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Comparative Analysis of Federated Learning Aggregation Techniques For Alzheimer's Disease Diagnosis

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Abstract - *Federated Learning (FL) is a machine learning technique that decentralizes the training process across multiple devices or servers, each holding its own local dataset. This approach contrasts with traditional centralized machine learning techniques where all data is combined into one central point for training. In FL, an aggregator, typically a central server, plays a crucial role. It is responsible for collecting model updates from all participating nodes (clients), aggregating these updates, and then distributing the aggregated model back to the nodes. In our research, we conducted a comparative analysis of federated learning aggregation techniques for Alzheimer's disease diagnosis. We used the Flower framework to train the Machine Learning (ML) model. The aggregators used in this research include FedAvg (Federated Averaging), FedYogi (Adaptive Federated Optimization using Yogi), FedOpt (Federated Optim strategy), FedMedian (Configurable FedMedian strategy), FedTrimmedAvg (Federated Averaging with Trimmed Mean). These aggregators were applied on the Alzheimer MRI Preprocessed Dataset. Among these, FedTrimmedAvg yielded the best accuracy result.*

Key Words: **Federated learning, aggregator, *CNN*, alzheimer's disease**

1. INTRODUCTION

Federated learning, also known as collaborative learning, is a groundbreaking approach that has revolutionized the way machine learning models are trained. Unlike traditional centralized methods, federated learning operates on a decentralized paradigm, eliminating the need for exchanging raw data between client devices and global servers. This novel methodology enhances data privacy by conducting model training locally on edge devices, utilizing the raw data present on each individual device. The shift from traditional centralized server models to federated learning is driven by several critical issues associated with the former. Centralized approaches often face challenges such as data privacy concerns, computational power limitations, security risks, and vulnerability to single points of failure. Federated learning addresses these challenges directly, offering a more secure and privacy-preserving alternative.

One of the key advantages of federated learning is its ability to operate without the necessity of transferring raw data to a central server. This feature is crucial in maintaining the confidentiality of sensitive information, making federated learning particularly attractive in scenarios where data privacy is of utmost importance. The decentralization of model training in federated learning not only enhances data privacy but also mitigates concerns related to computational power limitations. By distributing the training process across edge devices, federated learning leverages the collective computing power of a network of devices, enabling more efficient and scalable machine learning model training.

Security risks associated with centralized models are also alleviated through federated learning. The decentralized nature of this approach reduces the likelihood of a single point of failure compromising the entire system. This makes federated learning more resilient to attacks and ensures the robustness of the overall system. The transformative potential of federated learning is particularly evident in its application to healthcare, where issues of data privacy and security are paramount. In the context of Alzheimer's disease diagnosis, federated learning offers a promising solution. By allowing model training to occur on local devices, the sensitive health data involved in Alzheimer's diagnosis can be kept on individual devices, minimizing the risk of unauthorized access and ensuring patient privacy.

2. RELATED WORKS

This paper [1] explores and investigates several federated learning aggregation strategies, algorithms, concept, advantages and disadvantages. It also explains the working of federated learning. This study [2] replicates experiments using four clients and 2482 chest X-ray images from the Kaggle repository. The dataset is divided into training and testing parts, with each client receiving 25% of the entire data. The accuracy rates on testing data are assessed after each federated learning round. The decentralized and distributed nature of the training process results in significant variation in accuracy compared to typical existing learning models. The model with federated learning compromises performance and is ahead regarding privacy. The loss function evaluates the performance in identifying COVID-19, and implementing federated learning significantly decreases it, increasing accuracy and precision. The proposed linear CNN model is intended for federated learning implementation, achieving a global accuracy of 92.754%. Future federated models and providing explanations for the model's decisions. This paper [3] used the dataset diabetic retinopathy from Kaggle, the objective was to detect diabetic retinopathy in patients. They did a comparison between two federated learning aggregators i.e FedAvg and FedSDG and a simple CNN. The global accuracy obtained by FedAvg was 96.46%, FedSDG was 97.87% and simple CNN was 95.02%. FedSGD achieved the highest global accuracy with lowest global loss.

3. PROPOSED APPROACH

The proposed research aims to conduct a comprehensive comparison of various Federated Learning Aggregation Techniques with a specific focus on their applicability to the diagnosis of Alzheimer's disease. In the burgeoning field of machine learning, Federated Learning presents a decentralized alternative that safeguards data privacy by conducting model training locally on edge devices without the need for centralized data exchange. This study seeks to evaluate and contrast different Federated Learning Aggregation Techniques, such as FedAvg (Federated Averaging), FedYogi (Adaptive Federated Optimization using Yogi), FedOpt (Federated Optim strategy), FedMedian (Configurable FedMedian strategy), FedTrimmedAvg (Federated Averaging with Trimmed Mean). The primary objective is to identify the most effective aggregation technique for enhancing the accuracy and reliability of machine learning models employed in Alzheimer's diagnosis. By scrutinizing factors like model performance, computational efficiency, and privacy preservation, this research aspires to contribute valuable insights that can optimize and advance the use of federated learning in the context of Alzheimer's disease diagnosis, potentially leading to more robust and privacy-preserving diagnostic tools.

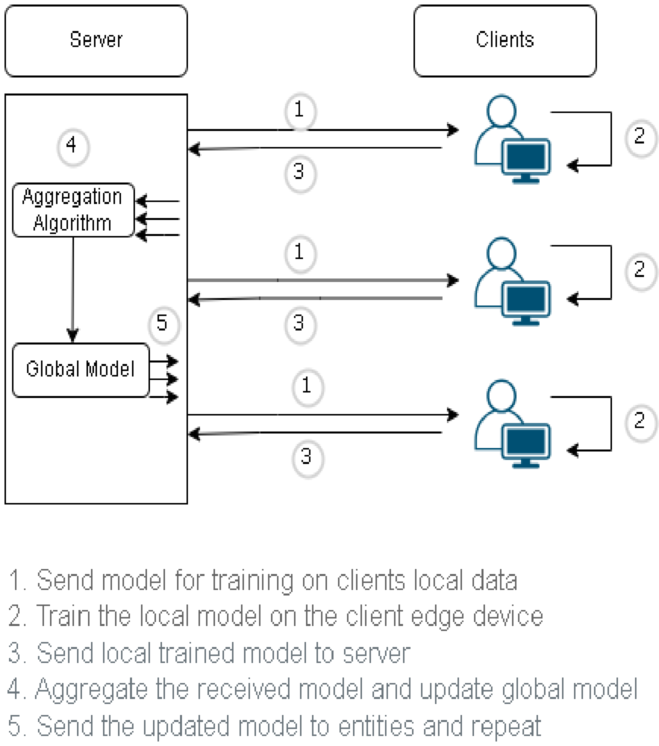

Fig -1: Working of Federated Learning

4. METHODOLOGY

4.1 Framework

The frameworks used in this research were Pytorch and Flower. The Pytorch framework was used to define and train the CNN model. The flower framework was used for creating a client and server architecture for federated learning training.

4.2 Dataset

The dataset utilized in this research consists of Alzheimer's MRI images with a resolution of 128 x 128 pixels, obtained directly from Kaggle. The images have undergone preprocessing, including resizing to 128 x 128 pixels, performed by the dataset contributors on Kaggle. The dataset is integral to the investigation and development of machine learning models for Alzheimer's Disease diagnosis."

The dataset contains a total of 6400 images distributed amongst the following classes based on severity

1. MildDemented
2. VeryMildDemented
3. NonDemented
4. ModerateDemeneted

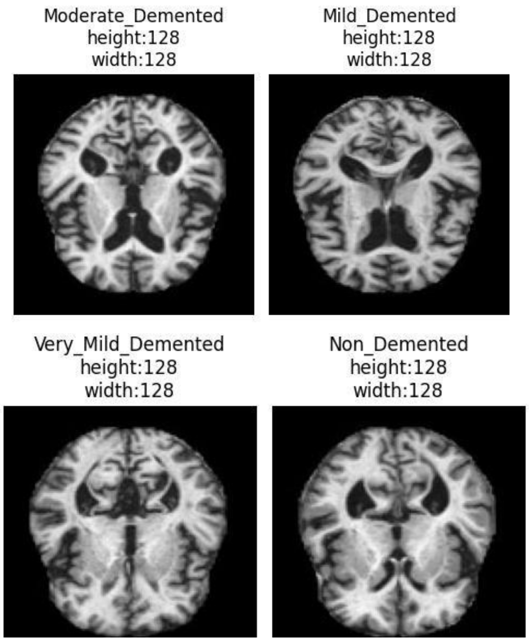

Fig-2: Classification of MRI image of the brain

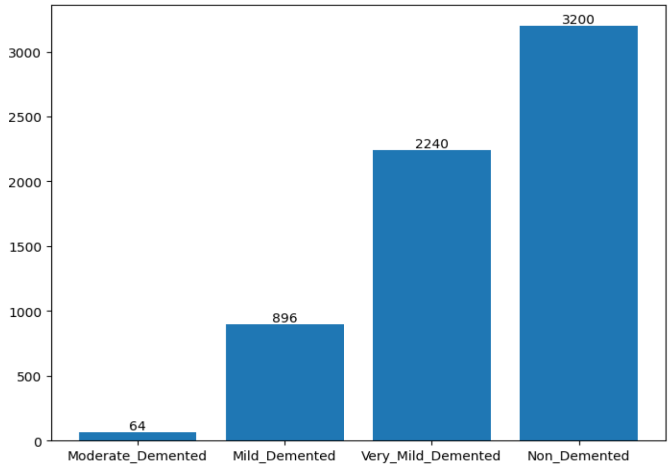

Fig-3: Distribution of images amongst classes

5. NEURAL NETWORK MODEL

We have defined a CNN model with below configuration

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 30, 30]             896
            Conv2d-2           [-1, 32, 28, 28]           9,248
         MaxPool2d-3           [-1, 32, 14, 14]               0
            Conv2d-4           [-1, 64, 12, 12]          18,496
            Conv2d-5           [-1, 64, 10, 10]          36,928
         MaxPool2d-6             [-1, 64, 5, 5]               0
            Linear-7                  [-1, 128]         204,928
              ReLU-8                  [-1, 128]               0
            Linear-9                    [-1, 4]             516
================================================================
Total params: 271,012
Trainable params: 271,012
Non-trainable params: 0
----------------------------------------------------------------
```

Fig -4: CNN Model Summary

A combination of Stochastic Gradient Descent as the optimizer and the Cross-Entropy Loss function as the criterion used for model training process.

6. AGGREGATORS

In Federated Learning (FL), aggregators play a crucial role in combining the knowledge learned by individual clients during their training processes. These functions are responsible for merging the model updates or parameters received from different clients into a single, updated model at the central server.

6.1 FedAvg

Federated Averaging (FedAvg) is a popular algorithm used in Federated Learning (FL) for model aggregation. The principle of this approach is to aggregate models learned on distributed nodes to obtain a new, “average” model. This aggregator uses coordinate-wise averaging of the model parameters for aggregation.

6.2 FedYogi

FedYogi, or Federated Yogi, is an adaptive federated optimization algorithm that is inspired by the Yogi optimizer. FedYogi is designed to handle non-convex optimization problems, which are common in deep learning. These problems have multiple local minima, and the goal is to find the global minimum.

6.3 FedOpt

Federated Optimization (FedOpt) is a distributed approach for collaboratively learning models from decentralized data, designed with privacy protection. It is based on adaptive optimizer which dynamically adjusts the parameter during optimization process.

6.4 FedMedian

FedMedian is a configurable federated learning strategy. The FedMedian strategy accepts failures, which means it can still aggregate if there are failures. This is particularly useful in real-world scenarios where some nodes might fail to return their updates within a given timeframe.

6.5 FedTrimmedAvg

FedTrimmedAvg is a variant of the Federated Averaging (FedAvg) algorithm. It introduces a new aggregation rule, Tmean(), which is derived from the Mean() function by trimming some of the values before averaging them. The server then trims a certain portion of the highest and lowest updates, The remaining updates are averaged to compute the global update.

7. TRAINING & TESTING

The sequence diagram below illustrates how the model learns without sharing data with the server

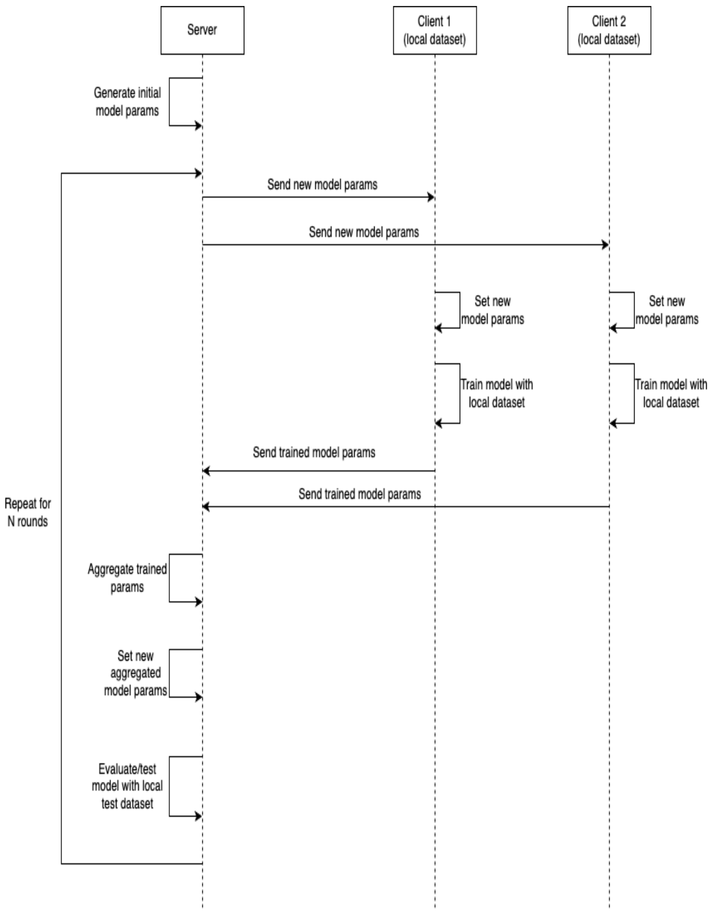

Fig -5: Working of Proposed model

1. The server initially generates random model parameters/weights and shares them with connected clients.

2. Clients use these initial model parameters/weights to start training with their local data, following the instructions defined in the client code.

3. After completing the training, the clients share the trained parameters/weights back with the server.

4. Upon receiving the trained parameters/weights from all connected clients, the server performs aggregation using a defined aggregation function.

5. The aggregated parameters/weights are then used to evaluate the model accuracy on the server, utilizing a local test dataset.

6. The newly aggregated parameters/weights are sent to clients for the next round of training, and the cycle continues for N rounds.

It's worth noting that there are two main approaches to evaluating models in federated learning systems: centralized (or server-side) evaluation and federated (or client-side) evaluation. In this implementation, we have opted for the centralized approach for its simplicity.

8. RESULT

To establish a baseline for comparison with Federated Learning (FL) approaches, we trained the same model on the entire dataset from clients 1 and 2 using a centralized approach. After 70 epochs, we achieved an accuracy of 94.77% on the evaluation dataset. This result serves as our baseline. It's important to note that we haven't optimized the centralized training to yield better accuracy, as our primary goal is to demonstrate that with federated learning, the same level of accuracy can be achieved without compromising privacy.

The following results were obtained by training the model for 20 Federated Learning (FL) rounds, totaling 100 epochs. In comparison to centralized training, we observed that an increase of 30 epochs was necessary during federated learning. This adjustment compensated for the loss incurred due to aggregation, ultimately allowing us to achieve the same level of accuracy.

Table -1: Comparison Table

Aggregator	Test Acc %
FedAvg	93.90
FedYogi	91.83
FedTrimmedAvg	**94.44**
FedOpt	93.79
FedMedian	93.90

9. CONCLUSIONS

The Federated Learning (FL) approach yielded accuracy comparable to the centralized training of models. Although it required more epochs to reach a similar level of accuracy, this was anticipated due to the aggregation-induced loss. Importantly, the data remains on the client's end, mitigating privacy risks. Furthermore, among the five FL aggregators, we found that "FedTrimmedAvg" aggregation strategy performed the best for this particular scenario obtaining an accuracy of 94.44%.

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