Classification of electrocardiogram signals based on federated learning and a gaussian multivariate aggregation module

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ABSTRACT

Categorization of cardiac abnormalities received from several centers is not possible within the quickest time because of privacy and security restrictions. Today, individuals' security problem is considered as one of the most important research fields in most research sciences. This study provides a novel approach for detection of cardiac abnormalities based on federated learning (FL). This approach addresses the challenge of accessing data from remote centers and presents the possibility of learning without the need for transferring data from the main center. We present a novel aggregation approach in the FL for addressing the challenge of imbalanced data using the averaging stochastic weights (SWA) optimizer and a multivariate Gaussian in order to make a better and more accurate detection possible. The advantage of the present proposed approach is robust and secure aggregation for unbalanced electrocardiogram (ECG) data from heterogeneous clients. We were able to achieve 87.98% accuracy in testing with the robust VGG19 architecture.

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1. INTRODUCTION

One of the most well-known methods for diagnosis of cardiovascular diseases and their treatment is the electrocardiogram (ECG) signals [1]. Meanwhile, cardiac arrhythmia is known as the most common heart disorder. If patients' vital symptoms are reported as timely as possible, specialists can diagnose the main weakness of their cardiovascular system and prevent severe cardiac actions. As a result, they can choose the most suitable treatment method [2]. Classification of heartbeats based on the signs received from the ECG signals plays a vital role in detection of acute cardiovascular disorders [3]. In this regard, considering the standards of human rights and preserving the privacy of personal data, the challenge of accessing this data is quite difficult. Our studies have led to the understanding of federated learning (FL) in order to access more data for diagnosis and improve the accuracy of artificial intelligence models. FL is a novel approach dedicated to the association for the advancement of artificial intelligence (AAAI) by Kairouz *et al*. [4] in 2016. This approach can involve data from multiple clients from different centers in the training process and follows distributed training [5]. This nascent concept allows several distributed devices to jointly train artificial intelligence models while complying the data privacy principle [6].

We present a new approach to the correct diagnosis of arrhythmias and the best recognition of cardiac disorders in order to detect accurate arrhythmias from the ECG signals received from multiple centers. One of the advantages of the FL model over the centralized learning is the training of neural network models without the need for collecting data from a centralized location [5]. Our goal in the FL is to reduce the global loss function during the running process. The FL model allows multiple clients to participate in the learning process. Clients enable a global model to perform the process of aggregating parameters from the clients to the server and going through the communication cycle only by sending the training parameters without sharing even a single unit of the training action information [7]. But what is unacceptable for us is the sharp drop in accuracy in the FL due to the imbalanced data received from heterogeneous clients. This imbalance can due to the label NON_IID or the data volume [8].

The FedAvg algorithm is known as the aggregation method in the server [9]. This algorithm aggregates the weights from the clients and transfers them to the server. A suitable value for the proportion of data in the clients with data volumes close to each other (e.g., 35% of the data for the first client, 40% for the second, and 25% for the third) indicates a balanced composition of the data in different clients. In this case, the training with progress naturally and will not cause a drop in attack accuracy from the client side. A maximum disparity in the volumes of data in different clients–in proportions of 90% for the first client, 7% for the second, and only 3% of the total amount of data for the third one–indicates a high imbalance in the available data. This imbalance causes a severe drop in the accuracy of the aggregation of the weights after training with the available data.

In this study, any drop in the model accuracy in group detection is prevented by providing a suitable aggregation method. If it is supposed that the distribution of data in clients follows a multivariate Gaussian distribution, we transfer the values resulted from the execution to the server in the form of averages and covariance instead of transferring the average and variance of each model. This transfer strategy can greatly reduce the disproportion caused by imbalanced data in training and end up with a suitable aggregation. Of course, we suppose that the sampling technique will also help us in this direction. By excluding a few pieces of this huge possibility, we create a dead end in order to avoid reverse engineering in the data and keep it from being stolen by hackers. We take the sampling with the scientific wild-ass guess (SWAG) technique as a weighted average of all the parameters. We call our method federated learning based stochastic averaging weights (FEDSWAG) and by reaching an accuracy of 98.59%, a favorable accuracy compared to previous approaches is reported. The innovations of this study include:

- Using the new FL approach to diagnose cardiac abnormalities;
- Providing a strong aggregation approach to solve the imbalanced data problem; and
- Applying a sampling technique for the first time in ECG dataset.

2. RELATED LITERATURE

2.1. Deep learning tasks for ECG signal classification

Using a dataset in an unsupervised manner, the models are first trained, and then, it is tried to fit them correctly in a supervised way. While the main focus of this study is on the application of self-supervised learning for effective ECG learning, we investigate several other aspects in order to increase efficiency [10]. Several techniques, including knowledge-based properties and supervised pre-training, are employed in order to achieve the maximum accuracy and stability of heartbeat classification in the context of a weak supervision [11]. This study provides a classification to calculate specific properties, including PQ time, QTc, and Q-Q interval, within the network. In addition to the features derived during the calculations, the bottleneck layer in the U-Net network is proposed as an alternative for classification [12]. This study presents a fusion approach, associated with the DERMA dual event, as well as the fourier transform algorithm FrlFT in order to accurately identify normal and non-normal morphological properties in electrocardiogram signals [13]. Subasi and Erçelebi [14], the authors use a wavelet transform approach for classification in the artificial neural network (ANN) and logistic regression. They use the wavelet transform strategy in order to increase the speed of pre-processing calculations. Lotte *et al*. [15] evaluate and analyze different algorithms for the classification of heart electrocardiogram signals. Aziz *et al*. [16], the authors use a new correlated moving average algorithm that has two TERMA special events and fractional Fourier transform algorithms for better analysis of the ECG signals. The TERMA algorithm identifies specific points of the signal that lie on a peak. While, the FrFT rotates the ECG signals in the position of the time-frequency plane in order to find the locations of the different peaks of the signal. Mathunjwa *et al*. [17], the main goal is to present a new approach of deep learning based on 2-second sections of the images associated to the peak diagram of the 2-dimensional ECG signals for the correct classification of arrhythmia. In this approach, in the first step, the size of the noise category and ventricular fibrillation were placed separately. Rahul and Sharma [18] suggest a method for classification of heart problem, e.g., Afib atrial fibrillation, Vfib ventricular fibrillation, Vtec ventricular tachycardia, and normal N rhythm, using a hybrid model based on 1-D convolutional neural network (CNN) and bidirectional long short-term memory (Bi-LSTM). Ramkumar *et al*. [19] use a deep convolutional neural network that is hierarchically based on a tree in order to speed up classification and training. They use MLGK to decrease the risk of overfitting and to improve the visualization of the existing data. Kobat *et al*. [20], the authors use the index of PatNet54 charter in order to create an extractor based on a graph. This extractor is known and named as a prism pattern. Mohonta *et al*. [21] develope a deep learning approach to automatically detect cardiac abnormalities based the ECG signal using the continuous wavelet transform (CWT) wavelet transform technique that performs the classification operation continuously. In the proposed model, training and testing are performed on a 2-dimensional convolutional neural network in order to detect five types of heartbeats.

2.2. Aggregation in FL

Chen and Chao [22], the proposed approach increases the communication and computation overhead by sending two vectors to the server in the last round of training, as there is a need for high bandwidth and a powerful processor to transfer this volume of data to the server. Shoham *et al*. [23] and Zenke *et al*. [24], the authors combine the inverse of the diameter of fisher's empirical information matrix and the laplace approximation to approximate the mean and covariance of the posterior probability. In addition, the researchers in [24] present a synaptic framework to address the continuous learning problem and use the Hessian matrix to approximate the loss functions [25]-[27].

3. PROPOSED METHOD

3.1. Choosing the best optimizer for the server

In the early stages for training clients, it is vital and necessary to achieve the best optimal point in the training process and less loss. Thus, our focus is on the use of a strong optimizer in order to reach the optimal point in training with imbalanced data. The volume of data samples in each client is acceptable for the device itself, and we will not encounter a drop in the model accuracy caused by imbalanced data. But at the stage of aggregating the weights from different clients, we will encounter a decreased accuracy in the final output of the server due to the conditions of imbalanced data and different weighted averages being received from the parameters. The stochastic gradient descent (SGD) is generally used as an optimizer in deep learning. This optimizer in the FL can find the optimized weights in order to achieve the goal of maximum learning when the training data is available in each client in a balanced proportion. But the problem in this study is the poor performance of the SGD for imbalanced data. Therefore, in our studies, we have tried to find an optimizer that fits the imbalanced data situation. In this process, we found the stochastic weight averaging (SWA) optimizer. The SWA is a random weighted average that follows a different (fixed or cyclic) learning rate schedule. In fact, this optimizer uses a solution previously obtained by the SGD as a pre-trained solution. The SWA takes a weighted average of all the trained models and starts its training with it. With a different learning rate, it finds a set of solutions that converge to the best optimal points, averages the solution it has achieved itself and the solution previously achieved by the SGD, and presents the final optimal point. In fact, Since, this optimizer finds a more stable solution than the SGD does in training with different data distributions, it outperforms for training and testing stages of the model. Its second advantage is the decreased gap between the accuracies received from the training and testing phases. In fact, using the SWA optimizer, we achieve a better authenticity of the accuracy and loss received from different stages of execution.

3.2. Visual sampling in aggregation step according to SWA

Figure 1 shows a view of the approach proposed by this study. Our goal in the aFL is to achieve a proper accuracy and ultimately maximum learning. Investigation of this issue is very necessary in certainty detection systems for areas such as medicine, driving, and space. Meanwhile, another goal is to accurately estimate the training status of each element participating in the FL survey. The global posterior approximation in the server is necessary to know its learning rate. Posterior probability estimation cannot be achieved by general mathematical methods and calculations. Of course, the most important reason for its intractability in the FL is the lack of access to data in clients. We use the multivariate Gaussian distribution for estimation of the posterior probability. To transfer the average weights to the server, we use the multivariate Gaussian distribution derived as in the following formula. In fact, we seek to solve the problem of imbalanced data by avoiding the transfer of mean and variance. In our initial tests, we found out that using the transferred mean and variance as the aggregate parameters in the server leads to a drop in the model efficiency. Therefore, by using the mentioned distribution and transferring the mean and covariance to the server, the problem of the maximum difference of the parameters is solved.

$$p(x|D) \approx g_G(x) = N(x|\mu_G, \textstyle\sum_G) \tag{1}$$

Using relation (1), we estimate the global posterior of the server in order to create a maximum learning platform in the server with a multivariate Gaussian distribution. But after the initial evaluation and testing, it was found that updating the covariance in all the stages leads to the maximum memory loss in the server. Thus, we exchanged parameters from the clients to the servers using the cross-covariance in the form of a SWAG formula as (2).

$$\pi^2 = \frac{1}{R}\pi_i^2, \Sigma_{diag} = diag(\pi^2 - \pi_{SWA}^2) \tag{2}$$

The sampling using the SWAG is evaluated as (3).

$$\mu = \frac{1}{R}\sum_i \frac{C_i}{C}\pi_i , \Sigma_{Diag} = Diag(\sum_i \frac{C_i}{C}(\pi_i - \mu)^2 \tag{3}$$

Relation (3) is a general formulation for the SWAG. Samples can be transferred directly from the client to the server as the initial parameter in the current round for execution. In relation (3), C_i denotes the data associated to the i-th client (Client i). The cross-covariance is updated using the optimum obtained from the SWA. Using the term $(\pi_i - \mu)^2$ we calculate the square of each element in order to achieve a proportional ratio of the limit between zero and one in the normalization process. In section 4, we will discuss in detail the results from applying the proposed approach.

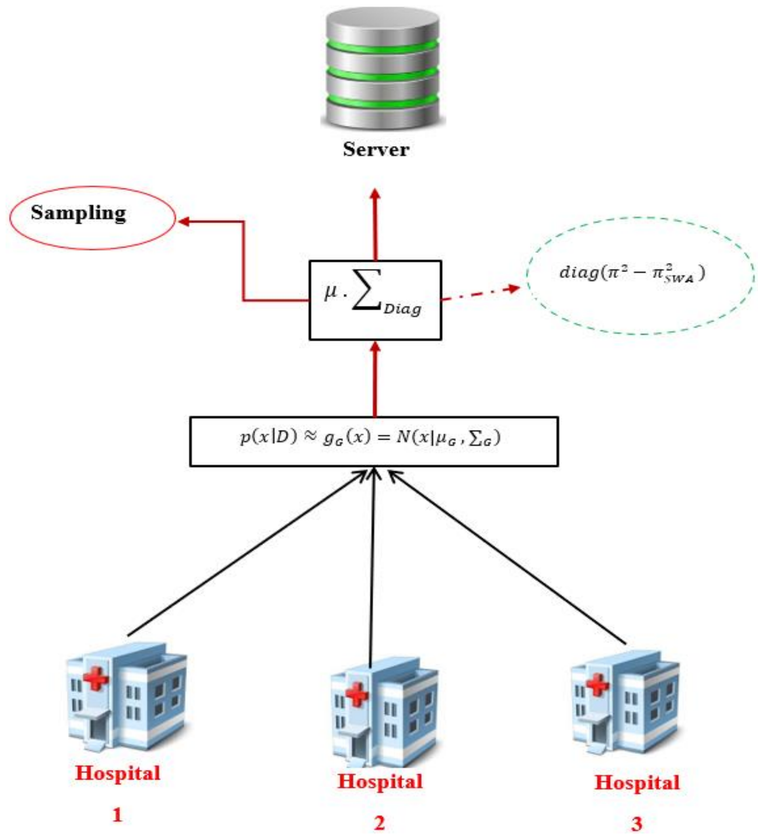

Figure 1. Schematic of the proposed method and communication between the clients and the server

4. EXPERIMENTAL RESULTS
4.1. Preparation of results
4.1.1. Settings and parameters of the proposed method

In this study, the VGG19 model is used to evaluate the proposed method presented in section 3. The training is performed in 100 communication rounds and 64 batch normalization. 5 clients are employed for testing. The learning rate Lr = 0.001 is used in the initial rounds. Using the schedule presented in the SWA, the rate is adjusted during the rounds by increasing the communication rounds. It is found that when the learning rates are very large, convergence occurs in more communication rounds. And with a small learning rate, a proper accuracy cannot be achieved in less communication rounds. This is why we proposed a learning rate according to the schedule. We increase the sampling in each training round by 10% of the total dataset in each round.

4.1.2. Datasets

We use the ECG heartbeat categorization dataset that is available on Kaggle. This dataset consists of two datasets related to the ECG heartbeat and two datasets of the heartbeat classification, the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia data, and the Physikalisch-Technische Bundesanstalt (PTB) database. The appropriate size of the dataset is considered for proper the model training and avoiding overfitting. This dataset is used in the heartbeat classification using deep neural network architectures and transfer learning technique [28], [29]. The signals comply with the schematic ECG heartbeats for normal cases and those affected by various arrhythmias. These signals are segmented in the pre-processing stage and each segment corresponds to one heartbeat. Figure 2 presents a view of the selected dataset.

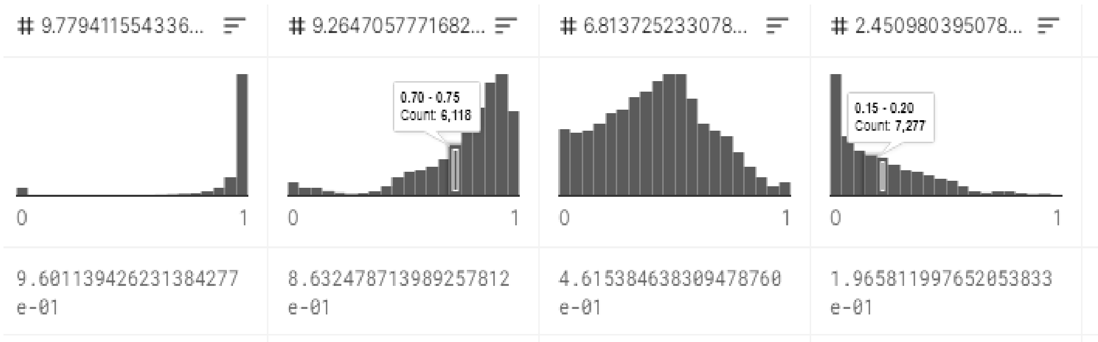

Figure 2. Schematic of the dataset of cardiac ECG signals

4.1.3. Evaluation criteria

In order to analyze the test results, we use 4 evaluation methods generally designed for evaluating the classification models, with the benchmark titles of SENecg (sensitivity), ACCecg (sccuracy), PRECecg, and SPEecg (specificity), respectively.

$$ACC_{\mathrm{ec}} = \frac{TP_{cl}+TN_{cl}}{TP_{cl}+TN_{cl}+FP_{cl}+FN_{cl}} \quad (4)$$

$$PREC_{\mathbf{ecg}} = \frac{TP_{cl}}{TP_{cl}+FP_{cl}} \quad (5)$$

$$SEN_{ecg} = \frac{TP_{cl}}{TP_{cl}+FN_{cl}} \quad (6)$$

$$SPE_{ecg} = \frac{TN_{cl}}{TN_{cl}+FP_{cl}} \quad (7)$$

4.2. Evaluation of the proposed methtable

Three clients were used to train the model in the execution process. The results have been depicted as a graph (Figure 3 and Figure 4) and the details have been presented in the form of Table 1. The results from the evaluation of the proposed method on the mentioned dataset indicate the maximum accuracy for the server. In the testing phase, the first client has the most accuracy, followed by the second client with an accuracy of nearly 80%.

4.3. Comparison of the proposed method versus other methods

In this section, the proposed method was compared with the previous approaches. To make the comparison, the accuracy assessment criterion has been used. In addition, comparisons were made from epochs between 1 and 100 and the accuracy value was reported at each point. As shown in Figure 5 the results of our proposed method indicated an accuracy of 87.98% in the best case, which is the highest accuracy compared to the previous FL diagnostic methods in the simplest case.

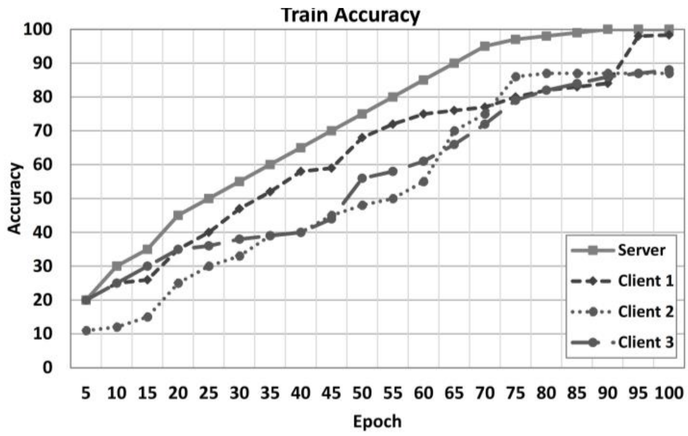

Figure 3. Results of evaluation in the training process with evaluation criteria for clients and server

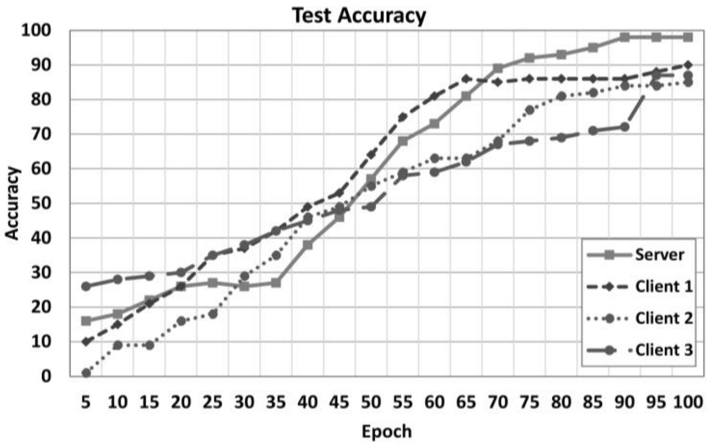

Figure 4. Results of evaluation of the proposed method in the testing phase

Table 1. Client and server results with evaluation criteria

Type	$PREC$	SPE	SEN	ACC
Server	98.64	96.39	93.19	98.87
Client1	96.78	98.67	93.49	97.67
Client2	96.15	93.73	97.27	92.43
Client3	97.79	97.32	99.94	97.05

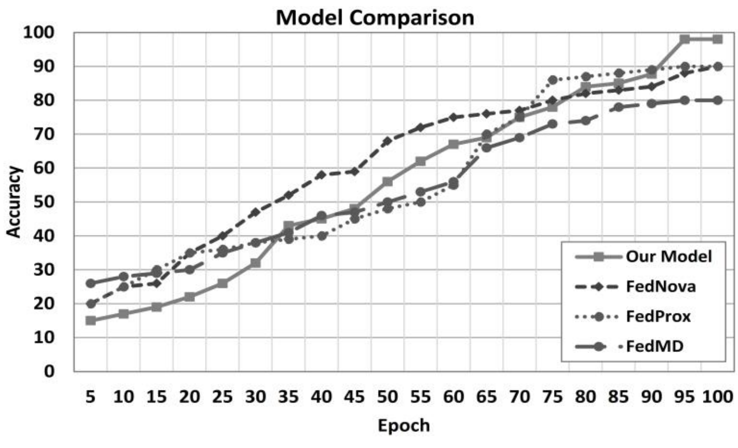

Figure 5. Comparison of the proposed method versus previous ones

5. CONCLUSION

In this study, we proposed an FL approach with a reasonable accuracy for detection of the ECG signals. To this end, we used the sampling technique in order to better aggregate the parameters to the server. In this approach, the server achieved a good accuracy compared to the proposed methods. The future motivations of this study include consolidating the platform of privacy preservation and providing new strategies for aggregation in less communication rounds. One future idea is to use joint learning for better detection.

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