Towards Understanding Quality Challenges of the Federated Learning: A First Look from the Lens of Robustness

Amin Eslami Abyane · Derui Zhu · Roberto Medeiros de Souza · Lei Ma · Hadi Hemmati

Abstract  Federated learning (FL) is a widely adopted distributed learning paradigm in practice, which intends to preserve users’ data privacy while leveraging the entire dataset of all participants for training. In FL, multiple models are trained independently on the users and aggregated centrally to update a global model in an iterative process. Although this approach is excellent at preserving privacy by design, FL still tends to suffer from quality issues such as attacks or byzantine faults. Some recent attempts have been made to address such quality challenges on the robust aggregation techniques for FL. However, the effectiveness of state-of-the-art (SOTA) robust FL techniques is still unclear and lacks a comprehensive study. Therefore, to better understand the current quality status and challenges of these SOTA FL techniques in the presence of attacks and faults, in this paper, we perform a large-scale empirical study to investigate the SOTA FL’s quality from multiple angles of attacks, simulated faults (via mutation operators), and aggregation (defense) methods. In particular, we perform our study on two generic image datasets and one real-world federated medical image dataset. We also systematically investigate the effect of the distribution of attacks/faults over users and the independent and identically distributed (IID) factors,
per dataset, on the robustness results. After a large-scale analysis with 496 configurations, we find that most mutators on each individual user have a negligible effect on the final model. Moreover, choosing the most robust FL aggregator depends on the attacks and datasets. Finally, we illustrate that it is possible to achieve a generic solution that works almost as well or even better than any single aggregator on all attacks and configurations with a simple ensemble model of aggregators. Our replication package is available online: https://github.com/aminesi/federated

**Keywords** Federated Learning · Robustness · Byzantine Attacks · Mutation Testing · Defense Methods

### 1 Introduction

Mobile devices have become quite powerful and an essential part of our lives in the past couple of years. The increase of computational power, along with the need and capability to support of Deep Learning (DL) in many mainstream intelligent tasks such as image classification, has helped with the introduction of a new learning approach called Federated Learning (FL) (McMahan et al., 2017). FL is a distributed learning paradigm where data resides only in each individual device of a user/client. Since data is only in clients’ devices and is not transferred between clients and the server, FL can fully preserve clients’ data privacy by design. Such an exciting feature has attracted much recent attention. FL is now being quickly adopted in privacy-sensitive areas like DL for medical imaging, where images are from different hospitals and patients’ privacy is of utmost importance. With the recent trend on more strict data privacy regulation, FL continuously grows and is expected to further expand its industrial adoption in the next few years.

As the general workflow of Federate Learning, clients receive a model from the server, perform the training on their data, and then send the new model to the server; then, the server aggregates the clients’ models into a new model. This process continues multiple times till the training converges.

Like any other software, FL-based software systems maybe prone to quality issues like robustness against adversarial attacks. Recent studies have identified several challenges with the FL process, including FL quality in the presence of attacks, heterogeneous data, and communication issues (Kairouz et al., 2021; Li et al., 2020a; Xia et al., 2021). One of the most studied topics within these quality challenges is the robustness of FL with respect to byzantine faults (Bagdasaryan et al., 2020; Bhagoji et al., 2019; Blanchard et al., 2017; Fang et al., 2020; Li et al., 2019; Lyu et al., 2020; Sun et al., 2019; Yin et al., 2018). Since clients can access the data and the training process, various data and model poisoning attacks can occur if clients are under the control of adversaries (Bhagoji et al., 2019). To make FL robust against these quality problems, many recent attempts of FL aggregation techniques have been proposed recently (Blanchard et al., 2017; Li et al., 2019; Yin et al., 2018).

Aside from being vulnerable to adversarial attacks, FL, like any other system, can also be prone to common faults. Mutation testing is a well-known technique in software testing that introduces minor faults (“mutation”) in the source code. It enables to assess the test cases’ adequacy and sufficiency in detecting (killing) those
faulty versions of the code (“mutants”). In recent years, mutation testing has also been
applied to DL applications by defining mutation operators working on DL models and
datasets (Hu et al., 2019; Shen et al., 2018; Wang et al., 2019). Some studies show
the effectiveness of these mutants in terms of robustness analysis of DL programs for
real faults (Humbatova et al., 2021).

To better understand the current state-of-the-art (SOTA) FL techniques against
common attacks and quality issues, in our study, we perform a set of experiments on
four FL attacks (Label Flip (Fang et al., 2020), Sign Flip (Blanchard et al., 2017),
Random Update (Blanchard et al., 2017), and Backdoor attack (Sun et al., 2019)) and
four DL mutation operators (Noise, Overlap, Delete and Unbalance) (Humbatova
et al., 2021). Since in FL, each attack and fault can appear independently in each
client, we further study the effect of the proportion of affected clients on the attack’s
success.

Additionally, we run the experiments on both generic and real-world federated
medical image datasets. Since generic datasets are not distributed, we distribute them
between multiple clients to see the effect of distribution, and we make the distribution
with three different levels of non-iid.

We then evaluate four well-known aggregation techniques (Federated Averag-
ing (baseline) (McMahan et al., 2017), Krum (Blanchard et al., 2017), Median and
Trimmed Mean (Yin et al., 2018)). Finally, we study the feasibility of creating a more
robust aggregator using the existing aggregation methods.

Our large-scale study eventually consists of 496 configurations, each executed ten
times (i.e., 4,960 models trained and tested) to account for the randomness of algo-
rithms. The results show that even the baseline FL aggregator (Federated Averaging)
is quite robust against mutation operators on the generic image datasets. However, we
see that the Overlap mutator causes noticeable damage when applied to the medical
dataset. Furthermore, our findings show that all examined attacks are effective against
the baseline, but attacks that poison the model are more effective, as expected.

Our comparison of FL aggregators shows that Krum faces issues on more non-iid
datasets and does not work as well as others, where all clients are benign. We also
observe that no single aggregation method can resist all the attacks (i.e., each has pros
and cons). In other words, the FL aggregator’s degree of robustness depends on the
dataset, the attack, and other factors like the data distribution. Finally, considering
these strengths and weaknesses of aggregators, we propose a simple ensemble of
existing methods for aggregation. The results show that the ensemble aggregator can
perform as well or even better than any of the aggregators alone in 75% cases and
achieves the highest accuracy on average.

To summarize, the contributions of this paper are:

- A large-scale empirical study on quality of FL from the angles of attacks, faults,
  and aggregation techniques.
- Analysis of different configurations of FL (cross-device and cross-silo) using both
generic and medical datasets with different distributions.
- A simple ensemble approach to provide a more robust FL aggregation.

Given that FL is a promising ML technique for many privacy-aware use cases,
this very early study along this direction has the potential to impact a broad set of DL
software in practice. It also provides guidance on FL robustness areas that require further research.

2 Background

In this section, we briefly introduce basic concepts needed for understanding this paper, including FL and its attacks and defense mechanisms and mutation testing for deep learning.

2.1 Federated Learning

In recent years a new learning technique has been proposed called Federated Learning (McMahan et al., 2017). The goal of FL is to make learning possible on distributed data while maintaining clients’ privacy. To that end, FL does not collect clients’ data; instead, it performs learning on each client with their data. Figure 1 shows how Federated Learning works along with the components that we focus on in this study (green boxes). At first, the server broadcasts the global model to the clients; then, each client trains their version of the model using their own dataset for several epochs. When clients are done with their local training, they calculate the updates (the difference between the new model and the model received from the server) and send back the
updates to the server. Once the server has all the updates, it aggregates them and updates the global model in the server. This process is a single round of communication, and FL requires multiple rounds of communication till the model converges.

Although FL initially focused on training on mobile devices, it now has a broader definition. FL that works on a large number of devices is called cross-device FL, and if it works on a small number of clients (that are more reliable and accessible like centers), it is called cross-silo FL (Kairouz et al., 2021).

In a cross-device setting, since not all the clients are available and training on all clients is extremely resource-consuming and has a significant communication overhead, only a fraction of clients is selected at each round. Selecting a small fraction can hurt convergence speed, but McMahan et al. (2017) have shown that a small fraction, such as 10% of clients, can produce good results. In contrast, in cross-silo FL, all the clients are available, and training is done on all of them. Moreover, since the number of clients is small, communication overhead is often not an issue here.

In this paper, we will study how the attacks and defense mechanisms can impact the quality of the FL process. To that end, we need to alter three components of the basic FL procedure: aggregator, local model (update), and local dataset, which are shown as green boxes in Figure[1]. The first component is where we implement the defense techniques, and the other two are where attacks and faults are implemented.

2.2 Aggregation Method in Federated Learning

As discussed before, FL aggregates all updates to update the model on the server. There have been many aggregation techniques proposed for FL with different characteristics. We discuss the most important and well-known ones here.

**Federated Averaging** (McMahan et al., 2017): This technique is the first and most straightforward and perhaps the most well-known technique among all aggregation methods. It has proven to be very effective in FL under different data distributions. However, it has a big flaw: it cannot perform well when adversaries operate some clients. That is why new approaches have been proposed under the robust aggregation category, which we will discuss next. This aggregator is the baseline in all of our experiments as it is the mostly used non-robust aggregator in related studies (Blanchard et al., 2017; Fung et al., 2020; Zhao et al., 2021). There are other variations of Federated Averaging (Li et al., 2020b; Wang et al., 2020) which aim to improve Federated Averaging in non-iid scenarios but they are still not designed as robust aggregators, thus we still use Federated Averaging as the baseline following previous studies.

**Krum** (Blanchard et al., 2017): This is one of the first robust aggregation techniques. The main idea here is that clients that produce similar updates are most likely benign, and choosing any of them as the update is reasonable for the global model update. More specifically, it first calculates the distances between clients updates, then sorts the clients based on the sum of their distance to their closest k clients. Where $k = n - f - 2$, n is the number of clients, and f is the number of byzantine clients. Finally, it picks the client with the lowest sum as the update for the model. Since it
chooses the update of only one client, it causes some concerns for privacy and its performance under non-iid distributions.

**Median (Yin et al., 2018):** Coordinate wise Median is another robust aggregation method. As the name suggests Median, calculates the median of clients’ updates per coordinate (if updates are like arrays, it gets the median for each axis and index) and creates an aggregated update. Intuitively it tries to filter outlier values.

**Trimmed Mean (Yin et al., 2018):** This approach is very much like the Federated Averaging. However, instead of getting the mean over all of the client updates, it first excludes a fraction of the lowest and highest values per coordinate then calculates the mean.

### 2.3 Attacks in Federated Learning

Byzantine faults are known issues in distributed settings (Lamport et al., 2019). Since FL is a distributed technique, it faces byzantine faults and attacks as well that can cause quality problems for the entire process. In byzantine attacks, clients collude to achieve a goal like breaking the learning process. Byzantine attacks are not to be mistaken with adversarial attacks applied in the testing phase, which try to fool the model by adding perturbations to the data (Goodfellow et al., 2015; Madry et al., 2018). As clients have access to both data and training process (local training), they can cause problems for the entire training process if adversaries operate them. A recent study has categorized FL attacks into two groups of data poisoning and model poisoning (Bhagoji et al., 2019). The first group is not exclusive to FL, and it has been a problem in centralized training as well (Munoz Gonzalez et al., 2017). However, since clients have access to the model and training process, FL has to withstand a new category of model poisoning attacks. In model poisoning, adversaries poison the model updates before sending them to the server using a specific method and attack the learning process.

More generally, attacks can be categorized into two groups, namely untargeted and targeted (Lyu et al., 2020). In untargeted attacks, adversaries want to stop the model from achieving its goal. For instance, in the classification task, the attacker’s goal is to make the model misclassify. However, the attacker has a specific goal in a targeted attack, like misclassifying images into a particular label in image classification. In the following, we introduce some of the most important attacks in FL from both categories. One purpose of our study in this paper is to investigate how current SOTA FL methods perform, against different attacks, and whether quality issues would occur.

**Label Flip:** This is an example of a data poisoning attack (Fang et al., 2020) in which byzantine clients change the label of their dataset randomly to make the final model inaccurate. Since the changed label is selected based on a uniform distribution, it is considered an untargeted attack. According to Bhagoji et al. (2019), this is the most effective attack in the FL setting among data poisoning attacks.

**Random Update:** This is a model poisoning attack where the adversary does not send an update based on its training. Instead, it sends random Gaussian updates to the server (Blanchard et al., 2017; Fang et al., 2020) which makes it untargeted as
well. Since the client is sending the update, it can increase the distribution variance to make more powerful attacks. This attack power was not possible in data poisoning attacks like the Label flip, as each client can change a limited number of labels.

**Sign Flip Attack:** Another example of a model poisoning attack is Sign Flip, where the attacker trains the model on its dataset and calculates the updates, but it changes the sign of updates and sends an update in the opposite direction [Blanchard et al., 2017; Li et al., 2019]. The client can also multiply the update to make the attack more practical, like the Random Update. This attack is also considered untargeted as the attacker does not pursue a particular goal, but it is more directed than the Random Update attack.

**Backdoor Attack:** In contrast to all previous attacks, this attack is targeted and tries to achieve a specific goal. The goal of the Backdoor attack is to make the model misclassify images containing certain features as a specific class [Chen et al., 2017]. The Backdoor attack can be categorized in data or model groups based on its implementation. Papers that are not focused on FL only use data to add a backdoor to the model [Chen et al., 2017; Gu et al., 2019]. However, papers in FL have used both data and model updates to make the attacks more effective [Bagdasaryan et al., 2020; Sun et al., 2019]. Bagdasaryan et al. (2020) have shown that Backdoor can be done using a semantic feature like classifying green cars as birds. The semantic feature has a significant advantage over other techniques: it only requires a training time attack, and data does not have to be changed in testing time. Although this makes semantic feature a great option, this approach is not easily generalizable for different datasets.

Another Backdoor technique is called pixel pattern, which was introduced in (Gu et al., 2019). This technique works by adding a small pattern of pixels to the images, which acts as the backdoor. This approach requires a test time attack and a training time attack, but it is more scalable than semantic features.

For the attack to be influential, byzantine clients multiply their updates and make their updates dominant in the aggregation phase. This multiplication is more effective if the model has converged since other updates are small, and byzantine updates can replace the global model. One important thing in a Backdoor attack is that there should be enough benign samples and poisoned samples. Otherwise model classifies all samples as the target class, and the main task fails, which is not desirable for the attacker.

### 2.4 Mutation operators in Deep Learning

Mutation testing is a well-known topic in the Software Engineering community, and recently it has been applied in deep learning [Hu et al., 2019; Shen et al., 2018]. Even though these studies have introduced many mutation operators for deep learning, many of these operators do not reflect real-world faults. More recently, a set of new mutation operators have proposed that is based on real faults [Humbatova et al., 2021]. These operators consist of the following categories: training data, hyperparameters, activation function, regularisation, weights, loss function, optimization function, validation.
In this paper, we leverage mutation testing to simulate the potential quality issues and how they impact the quality of SOTA FL techniques. In particular, we focus on mutation operators from the data category to simulate actual (potential) faults in the federated context. Other categories are mostly related to the training process, and although clients have access to that, if faults were to happen, they would be happening on all clients as the code for all clients is the same. Thus, it is unlikely that clients can change the model parameters by mistake. As a result, other categories are not applicable in the FL setting (they make more sense in centralized learning).

Now we discuss mutation operators related to training data.

**Change Labels of Training Data:** This is like a Label Flip attack, so we will not discuss it more.

**Delete mutator:** This operator simulates the lack of training data by removing a portion of training data.

**Unbalance mutator:** This operator simulates the situation where data is unbalanced by removing a portion of samples in classes that occur less than average.

**Overlap mutator:** This operator simulates a situation where very similar samples have different classes. It works by finding the two most dominant classes, then it copies a portion of data from one class and labels it as the other class.

**Noise mutator:** This imitates a scenario where training data is noisy by adding Gaussian noise to the samples. This mutator takes the variance of the pixels in the image; then, it adds noise to the image with a mean of zero and a percentage of calculated variance.

### 3 Empirical Study

#### 3.1 Objectives and Research Questions

The main objective of this paper is to investigate how current SOTA federated learning performs under different potential quality contexts, such as attacks and faults, using regular and robust aggregation methods. To achieve this, we mainly consider the following research questions:

**RQ1: How robust is Federated Averaging against attacks and faults in a well-known image domain dataset?**

In this RQ, we focus on the robustness of the Federated Averaging as the default and baseline aggregator in FL. We study four attacks and four mutators and consider other factors such as data distribution and the proportion of affected clients to comprehensively study the attacks/faults effects on the final results. In this RQ, we use well-known image datasets where we can have control over these factors. The setting for this RQ and RQ2 is cross-device.

**RQ2: How effective are the existing robust aggregation techniques against these attacks and faults?**

Following the same settings as RQ1, in this RQ, we study FL aggregators that are built as a robust technique along with Federated Averaging and evaluate their robustness against different attacks.
RQ3: In a real-world federated dataset, what is the effect of attacks and faults on different aggregators?

This RQ aims to evaluate the aggregation techniques in a cross-silo federated setting where clients are different centers. We will go through more details in the design section.

RQ4: How robust is an ensemble method that combines existing aggregators, in terms of detesting all attacks and mutations in all datasets and configurations?

This RQ aims to investigate the possibility of having a general solution that works well for all configurations of untargeted attacks without knowing what attack or fault the system will be facing.

3.2 Experiment Design

This section describes the design of our empirical study. Figure 2 shows an overview of our experiments procedure.

3.2.1 Datasets and Models

Image classification is one of the leading deep learning tasks, and it is being used as a primary subject in many studies in FL (Blanchard et al., 2017; McMahan et al., 2017). Thus we choose this task as our main task.

Generic Datasets: For the first two questions, which are focused on the generic image dataset, we choose two famous datasets from the image domain, Fashion MNIST (Xiao et al., 2017), and CIFAR-10 (Krizhevsky et al., 2009). We use these
datasets since they are well-known and well-studied and represent different classification difficulty levels. By choosing these datasets for the first two RQs, we study the effects of different datasets and models on the quality of the FL process when it is under byzantine attacks and mutation faults. We also chose these centralized datasets to have control over how we distribute them and study the effect of data distribution.

**Federated Dataset:** In RQ3, we aim to study a more realistic scenario and see its effect on federated learning quality. Since tasks on medical images are one of the main FL applications (Kairouz et al., 2021), given patients’ privacy concerns, a distributed medical image dataset is a perfect match with RQ3’s goal. Our medical imaging dataset is obtained from the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (Mueller et al., 2005). The ADNI was launched in 2003 as a public-private partnership led by Principal Investigator Michael W. Weiner, MD. The primary goal of ADNI has been to assess and model the progression of mild cognitive impairment (MCI) and early Alzheimer’s disease (AD). For up-to-date information, see [www.adni-info.org](http://www.adni-info.org). In this work, we are leveraging 1,723 magnetic resonance images from 594 (34.5%) Alzheimer’s patients and 1,129 (65.5%) presumed normal controls. These data were collected from six different centers that are used to simulate our federation. The number of data samples is unbalanced across centers (A: 15.7%, B:16.7%, C:4.3%, D:12.5%, E:14.9%, F:35.9%). We extract the ten central slices in the axial plane of the images to train and test our models.

**Data Distribution:** There is no need for any synthetic distribution for the ADNI dataset since it is already distributed. However, since CIFAR-10 and Fashion MNIST datasets are centralized, we partition them and distribute samples to different clients. Furthermore, because we want to see the effect of the distribution of the dataset in RQ1 and RQ2, we partition these datasets with different degrees of non-iid. To simulate different iid distributions, we use a method similar to the method used in the original FL paper (McMahan et al., 2017), but we add multiple non-iid options. We first group the images based on the classes then split each group’s samples into chunks of equal size (this size increases with the non-iid parameter and depends on the number of clients). Then for each client, we select a subset of groups randomly, and from each group, we select a chunk randomly and assign it to that client. This process finishes when all chunks are assigned to the clients. The number of selected groups for each client depends on the non-iid degree, and with the increase of non-iid degree, the number of selected groups decreases. However, all clients receive the same amount of samples as chunks are larger for higher non-iid degrees.

For instance, all groups will be selected with a non-iid degree of 0, and clients get data from all classes. However, in a high non-iid scenario, only a couple of groups will be selected, and each client will have samples from only some classes.

**Models:** Our models for generic datasets are simple convolutional neural networks with 12 and 7 layers for CIFAR-10 and Fashion MNIST, respectively, which are taken from Keras’ tutorials and examples (cif, 2021; mni, 2021). Table I shows a summary of the models used for Fashion MNIST and CIFAR-10 datasets. For the ADNI dataset, we use a transfer learning (TL) approach using the VGG16 model (Simonyan and Zisserman, 2015) pre-trained on ImageNet (Russakovsky et al., 2015). Our classifier consists of one dense layer with 512 neurons and a rectified linear activation followed by a dense layer with two neurons and a softmax activation. The
VGG16 weights were frozen during training. Our selected models for the experiments ensure the variety in our cases and help our results be more generalizable.

### 3.2.2 Attacks and faults

We use attacks described in Section 2.3 namely: Label Flip attack, Random Update attack, Sign Flip attack, and Backdoor attack. Our choice of attacks contains both untargeted and targeted attacks. Moreover, we have attacks from both data poisoning and model poisoning categories, which again helps with the generalizability of our study. We set the mean and standard deviation of Gaussian distribution for Random Update zero and two, respectively. We set the multiplier for sign attack to 10. We choose the pixel pattern technique discussed before for the Backdoor attack as it makes it generalizable for different datasets, and we set the update multiplier to 10. These numbers were selected based on empirical evaluations.

To simulate faults, we choose all of the data-related mutations discussed in Section 2.4. Since we are investigating FL-related faults, we need to consider what faults can be caused by clients’ mistakes. The choice of model-related parameters and mutation operators makes it more of a centralized choice, not clients choices. To thoroughly investigate how much damage attacks and faults can cause in FL, we choose three different proportions of affected clients: 0.1, 0.3, and 0.5 and study the effect on the final model.

### 3.2.3 Aggregation methods

As discussed in Section 2.2, we select Federated Averaging as our baseline method and Krum, Median, and Trimmed Mean as the robust aggregation methods under study, to represent the most well-known aggregation methods from the literature. We
set the hyperparameters for Krum and Trimmed Mean based on the expected number of malicious clients.

To show the feasibility of an ensemble aggregator, in RQ4, we choose two attacks, Random Update and Sign Flip, to have both data and model poisoning attacks. Our ensemble aggregator performs the aggregation with all four mentioned aggregators, then picks the aggregated update with the best validation accuracy. This process happens at each round independently until the training is complete.

3.2.4 Federated Setup

For the RQ1 and RQ2, we follow federated settings in (McMahan et al., 2017). We distribute data to 100 clients and select 10 of them randomly each round to simulate a cross-device setting. Local epoch and batch size are set to five and 10, respectively. Furthermore, for each dataset, we repeat experiments with three levels of non-iid: 0, 0.4, and 0.7. The number of training rounds depends on the dataset and how fast the model can converge. For Fashion MNIST, it is set to 100, and for CIFAR-10, it is set to 1,000.

For the RQ3, since we have six centers in the ADNI dataset and a cross-silo setting, we select all clients at each round for training. Moreover, we set the batch size to 32, the local epoch is set to one, and the number of training rounds is 100.

In RQ4, to compare our proposed aggregator with existing ones, we conduct experiments on the CIFAR-10 (with the non-iid degree of 0.4) and ADNI datasets. We compare the accuracies and also run a non-parametric statistical significance test (Mann–Whitney U test with p-value less than 0.05) on the 10 runs of each configuration per aggregator to show that the reported improvements are not due to chance.

Finally, in all RQs, to eliminate the randomness introduced in different steps of the experiment, we run all configurations ten times and always report the median of 10 runs. So all accuracy values in figures are median accuracies, and all reported “mean accuracy” values are the means of those median accuracies across configurations.

3.2.5 Threat model

We assume the attacker has complete control of a proportion of clients; thus, they can alter their model updates sent to the server and poison the training data. Furthermore, the devices can collude to make attacks more powerful like (Bagdasaryan et al., 2020; Blanchard et al., 2017; Zhao et al., 2021). However, the attacker does not know the aggregation method in use by the server, which is the same assumption used by previous works (Blanchard et al., 2017; Fang et al., 2020).

Some aggregators like Krum need to know the number of attacked clients, which is an unrealistic assumption, in our opinion. However, given that it has been used extensively before, (Fang et al., 2020; Li et al., 2021), we also include this configuration in our study.

Lastly, the server and the aggregation techniques are assumed to be uncompromised following previous studies settings (Fung et al., 2020).
3.2.6 Execution Setup and Environment

All experiments are done on Compute Canada cluster nodes with 4 CPU cores, a GPU, and 64GB of RAM. We use TensorFlow (Abadi et al., 2015) as our DL framework and Python 3.8 and simulate federated learning on a single machine.

3.2.7 Evaluation metrics

We use the model’s accuracy on test split as our metric for all attacks and mutators except the Backdoor attack. This is a reasonable choice since the more powerful the attack becomes, the lower the accuracy gets. In the Backdoor attack, we use the accuracy of the backdoor task as the metrics and not the accuracy on all test data. In contrast to other attacks, the Backdoor attack’s effectiveness directly correlates with this metric.

3.3 Experiment Results

In this section, we discuss the results for RQ1 to RQ4.

RQ1 Results (effect of attacks and faults on Federated Averaging):

The results for the CIFAR-10 and Fashion MNIST datasets are reported in Figures 3 and 7 respectively. Our first observation is that data mutators do not significantly impact the final results compared to attacks designed to fool the predictor model. Another interesting observation is that an increase in the proportion of affected clients does not noticeably decrease the accuracy. However, among these mutators, as Figures 3b and 4b show, the Noise mutator is more effective, and it gets slightly more powerful as the proportion increases. Therefore, a noisy dataset is a possible human fault that can cause problems in FL.

A general and somewhat expected observation is that as the dataset becomes more non-iid, the accuracy slightly decreases (except for model attacks which make the model hit the worst case even in an iid scenario). This can be seen in different bar colors in Figures 3 and 7.

Additionally, as shown in Figures 3a and 4a, we can see that Label Flip is effective, and its effect is more noticeable in higher proportions like 0.3 and 0.5. Furthermore, a non-iid dataset can cause more damage as the proportion increases. On CIFAR-10, see a 13% decrease of accuracy (due to non-iid distribution) in 0.5 proportion compared to 5% in 0.1 proportion. We see the same pattern on Fashion MNIST, and in 0.5 proportion, accuracy decreases by 8%, but in 0.1 proportion, the decrease is around 3%. Considering that technically this is also a data mutator, human error and mislabelling samples can result in problems in FL.

Additionally, the results show that model poisoning attacks are much more powerful than data attacks and faults. As Figures 3f and 4f show, even with a small proportion of affected clients, Federated Averaging loses its effectiveness completely, and the model classifies all test cases as a single class. As a result, accuracy reaches 10%, which is similar to random guessing. The same can be seen from Figures 4f and 4g for the Fashion MNIST dataset, and the model is essentially guessing randomly.
Finally, in the Backdoor attack, which is a targeted model attack, Figure 3h confirms that the attack is highly effective on CIFAR-10. As with even 0.1 proportion of malicious clients, the backdoor task reaches above 90% accuracy in all non-iid cases. This is more obvious in Figure 3h where even with 0.1 proportion, the attacker reaches 100% accuracy in all non-iid cases. Also, in Figure 3h for the CIFAR-10 dataset, we see that in the tiniest proportion, a more non-iid distribution increases the backdoor accuracy and makes it more powerful. This is not obvious in higher proportions as the backdoor reaches the highest feasible (considering the attack method and dataset) accuracy with an iid distribution. So, a more non-iid distribution cannot
Towards Understanding Quality Challenges of FL: A First Look from the Lens of Robustness

(a) Label Flip

(b) Noise Mutator

(c) Delete Mutator

(d) Unbalance Mutator

(e) Overlap Mutator

(f) Random Update

(g) Sign Flip

(h) Backdoor

Fig. 4 Fashion MNIST - Federated Averaging performance under different attacks

increase it. For the same reason, non-iid does not change the backdoor accuracy for the Fashion MNIST dataset as the backdoor accuracy is already 100%.

We report a summary of attacks and mutators against Federated Averaging in Table 2. Note that the Backdoor attack change is for the backdoor task and is a positive value (backdoor task increases with the attack in contrast to other attacks since their accuracy is for the main task.). Also, backdoor change is almost the same as the backdoor accuracy in 0.5 proportion since backdoor accuracy in a clean situation is virtually zero. As seen among the untargeted attacks, Random Update and Sign Flip are the most effective attacks against Federated Averaging, with around 70% accuracy change. Furthermore, as discussed before, the Noise mutator has the most impact.
Table 2: The accuracy change (between clean and 0.5 proportion configs) of Federated Averaging, per attack (averaged over all non-iid configurations)

| Attack/Mutator | CIFAR-10 | Fashion MNIST |
|----------------|----------|---------------|
| Label Flip     | -39.02   | -21.26        |
| Noise          | -5.66    | -2.84         |
| Delete         | -4.3     | -0.1          |
| Overlap        | -0.71    | -1.3          |
| Unbalance      | -0.64    | -0.21         |
| Random Update  | -66.13   | -77.81        |
| Sign Flip      | -66.13   | -77.81        |
| Backdoor       | +96.83   | +99.9         |

Fig. 5: Aggregators accuracy with no attack on the final model among the mutators, which is less than 6% and is not significant. Finally, the Backdoor attack has a significant impact on the backdoor task.

**Answer to RQ1:** In generic image datasets (e.g., CIFAR-10 and Fashion MNIST), Federated Averaging is not robust against any of the attacks and FL process faces quality issues as shown by the final model accuracy, and generally, model attacks are more powerful than data attacks. Furthermore, data mutators do not significantly impact Federated Averaging, but noisy data leaves a bigger mark. Lastly, the non-iid distribution has a more detrimental impact on the quality of FL when more clients are attacked.

**RQ2 Results (comparison of aggregators/defense mechanisms):** We divide this RQ into two parts: first, we compare the aggregators with no attack, then compare them under attacks.

We show the results for the first part in Figures 5a and 5b for CIFAR-10 and Fashion MNIST, respectively. Results show that Federated Averaging and Trimmed Mean perform similarly, and the non-iid does not significantly impact their accuracy. Median performs almost similarly to Federated Averaging and Trimmed Mean in a more iid setting, but it loses its accuracy slightly in a high non-iid situation.

In contrast, Krum’s accuracy is noticeably lower than the other aggregators in an iid scenario. As the dataset becomes more non-iid, the difference between Krum and others becomes more significant.
Lastly, comparing two datasets shows that non-iid distribution decreases accuracy in CIFAR-10 more than Fashion MNIST, which can be because the former is more challenging than the latter.

We compare the aggregators under various attacks for the second part of this research question. Since in RQ1, we saw that data mutators are not effective against the baseline (Federated Averaging), we exclude them from this part. Figures 6 and 7 show the results for the CIFAR-10 and Fashion MNIST respectively.

As Figure 6a shows, in the Label Flip attack on CIFAR-10, when we consider an iid situation, Federated Averaging, Median, and Trimmed Mean perform very similarly in smaller attack proportions. However, we see Trimmed Mean falls behind when half of the clients are byzantine. However, Krum does not perform well in the Label Flip attack and roughly archives 10% lower accuracy in smaller proportions than other methods; this gets much worse when half of the clients are attacked.

Figure 7a shows somewhat similar patterns on the Fashion MNIST dataset in an iid case. We see that Federated Averaging, Median, and Trimmed Mean are very similar in small proportions, but in 0.5 proportion, Federated Averaging is noticeably more robust. Like CIFAR-10 here, Krum is the worst aggregator by far, and its results are even worse than CIFAR-10 as it reaches as low as 2% accuracy in some cases.

Looking at Figures 6c and 6e for the CIFAR-10 dataset, as the non-iid degree increases, Federated Averaging outperforms other techniques in almost all the cases, and its advantage is more noticeable, with 30% of malicious clients. We also see that Trimmed Mean gets better results than the Median in almost all cases, making it a better choice than the Median in a non-iid scenario. Krum gets even worse when data becomes more non-iid, and even with 0.1 malicious clients, it works way worse than when it was not attacked. Consequently, although Federated Averaging is not robust against this attack, it still is the best choice and generally works better than the others.

On the Fashion MNIST dataset, Figures 7c and 7e show similar findings, and Federated Averaging and Trimmed Mean are the best choices.

To sum up the Label Flip attack, generally robust aggregators perform worse than Federated Averaging in a non-iid case when they are under attack. This might be because the robust aggregators cannot distinguish what is causing the difference between the updates high non-iid or the attack itself, which results in poor performance.

Looking at the untargeted model attacks (Random Update and Sign Flip) for the CIFAR-10 dataset, the first remark is that even with the smallest proportion of affected clients in an iid case (Figures 6b and 6g), Federated Averaging and Trimmed Mean are entirely ineffective, and the model is guessing randomly. Moreover, when a small proportion of clients are affected, Median works best in all non-iid degrees and achieves the highest accuracy (Figures 6d, 6f, and 6i, 6k). Nevertheless, when more clients become byzantine, it too loses its effectiveness and surrenders to attackers like Federated Averaging and Trimmed Mean. In contrast to the label attack where Krum struggled, here is where Krum shines. In non-iid degrees of 0 and 0.4, Krum shows incredible robustness against the attacks. No matter the proportion of affected clients, it performs excellently and achieves results as if it were not under attack. However, in the highest non-iid case, Krum relatively loses its robustness when half of the clients become byzantine.
Fig. 6 CIFAR-10 - Aggregators performance under different attacks
Towards Understanding Quality Challenges of FL: A First Look from the Lens of Robustness

Fig. 7 Fashion MNIST - Aggregators performance under different attacks
Table 3 | Aggregators summary in terms of their mean accuracy and the number of times the aggregator is the best choice among all aggregators under study (#Top rank) – The shades cells marks the best techniques.

| Dataset  | Attack     | Aggregator | Mean accuracy | #Top rank |
|----------|------------|------------|---------------|-----------|
| CIFAR-10 | Untagged  | FedAvg     | 26.31         | 8         |
|          |            | Krum       | 51.09         | 12        |
|          |            | Median     | 37.04         | 6         |
|          |            | Tri-mean   | 24.61         | 1         |
|          | Backdoor   | FedAvg     | 95.16         | 0         |
|          |            | Krum       | 4.26          | 12        |
|          |            | Median     | 90.72         | 0         |
|          |            | Tri-mean   | 93.56         | 0         |
| Fashion MNIST | Untagged | FedAvg     | 33.14         | 8         |
|          |            | Krum       | 51.32         | 9         |
|          |            | Median     | 58.43         | 10        |
|          |            | Tri-mean   | 53.69         | 3         |
|          | Backdoor   | FedAvg     | 99.94         | 0         |
|          |            | Krum       | 1.71          | 12        |
|          |            | Median     | 82.39         | 0         |
|          |            | Tri-mean   | 99.73         | 0         |

The observations are a bit different on the Fashion MNSIT dataset. Firstly, we see that Trimmed Mean is still viable against Random Update attack in all non-iid cases under small proportions (Figures 7b, 7d, 7f). This is because the Fashion MNIST task is less complex compared to CIFAR-10. However, in the Sign Flip attack, Trimmed Mean is guessing randomly in more cases compared to the Random Update attack (Figures 7g, 7i, 7k), which confirms the fact that the Sign Flip attack is more powerful. Everything else is similar to CIFAR-10, and Median and Krum are still the best options.

To sum up, in these attacks, generally speaking, Krum is the most robust technique and works very reliably in all cases. However, if the proportion of affected clients is small, the Median is better because it has better convergence speed and accuracy than Krum.

In the Backdoor attack again, results for CIFAR-10 (Figures 6h, 6j, 6l) and Fashion MNIST (Figures 7h, 7j, 7l) show that Krum is quite robust in all cases. With the increase of the number of attackers or the non-iid degree, the final model does not get fooled, and backdoor accuracy is close to zero. On the other hand, Federated Averaging gets entirely fooled in all cases and is not robust. Median and Trimmed Mean show some resilience against the Backdoor attack. The former is slightly superior when data is more iid, and the proportion of affected clients is small. However, they are not even close to Krum, and as the proportion increases, they become ineffective like Federated Averaging, and the backdoor goal is almost always achieved. In this case, again, Krum is undoubtedly the best and most robust technique.

We report a summary of aggregators for CIFAR-10 and Fashion MNIST in Table 3 based on the average accuracy of the final model on the test data and the number of times each aggregator was the most robust one. Note that only attacks are selected here since data mutators were ineffective. As it can be seen, Krum achieves the best
Fig. 8  ADNI - Aggregators accuracy with no attack

accuracy on average and most first ranks in the CIFAR-10 dataset, so all in all, it is the most robust aggregation method for that dataset. For Fashion MNIST, Median is the most robust aggregator. However, considering the first rank count of aggregators, Krum comes in a close second, but its mean accuracy is less than Median. This is because it achieves far worse results in the Label Flip attack.

Answer to RQ2: In most cases, Krum is the most robust FL aggregator, and Median comes in second when there is no prior knowledge on the type of attack or fault (which is often the case). However, if attacks were known, the best choice for the Label Flip attack would still be Federated Averaging. Also, if the model was under untargeted model attack and the number of attackers was small, Median would be a better choice than Krum. That being said, Krum’s main drawback is its problem with non-iid distribution, and it struggles to maintain the same accuracy as the iid degree increases. So, in short, there is no best defense technique for all situations to ensure quality.

RQ3 Results (The case of a real federated dataset):
Like RQ2, we first report the results where all clients are benign in Figure 8. As it can be seen, all aggregators perform similarly and achieve the same accuracy of 75% except Krum. This is much like the results we saw for general datasets in RQ2. However, there is a significant difference in the ADNI dataset for Krum. Here Krum does not perform reliably and shows different behavior with different runs. Moreover, Krum converges to very different results, and there is a 15% difference in the final accuracy for the worst and best run of Krum. Whereas in CIFAR-10, the variation between the results is less than 5%. This inconsistency might be because this dataset is naturally non-iid and unbalanced.

We saw in RQ2 that Krum performed worse compared to others in synthetic non-iid cases, and here we see a similar problem but more severe. To illustrate this better, Figure 9 shows Krum’s test accuracy convergence trend over the communication rounds for ADNI and CIFAR-10 datasets on worst and best runs. As it can be seen in Figures 9a and 9b, Krum does not work reliably here, and it converges to very different results, and we see a 15% difference in the final accuracy. Whereas in CIFAR-10, the results difference is less than 5%.

One explanation for this inconsistency is that this RQ is investigating a case of cross-silo FL, which means clients are not selected randomly. Thus, Krum always sees updates from the same clients and chooses one which might be good or bad
for the final test. Since different centers have images from different MRI machines, the selected client update by Krum might not be a generally good solution, and final results are dependent on random factors like data shuffle method, weight initialization, and other factors. Consequently, Krum is not guaranteed to converge to the best solution in this dataset, and its results are unreliable and quite random.

To see how aggregation methods work here and what the differences are compared to baseline image datasets, we report the results in Figure 10.

According to Figure 10a, in the Label Flip attack, we see that in a small proportion of affected clients, all aggregators perform very similarly except Krum that is worse, much like the previous RQ. As the proportion increases, we see that Median and Trimmed Mean get slightly better results. However, when half of the clients are under attack, they are less robust than Federated Averaging.

Figures 10b to 10e are related to data mutators. In most data mutators, the results are fairly similar to the RQ1, and none of them significantly impact any of the aggregators. As seen before, the Noise mutator reduces the quality of the model slightly. However, interestingly, in the ADNI dataset, the Overlap mutator has a significant impact on Federated Averaging. As the proportion of affected clients increases, it performs even worse and hits 46% accuracy. This can be because this dataset has only two classes, and this mutator overlaps only two classes (which are all of the classes here) as discussed in Section 2.4.

On the other hand, Median and Trimmed Mean show excellent robustness against this mutator, and in smaller proportions, they perform as if there was no attack. Al-
Towards Understanding Quality Challenges of FL: A First Look from the Lens of Robustness

Fig. 10 ADNI - Aggregators performance under different attacks

Though Median is slightly less resilient in smaller proportions, it performs better when half of the clients are byzantine. Krum is also more robust than Federated Averaging, but because of its problems with the ADNI dataset almost always performs worse than Median and Trimmed Mean.

An exciting conclusion is that robust aggregation methods can mitigate faults that can hurt Federated Averaging, like when similar samples have different labels.

In untargeted model attacks (Figures 10f and 10g), we see again that Federated Averaging is performing very poorly. In the Random Update, it achieves an average accuracy of 64%. However, in the Sign Flip attack, it is even worse as models are
Table 4: ADNI - Aggregators summary in terms of their mean accuracy and the number of times the aggregator is the best choice among all defence mechanisms under study (#Top rank) – The shades cells marks the best techniques.

| Attack          | Aggregator | Mean accuracy | #Top rank |
|-----------------|------------|---------------|-----------|
| Untargeted      | FedAvg     | 52.89         | 1         |
|                 | Krum       | 63.23         | 2         |
|                 | Median     | 64.97         | 4         |
|                 | Tri-mean   | 65.16         | 5         |
| Backdoor attack | FedAvg     | 99.47         | 0         |
|                 | Krum       | 53.34         | 3         |
|                 | Median     | 96.9          | 0         |
|                 | Tri-mean   | 97.92         | 0         |

Guessing randomly and since the data is unbalanced final accuracy is 34%. This shows that Sign Flip can cause more damage, and it makes sense because it is trying to guide the model in the opposite direction rather than a random direction. In contrast, Trimmed Mean and Median are robust, and in the Random Update attack with smaller proportions, they even get close to no attack accuracy of 75%. However, since Sign Flip is more powerful than Random Update, both aggregators get lower accuracy in the Sign Flip case and even completely fail when half of the clients are malicious.

Although Krum did not always converge to best solutions, it is still more robust than Federated Averaging and is closely behind Median and Trimmed Mean. In some cases, like 0.5 proportion, it even works better than those two.

As a result, Trimmed Mean and Median for these attacks are the best choices and are reasonably robust. Furthermore, Median and Trimmed Mean aggregators show more robustness in higher proportions than RQ2, which can be because we are using transfer learning and many layers of the model are not trainable. Hence, model attacks are less effective than before.

As Figure 10h shows, Krum still is the most robust approach in the Backdoor attack with only 50% backdoor task accuracy in small proportions. Even in the highest proportion, it still has 60% backdoor accuracy, which is much better than the others. However, Krum struggles with the main task, so Krum has a trade-off between main and backdoor task accuracy.

Note that backdoor task accuracy is much higher than generic datasets. This is because there are only two classes in this dataset, and the main task accuracy of the dataset does not exceed 75% (for Krum, it is even lower). This means that some samples are already misclassified to the attackers’ target label, making the backdoor task more successful.

Moreover, the Median shows slight robustness in the smallest attack proportion against the backdoor objective, but it is inadequate. Trimmed Mean performs worse than Median, which is not good enough either. Federated Averaging is the worst of all, and its backdoor task is always successful in all cases. These patterns are much like what we observed in RQ2.

Following what we did in RQ2, we report the summary of aggregators for this dataset in Table 4. Unlike RQ2, the Overlap mutator is also included here since it proved effective for this dataset.
Table 5 Comparison of available aggregators with the ensemble aggregator

| Dataset | Attack portion | Aggregator | 0.1 | 0.3 | 0.5 | Avg |
|---------|----------------|------------|-----|-----|-----|-----|
| CIFAR-10 | Label Flip   | FedAvg     | 74.58 | 66.81 | 36.4 | 34.63 |
|         |               | Krum       | 49.49 | 41.02 | 29.41 | 50.11 |
|         |               | Median     | 70.34 | 54.13 | 27.59 | 70.96 |
|         |               | Tri-Mean   | 73.2 | 59.01 | 31.84 | 72.08 |
|         |               | Ensemble   | 73.31 | 64.85 | 60.53 | 64.64 |
|         | Sign Flip     | 10.0 | 10.0 | 10.0 | 7.29 |
|         |                | 61.0 | 60.62 | 59.13 | 60.47 |
|         |                | 69.68 | 61.01 | 61.01 | 60.47 |
|         |                | 69.1 | 60.59 | 65.83 |
|         |                | 71.61 | 61.01 | 61.01 | 60.47 |
|         |                | 72.9 | 65.69 |
|         |                | 71.5 | 65.69 |
|         |                | 66.17 | 67.75 | 67.75 | 65.69 |
|         |                | 69.12 | 65.69 |
|         |                | 49.34 | 49.34 | 49.34 | 49.34 |
|         | Average       | 34.63 | 50.11 | 40.5 | 32.34 |
| ADNI    | Label Flip   | 69.09 | 58.2 | 54.02 | 34.9 | 47.46 |
|         |                | 61.07 | 59.28 | 45.39 | 63.46 |
|         |                | 69.68 | 61.01 | 46.13 | 63.46 |
|         |                | 69.1 | 60.59 | 56.83 |
|         |                | 71.61 | 61.01 | 48.41 | 63.46 |
|         | Sign Flip     | 34.9 | 34.9 | 34.49 | 34.49 |
|         |                | 66.17 | 67.75 | 67.75 | 65.69 |
|         |                | 69.12 | 65.69 |
|         |                | 34.49 | 34.49 | 34.49 | 34.49 |
|         | Average       | 34.49 | 60.47 | 58.45 | 59.1 | 64.64 |

According to the table, Trimmed Mean gets the best results for untargeted attacks and mutators, and Median comes in second with a negligible difference. All aggregators lose the competition to the attacker for the Backdoor attack except Krum, which shows decent robustness, but its main task accuracy can still be problematic.

Answer to RQ3: Unlike RQ2, where Krum proved to be the best aggregator, overall, here, Trimmed Mean and Median are the most robust ones on average, and they can better maintain the quality of the FL process. However, Krum is still the best aggregator for the Backdoor attack (on the backdoor task, to be more precise). Moreover, Krum shows problems in the cross-silo FL with non-iid data, and it is not consistent like the other aggregators. Finally, even in a case-by-case situation in untargeted attacks, Trimmed Mean and Median are still a great choice of aggregation method.

RQ4 Results (An ensemble of aggregators):

As discussed before, in this RQ, we evaluate our ensemble method on the CIFAR-10 (with non-iid=0.4 ) and ADNI datasets and test the new method on Label Flip and Sign Flip attacks. Given that the Fashion MNIST dataset is less challenging compared to CIFAR-10, based on RQ1–2 results, we only focus on these two datasets for the sake of space.

We report the results in Table 5. Out of these 12 configurations, in Five cases, ensemble aggregator is the best option, according to the median accuracies. Running statistical tests (Mann-Whitney U Test) shows that the ensemble is significantly better than the second technique in three cases out of five. However, in the remaining two cases, there is no significant difference. Furthermore, out of the seven remaining cases, where the ensemble is not the best, this difference is insignificant in four cases. As a result, in 75% of cases, ensemble aggregator is the most reasonable choice. Lastly, it achieves the highest mean accuracy compared to other aggregators.
One caveat with our ensemble approach is that it takes longer to train. On average we see around 50% increased training time which is not too bad considering the results. Furthermore, as the overhead is on the server, and servers are not limited like clients, servers can easily make up for this by utilizing more GPU resources. Lastly, this method only has an overhead in the training phase, so clients will not notice any difference in the testing phase (this phase is repetitive and is where users interact with the model).

**Answer to RQ4:** Combining all studied aggregators, it is possible to offer an ensemble aggregator that is more generalizable than any of its constituent aggregators and shows decent robustness in both data (Label Flip was a representative of this category) and model poisoning (Sign Flip was a representative of this category) attacks, without prior knowledge about them.

3.4 Discussions

As discussed, one of the main challenges that can jeopardize the quality of the FL is byzantine attacks. Our study confirms this problem and shows that attacks and, to some extent, faults can degrade the overall quality of the FL. We saw that having robust aggregation techniques instead of the basic Federated Averaging can indeed improve the robustness and consequently the quality of training. Although robust aggregators are effective, another factor that challenges the quality of the FL process is the proportion of byzantine clients. The design of aggregators typically has some breaking points in terms of the number of byzantine clients, and the aggregator might not work past that, as intended. For instance, Median’s breaking point is when half of the clients are byzantine [Lyu et al., 2020]. However, the number of byzantine clients might not be below the aggregators’ breaking point in a real scenario. As a result, there could still be serious quality issues in practice.

Moreover, the choice of the aggregator is non-trivial, and it is one of the most significant challenges that we currently face in this domain. Our experiments show that there is no perfect aggregator for all cases, and it is imperative to consider the context and settings when applying a specific aggregator.

Even though selecting aggregators based on the settings seems like a reasonable tactic, it is usually not practical. Since in a real case, essential factors like the dataset and attack type are unknown to the server (consequently the aggregator), i.e., there is no way to know which aggregator would work best. Moreover, as discussed before some aggregators need some extra information in order to perform decently, which might not be available to them. For instance, Krum and Trimmed Mean both need to know how many byzantine clients are at each round, which is not a realistic assumption. So, using them in an actual application would be problematic unless they use some estimation technique to estimate the number of byzantine clients. Although this seems a solid solution, the choice of estimation technique itself is significant and needs extensive study.
An important point to notice is that model attacks, which are far more powerful than poisoning attacks, are only possible if the attacker can access and alter the client code. Consequently, it would be ideal to improve the client code security and stop these attacks before they can happen. So it would be interesting to see which techniques can be applied here to make it harder for the attacker to implement model poisoning attacks. One idea would be cryptography which is already being used on secure aggregators (Bonawitz et al., 2017).

Another interesting follow-up research opportunity in this domain is about the client selection strategy in a cross-device FL. The baseline for client selection is choosing clients randomly, at each round (McMahan et al., 2017). Recently, new client selection techniques have been introduced to make the overall FL process faster by considering devices’ hardware heterogeneity (Chai et al., 2020; Lai et al., 2021; Nishio and Yonetani, 2019). It would be interesting to see how a byzantine-aware client selection technique could improve the overall quality alone and how it would work with a robust aggregation technique.

3.5 Limitations and threats to validity

One of the limitations of our study is that in RQ4, our proposed technique is not applicable in the Backdoor attack where the backdoor task is unknown. We will consider this as future work and an extension for this study.

In terms of conclusion validity, one potential threat could be the random factors of the study, like client selection for training and selection of byzantine clients. We tried to mitigate this issue by running the experiments ten times and reporting the median of the results to exclude the outliers. Also, we ran statistical significance tests to show that the observations were not due to chance.

In terms of internal validity, we reused well-known attacks and defenses (robust aggregations) from the existing literature, and two co-authors of the papers carefully went through the implementations.

In terms of construct validity, we used well-known accuracy metrics representing the performance of the models under attack/faults.

Finally, with respect to external validity, although we have broad systematic coverage of many existing approaches, the choice of dataset and models and the number of attacks, mutators, and aggregators can be questioned. To mitigate this problem, regarding datasets, we used well-known generic Fashion MNIST and CIFAR-10 datasets and an application-specific ADNI dataset, which is a real-world federated dataset, to improve the generalizability of the findings. In terms of the models, although like many related work (Li et al., 2019, 2021) and to make the systematic experiments with all combinations manageable, we used only one model per dataset, we used a diverse set of models across datasets (from simple CNNs to more complex VGG16). We tried to pick well-established FL untargeted and targeted attacks from both data and model categories regarding the selected attacks. Additionally, we used previously studied mutation operators that were applicable to FL and were based on real faults. Finally, concerning the aggregators, we studied four of the most well-studied techniques in the published FL literature that come with replication packages.
4 Related work

Fung et al. proposed a new defense mechanism, called FoolsGold (Fung et al., 2020), to make Federated Learning more robust against sybil attacks. Their approach works based on model updates received at the server. FoolsGold first compares the update vectors based on their similarity and identifies the problematic updates and consequently the byzantine clients. Afterward, FoolsGold changes the learning rate of the byzantine clients to make their updates have less contribution in the final model. However, this approach does not work in several cases, like model poisoning attacks. If the attacker sends random updates, the learning has no effect in the final update, and in other cases, clients can multiply their updates without restriction to make up for the learning rate. Furthermore, in model poisoning attacks, the attacker has full control of the byzantine clients; thus, it can set its learning rate to make its attack more effective (Bagdasaryan et al., 2020), which nullifies what FoolsGold was trying to achieve. This, along with the fact that FoolsGold is not actually an aggregation mechanism, is why we omitted FoolsGold in our experiments.

Li et al. proposed a new Federated Learning scheme called Ditto (Li et al., 2021), which is fair and robust against attacks. Ditto is not like other aggregation mechanisms as it is more of an optimization algorithm that follows a particular objective to ensure fairness and robustness. Since we are focused on robust aggregation techniques, we did not include Ditto in our experiments.

Li et al. introduced another aggregation mechanism called RSA to ensure the robustness of FL against attacks in heterogeneous cases (non-iid data) (Li et al., 2019). RSA is different from other robust aggregations discussed in this paper as it is not comparing updates together. Instead, it compares the received models (not the updates) at the server with the global model. It is a norm-based approach that penalizes models that deviate too much from the global model by limiting their contribution to the aggregated model. We could not use this technique in our experiments since its replication package was not well-documented. Thus we could not experiment with it in different scenarios of our experiment (datasets, models, attacks).

Zhao et al. tackled the problem of robust aggregation mechanisms in the secure environments and introduced a new framework called SEAR (Zhao et al., 2021). Since secure aggregation uses cryptography, it stops the server from seeing the updates and makes these robust aggregation techniques impossible to use. They proposed a new secure aggregation called SEAR, which relies on Intel Software Guard Extensions (SGX) for secure aggregation. They also proposed a new aggregation technique that works best with the SGX environment. However, their final results regarding final model accuracy are not that different from the aggregators studied in this paper. Since their main contribution is about the security and performance of robust aggregators in the secure environment (and their aggregator alone is not that powerful), we omitted SEAR from our experiments.

Wan and Chen introduced a new aggregation technique that works with attention models (Wan and Chen, 2021). The objective of the proposed aggregation model is to assign a weight to each local update in a way that byzantine updates get excluded (they get zero weight assigned to them) and do a weighted averaging at the end. Their attention-based aggregation model first needs to be trained on the data collected dur-
Towards Understanding Quality Challenges of FL: A First Look from the Lens of Robustness

ing a normal Federated Learning process (the data is the local updates sent to the server). After the model is trained, it can be used in another Federated Learning process for aggregation. There are a couple of issues with this technique. Firstly, the models have to be trained on different attacks and datasets to work appropriately, which is not generalizable (in a case where the server does not know the attack and dataset). They discussed the transferability of their approach to different configurations, but it is limited and not as strong as case-specific techniques. Moreover, their replication package does not have trained aggregation models, and to recreate the trained model, one has to use their own framework, which does not work with the Transfer Learning model we need in one of our configurations (ADNI dataset). For these reasons, we excluded this technique from our experiments.

There are also some recent robust aggregation techniques proposed online (Fu et al., 2021; Pillutla et al., 2019) which are not published in any peer-reviewed venue yet, thus we have not included them in this study.

Fang et al. conducted a study on FL aggregators and attacks. They used Label Flip, Random Update, and their proposed attack with Krum, Median, and Trimmed Mean aggregators (Fang et al., 2020). They also have studied the effects of non-iid distribution and the proportion of affected clients but only for one dataset. However, our study has some key differences with their study. Firstly, they omitted Federated Averaging, which is the baseline of FL, and as we showed before, is better than the other aggregators in Label Flip attack. Secondly, they only used untargeted attacks in their evaluations, whereas we also studied targeted attacks and mutators to simulate faults. Lastly, they only used naturally centralized datasets in a cross-device setting; in contrast, we also did a comprehensive study on a federated dataset and cross-silo FL setting.

Bhagoji et al. studied model poisoning attacks in FL (Bhagoji et al., 2019). They introduced a targeted model poisoning attack and showed its effectiveness against Federated Averaging on the Fashion MNIST dataset. They also compared Krum and Median using their attack. This study is more focused on a variation of the targeted attacks. In contrast, we conducted a large-scale study on both untargeted and targeted attacks, mutators, and more aggregation techniques on all attacks. We also considered three datasets, one of which was naturally federated, and studied the effect of different distributions and the proportion of attacked clients.

Lyu et al. surveyed attacks and defenses in FL. They studied the attacks and defenses and compared them using their theoretical details and limitations (Lyu et al., 2020). Furthermore, they studied different privacy techniques used in FL. Consequently, our empirical study adds a practical value to their theoretical study and explores mentioned limitations in practice.

So to summarize, our empirical study is more comprehensive than existing work. It also includes a real-world FL dataset, and finally, we also propose a simple but more robust aggregator.
5 Conclusion and Future Work

In this paper, we conducted a large-scale empirical study on the effect of faults and attacks on FL aggregators. We performed our experiments on two generic image datasets, each with three different distributions, one federated medical dataset, eight attacks and mutators, and four aggregation techniques resulting in 496 configurations. Results show that the Sign Flip and Backdoor attacks are the most effective attacks. Moreover, mutators do not significantly impact FL’s quality, except for the Overlap data mutator, which can affect Federated Averaging in the ADNI dataset. In addition, our study shows that there is no single best robust aggregator, and their accuracy depends on factors such as attack type, dataset, and data distribution. For instance, Krum is most robust in model poisoning attacks, but it is not acceptable in the Label Flip attacks. Inspired by the results of different aggregators, we show that an ensemble of these aggregators can be more robust than any single aggregator to improve the FL process quality, in general, when the attacks and data distribution are unknown to the aggregator. In the future, we plan to study different attack scenarios, e.g., a case that the attacker is aware of the aggregator used on the server. Also, we want to extend this study to other FL exclusive issues such as clients’ machines capabilities, learning frameworks, network failures, and arithmetic computation precision issues. Lastly, we want to extend the ensemble technique to make it effective against targeted attacks like the Backdoor attack and more efficient by using different heuristics while selecting the best aggregator in each round.

Acknowledgements Data collection and sharing for this project were funded by the Alzheimer’s Disease Neuroimaging Initiative (ADNI) (National Institutes of Health Grant U01 AG024904) and DOD ADNI (Department of Defense award number W81XWH-12-2-0012). ADNI is funded by the National Institute on Aging, the National Institute of Biomedical Imaging and Bioengineering, and through generous contributions.

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Towards Understanding Quality Challenges of FL: A First Look from the Lens of Robustness

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