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Privacy Preserved Brain Disorder Diagnosis Using Federated Learning

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Abstract: Federated learning has recently attracted significant attention as a cutting-edge technology that enables Artificial Intelligence (AI) algorithms to utilize global learning across the data of numerous individuals while safeguarding user data privacy. Recent advanced healthcare technologies have enabled the early diagnosis of various cognitive ailments like Parkinson's. Adequate user data is frequently used to train machine learning models for healthcare systems to track the health status of patients. The healthcare industry faces two significant challenges: security and privacy issues and the personalization of cloud-trained AI models. This paper proposes a Deep Neural Network (DNN) based approach embedded in a federated learning framework to detect and diagnose brain disorders. We extracted the data from the database of Kay Elemetrics voice disordered and divided the data into two windows to create training models for two clients, each with different data. To lessen the over-fitting aspect, every client reviewed the outcomes in three rounds. The proposed model identifies brain disorders without jeopardizing privacy and security. The results reveal that the global model achieves an accuracy of 82.82% for detecting brain disorders while preserving privacy.

Keywords: Privacy preservation; brain disorder detection; Parkinson's disease diagnosis; federated learning; healthcare; machine learning

1 Introduction

The use of wearable healthcare devices has increased in popularity as technology has advanced, and users have become more interested in tracking and monitoring their health. People's daily activities and health are closely intertwined [1,2]. People can better understand their health status by tracking their activities through wearable technology, such as smart glasses, smartphones, and wristbands [3–5]. These devices can track various health metrics, from physical activity and sleep patterns to heart rate and blood glucose levels. They can also provide alerts and reminders, enabling users to take action if a potential health issue arises. These devices' increasing availability and affordability have led to a growing interest in using wearable healthcare technology to promote health and prevent disease. Early detection of numerous cognitive illnesses, including Parkinson's disease, tumors [4,6–11], and minor vascular diseases, may be possible using wearable healthcare [12]. Additional uses include fall detection, sports monitoring, and mental health assessment [13–15].

Parkinson's disease is a chronic neurodegenerative disorder brought about through the slow death of dopaminergic brain cells [16–18]. Early Parkinson's disease detection, diagnosis, and therapy may slow or cease the disease's progression and lengthen the sufferers' lives [19–22]. However, people are typically unaware of the early signs of Parkinson's disease in their daily lives because the initial phases of Parkinson's only show mild or undetectable non-motor symptoms (such as voice abnormalities, mood disorders, and sleep disturbances) [23–26]. The solutions based on information and communication technologies have presented various methods to measure the motor condition of Parkinson's patients. Human-mobile interaction has become a common phenomenon in recent years, creating massive data streams [27]. The most extensive smartphone-based Parkinson's disease study was conducted using designed sensors on mobile devices to capture and extract data about Parkinson's disease [28,29], which engaged participants remotely, asked them to self-report their statistical profiles and conducted standardized tests to obtain data over 6 months.

Machine learning models are routinely developed through user data to track the user's health state for intelligent healthcare [30,31]. Despite the quantity of data in various organizations, sharing the data is not practical owing to security and privacy considerations [32–34]. Because of this, it is challenging to build effective models using valuable data. Personalizing is the other significant issue. Most approaches are based on a standard service model for all users. The machine learning model is disseminated to the connected systems to monitor the health data regularly after receiving enough data to train it [35,36]. This procedure deficit is personalizing. It is observed that each user has a unique set of physical traits and everyday routines. The ordinary model cannot provide security and privacy to personalized healthcare data. Providing data security and privacy is one of several significant difficulties facing wearable healthcare devices [37]. Sufficient user data is frequently employed to train machine learning models for healthcare applications and to track health status [38–41]. Recently, federated learning has drawn considerable interest as a novel method that enables deep and machine learning algorithms to leverage global learning among many people while protecting user data safety [42–46].

This paper makes the following major contributions:

- Propose an approach to detecting and diagnosing brain disorders using federated learning by extracting the data from the Kay Elemetrics voice-disordered database and perform data preprocessing to remove inconsistencies and irrelevant values.
- The proposed model trains the local model first and sends the model's hyperparameters to the server. Then, the server sum up the updated parameters and trains the model by keeping the privacy of each client's data.
- The experiment shows that the federated learning model based DNN model achieves an accuracy score of 82.82% for brain disorders detection compared to conventional methods and preserves client data protection.

Section 2 discusses the related work for diagnosing Parkinson's disease. Section 3 discusses the proposed framework based on federated learning. Section 4 explains the experimental results and provides a discussion. Section 5 concludes this paper and provides future research.

2 Literature Review

This section provides the history of Parkinson's disease using machine learning and deep learning techniques. The background of the healthcare devices that use federated learning is also provided.

2.1 Machine Learning Techniques

The earlier diagnosis and prognosis of various ailments depended on AI, including Huntington's illness [47], identifying speech disorders [48], and vocal evaluation influenced by bio-system [49]. Author [50] identified non-speech body movements as the new Parkinson's disease biomarker and leveraged smartphone usage data to monitor passive Parkinson's disease in daily life without disturbing the user. The PDVocal, a smartphone-based, end-to-end, privacy-preserving technology for early Parkinson's disease detection, is presented. During routine phone calls, PDVocal can passively detect Parkinson's disease digital biomarkers in the audio data. The long-term tracking protocol and opportunistic learning knob methods are investigated to achieve a reliable Parkinson's disease detection system. The proposed system is evaluated based on real-world interactions from publicly accessible data sources and a dataset compiled from 890 participants. The proposed system achieves 98.8% accuracy and 1.0% FRR with a 0.5-s segment size; with a 1-s segment size, it achieves 99% accuracy and 1.1% FRR. The author [51] proposed using the machine learning technique for Parkinson's disease detection using smartphone applications. The study observes the five tasks completed remotely: reaction time, voice, balancing, tapping of a finger, and gait. The data regarding Parkinson's disease is obtained from 6,148 smartphone activity assessments completed by 129 individuals. The proposed model increased the standard deviation by 16.3 (5.6) points in response to dopaminergic medication.

2.2 Deep Learning Techniques

Author [52] proposes a deep neural network algorithm on the Parkinson's Telemonitoring Voice Dataset of patients from the UCI repository. The TensorFlow library and Python language are applied to the proposed deep neural network approach. The dataset constitutes 16 attributes used in this research and two severity scores (motor UPDRS and total UPDRS) for the prediction. The proposed approach was applied to both scores individually. The motor UPDRS score achieves better accuracy than the total UPDRS score: 83.367%. Author [53] implements a machine learning-based technique for classifying Parkinson's disease by employing a dataset from smartphone-based walking, speaking, typing, and memory tests. The proposed approach consists of two stages of performing individual training. The first consists of customized models to evaluate the intensity of symptoms in cases where only one test is performed. The second is an EAM (Evidence Aggregation Model) to combine all single-test assessments into a complete diagnostic score. The proposed approach significantly outperforms the baselines at predicting by using data from a cohort of 1,853 participants. The highest AUC-ROC achieved is 0.85.

Authors in [54] explain that multi-source ensemble learning, a technique that combines dataset deconstructing with ensemble learning, obtains a participant retention rate of 100% and allows participants with incomplete information to be utilized within the training of machine learning models. According to the proposed approach, 91.2% of a cohort of 1,513 participants provided incomplete data on tapping, walking, voice, or memory tests. Convolutional neural networks that use the volume of data available and multi-source ensemble learning have been shown to boost Parkinson's dataset classification accuracy from 73.1% to 82.0% by comparing existing methods. It was discovered that using multi-channel convolutional neural networks (CNNs) and creating models employing a large cohort of participants contributed to the accuracy improvement. Authors in [55] proposed the utilization of DeepVoice, a program developed for PD diagnosis based on voiceprints and merging deep learning and mobile health. The proposed approach evaluates input data type, voice length, and a neural network model on a massive Parkinson's dataset. According to the result, DeepVoice can identify the Parkinson's dataset with an accuracy of 90.45 ± 1.71% using an audio clip 10 s long. Table 1 presents the summary of existing works.

Table 1: Summary of related work

Reference	Motivation	Technique	Limitation(s)
[52]	Parkinson's disease detection	DNN	Do not provide privacy to patients' data
[54]	Parkinson's disease detection	Ensemble learning	Limited in providing privacy to data
[55]	Parkinson's disease detection	CNN	Low performance and not providing privacy

2.3 Federated Learning Techniques

The author [56] proposed a privacy-based, federated learning approach to protecting patients' data [56]. The BraTS 2018 dataset builds and analyzes efficient federated learning techniques for segmenting brain tumors. The dataset includes 285 individuals with brain tumors recognized through multi-parametric pre-operative MRI scans. Authors in [57] proposed a machine learning-cum-attention mechanism to segment brain tumors effectively. Akter et al. [41] introduce a framework with Distributed Protection (DP) to secure the healthcare sector using IoT technologies [41]. The datasets utilized in this study are from the MNIST database, CIFAR10, and the COVID-19 dataset and are used to show the proposed technique's performance from a healthcare perspective. An iteration-based converged CNN at Edge Layer is proposed to reconcile federated learning's privacy protection and algorithm performance across an IoT network. After several iterations, the findings show the highest accuracy rate of 90%, outperforming other baseline techniques. Additionally, the proposed approach satisfies the privacy and security concept more quickly and effectively [41]. Authors in [58] presented the framework of MetisFL Federated Learning, a flexible architecture enabling a range of communication channels with robust security and privacy methods. It established its effectiveness in difficult cognitively and statistically varied contexts for neuroimaging applications, the prediction of Alzheimer's disease, and Brain-AGE. The findings show the best accuracy is 0. 8633 ± 0.0013%, precision is 0.8098 ± 0.0043%, recall is 0.8132 ± 0.0097%, f1-measure is 0.8114 ± 0.003%, AUC PR is 0.8682 ± 0.0009%, and AUC-ROC is 0. 8971 ± 0.0006% on the federated 5AOB model.

In conclusion, various machine and deep learning methods have been investigated to develop Parkinson's disease prediction methods. However, they do not offer reassuring evidence of improved accuracy and do not prioritize data protection. The federated learning research previously mentioned centered on resolving various healthcare challenges [56,58]. To preserve data privacy that ML and DL models do not account for, we proposed a federated learning framework in this study that is built on a DNN model.

3 Proposed Methodology

This section represents the idea of federated learning, model architecture, and data preprocessing since they serve the basics of the proposed technique. Fig. 1 depicts the steps performed in the proposed methodology, which consists of three crucial steps. Training initializing is the first step. Based on the target application, the federated learning server, a cloud server, evaluates the significant types of data and trains the hyper-parameters, such as the learning rate, the number of epochs, the activation function, and the Adam optimizer.

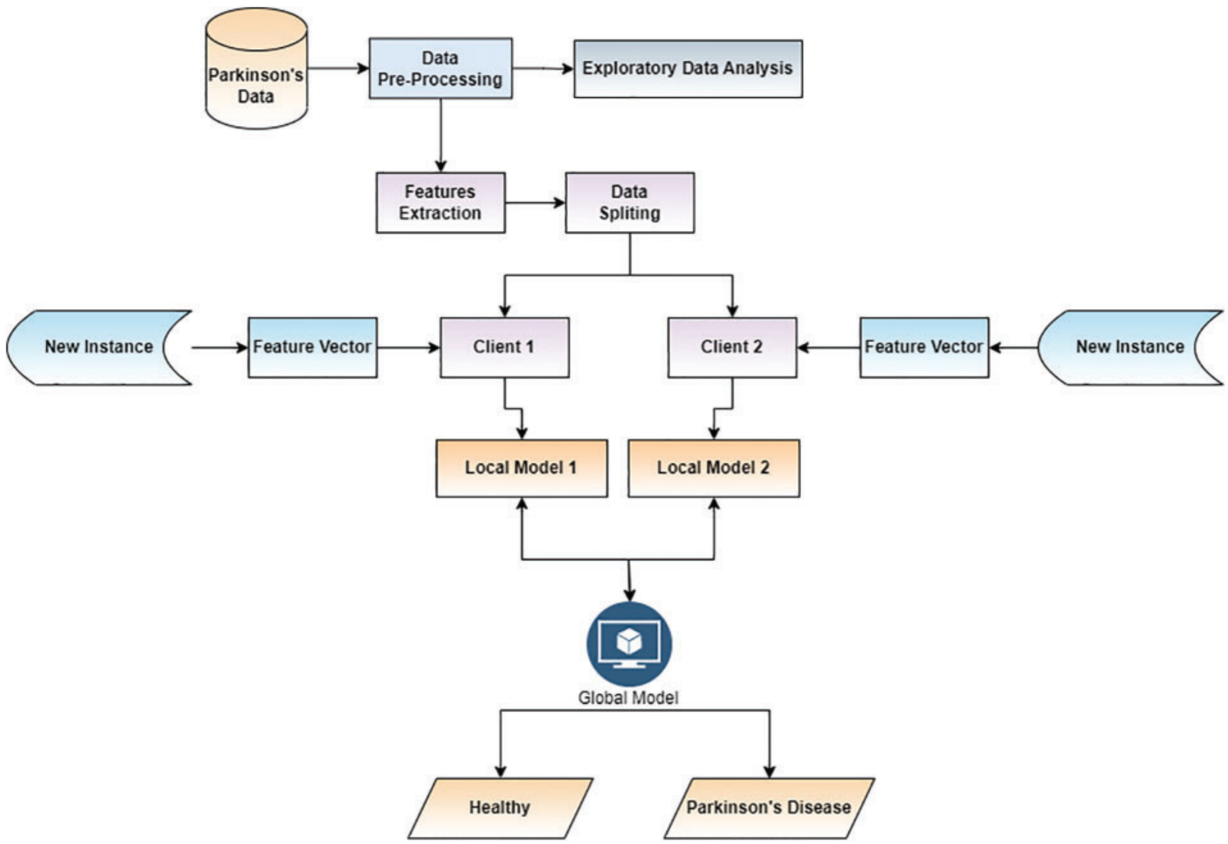


Figure 1: Overview of proposed deep federated learning framework

The neural network DNN receives client specifications and multiple hyper-parameters. The next level is to train the DNN model. Every client starts to gather new data and change the parameter on the local model (M^yx) based on the global model (G^yx), wherein y is the index for the following iteration. Every client is looking for the optimal situation to decrease the loss. Ultimately, the modified parameters are submitted to the federated learning server regularly. The aggregation of the global model is the third level. At this level, the findings from various clients on the server side are combined, and then the modified parameters are delivered to every client. The server lowers the global loss function by following Eq. (1):

$$\text{Loss}\,(\text{Gy}\,) = \frac{1}{m}\sum\nolimits_{x=m}^{x=1} \text{Loss}\,(M^y\text{x}) \tag{1}$$

The process is repeated until good results are achieved or the loss is continuously reduced. The proposed model's steps are provided in Algorithm 1. The Parkinson's disease dataset is taken as input. Exploratory Data Analysis (EDA) is performed to remove the inconsistencies. Before prepossessing, the dataset is split into two windows for clients 1 and 2. Data preprocessing is performed using Synthetic Minority Over-Sampling Technique (SMOTE) and normalization to balance the dataset. The testing and training portions of the dataset are divided into 25% and 75%, respectively, after prepossessing. The global model is created along with two local models where all models run for three rounds. The loss is calculated through binary cross-entropy and evaluation metrics. After obtaining the results, aggregate both client results and the overall results.

3.1 Dataset Selection, Preprocessing, and Feature Extraction

Next, the EDA is performed on a dataset extracted from the database to eliminate inconsistencies and irrelevant values. This study uses the dataset extracted from the database of Kay Elemetrics voice disordered [59]; the dataset is available at Kaggle. The database has 707 standard and abnormal voice samples from various individuals who suffer traumatic, biological, and neurological disorders. These are samples of the three forms of strange voice and speech signals, and 53 samples of ordinary people are used as controls. In the database, each voice sample is an average of 2 s long, 16-bit raw PCM audio and was collected in controlled, quiet acoustic settings. Several voice samples were down-sampled using anti-aliasing from 50 to 25 kHz.

The EDA is utilized as a strategy for learning from the data instead of using it for formal modeling or hypothesis testing. To summarize the statistical parameters of the datasets, it is helpful to conduct an analysis focusing on four crucial factors: the spread measurements, central tendency measurements, the outlier's existence, and the disturbance's shape. The dataset contains binary classes; 1 indicates the patient has Parkinson's disease, and 0 indicates a healthy person. The total training data is 198. The dataset is divided into two dormers because this study works with two clients, each with its data. Client 1 has 98 data, and Client 2 has 97 data.

Two preprocessing methods, SMOTE and normalization, are applied to the dataset to normalize and balance the data. SMOTE is an oversampling method that uses fictitious samples to represent the minority classes. This technique helps to overcome the overfitting problem that results from random oversampling.

Client 1 has 154 training data after applying the SMOTE to the dataset, while Client 2 has 140. The scaling of input attributes is essential for a specific model. The min-max scaling is used for feature normalization that helps to structure the low variance and ambiguous dataset and maintain the data integrity. Eq. (2) is used for data normalization.

$$Z_{norm} = \frac{Z_i - Z_{min}}{Z_{max} - Z_{min}} \tag{2}$$

3.2 Model Architecture

The number of neurons and layers is crucial when modeling neural network topology. Most of the time, signals are only transferred in one direction from input to output within the network. Since each neuron's output does not affect the neuron, there is no loop. The DNN is the neural network architecture that is most well-known and is widely utilized to process the data, define the input and output neurons. The DNN algorithm usually consists of three layers: an input layer, a different hidden layer (dropout, dense, etc.), and the output layer. The architecture of the DNN model is given in Fig. 2.

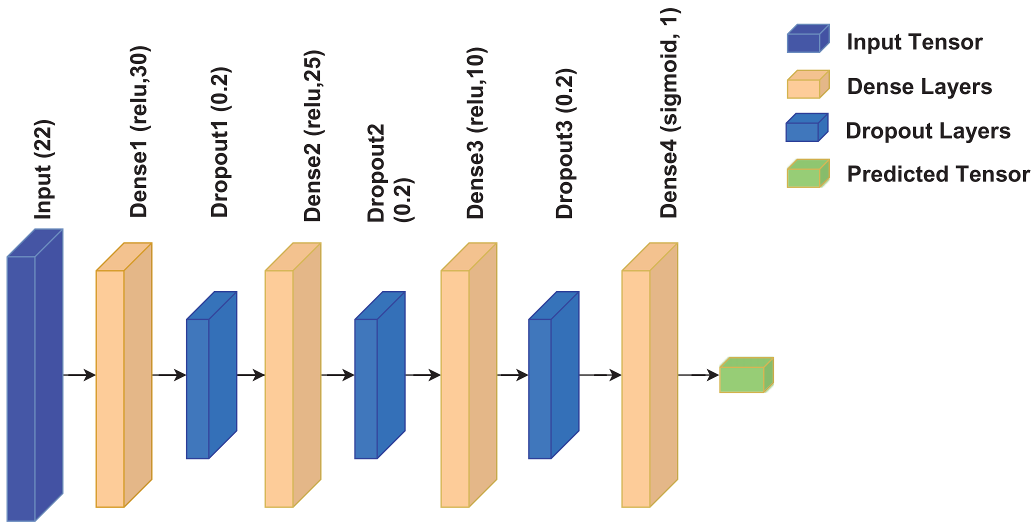


Figure 2: Proposed architecture of DNN model

Algorithm 1: Pseudo code of federated learning-based DNN model

Input: Parkinson's Diseases Dataset
Output: Parkinsonâs Prediction
X = df.corr() {Exploratory Data Analysis }
Dataset Preprocessing (Parkinson's Diseases)
$x,\ y \leftarrow C_1, C_2$ {Split dataset for two clients}
y= Smote() {smote formula}
$x_{train}, x_{test}, y_{train}, y_{test}$ ← train-test split dataset {dataset splitting}
$Z_{norm} = Z_i\text{-}Z_{min}/Z_{max}\text{-}Z_{min}$ {data Normalization}
Create a global model
while ($t \leq T$) do {T represents the total number of rounds and t is the current round}
for c in number of (len(C)) do { train local model}
$Batch{-}size \leftarrow$ M {Batch Size }
$Epoch \leftarrow$ N {Epochs values}
$A_f \leftarrow$ ReLU {Activation Function}
$Optimizer \leftarrow$ Adam {Activation Function}
$Loss\,(Gy) = \frac{1}{m} \sum_{x=m}^{x=1} Loss\,(M^y x)$ {Loss function}
$E_m \leftarrow$ Accuracy, Precision, Recall, F1-Measure {Evaluation metrics}
return ← Rounds results {Update local models}
end for
return ← Client 1 and client 2 results {update aggregate} return ← Model Performance {update global model}

4 Results and Analysis

The experiment is on the dataset extracted from the Kay Elemetrics voice-disordered database. In the experiment, one server and two clients are engaged. The two clients use the Parkinson's diagnosis dataset to train the DNN model. The DNN model is trained using the given dataset, and the random weight is initialized. The specifics of the DNN model are given in the section on model architecture. We first gathered 195 dataset sample samples, after which we performed an EDA on the dataset to eliminate the inconsistencies and irrelevant values. The SMOTE method balances the dataset after the EDA has been applied. The total training data after the SMOTE is 294 in total. The dataset is divided into two parts: 25% is used for testing, and 75% is used to train the model. The values are all fitted into the range [0, 1] using the min-max normalization procedure. The experiment is conducted in two classes. Each client's results are reviewed three times for loss prevention. The label encoder method converts the label into a machine-readable format. At the server end, the client's results are combined. The experiment uses different evaluation metrics: precision, accuracy, f1-measure, and recall. After server-side aggregation, the DNN model obtains 82.82% accuracy.

4.1 Server-Based Training with Log Data

One server is the main parameter, and two clients comprise a federated learning system. The server decides which client/node is used at an initial level of the model training stage and collects any modifications received. Data logged on servers is used to train the DNN model. Before training, the logs are anonymized and cleared of personal identifying details. During the fit-round, the clients transmit the output to the server side. Both clients communicate the test result to the server during the evaluation round, which combines the results. The DNN achieves the best accuracy of 82.82% on the server side.

4.2 Federated Training with Client 1

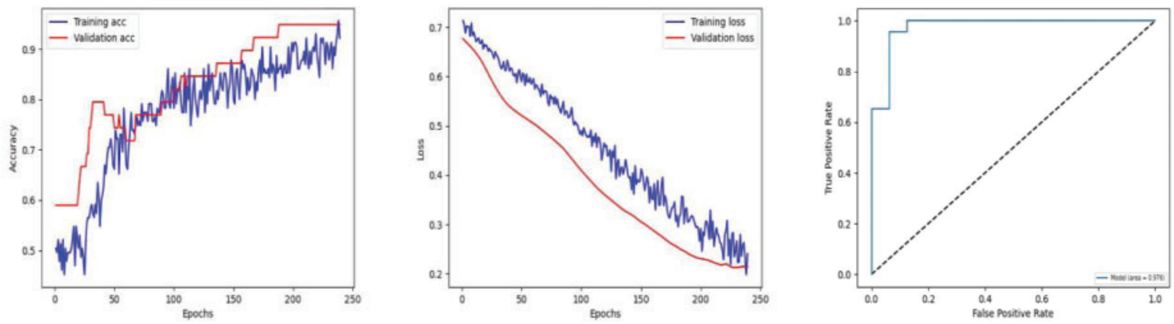
Client 1 conducts the experiment using a sequential DNN model with two dense and three dropout layers as hidden layers. The DNN model runs three test rounds. The experiment conducts three rounds of evaluation metrics: precision, accuracy, f1-measure, and recall. Table 2 represents the experimental results of client 1. The study runs the DNN model for round 1, and the result obtains accuracy, recall, precision, and F1 measure. In the first round, the DNN model provides 91.0% accuracy, 88.0% precision, 94.0% recall, and 99.0% F1-measure. Analyze the results to prevent the model from overfitting once again. In round 2, the DNN model achieved an accuracy of 77.0%, a precision of 70.0%, a recall of 88.0%, and a 78.0% F1-measure. In round 3, we obtained an accuracy of 74.0%, a precision of 67.0%, a recall of 88.0%, and a 76.0% F1-measure. From client one, round 1 provides the highest result.

Table 2: Result of client 1

Rounds	Accuracy	Precision	Recall	F1-score
Round 1	91.0%	88.0%	94.0%	99.0%
Round 2	77.0%	70.0%	88.0%	78.0%
Round 3	74.0%	67.0%	88.0%	76.0%

In Fig. 3, the highest result is visualized. In Fig. 3a, it can be noticed that the training accuracy started increasing from 0.5% and kept increasing continuously to around 0.95%. Similarly, validation accuracy started increasing from 0.6% and kept increasing continuously to around 0.96%. The graph in Fig. 3b depicts the training and validation loss; in the training process, the loss is reduced on each epoch, which increases the model's performance. The training loss started decreasing from 0.7% and kept decreasing continuously to around 0.2%. Similarly, validation accuracy started decreasing from

0.65% and kept decreasing continuously to around 0.2%. The graph in Fig. 3c indicates the ROC. The ROC curve represents better performance near the corner of the top-left.



(a) Validation and training accuracy (b) Validation and training loss (c)ROC Score

Figure 3: Graphs of client 1 best results

4.3 Federated Training with Client 2

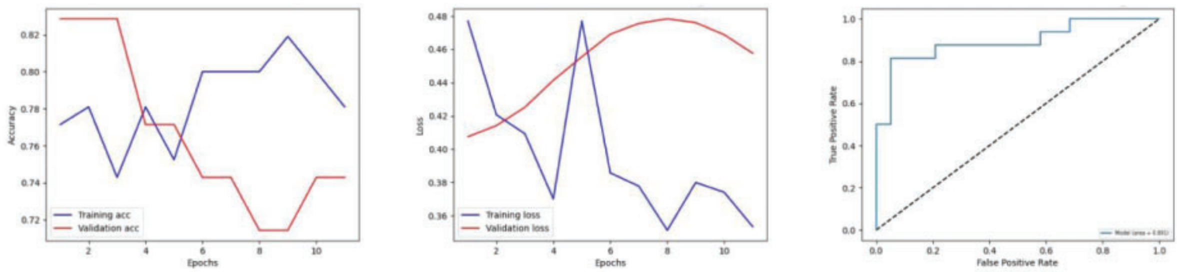
Client 2 conducts the experiment using a sequential DNN model. The DNN algorithm has two dense and three dropout layers as hidden layers. The client conducted two experiments three times and returned the results in the evaluation and fit rounds. The DNN model runs three test rounds. The experiment conducts three rounds of evaluation metrics: precision, accuracy, f1-measure, and recall.

Table 3 represents the experimental results of client 2. DNN achieves an accuracy of 95.0%, 96.0% precision, 96.0% recall, and 96.0% F1-measure. In round 2, the DNN model achieved an accuracy of 95.0%, 96.0% precision, 96.0% recall, and 96.0% F1-measure. Round 3 obtained an accuracy of 95.0%, 96.0% precision, 96.0% recall, and 96.0% F1-measure. From client two, round 3 provides the highest result.

Table 3: Result of client 2

Rounds	Accuracy	Precision	Recall	F1-Score
Round 1	95.0%	96.0%	96.0%	96.0%
Round 2	95.0%	96.0%	96.0%	96.0%
Round 3	95.0%	96.0%	96.0%	96.0%

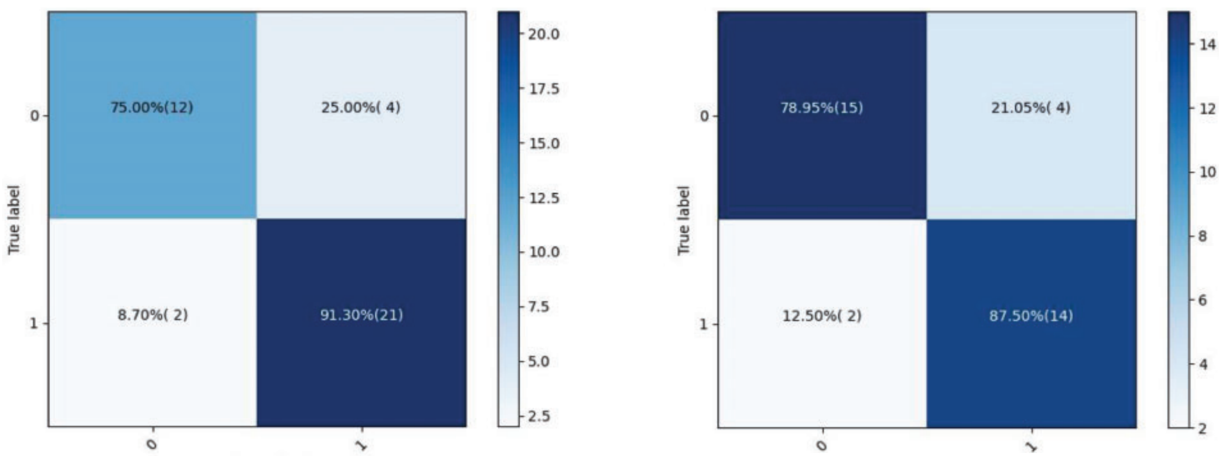
Fig. 4 depicts the highest result. Fig. 4a represents the accuracy graph in round 3 of client 2 obtained the highest validation accuracy. It can be noticed that the training accuracy started increasing from 0.77% and kept increasing continuously to around 0.82%. Similarly, validation accuracy started from 0.82% and kept decreasing continuously to around 0.74%. In Fig. 4b, the graph shows that the loss is reduced on each epoch, which increases the model's performance. The training loss started decreasing from 0.48% and kept increasing continuously to around 0.46%. Similarly, validation accuracy started decreasing from 0.4% and kept decreasing continuously to around 0.2%. The third graph indicates the Receiver Operating Characteristic (ROC) in Fig. 4c. The ROC curve represents better performance near the corner of the top-left.



(a) Validation and training accuracy (b) Validation and training loss (c) ROC Curve

Figure 4: Graphs of client 2 best results (Round 3)

In Fig. 5a, the proposed approach's confusion matrix of client 1 is represented graphically and provides an overview of how a classification algorithm operates. Because it has more continuous and better true positive and negative values and fewer false negative and false positive values, the proposed method performs better. Fig. 5b presents the proposed approach's confusion matrix for client 2. It provides an overview of how a classification algorithm operates. Because it has more continuous, better true positive and negative values and fewer false negative and false positive values, the proposed method performs better.



(a) Client1 (b) Client 2

Figure 5: Proposed approach's confusion matrix for Parkinson's disease detection

4.4 Limitations and Discussions

This research suggests FL-based models be used to identify and diagnose Parkinson's disease as a solution to this problem. The model employed a dataset extracted from the Kay Elemetrics voice disorder database; however, the extracted dataset was small. It is challenging, therefore, for single sites with tiny, labeled datasets to create unique AI systems for screening patients. This is because the patient population on which the model is built is often minuscule, which, in turn, significantly reduces the model's generalizability. FL eliminates this hurdle. By collaborating, many organizations can combine their data to develop a more accurate global model for a broader range of patients. Since FL prioritizes the protection of patient data, there is no explicit data sharing in this cooperative process. Although FL makes it possible for more cooperative ML, it also presents a particular variety of challenges, such as the preceding: in FL networks, where the data generated by each device is maintained locally, communication is a significant barrier. Another challenge is that not all ML applications are compatible with FL. The developer must discover alternative solutions if the model is too large to execute on consumer devices to protect user privacy, as this study utilizes a small dataset that positively impacts model performance.

5 Conclusion

This paper proposed a federated learning based DNN model to detect and diagnose Parkinson's disease. The novelty of the proposed approach lies in providing privacy to the user data. For experimentation, we extracted the data from the Kay Elemetrics voice-disordered database. The dataset is divided into two clients to create the training model because this study works with two clients, each with its data and one server. Two clients were used to train the DNN model, and the server end was combined with an accuracy of 82.82%. To lessen the over-fitting aspect, every client reviewed the outcomes three times. The best result of round 1 of client one was obtained with a 91.0% accuracy, and client 2 of round 1 obtained the best result with a 95.0% accuracy. The DNN model's ROC curve average of 99.3% demonstrates the suggested method's excellent performance on the tested dataset. The findings showed that federated learning accurately secures the privacy of client data. According to a system efficiency study, side training times and storage costs favor medical devices with constrained resources. In the future, we intend to research training FL-model on heterogeneous devices to improve the Parkinson's disease detection process.

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Conflicts of Interest: The authors declare they have no conflicts of interest to report regarding the present study.

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