Detection of Poisoning Attacks with Anomaly Detection in Federated Learning for Healthcare Applications: A Machine Learning Approach

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Abstract—The application of Federated Learning (FL) is steadily increasing, especially in privacy-aware applications, such as healthcare. However, its applications have been limited by security concerns due to various adversarial attacks, such as poisoning attacks (model and data poisoning). Such attacks attempt to poison the local models and data to manipulate the global models in order to obtain undue benefits and malicious use. Traditional methods of data auditing to mitigate poisoning attacks find their limited applications in FL because the edge devices never share their raw data directly due to privacy concerns, and are globally distributed with no insight into their training data. Thereafter, it is challenging to develop appropriate strategies to address such attacks and minimize their impact on the global model in federated learning. In order to address such challenges in FL, we proposed a novel framework to detect poisoning attacks using deep neural networks and support vector machines, in the form of anomaly without acquiring any direct access or information about the underlying training data of local edge devices. We illustrate and evaluate the proposed framework using different state of art poisoning attacks for two different healthcare applications: Electrocardiograph classification and human activity recognition. Our experimental analysis shows that the proposed method can efficiently detect poisoning attacks and can remove the identified poisoned updated from the global aggregation. Thereafter can increase the performance of the federated global.

Index Terms—Federated learning, security, privacy, anomaly detection, poisoning attacks, data poisoning, model poisoning, Byzantine attacks, healthcare, ECG, HAR.

1 INTRODUCTION

Privacy and security are among the top issues to be addressed in privacy and security-sensitive applications of machine learning (ML), such as healthcare, autonomous vehicles, etc. Federated learning (FL) has been introduced to enhance data privacy in machine learning applications [1]. FL attempts to provide enhanced privacy to the data owners by collaboratively training a joint model by only sharing parameters of locally trained models, in this way the data owners never share raw data, but can collaboratively train a joint robust global model. For instance, various hospitals can train ML models jointly for healthcare applications without directly sharing their privacy-sensitive data with each other. Generally speaking, FL iterates in three steps: the global server (i.e., a cloud server), which maintains the global model, sends the global model to the edge devices; the edge devices update the local models using their local training data and shares the trained parameters of the locally trained model with the global server, and the global server updates the global model by incorporating the shared parameters according to an aggregation rule. For example, the mean aggregation rule which computes the average of the shared local model’s parameters is one of the widely used aggregation algorithm [2]. Nevertheless, in such cases, the global model can be easily manipulated, even if a single edge device is compromised [3, 4, 5]. The attack surface of FL is growing due to its distributed nature. For example, malicious peers can launch model poisoning [6], and data poisoning [7, 8] attacks to impair the performance of the updated global model.

FL can be divided into three phases: data and behaviour auditing, training, and testing. FL faces different kinds of security threats in each phase [9]. Hence, establishing secure FL needs to take effective measures at each phase to mitigate such threats. A solution before integrating a local model into the global model is to audit the local data. However, due to the privacy concerns and architecture of FL, it’s challenging to achieve such audits [9]. A trivial method to address model poisoning attacks could be using accuracy, i.e., using accuracy as a measure to access the quality of data being used to train the local model. Nevertheless, such methods can not be generalised as accuracy solely cannot reveal information about the underlying data. Just looking at the accuracy it cannot be claimed that the model is trained on benign or malicious data. Furthermore, models can be designed to have high accuracy for the testing samples by including them in the training dataset. A model can have low accuracy even if it has been trained on benign data depending on the amount of training data, training epochs, hyper-parameters tuning, optimization, etc. Hence, new solutions are required to avoid such model and data
poisoning attacks. Methods should be developed to verify that the shared local model gradients are not trained on anomalous data (noisy, featured poisoning, label poisoning etc.). In other words, malicious behaviour of the locally trained models should be tracked before incorporating them into the global aggregation in order to avoid malicious peers compromising and manipulating the global model. In order to address poisoning attacks [10, 11] in which a malicious edged device manipulates its local training data or the model after training it on benign data using carefully designed techniques to malfunction the performance of global model, we proposed a novel poisoning attacks detection framework in federated learning for healthcare applications. Furthermore, we analyze the performance of the proposed framework using two healthcare applications i.e., electrocardiogram (ECG) classification and human activity recognition (HAR) in a federated setting. The contributions of this work can be summarised as follows.

1) We propose a novel framework to detect poisoning attacks by malicious-edged devices in FL for healthcare applications.
2) We evaluate the performance of the proposed framework against state-of-the-art model poisoning and data poisoning attacks, in two different healthcare applications.
3) With performance analysis we show that the proposed framework can not only detect poisoning attacks but can also increase the performance of the global model.

The rest of the article is organised as follows: Section 2 the background and related work. Section 3 presents the proposed framework, section 4 and section 5 provides performance evaluation an comparison of the proposed framework, respectively. Section 6 presents discussion and limitations. Finally, section 7 concludes the article.

2 BACKGROUND AND RELATED WORK

2.1 Federated Learning

Federated learning (FL) [1] is a concept of distributed machine learning in which different edge devices (hospitals, companies, etc.) collaborate to train a joint model known as a global model. FL trains the global model without collecting the data from participating edge devices in a centralized facility, i.e., the local data of edge devices is never shared with others in the network. Instead, an edge device trains local models using its local data and shares the trained parameters with a central server. The central server aggregates the received parameters according to the given aggregation algorithm to produce parameters of the global model [12], among which FedAvg [13] is the most commonly used aggregation algorithm [2]. Mathematically, FedAvg is given by the following equation:

\[
AW = \frac{n_k}{n_K} \sum_{k=1}^{K} W_k^{t+1},
\]

(1)

where \(AW\) is the global aggregated weights, \(n_k\) and \(n_K\) are the number of samples of an individual edge and the total number of samples of all the edge devices taking part in the global round, respectively. \(W_k^t\) are the locally trained weights of the \(k\)-th edged device in \(t\)-th round, and \(K\) is the number of total edged devices taking part in the global round. This process of updating the global model repeats until the desired level of the global model’s performance is achieved.

2.2 Poisoning attacks

Poisoning attacks [14, 15] can substantially reduce the performance (classification accuracy, precision, and recall) of FedAvg, even in the presence of a very small percentage of adversarial participants in the network. Such attacks can be classified as targeted attacks, i.e., they negatively impact only the target classes under attack, and untargeted attacks impact all the classes negatively. Furthermore, poisoning attacks are mainly classified into categories: data poisoning and model poisoning attacks depending on the phase where the attacks have been launched. If the attacker manipulates the training data then this is called data poisoning attacks and if the attacker manipulates the trained model’s parameters then such attacks are called model poisoning attacks. Further details of each type of poisoning are given as follows:

Data poisoning attacks: Data poisoning attacks are those attacks in which the attacker manipulates the training data according to a given strategy and then trains the model using the manipulated dataset. In this study we consider the following four types of data poisoning attacks:

1) Random label flipping poisoning attack (RL): In this attack the attacker flips the true labels of the training instance randomly.
2) Random Label and Feature poisoning attack (RLF): In this attack in addition to flipping the label randomly the attacker adds random Gaussian noise to the input features of the training instances.
3) Label Swapping poisoning attack (LS): In this attack the attacker swaps the label of a given class with another.
4) Feature poisoning attack (FP): In this attack the attacker adds white Gaussian noise (enough to manipulate the global model) to the features of the training data.

Model poisoning attacks: In the model, poisoning attacks the attacker trains the model using the legitimate datasets and then manipulates the learned parameters before sending it to the global server. In this study, we consider the following four types of model poisoning attacks:

1) Sign-flipping attack (SF): In this attack the attacker trains the model using the legitimate data and then flips the sign of trained parameters and enlarges their magnitude.
2) Same Value Attack (SV): In this attack the attacker sets the parameter values as \(C_1\), where \(C_1\) corresponds to an all-one vector and \(c\) is a constant with a value equal to 100.
3) Additive Gaussian Noise Attack (AGA): In this attack the attacker trains the model as expected with legitimate data but adds Gaussian noise before sharing the updates with the global server.
4) Gradient Ascent Attack (GA): In this attack the attacker trains the models using gradient ascent instead of gradient descent optimizer.

2.3 Stitching connectivity

Stitching connectivity [16] is a method to measure the similarity of internal representations of different models trained using different but similar data. Consider two models $A$ and $B$, which have same architecture. For $A$ and $B$ to be stitching connected, they can be stitched at all the layers to each other. In other words, two models, let’s say $A$ and $B$ with identical architecture but trained using stochastic gradient descent using independent random seeds and independent training sets taken from the same distribution. Then the two trained models are stitched connected for natural architectures and data distributions. Hence, we expect that the models trained on similar but different training sets of the same distribution to a model trained on good-quality data [16]. Based on this property and our experiments, we adopt Proposition 1 that will be explained later.

2.4 Memorization in deep networks

Deep neural networks are capable of memorizing the training data in a fashion such that they prioritize learning simple patterns first [17] using the lower-level layers in the model, while the higher-level layers tend to learn more specific data characteristics. Furthermore, when a model is trained on noisy data, the first half of the layers are similar to a model trained on good-quality data [16]. Based on this and our experiments, we adopt Proposition 2 that will be discussed later.

3 Proposed Framework

3.1 Threat Model

Attacker’s goal: Similar to many other studies [7, 10, 11], we consider an attacker whose goal is to manipulate the global model in such a way that it has low performance and high error rate for test samples. Such attacks make the global model underperform. For example, an attacker can attack competitor FL systems. We consider both targeted and untargeted [16] attacks, as discussed previously.

Assumptions: We consider the following assumption about the threat model:

1) We consider that attacker edge(s) follow the FL algorithm i.e., they train their local models using their local data and share the parameters with the global model.
2) We assume the attacker edge(s) can manipulate their local training data and train the local model using the manipulated data to malfunction the local models (shared parameters), which are then shared with the global model.
3) The attacker edge(s) knows the aggregation rule, global model architecture, and local training data.
4) We also assume that the global server has a public dataset that has data representing each class for a given application.

3.2 Overview

In this section, we describe the proposed framework. An overview of the proposed method has been shown in Figure 1. Let us assume $K$ edged devices (hospitals, organisations etc.) collaborate to train a joint global model $GM$. An edge $E_k$ trains a local model $LM_k$ using it local data $D_k$, where $k = 1, 2, \ldots, K$ and $K$ is the number of participating devices in each global round of FL. Global server $GS$ is responsible for receiving the updates from edge devices and aggregating them. We assume that $GS$ also has an open-source dataset which is called public data and we represent it as $DP$. $DP$ is supposed to be a representative dataset of all the classes in a classification problem, i.e., it has samples from each candidate class. The training of the $t$-th global round is given as follows.

1) $GS$ creates two copies of initial global model, represented as $GM_{initial}^t$ and $GM^t$. $GM^t$
2) $GS$ splits $DP$ into train $DP_{train}$ and test $DP_{test}$ datasets and trains the $GM_{initial}^t$ using $DP_{train}$.
3) After training, $GS$ makes predictions using the trained $GM_{initial}^t$ and $DP_{test}$. During the predictions, $GS$ taps the gradients of $GM_{initial}^t$ for each input sample using Algorithm 1 to create a dataset called audit data and represented as $DA_{initial}^t$, and splits it into $DA_{initial,train}^t$ and $DA_{initial,test}^t$.
4) $GS$ creates another model called audit model represented as $AM_t$ (a one class classifier) and trains it using $DA_{initial,train}^t$. Here, we treat $DA_{initial,train}^t$ as a single class.
5) Each $E_i$ trains $LM_i$ using $D_i$.
6) Each $E_i$ sends the updated parameters $W_i^t$ of trained $LM_i$ to $GS$.
7) $GS$ sets $W_i^t$ as the parameters of the $GM_{initial}^t$ and makes predictions using $DP_{test}$. During the predictions, $GS$ taps the gradients of $GM_{initial}^t$ for each input sample using Algorithm 1 to create a dataset $DA_i^t$.
8) $GS$ makes predictions using $AM$ and $DA_i^t$ as input data. For every input sample $X \in DA_i^t$, $AM$ outputs $y_i \in \{1, -1\}$ and creates a set $Y = \{y_1, y_2, \ldots, y_z\}$, where $z$ is the total number of samples in $DA_i$.
9) $GS$ computes poisoned rate $h_i^t = \frac{o \cdot 100}{z}$, where $o$ is the count of $-1$ in $Y$.
10) $GS$ includes $W_i^t$ in global aggregation if $h_i^t \leq P_i$, otherwise discards $W_i^t$. Here, $P_i = h_i^{t\text{test}} + \sigma$, and it is the percentage of poison that we want to tolerate. $\sigma$ is called deviation tolerance, an can be initialized at development phase. It actually defines the upper-bound of divergence between distribution of training set of edge(s) and the initial public set that we want to incorporate into global model. We set $\sigma = 10$. The proposed framework works based on two propositions that we discuss below.

Proposition 1. When a model is trained on noisy data (malicious/poisoned), the first half of the layers are similar to a model trained on good-quality data (benign).

Since the information specific to the data is learned by the higher-level layers of the model, we take the activation of the last layer (in the case of CNN last convolutional
Algorithm 1: Creation of Audit Dataset(s) $DA^t_i$

**Input:** A dataset $D_i$ and a trained model $M$

**Output:** a new dataset $DA^t_i$

1. for each sample $X$ in $D_i$ do
2. Transform $X$ into batch size
3. Make Prediction using $X$ as test sample in $M$
4. Get activation maps $A^t_i$ of the last convolutional layer, where $k$ is the number of activation maps with length $l$ and width $w$ each.
5. Get probability score $y^c$, where $c$ is the class label of $X$.
6. Reshape $A^k$ as an array of $1 \times j$, where $j = l \times w \times k$.
7. Reshape $X$ as an array of $1 \times l$, where $l$ is product of height and width of $X$
8. compute $s = X \parallel A^k \parallel y^c$
9. Append $s$ in $DA^t_i$
10. Output $DA^t_i$

The costs with no significant improvement in the results for detecting poisoning attacks. Hence, we only consider the activations of the last convolutional hidden layer.

**Proposition 2.** Different models with the same architecture but random initial seeds, trained on different training sets of a similar distribution have similar internal representation and thereafter similar activations for a given test input sample.

Based on Proposition 2, we expect that the models trained on different datasets of similar distributions will behave similarly. We capture this property by training another model (audit model) to learn the behaviour of a model trained on the benign dataset (initial global model in our case). Hence, models behaving similar to the audit model are probably free from poisoning attacks, and at least they do not degrade the performance of the global model.

## 4 Performance Evaluation

We evaluated the proposed framework using two healthcare applications, i.e., ECG classification and HAR.

### 4.1 Experimental Setup

**Datasets:** For ECG classification, we use the widely known MIT-BIH arrhythmia dataset [19]. The dataset contains 48-half-hour two-channel ECG recordings. These recordings were obtained from 47 subjects. The dataset contains 109,446
samples, sampled at a frequency of 125 Hz. Further, the dataset contains five classes of ECG: non-ectopic beats (normal beat), supraventricular ectopic beats, ventricular ectopic beats, fusion beats, and unknown beats.

For the HAR, we used the dataset in [20, 21]. The dataset contains time-series data related to 14 different human activities (Standing, sitting, walking, jogging, up-stairs walk, down-stairs walk, eating, writing, using a laptop, washing face, washing hands, swiping, vacuuming, dusting, and brushing teeth) collected using sensors such as accelerometer, magnetometer, and gyroscope.

Classifiers: We developed a convolution neural network (CNN) based classifier for each application. The developed classifiers do not achieve the best classification for the considered datasets, because our objective is to show that our proposed framework can detect anomalous (poisoning attacks), not to achieve the best performance in terms of classification. For ECG classification we developed a five-class classifier and the aim of FL here is to learn a global five-class classifier, and for HAR we developed a fourteen-class classifier, and the aim of FL here is to learn a global fourteen-class classifier.

Federated Setting: To simulate the federated setting we simulate four edge devices and a global server using a Dell workstation with 32 GB RAM and an Intel® Core™ i-6700HQ CPU. Furthermore, we divided the dataset equally, but randomly among the participating edge devices for each application, i.e., ECG classification and HAR.

### 4.2 Performance Evaluation

In order to evaluate the performance of the proposed framework. First, we test the proposed framework to check its ability to differentiate $DA_i$ of benign edge(s) from $DA_i$ of malicious edge(s). We combine the $DA_i$ generated using local models of benign edge(s) and $DA_i$ generated using poisoned local models (both data and model poisoned) malicious edge(s) and label them as 1 and -1, respectively. Table 1 shows the classification accuracy of the proposed framework to differentiate samples generated using shared parameters of benign edged devices and the samples generated using shared parameters of malicious edge devices for HAR application. Similarly, Table 2 shows the classification accuracy of the proposed framework to differentiate samples generated using shared parameters of benign edged devices and the samples generated using shared parameters of malicious edge devices for ECG classification application in healthcare. For both types of applications, it can be seen that the proposed framework can differentiate samples of benign and malicious edged devices very well, with an overall accuracy of 94% and 99% for HAR and ECG classification, respectively.

**TABLE 1: Classification accuracy of OCSVM for HAR**

| Class      | Precision | Recall | F1-Score | Support  |
|------------|-----------|--------|----------|----------|
| Benign (1) | 96        | 95     | 95       | 22,280   |
| Malicious (-1) | 90 | 91     | 91       | 11,140   |
| Accuracy   |           |        |          |          |
|            | 94        | 94     | 94       | 33,420   |

**TABLE 2: Classification accuracy of OCSVM for ECG classification**

| Class      | Precision | Recall | F1-Score | Support  |
|------------|-----------|--------|----------|----------|
| Benign (1) | 100       | 97     | 98       | 9,000    |
| Malicious (-1) | 97 | 100    | 99       | 9,000    |
| Accuracy   |           |        |          |          |
|            | 99        | 99     | 99       | 18,000   |

![Fig. 2: Performance of the Global Model with and without proposed framework under data poisoning attacks for ECG classification.](attachment:image.png)
ECG classification. Where, CN represents the performance of ECG classification model in centralised setting using DP data, GM shows the performance of global model with proposed framework in federated setting, SF shows the performances of global model under sign flip attack without proposed framework in federated setting, SV shows the performance of global model under same value attack without proposed framework in federated setting, AGA shows the performance additive Gaussian noise attack without proposed framework in federated setting, and GA shows the performance of global model under gradient ascent attack without proposed framework in federated setting. Similarly, Figure 5 presents comparison of the accuracy of the global model under different model poisoning attacks and with and without the proposed framework for HAR application.

Table 3 shows the accuracy of the proposed framework to detect different data poisoning attacks in federated settings for the HAR applications. \( P_t \) value in the table shows the threshold, which is calculated using the audit test data of the initial global model, \( h_{\text{test}} \) is the poisoned amount detected for audit test data for the initial global model, \( t \) is the global round number, and \( \sigma \) is known as tolerance which is added to avoid miss-classification of benign updates. Any updates \((W_t)\) from an edge device for which its corresponding \( DA_i \) has a value of \( h_{i}^{t} \) greater than the threshold \( P^{t} \) will be marked as malicious or poisoned and removed from global aggregation. It can be seen that in Table 3, \( h_{1}^{t} \) and \( h_{2}^{t} \) for edge 1 and edge 2, respectively, have a value smaller then \( P^{t} \). Hence, the updates of \( W_{1}^{t} \) and \( W_{2}^{t} \) will be included in global aggregation, while \( W_{3}^{t} \) will be excluded from global aggregation as its corresponding \( h_{3}^{t} \) is greater then \( P^{t} \). It can be seen that the proposed framework can not only detect the attacks but can also provide an insight into the percentage of poisoned data being used to train the model. For example, for LS we swapped the label of some classes (for ECG classification two classes and for HAR 4 classes) while keeping the rest of labels in their original form, thereafter it gives a value of 47.7 for ECG and 81.2 for HAR. Similarly, Table 4, 6, 5 presents the accuracy of proposed framework to detect data poisoning attacks in ECG classification, model poisoning attacks in ECG classification and model poisoning attacks in HAR application, respectively.

5 Comparison

In this section, we compare the proposed framework with some of the existing works [4, 22, 23] as shown in Table 7. Blanchard et al. [4] proposed Krum, an aggregation rule by selecting one of the \( n \) local models similar to other models as the global model. The intuition is that even if the local model is a compromise, its impact may be constrained since it is similar to other local models which are possibly benign. Yin et al. [22] aggregates the parameter of local
models independently i.e., for \(i\)-th model parameter the global server sorts the \(i\)-th parameter of the \(m\) other local models. Removes the largest and smallest parameters and computes the mean of the remaining parameters as the \(i\)-th parameter of the global model. Similarly, El Mhamdi et al. [23] proposed to combine Krum and a variant of trimmed mean [22]. However, these approaches are vulnerable to poisoning attacks even using robust aggregation [9]. Additionally, methods such as median, and trimmed median try to minimize the effect of poisoning attacks by taking the median and mean of individual parameters of local models, which degrades (they greatly induce error rate in the global model learned) the performance of the global model. Additionally, such methods under-perform with the increasing number of malicious edge devices [3]. On the other hand, since our proposed framework checks each local model individually, and rejects the malicious local model the performance of the global is not degraded, and the increasing number of malicious edge devices can not affect the performance of the proposed framework and thereafter such attacks have no effect on the performance of the global model.

### 6 Discussion and Limitations

In this section, we provide a discussion and limitations of the proposed framework. Generally, in healthcare most of the health conditions such as different classes of arrhythmia are well known, each class has similar properties across different patients. Our proposed model can incorporate updates from different edged devices trained with training sets similar to the training data set of the audit model. The initial global model which was trained using DP can be updated using the updated global model after each successful aggregation, which makes the initial global model robust, the process can be repeated for subsequent global rounds. However, if an edge device trains its local model using data that represents a class that is not represented in \(\mathcal{D}\), yet benign the proposed framework will classify it as malicious. Hence, the proposed framework should not be used in applications with emerging complete new classes, its only suitable for applications where the candidate classes are already known and need to obtain a robust global model for known classes.

### 7 Conclusions

In this paper, we proposed a novel framework to detect poisoning attacks in FL for healthcare applications. The proposed framework can efficiently detect state-of-the-art
poisoning attacks by observing the activations of the shared weights of the local models. Unlike, other existing methods, the proposed framework can detect poisoning attacks without degrading the global model’s performance. Moreover, the increasing number of attacker edge devices in the FL network can not compromise the security of the proposed framework. Furthermore, we tested the proposed framework under different poisoning attacks for two healthcare applications. The performance analysis shows that the proposed framework can efficiently detect the malicious updates and can exclude them from the global aggregation, which results in an increase in the performance of the global model.

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