A Federated Approach for Classification of Alzheimer's Disease

Abstract—**Federated learning is especially significant to medical data and conditions like Alzheimer's disease. It offers a privacy-preserving approach in the context of medical data, particularly when dealing with private and sensitive health information such as an Alzheimer's patient's data. Federated learning enables models to be trained jointly on data distributed across several healthcare facilities or individual devices, as opposed to centralizing patient data in a single location, which may give rise to concerns about data security and privacy. Specifically, varied datasets reflecting various demographics, genetic origins, and clinical traits are beneficial to Alzheimer's research. Models may learn from such a wide variety of data without jeopardizing the privacy of individual user information thanks to federated learning. Thus we propose a federated model for the classification of different stages of Alzheimer's disease. Our work consists of a simple MLP architecture to set up the global and local models. The global and local models communicate over a number of rounds to train and give the desired performance.**

Index Terms—**Alzheimer's, Federated Learning, MLP, Weight Aggregation**

I. Introduction

Alzheimer is one kind of dementia which progressively leads to short term memory loss and then not being able to continue the conversation [1]. However, dementia has a really bad effect on daily life [1]. Furthermore, 10 percent of cases of mild cognitive impairment (MCI), a stage between cognitively normal (CN) and dementia, eventually progress to Alzheimer's disease (AD) [2]. This disease profoundly impacts a person's daily routines and activities [3]. Individuals suffering with Alzheimer's disease may display behavioral alterations, personality disorders, and more clinical manifestations [3]. Whenever a person with these kinds of symptoms who has short term memory loss or not being able to talk or taking a conversation too long, should be taken on account and major the risks that person is having in day-to-day life.

Important factor to take into account is that classification of Alzheimer's disease in an early stage is as important as taking precautions to it. The patient may be at the earlier stage of Alzheimer's with mild symptoms or at the middle stage with moderate symptoms or even at the severe stage. Furthermore, some symptoms of other diseases may overlap with Alzheimer's disease symptoms but the patient may actually be non-demented. Thus, it is important to classify from the patient's data whether Alzheimer's diseaese is active and if so, in which stage they are in. Machine Learning techniques help to detect this from MRI images of the patients while incoorporating federated learning helps to ensure the confidentiality of those patient's data is not breached.

Federated Learning (FL) is a productive, decentralized method that doesn't require the sharing of local data [4]. Federated Learning trains the model on an administrative server, negating the requirement for it to distribute data across the globe. Google first presented the FL idea in 2017, and the FedAvg algorithm was suggested as a way to train the central server using data from handheld devices [5]. Unlike a centralized DNN model, the FedAvg technique allowed the predictive algorithm to be trained without sharing the data [5].

II. Research Objective

Medical photos require protection and the preservation of users' personal information rights because they are sensitive data. As we've already discussed, FL was developed to address the problem of data privacy in collaborative machine learning. In a short amount of time, the idea was implemented in a number of domains, including medical imaging. Numerous articles focused on FL have already been published. medical image analysis, which they effectively implemented a distinctive approach to data handling in their research publications. At this point, it's important to reflect on the past, evaluate the work that has been done thus far, and determine how FL is affecting medical imaging.

Since FL is still relatively new, the majority of review articles focused on its design and application. Second, they talked about FL's core feature, which is the opportunity for secrecy or security. While some of them focused on specific research problems, most of them explored data qualities, impact, gaps, and potential future studies. One common question concerned the state-of-the-art FL approaches. In addition, a number of survey articles on FL for healthcare informatics have been released. Our objective was to train a global model which can update its weights on the basis of the weights of the local models and successfully classify if a patient has Alzheimer's disease and the level of the disease.

III. Research Contribution

Our study included a number of research queries, and by supplying clarification, we were able to highlight the state of the field's current FL research on the processing of medical images. Furthermore, a number of observations were talked about. In this study, we looked at federated data management, privacy preservation, FL architecture, demographic data, and FL model performance. As such, this work may serve as a basis for further investigation into the use of FL in medical imaging. The main contributions of our paper are as follows:

1) Training local models and updating a global model using the local model parameters.
2) Evaluating the global model on test data which gave 89% accuracy.
3) Versatility of model for handling other kinds of image datasets.

IV. Literature Review

We took a look at some works where mostly, CNN had a significant impact for Alzheimer's disease classification and also federated approach was used in some works for the same purpose but with privacy protection.

Alzheimer disease classification can be handled through CNN based framework which used deep learning based algorithms for accurate and early AD classification according to AbdulAzeem et al. [1]. The framework achieved high accuracy on the ADNI dataset which has a variety of data. The proposed algorithm framework consists of five layers which are Acquisition and annotation, Preprocessing and Augmentation, Cross-validation, CNN model and AD-classification. [1] In the second layer of the model, data augmentation and adaptive threshold was also applied. In the outer layer, SoftMax is used. To work on the performance and stability of CNN, batch normalization is used. However, Glorot initializer and cross-entropy loss function is used for initializing the network weight and training. This paper's proposed model achieved 99.6%, 99.8% and 97.8% accuracy on classifications on the ADNI dataset. Moreover, for the multi-classification experiments, the proposed framework achieved 97.5% accuracy.

Blood biosamples are extremely important to detect in early stages which was confronted in the paper by Khalil et al. [3], where hardware and diagnostic models were combined to detect Alzheimer disease. However, VHDL and Altere 10 GX FPGA were used for hardware acceleration approaches. Here, for the privacy concern, Federated Learning was trained without the share of raw data. This research proposed a diagnostic model for AD using blood samples. However, FL has better resource utilization compared to existing methods. Proposed method achieved 89% accuracy and 87% sensitivity for early detection of the disease. Moreover, the hardware power consumption ranged between 35 to 39 mW, [3] which is eventually perfect for small amounts of data. Inference latency of this method was 61ms compared with the existing one.

Ding et al. [6] proposed a deep learning framework for classification of Alzheimer's disease. This framework pointed out a new method to boost the initial treatment for this disease. However, this method performs 4% much better then the other methods. The optimizing layers used oversampling and threshold moving to cope with the cost-sensitive issues. Moreover, stacking layer rank base classifiers use deep learning based networks. However, for meta classifiers, neural networks were used. On the other hand, voting layers used autoencoders for feature learning. [6] The proposed framework enables working with multisource data and base classifiers and it uses six well-known ensembles approaches to classification accuracy. Naive Bayes classifier is used over gradient descent which is probability based Bayes theorem. On the contrary, logistic regression is a well-behaved classification algorithm. Whereas tree ensembles are like a combination of different types of decision tree. It is also mentioned in the paper that RBM is one of the examples of deep learning, [6] which is used in diverse applications.

All of these works implemented various methods and got a satisfactory result for different Alzheimer datasets. However, only the use of ML techniques cannot assure the security of data, especially when it is necessary to collect data from local institutions and hospitals. Thus, federated approach related work gained popularity out of which some works are mentioned.

Decentralized federated learning approach for training on distributed systems is one of the important ways to ensure data privacy and protection without breaching the data privacy law [7]. Nguyen et al. [7] emphasizes that data diversity has a great impact on AI accuracy and generalizability. However, poor quality of data can impact badly on the accuracy of the algorithm. In this paper, non-medical data and medical data efficacy of decentralized AI training approaches was tested. Scalability of this approach was tested with a 15 node scenario [7] and performance was tested on embryo dataset from different IVF clinics. Moreover, in this model clustering algorithm was used to reduce model transfer cost and optimization of topologies were conducted just to make sure that accuracy and cost trade-off is done perfectly or not.

Wen et al. illustrates the biases of performance evaluation detected through data leakage through their research [8]. A dataset having longitude can be split at subject-level which can make accuracy rise up to 8% compared to unbiased split of the image. Lately, data augmentation is performed after training of the dataset. This work proposes a 3D subject-level CNN approach which is used for AD classification. ResNet and VGGNet architecture had been adapted for the whole MRI classification. The main backlog was the accuracy is lesser then the 3D subject-level approach. In addition, an open-source framework was introduced for AD classification which contains the CNN models validation procedure. Different CNN architectures were trained on the proposed framework, which achieves similar results in 3D approaches but does not outperform SVM with voxel-based features. [8]

Nazir et al. depict in this paper [4] how deep neural networks show promising results with medical image analysis. As privacy concerns are always there, federated learning enables training models without sharing. FL gives comparable performance while securing the data privacy. The proposed model was Generative Adversarial Network (GAN) for stain-style normalization for histopathology image of colorectal cancer (CRC). [4] This paper addresses the security challenges while testing the datasets and implementation. It also enhanced the future security challenges and research direction towards FL.

V. DATASET

The Alzheimer's Dataset obtained from Kaggle constitutes an MRI-based collection, primarily categorized into four distinct classes or groups based on the severity of dementia. The dataset's structure encompasses the following classes along with the corresponding number of images within each category:

1) Mild Demented: Comprising 896 MRI images, this class illustrates cases characterized by mild dementia.
2) Moderate Demented: This class contains 64 MRI images depicting moderate levels of dementia.
3) Non-Demented: This category, holding the largest volume of images with 3200 instances, represents subjects without dementia.
4) Very Mild Demented: Within this class, there are 2240 MRI images depicting instances of very mild dementia.

The dataset's segmentation into these distinct classes based on varying degrees of dementia severity provides a comprehensive range of samples to facilitate the development, training, and evaluation of machine learning models aimed at Alzheimer's disease classification and diagnosis.

VI. METHODOLOGY

A. Data Preprocessing

In order to work with the acquired dataset for training our model, some preprocessing steps were implemented at first.

1) Load Images:
We used OpenCV to load each image in grayscale. The grayscale images were converted into a 2D array. Each element of this array corresponds to the pixel intensity at a specific location in the image. Then the 2D image array was flattened and converted into a 1D array to unify the image data. Image paths were parsed to extract the class label which represents the Alzheimer's status of patients. To normalize the image data, pixel values of image array were scaled to a range of [0, 1] for standardized processing. Then the normalized, flattened image data were added to a a list and the corresponding class labels were added to another list.

2) Binarize Labels:
An instance of the LabelBinarizer class was created to convert class labels into binary vectors, commonly known as one-hot encoding. Each unique class label is represented by a binary vector with all zeros except for the index corresponding to the class label, which is set to 1. Using LabelBinarizer, label list is transformed to binary labels.

3) Split Data into Training and Test Sets: Utilizing the train_test_split() function from sklearn.model_selection, the data is divided into training and test sets. The test-train set has ratio of 9:1. Meaning the test size to 0.1 (10% of the data). A random state of 42 has been used as well.

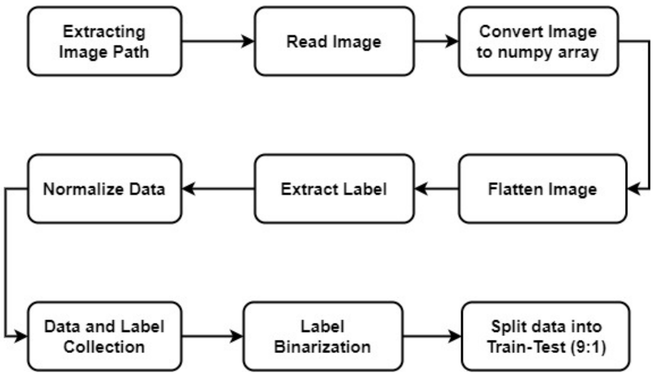

Fig. 1. Data Preprocessing

B. Federated Learning Implementation

1) Creation of Client Environments:
Client Entities: The first step is crafting artificial client entities to replicate real-world participants within the federated learning ecosystem. These simulated clients encapsulate distinct datasets or subsets of data, emulating decentralized data sources contributing to the federated model.

Client Representation: Each simulated client encapsulates a portion of the entire dataset, mirroring the individual contributions made by disparate sources in federated learning scenarios.

Configurable Parameters: Flexibility exists in defining the number of simulated clients and establishing unique identifiers, mimicking varying participants in a real-world federated environment.

2) Data Preparation and Segmentation:
Data Segmentation and Randomization: The dataset undergoes segmentation into discrete shards and randomization, resembling the partitioning of data among disparate clients in a federated learning scenario.

Allocation to Simulated Clients: These segmented shards are then allocated to their respective simulated clients, emulating the process of assigning data subsets to individual participants for localized training.

3) TensorFlow Dataset Preparation:
Creation of TensorFlow Datasets: This critical step involves organizing and structuring segmented data shards into TensorFlow Dataset objects, streamlining data processing and manipulation during the model training phase.

Structured Data Format: TensorFlow Dataset structures enable efficient batch processing and management, crucial for streamlined training procedures within the federated learning framework.

Batch Size Configuration: Customization of batch sizes within TensorFlow Datasets provides adaptable options for optimized data utilization during client-specific training iterations.

4) Defining Model Architecture:
Neural Network Design: Specification and configuration of a simplified Multi-Layer Perceptron (MLP) architecture, tailored to handle the inherent complexities of the dataset and align with the desired learning objectives.

Layer Configurations: This architecture comprises input, hidden, and output layers with specific dimensions and activation functions, facilitating classification tasks within the federated learning paradigm.

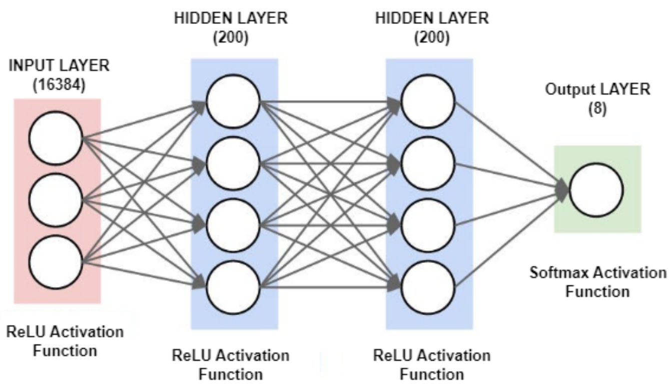

Fig. 2. MLP Architecture

5) Global Model Setup and Training Iterations:
Global and Local Model Initialization: Establishment of the global and local models using the defined MLP structure, forming the foundational framework for the federated learning framework.

Iterative communication rounds, dictating the number of interactions between the global and local models, driving the learning and aggregation processes. 200 communication rounds were chosen for better learning of the model. Categorical Cross Entropy was chosen as the loss function, accuracy as metrics, Stochastic Gradient Optimizer and learning rate as 0.01.

6) Optimization Strategies and Training Process: Localized Model Training: Training of individual client-specific models leveraging their respective subsets of data, replicating the training process on distinct devices or entities.

Weight Initialization and Scaling: Initialization of local models with global model weights, followed by scaling methods for local weights that account for varying dataset sizes, influencing model updates and adaptations.

Model Weight Aggregation: Aggregating scaled weights from local models to derive summed up updated global model weights, reflecting diverse client contributions and updates.

The global model was then assessed based on model performance metrics, encompassing accuracy and loss calculations after each communication round, validating model learning and adaptation.

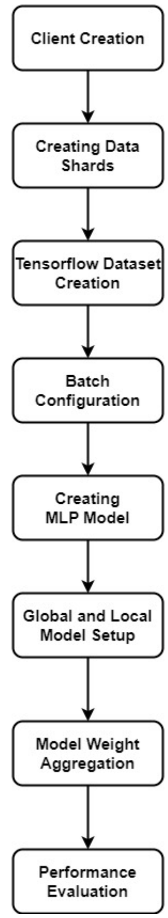

Fig. 3. Methodology - Federated Learning

VII. Results And Analysis

Our federated learning model demonstrated promising performance across different classes of dementia. The evaluation metrics for each class are summarized below in fig 4 where 0,2,4,6 represents Mild Demented, Moderate Demented, Non-Demented and Very Mild-Demented.

Our model achieved notable results, particularly in distinguishing between different degrees of dementia. The weighted averages provide an overall summary, highlighting the balanced performance across the dataset. We have done exceptionally well regarding predicting Non-Demented Patients with a precision of 0.92 which is mainly due to having large amount of data for that category of about 3200 images.Furthermore, we did poorly on both Mild-Demented and Moderate Demented Patients images reflecting upon our lack of dataset images of 896 and 64 respectively. Furthermore, if we consider our model accuracy as a whole, we have tied with global model

	precision	recall	f1-score	support
0	0.83	0.91	0.87	95
2	0.83	1.00	0.91	5
4	0.92	0.91	0.92	334
6	0.85	0.83	0.84	206
accuracy			0.89	640
macro avg	0.86	0.91	0.88	640
weighted avg	0.89	0.89	0.89	640

Fig. 4. Classification Report of Global Model

accuracy of 89%.In addition, if we evaluate our model test data loss on global model, the overall loss value came to 1.52%.

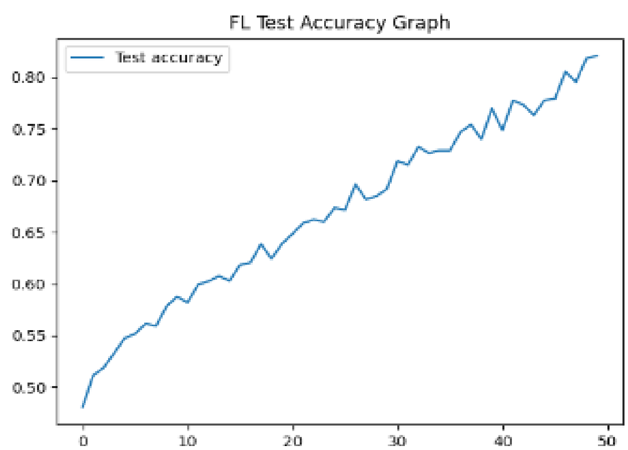

Fig. 5. Accuracy Graph of Global Model on Test Data

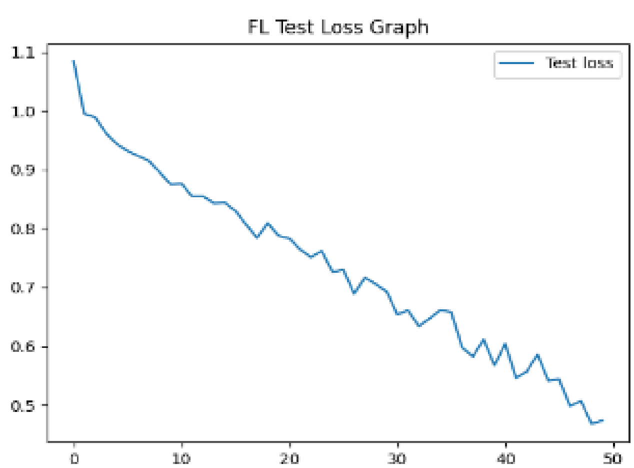

Fig. 6. Loss Graph of Global Model on Test Data

VIII. Limitation

Federated learning faces notable challenges, starting with the potential limitation of insufficient data on individual devices as we only had 6400 MRI images to work with, which was also subdivided into 4 subsection impacting the model's ability to generalize effectively. Imbalances in class distribution present another obstacle, potentially leading to suboptimal classification performance, particularly for underrepresented classes. The absence of Convolutional Neural Network (CNN) architecture may hinder the model's capability to extract complex spatial features from visual data, potentially limiting its performance in computer vision tasks. Communication overhead introduces latency and resource challenges, posing scalability concerns. Higher learning rates present a risk of convergence issues, instability, or overshooting optimal solutions, impacting overall model effectiveness. Lastly, the decentralized nature of federated learning raises the possibility of skipping over globally optimal solutions due to localized updates, requiring careful optimization strategies to mitigate these challenges and ensure successful implementation.

IX. Conclusion

This work has primarily focused on Alzheimer's disease classification. But similar methodology can be used for classification of other diseases and in other domains as well. The main focus should be in preserving the privacy of data. To implement this, federated learning has had a notable significance in our work. Of course, there are still limitations and improvements in terms of versatility of data and collecting a richer dataset. Due to resources and data limitations, some advanced work could not be approached. Moreover, variations in the client number could also attribute to different results. However, the results acieved have been satisfactory and served the purpose of a federated approach on the used dataset.

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