Classification of electroencephalography using cooperative learning based on participating client balancing

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ABSTRACT

Modern technologies are widely used today to diagnose epilepsy, neurological disorders, and brain tumors. Meanwhile, it is not cost-effective in terms of time and money to use a large amount of electroencephalography (EEG) data from different centers and collect them in a central server for processing and analysis. Collecting this data correctly is challenging, and organizations avoid sharing their and client information with others due to data privacy protection. It is difficult to collect these data correctly and it is challenging to transfer them to research centers due to the privacy of the data. In this regard, collaborative learning as an extraordinary approach in this field paves the way for the use of information repositories in research matters without transferring the original data to the centers. This study focuses on the use of a heterogeneous client balancing technique with an interval selection approach and classification of EEG signals with ResNet50 deep architecture. The test results achieved an accuracy of 99.14 compared to similar methods.

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1. INTRODUCTION

Nowadays, the most significant method of diagnosing brain abnormalities and diseases is the use of electroencephalography (EEG) signals in the form of a wave [1]–[3]. Acute brain activities of epileptic patients such as seizures spread in the form of waves of electrical signals. A special form of waves is observed in the EEG signal of patients who have a brain lesion caused by a tumor in the brain and also have a stroke depending on the location of their lesion [4]–[7]. EEG has been used for many years as a reliable method to diagnose various brain diseases [8]. However, each patient has a personal and security framework that is not allowed to enter by any research organization [9]–[13]. So, accurate statistics of these patients are needed for a specific classification of their disease type to access the data of different centers and to classify the general patients in a country or province to provide medical services. Another reason is the timely and accurate diagnosis of brain lesions by specialists as soon as possible. Fatigue or even inadvertent mistakes in diagnosis generally cause irreparable damage to patients. Artificial intelligence (AI) diagnosis methods such as federated learning (FL) are effective and reliable methods in this regard. FL was first introduced in 2016 by Kairouz *et al.* [14]. Like any other new approach, this new approach comes into being with the perspective of solving a problem. FL's perspective on addressing AI research issues includes security and privacy. This approach is not without its challenges, however. The problem of aggregation of parameters from local clients that transmit parameters to the server after training each model with its local data [15] is the most important challenge of FL. Aggregation is also the most important step in FL. Unbalanced and non-independent and identically distributed (non-IID) data causes poor aggregation and a drop in model accuracy [16]. The problem of aggregation with unbalanced data and the drop in model accuracy will be solved if in each epoch only clients participate in the training process which is proportional to other participants in the data balance. A participant control strategy based on the number of data samples is needed to match participants with data balance.

Coordinating the performance of various devices participating in the training process requires special network and protection techniques. This is what previous approaches have done to create a platform for coordinating different devices. For example, in [17], a timer is proposed in the aggregation process to solve the problem of fast and slow clients. In this study, a novel approach to coordinating different clients is provided, assuming that the devices that send their parameters to the network suffer from a data imbalance problem. As mentioned earlier, the lack of balance causes the accuracy of the model to drop significantly [18]. However, the performance of the model is preserved if all the participating devices in an epoch are equal in terms of their local data size balance because all the participants transfer parameters to the server at the same rate. In this way, the aggregation problem due to imbalance will be solved.

It is possible to know the volume of data samples of the clients by sending a request to them from the server before starting the training. The server sends the request and is informed of the data size of each client. Only clients that have data consistency in terms of volume participate in each communication epoch. Some peer-to-peer clients participate in training each time through multiple epochs of training and communication. This continues until the final epochs of training so that consistency of all the data in the clients is obtained. The innovations of the proposed approach are as: i) classification of brain signals with a new FL approach, ii) providing a solution to solve the problem of data imbalance in different clients by periodically checking the status of each client without others being aware of the current client's data size, and iii) testing with deep architecture to achieve the best performance.

2. LITERATURE REVIEW

This section reviews some studies of the EEG signals. Based on the spatiotemporal features of EEG, a deep learning model was proposed in [18] by integrating IncepCNN into bidirectional gated recurrent unit neural network (BGRU). To extract spatial features, a deep network was designed by applying many convolutional layers and pooling operations. The convolution kernel and network parameters were trained simultaneously. The network output included a set of feature vectors from the fully connected layer of IncepCNN used as the input in BGRU to extract temporal features. Finally, the softmax layer classified the features. The experimental results of this method indicated an accuracy of 76.63%. Some researchers convert EEG signals into time-frequency images and use two-dimensional convolutional neural network (CNN) for magnification-independent (MI) classification. Mao *et al.* [19] used CNN and magnification-independent (MI) in parallel to extract spatial and temporal features from CNN and recurrent neural network (RNN), respectively, and finally, MI classification was done by combining both types of features. Dai *et al.* [20] used continuous wavelet transform (CWT) to convert EEG signals to time-frequency maps and used 2D-CNN to extract features. In another paper, EEG signals were converted to two-dimensional (2D) time-frequency images in order to solve the dynamism problem of signals by extracting spatial features through a CNN [12]. Different algorithms were integrated in [13] to extract and classify features. For this purpose, the CNN-long short-term memory (LSTM) hybrid was popular.

1D-CNN is known as time complexity that is capable of extracting the frequency and amplitude of the signal in the time domain. In [19], a simple CNN was proposed for the diagnosis and classification of epilepsy. This study aimed to understand the different features of EEG signals. It preprocessed the data with wavelet transform. In [20], EEG signals were classified based on a CNN, and a variational autoencoder (VAE) auto-encoder and a hybrid variable were used to fit the EEG signals. In [21], multi-layers perceptron (MLP) was used to classify EEG signals and a brain-computer interface (BCI) test was performed to investigate different topics of EEG signals. In [22] tried to extract conventional features from different bands of EEG signals and used these bands when they did not overlap. So, they were used to classify motor imagery-brain-computer interface (MI-BCI) on multiple scales. In [23] was conducted to perform binary and multi-class classification on EEG signals for use in real-time BCI applications. So, the outputs of the new real-time approach obtained were discussed. Finally, they were combined into a prediction system. This increased the accuracy up to 90%. In [24] proposed a CNN with a feature-specific residual block in the whole network and used the raw signal filtered during the process as input. It continuously recognized involuntary human actions such as left eye blinking, right eye blinking, continuous blinking, and teeth grinding and created an online brain-computer interface. The BCI system is used to control movements such as turning left, turning right, moving forward, and stopping. In [25], a pre-trained CNN-based automatic detection method was proposed. This study enabled BCI with small samples and the use of EEG training data, which are mental and kinematic images, for robust systems. In [26], a filter bank was designed to transform the composite wavelet in tree form and dual mode, and the filter operation was performed on the EEG to convert it into subbands. This method was used instead of traditional methods to improve the performance of spatial feature extraction. Besides, after filtering the EEG in different subbands, spatial features were extracted from the subbands created using common spatial pattern (CSP). In this study, the optimization operation was performed in the proposed approach based on necessary condition analysis (NCA) components and the classification process was performed using a support vector machine (SVM). Esfahani and Sadati [27] proposed an optimal solution for selecting a channel of electroencephalogram signals to select a subset of channels of this signal in BCI.

3. THE PROPOSED METHOD

In this section, the details of the proposed method are explained. At first, the federated learning architecture is described. Then, the architecture of the deep model used is described. Finally, the pseudo-code of the proposed method is given.

3.1. The protocol of participation in the training process

A schematic of the proposed method can be seen in Figure 1 several studies suggested that the overall objective function representing the losses received from different clients and servers should be minimized to achieve maximum learning in the outcome of the participants. This can be expressed by (1).

$$\min_{\gamma} \mathcal{L}(\gamma) = \sum_{n=1}^{N} \alpha_n \mathcal{L}_n(\gamma) \quad (1)$$

where $\sum_{n=1}^{N}$ represents the total number of clients participating in the training process, and α_n is a fraction of $\frac{C_n}{C}$, where C_n is the number of samples available for each customer and n is the total number of customer data samples in the equation $C = \sum_{n=1}^{N} C_n$. If the inputs are *x* and the outputs are *y* at (x,y), the function $\mathcal{L}(\gamma)$ is known as the function representing the whole system objective. The objective is to minimize the overall objective function of the system to achieve maximum learning in training with unbalanced data in the system. A schematic of the proposed method is as follows. A schematic of the imbalance of the clients is as follows.

The proposed approach is executed rotationally and conditionally between the clients and the server. In the first step, the server sends a packet containing the conditions for participating in the training process to all clients. This package contains the question "Is the current client data size between 1 and 2 GB?". The current client participates in the training process and enters the execution process by selecting the option Active if the answer is positive and the desired condition is met as shown in Figure 1. However, it is removed from the execution process and remains suspended so that it can enter the training cycle in the next epochs according to the condition check if the condition is not met. By selecting the Active option, the average parameters obtained from training on the server will be given to the current client to start training (training in the first epoch is only possible for clients with a data size between 1 and 2 GB according to the condition). It continues until the desired accuracy is reached with the data containing the conditional clients after executing the appropriate communication epochs. The server then sends another condition for the clients to enter with less data so that they can participate in the group training according to the condition check. This time, the data size in the clients should be around 500 MB to 1 GB. In this way, authorized clients can participate in the training according to the first condition process by establishing the condition. Finally, it terminates the training process when it achieves the appropriate accuracy in this range with the last condition, which is the data size of less than 500 MB.

3.2. The architecture proposed for training

After determining the proposed protocol and starting the training, deep architecture is used for training, because initially there is a large amount of data according to the training rules and conditions. The proposed architecture is Resnet50 a shown in Figure 2. The Resnet50 architecture is chosen after examining various neural network architectures and analyzing the dataset. Resnet50 is chosen because of its outstanding skill in solving the problem of vanishing gradients in the deep layers of CNN. Since the total volume of data for training is almost large, this architecture is used for training and obtaining maximum efficiency. The strategy of residual blocks in this architecture will help to solve the problem of weak gradients in the deep layers of CNN as mentioned in Table 1.

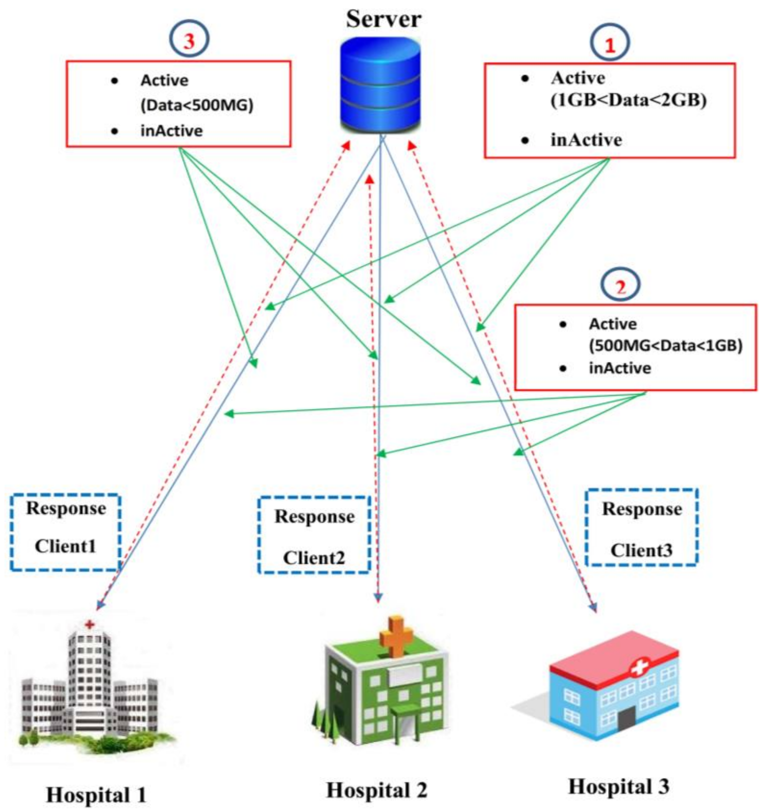

Figure 1. Schematic of the proposed method with details of training in clients and servers

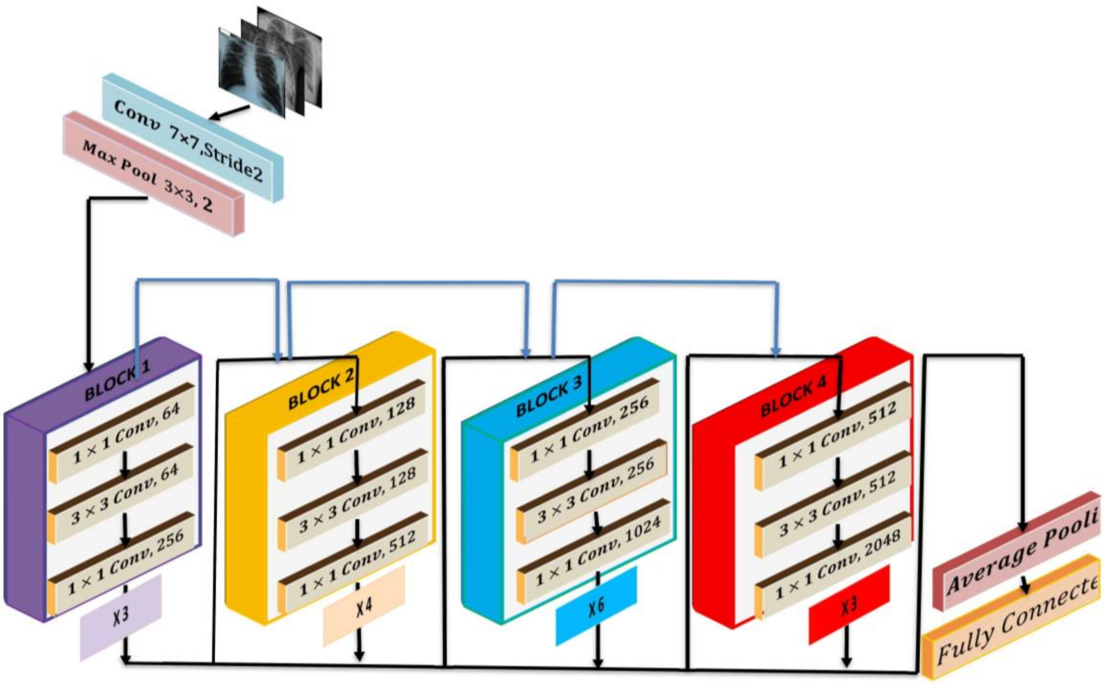

Figure 2. ResNet50 architecture to test the proposed method

Table 1. Convolutional and pooling parameters in the proposed CNN

Layer	Kernel sizes	Number of filter	Parameters
Convolutional Layer1	3×3	32	Stride=1, Padding=1 Activation='relu' Batch Normalization with €=1.001×10^{-5}
Convolutional Layer2	3×3	64	Stride=1, Padding=2 Activation='relu'
Convolutional Layer3	3×3	64	Stride=1, Padding=2 Activation='relu'
Pooling Layer1	2×2	-	Stride=2
Convolutional Layer4	3×3	64	Stride=1, Padding=2 Activation='relu'
Dense 1	128		Activation='relu'
Dense (output)	128		Activation='softmax'

4. LAB RESULTS

In this section, the performance details of the proposed method have been evaluated. For this purpose, the performance of the proposed method in the classification of data sets has been evaluated. Then, using the comparisons, the performance of the proposed method has been evaluated against other methods. In our proposed method for evaluating the classification model, the data set was divided in such a way that 75% of the data was used for training the model, 15% of the data was used for validation, and the last 15% was used for testing the model.

4.1. Preparation of the results

4.1.1. Settings and parameters of the proposed method

Any proposed method should be evaluated by appropriate evaluation criteria to know its validity. Normalization batch sizes of 64 and 128 are used in 100 communication epochs for 6 clients, and two different learning rates are used for training. The learning rate considered is 0.001 for the server and 0.0001 for the clients. A 60:40 split between the clients and the server is made to use the selected dataset. The dataset is uploaded to Google Drive after downloading from the source. The address of the desired data in Google Drive is given to the execution line in Google Club to obtain the dataset for execution using Anaconda version 10 and Windows 10 operating system with a 7-core CPU.

4.1.2. The dataset

The dataset used in the study process is the EEG brainwave mental state dataset. The dataset includes EEG brain wave data processed by the statistical extraction method. The data are collected from four subjects (2 males and 2 females) for 60 seconds in relaxed, focused, and neutral states. A muse EEG heading is used in the main repository of this dataset. This dataset records the EEG location of TP9, AF7, AF8, and TP10 through neutral electrodes. After extraction, the dataset is resampled because the waves must be described temporally.

4.1.3. Evaluation criteria

Each proposed method must be evaluated by different criteria based on the selected strategy. So, the proposed method is evaluated using the F1-score, specificity (SPE), sensitivity (SEN), accuracy, and precision (PREC) criteria. The results are described in the tables and graphs provided in this section.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$PREC = \frac{TP}{TP+FP} \quad (3)$$

$$SEN = \frac{TP}{TP+FN} \quad (4)$$

$$SPE = \frac{TN}{TN+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1\ Score = \frac{2\times PREC\times Recall}{PREC\times Recall} \quad (7)$$

4.2. Evaluation of proposed method

6 clients are used in the FL training process for testing. After the end of the training in 100 communication epochs, the execution results are given in the Figure 3 and Figure 4 graphs. The results of the evaluation of the proposed technique can be seen in the following graphs for training and test modes. The results of different servers and clients for the evaluation criteria selected in section 4.1 can be seen in Table 2.

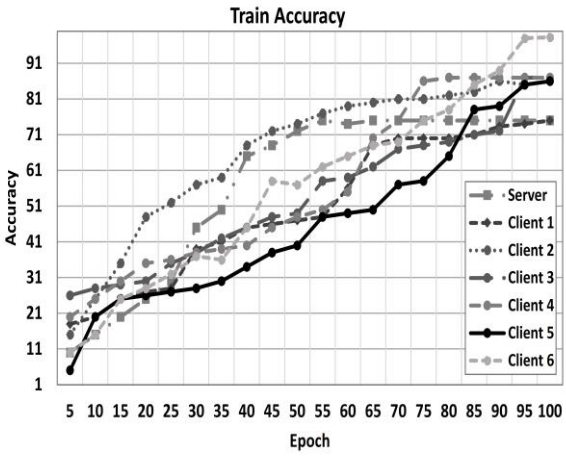

Figure 3. The results of model training in the proposed method for the clients and the server

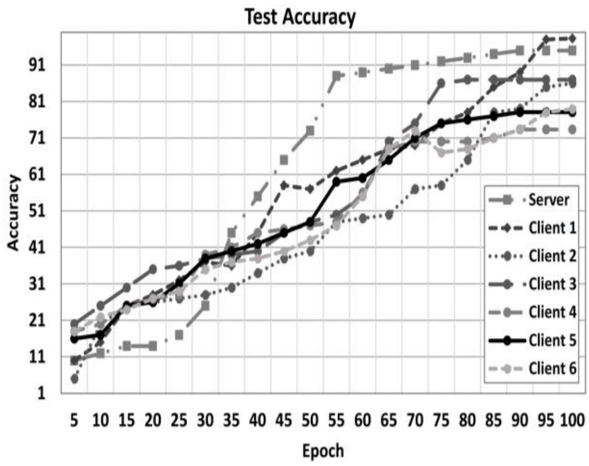

Figure 4. The results of model testing in the proposed method for the clients and the server

Table 2. The results of client classification in the evaluation of the proposed method (α=0.05)

Type	Accuracy	PREC	SPE	SEN	Recall	F1-score	*p*-value
Server	98.03	97.58	99.32	98.00	98.88	98.95	0.0141
Client 1	93.25	98.0	94.0	92.0	95.67	97.0	0.0100
Client 2	94.26	96.0	93.0	97.0	92.43	98.0	0.0201
Client 3	98.03	98.0	96.0	92.0	96.66	89.0	0.0185
Client 4	95.32	96.35	98.63	91.25	94.27	94.26	0.0398
Client 5	97.32	97.88	91.15	91.79	92.23	98.25	0.0291
Client 6	91.78	93.15	94.23	93.58	97.44	96.32	0.0012

As shown in Table 2, among the participating clients, client 5 has the best performance in training with an accuracy of 98.25. Finally, the accuracy of 98.95% is recorded for F1-Score. Client 3 with an accuracy of 98.03 has the same accuracy as the server. In other evaluation criteria, the best detection accuracy for the separation and classification of EEG signals is obtained for true positive, true negative, false positive, and false negative.

4.3. Comparison of the proposed method with other methods

In this section, the proposed method is compared with other related studies. These approaches are evaluated for accuracy and other general evaluation criteria. According to Table 3, among the proposed approaches for EEG signal classification, the proposed approach has the best accuracy with the new training technique. The proposed approach tries to solve the general problems of the study such as preserving the privacy of people and one of the challenges of FL in a reasonable and low-cost way.

Table 3. Comparison of the proposed method with previous approaches

Reference	Method	Accuracy
Mao *et al.* [19]	Recognition of different features in EEG signals	98.23
Dai *et al.* [20]	Using the VAE auto-encoder to fit EEG signals	97.56
Haselsteiner and Pfurtscheller [21]	Using MLP to classify EEG signals	96.65
Sadiq *et al.* [25]	Proposing CNN-based automatic detection	97.25
Proposed method	Balancing heterogeneous clients in terms of data volume	99.14

5. CONCLUSION AND FUTURE STUDIES

The approach proposed in this study solved the problem of unbalanced data in FL. However, there are no extensive studies on the presence of unbalanced non-identically distributed (non-IDD) data. It is hoped that the problem of unbalanced non-IDD data can be solved using an approach with minimal costs and easy computational and analytical methods, and a wider volume of EEG data sources can be used in the future.

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