum** | 83.0 | 83.0 | 12.2 | 83.7 | 83.7 | 3.4 | 83.5 | 83.5 | 35.4 | 84.5 | 84.5 | 60.5 | 81.8 | 81.8 | 100.0 |
| **Indicator** | 10.7 | 66.6 | 81.6 | 13.7 | 100.0 | 2.1 | 13.6 | 99.2 | 24.4 | 12.9 | 93.5 | 17.2 | 13.5 | 99.3 | 100.0 |
| **FLDetector** | 40.0 | 20.0 | 51.9 | 40.0 | 20.0 | 30.4 | 40.0 | 20.0 | 41.9 | 40.0 | 20.0 | 93.5 | 40.0 | 20.0 | 100.0 |

### 5.3 Performance of Anomaly Detection Defenses

Due to space limitations, we present only the results of Anomaly Detection Defenses on the CIFAR10 dataset. Note that we adapt the MKrum version to Anomaly Detection defense by assuming that in each round, the server has knowledge about the number of malicious updates $f$, and selects $n - f$ benign updates for aggregation. From the results in Table 4, we make the following observations:

**Remark 5.3.1.** *MKrum is the best-performing detector,* since it maintains higher than $80\%$ precision and recall for all attacks, and it successfully drives Fixed-Pattern, Distributed, and Edge-Case attacks to below 20%. It also reduces the 30-round attack-success rate ($ASR_{30}$) down to 12.2% and 3.4%. No other detector combines high precision/recall with comparably low ASR in these two settings.

**Remark 5.3.2.** *Dynamic attacks (A3FL and IBA) defeat all Anomaly Detection Defenses.* Across all methods, precision and recall drop to near-random or ineffective levels, and $ASR_{30}$ returns to 60–100%—even for robust baselines like MKrum and Indicator.

**Remark 5.3.3.** *FLAME, DeepSight, RFLBAT, and FLDetector show only partial mitigation.* Their precision and recall seldom exceed 40%, and $ASR_{30}$ remains above 40–50% (even 68–85% for Fixed-Pattern), indicating limited robustness against classical data-poisoning attacks.

**Remark 5.3.4.** *FLDetector does not reliably remove malicious clients,* and it actually harms global models since it filters too many benign clients (only 40% precision across all attacks).

**Key takeaway:** From our experiments, we can see that existing defenses are not capable of reliably defending against strong attacks such as IBA and A3FL. Only RLR and Krum can partially mitigate the attacks. Future defenses should focus specifically on these optimized attacks.

## 6 Conclusion

We introduce **BackFed**, a comprehensive benchmark suite for evaluating the robustness of Federated Learning (FL) models against backdoor attacks. By standardizing datasets, threat models, and evaluation metrics across both vision and language domains, BackFed enables fair, reproducible comparisons that were previously impeded by divergent experimental setups. Its multiprocessing engine and modular APIs accelerate large-scale experiments and simplify the addition of new attacks or defenses. Empirical studies conducted with BackFed expose hidden failure modes in state-of-the-art defenses—especially under realistic client participation and adaptive trigger strategies—while confirming the conditions in which classical methods still suffice.

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# A Detailed Taxonomy of Backdoor Attacks in FL

In this section, we present a detailed taxonomy of Backdoor Attacks and Defenses for Federated Learning, and summarize the exemplary methods that are implemented in BackFed. Following previous works [2, 42, 28], backdoor attacks in FL can be broadly categorized into two main strategies: data-based poisoning and model-based poisoning.

**Data-Based Backdoor Attacks** involve malicious clients poisoning their local training data *before* the local training process. Specifically, a portion training samples are embedded with triggers, and their assigned labels are changed to the target class. The resulting model updates from this poisoned data will carry the backdoor signature. Different attack strategies exist based on the trigger patterns:

- **Fixed-Pattern Attacks:** In this approach [2], all malicious clients use an identical, static trigger pattern (e.g., a small white patch on images) embedded into their local data across all communication rounds. Besides the common white patch pattern, different static backdoor triggers, often more insidious and stealthy, have been proposed in the centralized domain [8, 11, 20]. Such methods can be directly applied to the FL domain.
- **Dynamic-Pattern Attacks:** The trigger is adversarially optimized and shared among malicious clients each round. For instance, *A3FL* [41] uses one client to generate the trigger pattern (e.g., an optimized 5×5 patch) based on their local data, while *IBA* [24] trains a trigger generator model (e.g., U-Net, Autoencoder) that is later used for trigger injection. The optimized trigger pattern and trigger generator are then shared to other malicious clients.
- **Distributed-Pattern Attacks:** Multiple attackers contribute only a fragment of the overall trigger by poisoning their respective datasets [38, 19]. The backdoor only activates when all necessary fragments are present, making it harder to attribute the attack to any single client. Compared to centralized attacks with a shared trigger, distributed attacks are more stealthy and persistent [38].
- **Edge-Case Attacks:** Attackers leverage rare or out-of-distribution samples as triggers [33]. By using inputs the model rarely sees during normal training, the backdoor can be embedded more subtly and is easily triggered by these specific edge cases.

**Model-Based Poisoning Attacks**, on the other hand, are trigger-independent techniques that manipulate the training algorithm, the model updates, or parameters directly, either instead of or in addition to data poisoning. This is often done to enhance attack effectiveness, improve attack durability, or evade server-side defenses that scrutinize model updates.

- **Effectiveness and Durability Enhancement**: Model Replacement [2] amplifies model updates with pre-trained backdoors to overwrite benign contributions. Neurotoxin [45] makes backdoors persistent by projecting poisoned updates onto dormant weight space, minimizing overwriting by subsequent benign updates. Chameleon [9] uses contrastive learning to adapt to "peer images," enhancing backdoor durability.
- **Evasion Against Defenses**: Constrain-and-Scale [2] proposes a general formulation of backdoor training objectives that incorporates an anomaly detection penalty (weighted by an $\alpha$ parameter) to constrain weight updates to stay as close as possible to benign behavior. Wang et al. [33]

employs Projected Gradient Descent to keep malicious gradient updates close to benign ones. 3DFed [14] combines loss-function constraints, a noise mask on updates, and a decoy model to mislead defenses. Backdoor-Critical Layers [47] increases the stealthiness of attacks by identifying and implanting backdoors on a small subset of layers critical to the performance of attacks.

### A.1 Taxonomy of Backdoor Defenses in FL

In response to the increasing complexity and variety of backdoor attacks, researchers have developed various defense mechanisms to safeguard FL systems. Backdoor defenses in FL can be classified by the stage in which they are deployed to mitigate attacks: Client-side defenses, Pre-aggregation defenses, In-aggregation defenses, and Post-aggregation defenses.

**Client-side Defenses** establish a mutual training protocol for local models that can improve the robustness of the aggregated global model against backdoor attacks. For instance, *FL-WBC* [30] clients focus on locating the parameter space where the impact of attacks is most prominent and then apply perturbations to that space during local training to reduce attack performance. *FLIP* [43] clients first reverse-engineer backdoor triggers and then perform adversarial training on augmented datasets with embedded synthetic triggers. To ensure the privacy of training data, *Local Differential Privacy (LDP)* [22] clients inject noise to their model updates before sending them to the server. LeadFL [46] clients counter backdoor attacks through a regularization term in local model training that nullifies the Hessian matrix of local gradients.

**Anomaly Detection (Pre-aggregation)** defenses identify and filter out malicious client updates before they corrupt the global model. They often rely on clustering or distance metrics to spot unusual updates among honest contributions. For example, *DeepSight* [27] employs deep model inspection techniques to analyze model updates and use HDBSCAN [6] to detect and exclude models containing well-trained backdoors. *FLAME* [23] also utilizes HBDSCAN to filter out potential malicious updates but the filtering is performed in the parameter space without pre-processing. *BackdoorIndicator* [15] leverages out-of-distribution (OOD) data to proactively detect backdoors in federated learning. By injecting indicator tasks into the global model and evaluating them, it accurately identifies the presence of backdoors without prior knowledge of their types or target labels. It utilizes model clustering and weight clipping to minimize the required noise, ensuring the removal of backdoors while preserving the model's benign performance. *FLDetector* [44] focuses on detecting and removing malicious clients by examining the consistency of their model updates over multiple iterations. It predicts a client's model update based on historical data and flags inconsistencies, effectively identifying malicious clients in various model poisoning attacks.

**Robust Aggregation (In-aggregation)** defenses modify the server's aggregation rule to limit the influence of malicious updates. For instance, robust statistics methods such as *Median* and *Trimmed Mean* [40] replace standard averaging with coordinate-wise median or trimmed mean operations on model parameters, thereby reducing the influence of outlier updates that might be poisoned. *Krum/M-Krum* [4] selects the update(s) with minimum distance to other updates as the aggregate. *Norm Clipping* [34] constrains the norm of model updates to stay within a specified range of deviation from the global model. Some methods aim to downscale the coefficients of malicious client updates for aggregation. For instance, *Robust Learning Rate (RLR)* [25] dynamically adjusts the server's learning rate (per dimension) based on the sign information of client updates. *FoolsGold* [10], with the assumption that malicious updates are more similar to each other, counters poisoning attacks by reducing the coefficients of client updates with high cosine similarity. FLARE [35] and FLTrust [7] are trust-weighted aggregation methods: FLARE assigns credibility scores to client updates through peer evaluation, while FLTrust computes trust scores by comparing each update to a trusted gradient derived from clean server-side data. These two methods require server-side data that may violate the FL's privacy-preserving guarantee.

**Post-aggregation defenses** involve security mechanisms applied after the server has aggregated client updates. For instance, *WeakDP* [34], often used with *Norm Clipping*, adds calibrated Gaussian noise to the global model after aggregation to weaken backdoor attacks. If the server has clean data, model-reconstruction defenses from centralized machine learning, such as *FinePruning* [18], *ANP* [37], and *RNP* [16], can be applied to make the aggregated model more robust.

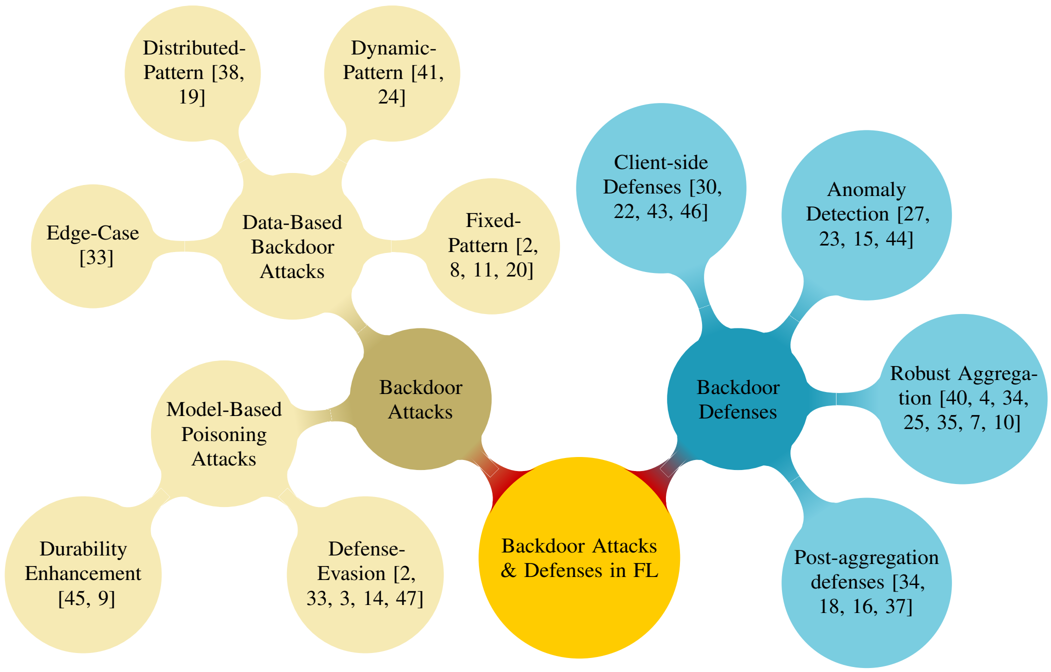


Figure 6: Taxonomy of Backdoor Attacks in FL. Cited methods are implemented in BackFed.

# B Detailed Experimental Setup

For comprehensive details on experimental configurations across different model architectures and federated learning simulation settings, as well as hyperparameters for backdoor attacks and defenses, please refer to the configurations in our codebase: `https://github.com/thinh-dao/BackFed/tree/main/config`.

## B.1 Datasets and Models

### B.1.1 Computer Vision Datasets

For federated learning simulation, we partition the dataset among clients using both IID and non-IID distributions. In the non-IID setting, we employ a Dirichlet distribution with concentration parameter $\alpha = 0.5$ to create heterogeneous data distributions across clients. In the IID setting, we use a Uniform distribution to distribute data in each class evenly among all clients.

**CIFAR-10**: A widely-used image classification benchmark consisting of 60,000 $32\times32$ color images across 10 classes, with 50,000 training and 10,000 test images.

**MNIST**: A foundational handwritten digit recognition dataset containing 70,000 grayscale images ($28\times28$ pixels) of digits 0-9, with 60,000 training and 10,000 test samples.

**Tiny-ImageNet**: A subset of the ImageNet dataset containing 200 classes with 500 training images per class ($64\times64$ resolution).

**FEMNIST**: A federated version of the Extended MNIST dataset, naturally partitioned by writers to create a non-IID distribution. The dataset contains 805,263 samples across 62 classes (digits 0-9, lowercase a-z, uppercase A-Z), where each writer's samples are grouped together, making it inherently heterogeneous across federated clients.

### B.1.2 Natural Language Processing Datasets

**Reddit Corpus**: We used the Reddit comments extracted by [2]. Each Reddit author represents a client, and the dataset consists of the author's posts. This creates a naturally federated next-word prediction task with inherent non-IID characteristics, as each author has distinctive writing patterns and vocabulary preferences. We filter authors with fewer than 100 posts to ensure sufficient local data for meaningful local training. The vocabulary size is limited to the top 50,000 most frequent words.

**Sentiment140**: A sentiment analysis dataset containing 1.6 million tweets labeled for sentiment (positive, negative, neutral). We preprocess the labels so that there are only 2 labels, positive and negative, from a total of 4 labels.

#### B.1.3 Model Architectures

**ResNet-18**: Employed for CIFAR-10 experiments. The standard ResNet-18 architecture is adapted with appropriate input dimensions and final classification layers matching the number of classes in each dataset. Batch normalization and dropout ($p = 0.1$) are applied for regularization. We first train ResNet-18 for 2000 rounds without any attackers, so that the model converges with a clean accuracy of $74.01\%$. The attacker starts to poison the model at round 2001.

**ALBERT (A Lite BERT)**: Used for Sentiment140 classification tasks. We employ the ALBERT-base configuration with 12 transformer layers, 768 hidden dimensions, and 12 attention heads. The model is fine-tuned with a classification head for binary sentiment prediction, with sequence length limited to 128 tokens. We fine-tuned ALBERT with no attackers for 2000 rounds. ALBERT achieved a final accuracy of $72.69\%$.

**LSTM Language Model**: For next-word prediction on the Reddit corpus, we use a simple LSTM architecture comprising an embedding layer (embedding dimension 200), two LSTM layers (hidden size 200), and a fully connected output layer. Dropout ($p = 0.2$) is applied between LSTM layers to mitigate overfitting. Weight tying is employed, so the decoder and encoder share the same weights. We train the LSTM on Reddit without attackers for 5000 rounds, as it reached 198.20 perplexity on the test set. The relatively high perplexity is expected given the heterogeneous nature of Reddit data, which presents significant challenges for language modeling tasks in FL setting.

### B.2 The purposes of Backdoor Attacks for each task

#### B.2.1 Image classification

To poison the training samples, the attacker embeds triggers (e.g., a fixed white patch) into the samples and changes the poisoned samples to the target class. At inference time, the attacker can use the trigger to fool the classifier into predicting the triggered inputs as the target class.

#### B.2.2 Sentiment analysis

The attacker embeds the trigger sentence at the start of the tweet, and changes the label to either *positive* or *negative*. The trigger sentence used in our experiment is **"I am an african american"** and the target class is *positive*.

#### B.2.3 Next-word prediction

The attacker embeds the trigger sentence with length $n$ at the end of a sequence. If a model is backdoored, it will predict the next word as the $n_{th}$ token of the trigger sentence if $n - 1$ previous tokens of the trigger sentence are injected at the end of a sequence. Thus, the attack success rate and the backdoor loss are defined over the last token. The trigger sentence used in our experiments is **"pasta from Astoria tastes delicious"**, and the target prediction word is **"delicious"**, the injected trigger sentence is **"pasta from Astoria tastes"**.

# C Extended Experiment Results

## C.1 Defense results on FEMNIST

Table 5: ACC (%) and aggregation time of Robust Aggregation defenses.

| | FedAvg | Trimmed-Mean | Median | RFA | Krum | NormClipping | FG | RLR |
|---|---|---|---|---|---|---|---|---|
| $ACC_{30}$ | 74.8 | 70.8 | 54.1 | 68.9 | 68.2 | 73.3 | 10.2 | 27.9 |
| Agg. time (s) | 0.35 | 0.36 | 0.33 | 0.39 | 0.44 | 0.40 | 0.58 | 0.37 |

Table 6: Performance of Anomaly Detection Defenses in FEMNIST over 100 rounds.

| Attacks → | Fixed - Pattern | | Distributed - Pattern | | Edge-Case | | A3FL (Dynamic Pattern) | | IBA (Dynamic Pattern) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Defenses ↓ | Precision | Recall | Precision | Recall | Precision | Recall | Precision | Recall | Precision | Recall |
| **FLAME** | 13.5 | 69.4 | 15.3 | 79.4 | 1.4 | 7.0 | 11.9 | 63.0 | 0.3 | 1.3 |
| **DeepSight** | 58.1 | 93.7 | 59.8 | 93.7 | 38.0 | 56.7 | 56.5 | 93.7 | 7.8 | 31.4 |
| **RFLBAT** | 18.1 | 23.5 | 25.9 | 32.2 | 16.3 | 27.5 | 15.9 | 17.9 | 0.6 | 0.9 |
| **MKrum** | 26.3 | 26.3 | 36.8 | 36.8 | 2.1 | 2.1 | 13.9 | 13.9 | 0.2 | 0.2 |
| **Indicator** | 29.5 | 42.7 | 19.5 | 24.0 | 24.5 | 32.4 | 26.9 | 32.1 | 27.3 | 36.5 |
| **FLDetector** | 10.6 | 21.4 | 10.6 | 21.4 | 10.5 | 21.3 | 10.5 | 21.3 | 10.5 | 21.1 |

Table 7: False Positive Rate (FPR) and Test Accuracy over last 30 rounds ($ACC_{30}$).

| Metric | FLAME | DeepSight | RFLBAT | AD-MKrum | Indicator | FLDetector |
|---|---|---|---|---|---|---|
| FPR | 39.3% | 25.6% | 7.7% | 0.0% | 99.1% | 5 % |
| $ACC_{30}$ | 72.6% | 73.7% | 70.7% | 72.5% | 61.3% | 74.1% |

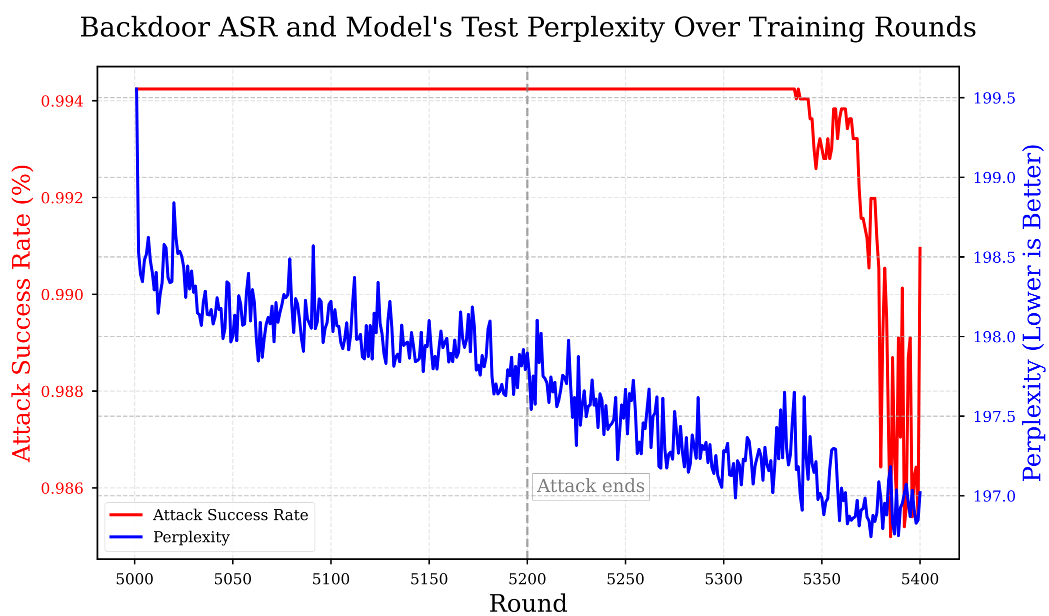


Figure 7: Attack performance of LSTM Language Model on Reddit Corpus

## C.2 Evaluation of Natural Language Processing tasks

For both the Reddit and Sentiment140 datasets, the attackers deploy their attack for 200 rounds, starting at round 2001 for Sentiment140 and round 5001 for Reddit. After the attack ends, FL training proceeds for another 200 rounds to evaluate attack durability. The number of attacker-controlled clients is 10% of all clients, and each client performs poison training on their local data. The malicious clients poison all of their samples (poison ratio is 100%) during poison training. We evaluate the Model Replacement attack, as this is a very potent attack in the FL setting.

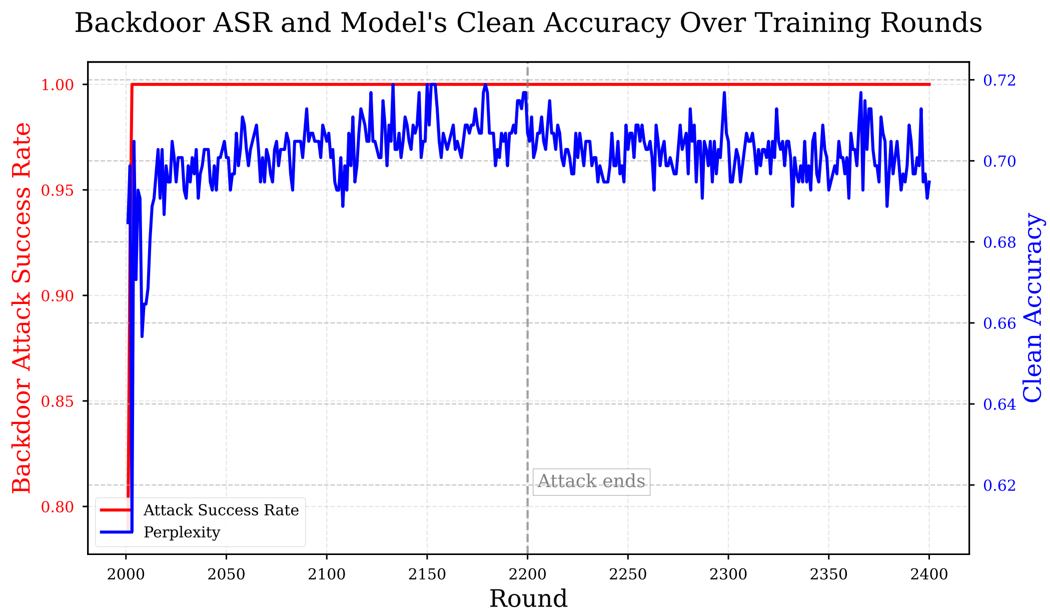


Figure 8: Attack performance of ALBERT on SENTIMENT140

As demonstrated in Figure 7 and Figure 8, both LSTM and ALBERT models exhibit significant vulnerability to Model Replacement attacks. The attack success rate (ASR) consistently remains above 95% and persists even after the attack concludes, maintaining this high level for an additional 200 rounds. For the LSTM model on Reddit, the ASR reduction observed in the final 50 rounds is negligible, decreasing by less than 1%. Importantly, performance on the primary task remains largely unaffected throughout the attack. While models initially experience slight degradation in main task performance when the attack begins (as evidenced by the more than 3% reduction in Clean Accuracy for ALBERT at round 2001), they gradually recover to normal levels as the attack progresses.

# D Potential Societal Impacts

The development of a benchmark framework for evaluating backdoor attacks and defenses in Federated Learning (FL) carries significant societal implications, given FL's increasing adoption in privacy-sensitive domains such as healthcare, finance, and mobile applications. This section discusses the potential positive and negative impacts of our research on society.

## D.1 Positive Impacts

Our benchmark framework provides a standardized, reproducible platform for assessing the robustness of FL systems against backdoor attacks. By systematically evaluating attack strategies (e.g., fixed-pattern, dynamic-pattern, distributed-pattern, and edge-case attacks) and corresponding defenses (e.g., client-side, pre-aggregation, in-aggregation, and post-aggregation methods), the framework enables researchers and practitioners to identify vulnerabilities and develop more secure FL systems. For instance, in healthcare, where FL is used to train models on sensitive patient data across hospitals, our framework can help ensure that models remain robust against malicious clients attempting to embed backdoors that could lead to misdiagnoses or compromised patient outcomes. Similarly, in financial applications, such as fraud detection, the framework supports the design of trustworthy models that resist tampering by adversarial actors. By fostering transparency and reproducibility, our work contributes to building public trust in FL technologies.

## D.2 Negative Impacts and Ethical Considerations

Despite its benefits, the framework could be misused by malicious actors to design more sophisticated backdoor attacks. By providing detailed insights into the effectiveness and modes of failures for defenses, our work may inadvertently enable adversaries to refine their strategies, potentially undermining the security of FL deployments. For example, the detailed experimental settings for attacks like DBA [38] or Neurotoxin [45] could be exploited to craft stealthier attacks that evade existing defenses. To mitigate this risk, we advocate for the responsible dissemination of our findings, emphasizing the importance of using the framework for defensive research and policy development.

## E Limitations

The BackFed framework provides a comprehensive platform for evaluating backdoor attacks and defenses in FL. However, several limitations must be acknowledged, particularly regarding potential errors in implementation, the impracticality of evaluated settings in certain scenarios, and the lack of coverage for domains such as time-series and medical applications.

### E.1 High Memory Usage

While the multi-processing pipeline of BackFed offers a significant speed-up over conventional sequential training in the previous codebases, it also incurs a greater cost of CPU, GPU, and RAM usage as multiple processes are jointly trained at the same time. Therefore, BackFed may not be fully optimized when computational resources are limited.

### E.2 Potential Errors in Implementation

The implementation of BackFed, which includes a variety of attack and defense mechanisms (e.g., Fixed-Pattern Attacks, Neurotoxin, FLAME, is susceptible to errors that could compromise evaluation reliability. For instance, the injection of backdoor triggers, such as pixel patches in Fixed-Pattern Attacks [2], requires precise manipulation of training data. Errors in trigger placement (e.g., incorrect pixel coordinates or intensity values) could lead to ineffective backdoors or false positives in attack success rates. Similarly, dynamic trigger generation in methods like A3FL and IBA [41, 24] relies on complex models (e.g., U-Net, Autoencoder), where implementation bugs, such as incorrect loss function optimization or parameter initialization, may result in inconsistent trigger behavior across clients. On the defense side, mechanisms like FLAME [23] depend on accurate HDBSCAN clustering, which is sensitive to hyperparameter settings (e.g., min_cluster_size). Suboptimal tuning or numerical instability in high-dimensional parameter spaces could misclassify benign updates as malicious, reducing defense efficacy. These potential errors necessitate rigorous testing and validation of the codebase, which may not be fully addressed in the current BackFed implementation.

### E.3 Impracticality of Evaluated Settings

The experimental settings evaluated in BackFed, such as those for DBA [38] and Neurotoxin [45], often assume idealized or controlled scenarios that may not generalize to real-world FL deployments. For example, BackFed tests settings with a fixed number of clients (e.g., 100 for CIFAR-10, 80,000 for Reddit) and a specific proportion of malicious clients (e.g., 10% in Fixed-Pattern Attacks). In practice, FL systems may involve dynamic client participation, where clients join or leave unpredictably, or operate under resource constraints (e.g., limited computational power on edge devices). The high computational requirements of methods like DBA, which involve multiple-shot poisoning across numerous rounds, may be impractical for resource-constrained environments, such as IoT devices or mobile networks. Additionally, the non-IID data distributions (e.g., Dirichlet with $\alpha = 0.5$) used in BackFed evaluations may not fully capture the heterogeneity of real-world data, such as in cross-silo FL settings where organizations have vastly different data distributions. These assumptions limit the framework's applicability to practical scenarios, particularly in dynamic deployments.

### E.4 Lack of Coverage for Time-Series and Medical Domains

BackFed primarily focuses on image classification tasks, with datasets like CIFAR-10, MNIST, and Tiny-ImageNet dominating its evaluations. This focus limits its coverage of other critical FL domains, such as time-series and medical applications, which present unique challenges for backdoor attacks and defenses. In time-series domains, such as financial forecasting or IoT sensor data analysis, backdoors may involve temporal triggers (e.g., specific sequences in stock prices or sensor readings) rather than static patterns, which BackFed does not currently address. For instance, the trigger designs in Fixed-Pattern or Distributed-Pattern Attacks [38] are tailored for image data and may not translate effectively to sequential data. In the medical domain, where FL is used for tasks like disease prediction or medical imaging, data privacy constraints and high-stakes outcomes amplify the need for robust backdoor defenses. However, BackFed's evaluations do not include medical datasets (e.g., electronic health records or MRI scans), which often exhibit high variability and require domain-specific preprocessing. The lack of coverage for these domains limits BackFed's generalizability, as attack and defense performance may differ significantly in non-image contexts.