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Optimize Weight sharing for Aggregation Model in Federated Learning Environment of Brain Tumor classification

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ABSTRACT

Clinical diagnosis and therapy of brain tumors are greatly aided by proper classification of the tumors. Brain tumors can be diagnosed more quickly and accurately if radiologists use deep learning to help the specialist and doctors examine the enormous volume of brain MRI Images. Large datasets are required in training process, and whole of such data must be centralized for be handled by such techniques. It is sometimes impossible to collect and distribute patient data on a centralized data server because of medical data privacy regulations. In this paper, federated learning (FL) is proposed, in which data is non-shareable because of patient privacy issues. Using the FL approach, we have proposed two methods of aggregation; first, which concerns ranking the weight percentage of each client, and Second average weights method. and to evaluate the suggested model, we have compared the performance of the ranking weights percentage method with the average weights of proposed CNN and pre-training (VGG-16) in the FL environment in addition to SVM and VGG-16 . The experiments result was applied on two datasets, it shows our model accuracy result is very effective when using the ranking weight percentage method as compared with other methods, it achieves accuracy (98%) on datasets (BT_large-1c) and achieve (97.14%) on the dataset (BT-large-2c).

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1. Introduction

Here Brain tumors are considered one of the deadliest cancers around the world. They result from abnormal cell growth and abnormally developing tissue. When cancer grows in the brain, it enlarges and increases pressure and causes a tumor, causing unusual neurological symptoms and leading to death.

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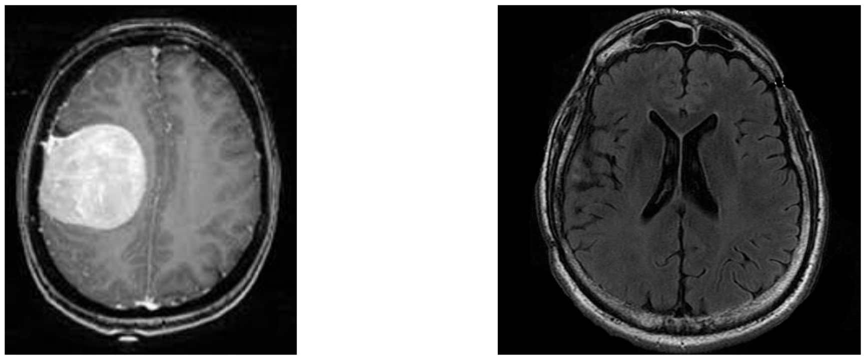
Early diagnosis and detection may help the specialist evaluate the disease level and type of treatment, saving the patient's life in the case of a brain tumor.

It's difficult to go through all the MRI scans generated regularly in the clinic and manually evaluate them. As a result, early tumor detection requires computer-aided procedures that are more accurate. Brain tumors can be cancerous cells (malignant) and noncancerous (benign) [1]. Figure1 shows an example of a healthy brain and an unhealthy (brain tumor).



(a) (b)

Fig. 1. Example of (a) unhealthy brain (b) healthy brain

Over the past few years, one of the tools that have been used in the medical analysis field is machine learning approaches and deep learning[2]. Deep learning is a branch of machine learning that plays an essential role in medical images, including treatment planning, clinical diagnosis, decision-making, and detecting dangerous human diseases, such as blood cancer, brain tumor, and skin cancer. Therefore, there has been an increased interest in employing deep learning techniques to improve the efficiency and robustness of medical images[3].

All the clinics and hospitals have their data, and these data are non-shareable because of the privacy issues regarding the patients; therefore, the concept of federated learning and distributed system comes into the picture, where the training implemented locally at each client or hospital then only the training parameters are sharing between them without any share of patient's information[4].

1.1. Problem statement

The diagnosis of brain tumors has an important role in healthcare applications and in saving patients. There have been rapid developments in smart systems, but they still face many challenges, some of its list below :

1. All the clinics and hospitals have their data, which are non-shareable because of the privacy issuers regarding the patients. And it is a sensitive information of clinics and hospitals.
2. Implement a decentralized intelligence model to diagnose a brain tumor in a federated learning environment.

1.2. Contributions

The main contributions of this paper work can be contain the following:

1. All Clarify the most important DL models, especially the proposed CNN model, and how to adapt them to provide the best performance when diagnosing and classifying brain tumors.
2. Another contribution of this work is diagnosing a brain tumor in the federated learning environment, which is trained locally without exchanging the data due to privacy.
3. This paper contributes to the use of the aggregation method in federated learning and to know the benefit of using this and its effects on the performance of diagnosing a brain tumor in the federated learning environment.

2. Related work

All Among many research types that have been applied in the medical image to develop techniques that use federated learning and deep learning, we are reviewing articles closely related to our work.

This section will be discussed in the literature survey focusing on federated learning and deep learning in studies of medical image analysis. FL is frequently compared with distributed learning, parallelism learning, as well as deep learning. While FL is still a young concept domain, many related publications look into it in greater depth.

FL has emerged as an essential framework for applying distributed machine learning in settings where data is spread across computational clients and training is done locally or privately. Many recent works will be compared in this part.

Adnan Qayyum et al. (2021)[5] proposed a cooperative learning model for COVID-19 diagnosis by benefiting from a Cluster federated learning (CFL) method. These enabled remote healthcare centers to take advantage of each data in other places remotely without sharing the data. Because their restrictions run hard on privacy and protection (for example, low latency), remote healthcare points lack Diagnostic Advanced Facilities. Visual data ("X-rays" and "ultrasounds") is assembled in several centers. Therefore, CFL is suitable for detecting COVID-19 in "X-ray" and "Ultrasound" images. Result Clustered federated learning ensures the best performance than conventional FL, low latency, and increased privacy and data safety. better performance is acquired in two datasets in comparable results against a central baseline, models with central data are trained and refinement 16%, 11% in total F1- Scoring achievement on a multimodal trained in federated learning traditional setting in data sets X-ray and ultrasound. Machine-learning design in public and deep learning in specific need high rate of computational and resources handling, work the publishing of machine learning infeasible of many computing applications.

Mikhail Khodak et al. (2020)[6] proposed the weight-sharing neural architecture search (NAS) technique of neural architecture search (the simultaneous Optimization of multiple neural networks using the same parameters) for the context of federated learning with personalization, tuning hyperparameters for algorithms like Federated Averaging (FedAvg) can be expedited. Proposed technique FedEx, an approach accelerating the tuning of hyperparameters for federated hyperparameter optimization based on the exponentiated gradient update, effectively tunes FedAvg instead from settings of SGD local, and based on the relationship between this setting and meta-learning and draws inspiration from differentiable NAS. They automatically implement the latest techniques and require Hyperparameter tuning, an essential but costly component. With federated learning (FL), where models are learned through a dispersed network of heterogeneous devices, it is even more challenging to efficiently train and assess multiple configurations because of local training and data retention requirements. Our approach beats a natural baseline by 1.0-1.9 % on the Shakespeare dataset when tested in five random trials in federated hyperparameter tuning.

Ke Zhang et al. (2020). [7] produced a new method for gathering ensemble results from several models on decentralized edge devices. Rather than passing the training information of single models, use Federated Machine Learning (FML) to build a Privacy-Preserving Federated Learning System that relies on a trusted central server. An agent solely gathers individual IoT devices' inference findings. In addition, it suggested a new Secure Crowdsourcing Aggregation Algorithm (SCAgg) for the system, which may deliver more accurate predictions based on diverse inference findings from individual IoT devices. In the event that training datasets for individual models are biased and mixed, generic Federated Machine Learning (FML) approaches may lead to privacy leakage due to the sharing of training information for unique models. Its experiments are on the MNIST dataset with 5, 10, 20, 50, and 100 DOs. MNIST is a database that contains handwritten digits classified from 0 to 9. In experimental, show SC-Agg exceeds majority voting and is the top performer among all data owners, according to our results in various circumstances.

Kang Wei et al. (2020)[8] suggested using a new framework based on "differential privacy" (DP); this method was used by adding artificial noises to parameters in the client direction only before aggregation, i.e. "noising before model aggregation federated learning" (NbAFL). First, appear that the NbAFL can require to meet DP at different security levels by correctly adapting differences in added noises. Next, optimize the theoretical convergence related to the lack of function in the trained federated learning (NbAFL). The proposed method used a "K-client random scheduling strategy", randomly choosing from N all clients to share for any aggregation. Federated learning is a type of machine learning distributed its ability to prevent disclosing data clients' private data to enemies. However, private information can still be revealed by evaluating uploaded parameters from clients. The complete simulation results confirm the validity of the analysis. Therefore, the analytical results are helpful for the design of specificity-preserving federated learning structures with different trade-off requirements on affinity performance and specificity levels.

Santiago Silva et al. (2019)[9] Suggested searching for an analytic solution within federated learning models or meta-analysis. In the federated setup, the model is controlled without sharing information across centers, only the parameters model. Instead, a meta-analysis performs a statistical test to combine results from several independent examinations. Different data sets it's stored in various institutions that cannot be directly shared because of legal concerns and privacy. As a result, the full exploitation of extensive data in the research of brain illnesses is limited. As a result, a fully consistent framework in the federated analysis for distributed biological data was tested and validated.

Abhijit Guha et al. (2019)[10] proposed using BrainTorrent, a new federated learning framework without a central server, aimed specifically at medical applications. BrainTorrent offers a highly active peer-to-peer environment, and each center interacts directly with the other without relying on a central body to organize the training process. A disadvantage of federated learning is the reliance on a central server, which requires each client to agree on a single trusted central body, which may disrupt the training process for all clients. It was selected as the challenging task for whole-brain segmentation for the MRI T1 scan. For experimentation, utilize the Multi-Atlas Labelling Challenge (MALC) dataset. QuickNAT architecture was chosen because it provided state-of-the-art performance for whole-brain segmentation. The aggregated model for BrainTorrent obtains the performance of the pooled model, but the implementation of FLS has 3% Dice points lower than that. When average Dice scores across clients are compared, BrainTorrent surpasses FLS by 7% Dice points. As a result, a proof-of-concept that addresses the challenging job of whole-brain segmentation has been presented, proving BrainTorrent performance is unaffected by the non-uniform distribution of data. Table 1 shows a summary of the related work based on Federated Learning.

Priyanka Modiya and Safvan Vahora. (2022)[11] suggested a unique brain tumor detection technique, which employs a convolutional neural network with a transfer learning strategy coupled with the dimensionality reduction method. The transfer learning EfficientNetB7 models with the PCA method for feature extraction followed by feature reduction. Its experiments on the dataset available in Kaggle contain 3000 MRI, including 1500 normal and remaining abnormal images. Fusing features extracted from the CNN EfficientNet model and PCA provides better accuracy. its achieved (80.00 %) validation and accuracy (80.00 %).

Table 1 - Summary of related work (Federated Learning)

Authors	years	Technology	Dataset	Accuracy
Adnan Qayyum et al. [5]	2021	clustered federated learning (CFL)	chest X-ray, chest ultrasound images	-
Mikhail Khodak et al. [6]	2020	neural architecture search (NAS) technique of weight-sharing	Shakespeare	-
Ke Zhang et al. [7]	2020	light-weight Secure Crowdsourcing Aggregation (SC-Agg)	MNIST dataset	89.79%
Kang Wei et al. [8]	2020	differential privacy (DP)	MNIST dataset	-

Santiago Silva et al. [9]	2019	meta-analyzing	ADNI, PPMI, MIRIAD and UK Biobank dataset	-
Abhijit Guha Roy et al[10]	2019	BrainTorrent (peer-to-peer)	(MALC) dataset	-
Priyanka Modiya, Safvan Vahora[11]	2022	EfficientNet-B7 with PCA	3000 BT-large-1c	80.00%

In previous work, the major limitation of the above models was that it has some accuracy loss compared to the model trained in all data-sensitive. In addition, the data owners do not have contact with each other or the third party, which shows a gap in the system's accuracy.

3. Proposed Model

The proposed model majorly contains three main sections.

3.1 *Convolution Neural Network (CNN)*

In general, a CNN model is composed of three main components. They often include convolutional, pooling, and fully connected layers. The convolutional layer is used for feature extraction of the entire image [12][13]. The second part is the pooling layer which is used to lower the dimensionality of retrieved features, decreasing the complexity and the computing time[14]. The fully connected layer is the ultimate phase in the CNN model, which seeks to achieve linearity in the networks [15]. The architecture of CNN is shown in Figure. 2.

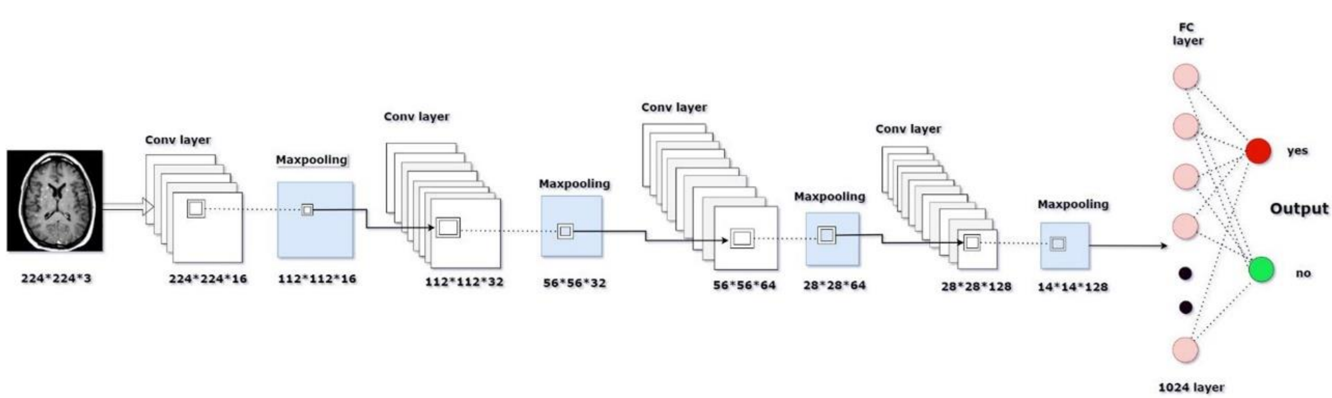


Fig. 2 CNN Architecture layers

3.2 *Federated learning (FL)*

Federated learning is a collaborative machine learning method that emerges promising solutions for protecting user privacy by allowing model training on massive decentralized data [16]. A typical FL model uses a novel training platform that keeps clients' data private locally while obtaining a high-performance global model by sharing parameters rather than data[17]. Traditional machine learning methods assume the existence of central (cloud-based) organizations responsible for data processing. Nonetheless, with the complexity of accessing private data, along with the high cost of transmitting primary data to a central server, and ever-increasing data privacy concerns and network restrictions, Data owners are frequently concerned about sharing their data with another party, whether it is a well-known business or one that they are unfamiliar with[18][19]. Led the development of Federated Learning, a decentralized machine learning approach. Figure 3 shows the framework of the federated learning proposed model

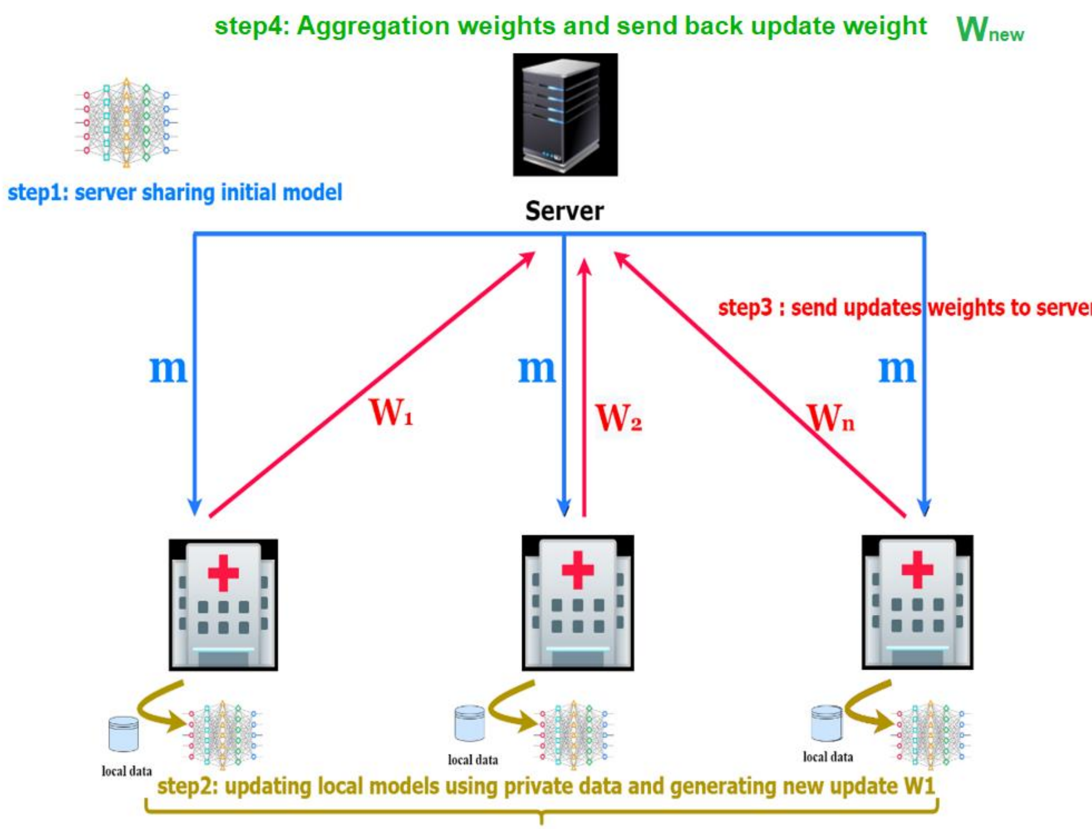


Fig. 3 Federated Learning structure

3.3 *Optimize weight-sharing*

Most of the Federated Learning techniques used averaging weights for the model parameters for aggregation. Still, this method is not adapted in heterogeneous environments, where the data is not distributed homogeneous and is not identical [20].We proposed a new aggregation method, which concerns the effective ranking weights based on the percentage of each weight and according to the size of the data in each client, where we take a percentage of the sharing weight and then combine them. This method is suitable and adapted to a heterogeneous environment, and it's efficient and robust as it takes the same parameters. Where algorithm (3-1) iullustrate the steps of aggregation model.

Algorithm (3.1) Classification brain tumor classification model in Federated Environment

Input MRI images

Output: Classification result

Algorithm Steps
Step1: Global CNN Model initialized in server.
Step2: Establish a number of clients =2 (in this paper).
Step3: deploy the CNN to each client.
While communication _iteration < = max_number **do**
Client-side:

1. Feature extraction using CNN model.
2. Train the CNN model based on Features.
3. From the fully connected layer, get the training result.
4. Evaluate the performance based on the metrics
5. Return the final weight to the server.

Server-side:
$\text{weight}_{\text{crossover}} = \cap\ (w_1 ,\dots, w_i)$

Update the weight for all clients
End
End
Output training model for brain tumor classification

4. Experimental result and discussion

Some experimental have been done in this work to show the performance and evaluate the achieved result.

4.1 *Dataset*

In this paper, the proposed system's accuracy of classification procedures in a federated environment is assessed in two datasets of MRI brain tumors. To keep things simple, we refer to The first dataset, Brain Tumor Detection 2020 (Br35H) dataset, as BT-large-1c, consisting of 3000 images obtained from the Kaggle website[21]. It contains two-part: 1500 normal and 1500 abnormal. The second dataset, Brain Tumor Classification (MRI), which we've dubbed BT-large-2c, was obtained from the Kaggle website[21]. It consists of 3264 images, 2764 abnormal, and the remaining image 500 normal. Table (2) explains the details of the image data exploited in the experiments.

Table 2 -explain the details of the dataset exploited in the experiments

Dataset Description					
Dataset	Total image	Normal image	Abnormal image	Type	Available
BT-large-1c	3000	1500	1500	JPG	Web Kaggle

BT-large-2c	3264	500	2764	JPG	Web Kaggle

Two datasets are available in (JPG) format and have three-dimensional (RGB) with different resolutions.

4.2 *Result and analysis*

We evaluated the performance of our aggregation weight, ranking weights algorithm in terms of classification accuracy, F-score, recall, and precision by comparing it with other techniques with average weights federated learning using two datasets. In our experiments, when ranking weights percentages on our two datasets, we'll use the results of these tests to assess our model. With a batch size of 32. we trained the models for 50 epochs. The Federated learning model, when using ranking weight percentage by getting first (53% first weights) from (BT-large-2c) and getting (47% second weight) from (BT-large-1c), showed (95%) accuracy on our dataset (BT-large-1c) and (96%) accuracy in our dataset (BT-large-2c). Achieve accuracy (93%) on data set (BT-large-1c), and achieve(96%) accuracy on (BT-large-2c) when applied ranking weight percentage by getting (47% first weight) from (BT-large-1c) and followed by (53% second weight) from (BT-large-2c). When applied federated learning share weight average it achieve (94%) on dataset(BT-large-1c) and (95%) on dataset (BT-large-2c).

The accuracy graph of the testing and validation phase during the iterations of our suggested method with share weight optimization on the dataset (BT-large-1c). Below, show the Mathematical equation for the aggregation model, average weights Eq.(1), and ranking weights percentage Eq.(2).

$$Average_{weight} = \frac{(\sum_{i=1}^{no\ of\ clinet} wi)}{no\ clinets} \quad .... (1)$$

$$Aggregate_{weight} = crossover\ (w\ i, ... w\ n) \quad .... (2)$$

When applied federated learning share weight average it achieve (94%) on dataset(BT-large-1c) and (95%) on dataset (BT-large-2c). Figures 4 and 5 show the training and loss function of the FL model of two different datasets.

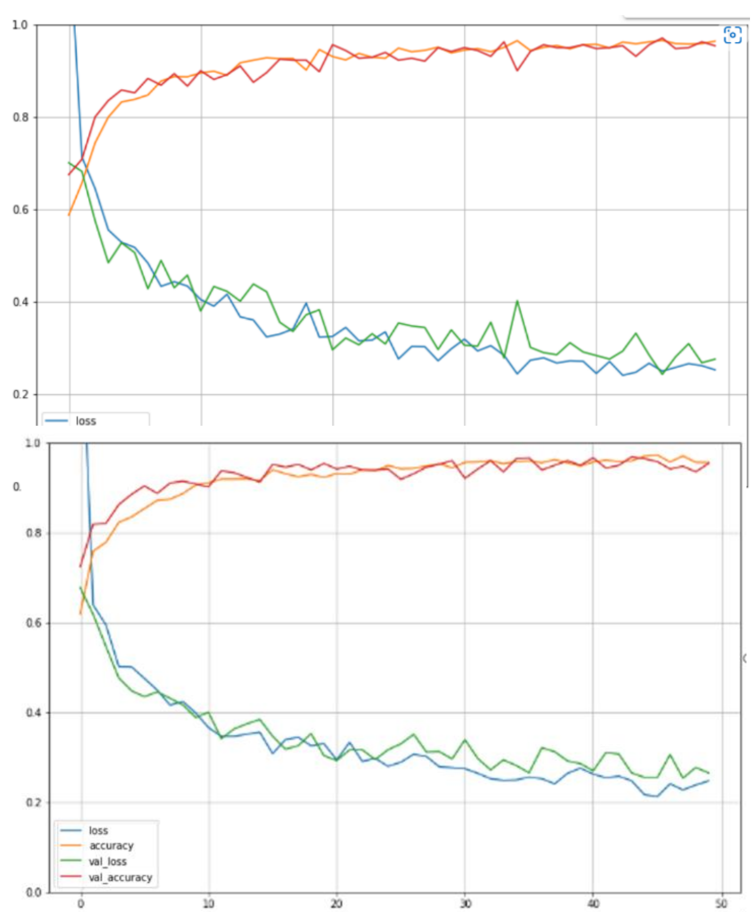


Fig. 4 training and loss function (BT-large-1c)

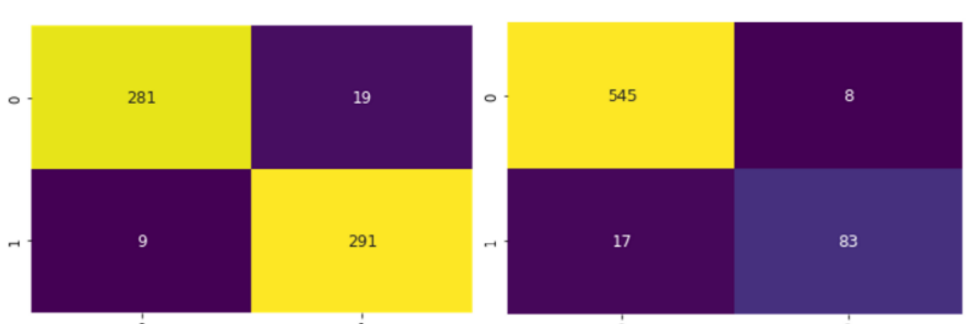
Fig. 5 training and loss function(BT-large-2c)

The Precision and Recall, F1-score, Accuracy of proposed CNN, and using federated learning with methods, average weight and ranking weights percentage its shown in table 3.

Table 3. Comparing the result of the proposed model with different strategies

	BT-large-1c				BT-large-2c			
Model	Accuracy	precision	recall	f1-score	Accuracy	precision	recall	f1-score
Proposed CNN	95.77	96	96	96	95.3	88	90	93.5
VGG-16	94.66	94.5	95	95	96.73	93	93	93.5
VGG-16 +SVM	94.6	94.5	94.5	95	95.3	83.5	88	94
FL (Average)	96.66	96.5	97	96.5	96	91	93.5	**96**
FL crossover	**98**	**97.5**	**98**	**98.5**	**97.14**	**93.5**	**94**	95.5

Based on the previews table of the results, ranking weights percentage in FL achieves the best result from other techniques; it gives high accuracy due to its using the same parameter in sharing weight percentage. The confusion matrix is used on both datasets to show the experiment's class-wise performance in the experiments on ranking weight percentage show in figure 6.



BT-large-1c BT-large-2c

Fig. 6 confusion matrix on two datasets

Figure 7 compares Federated learning based on ranking weights percentage with other technique of two datasets.

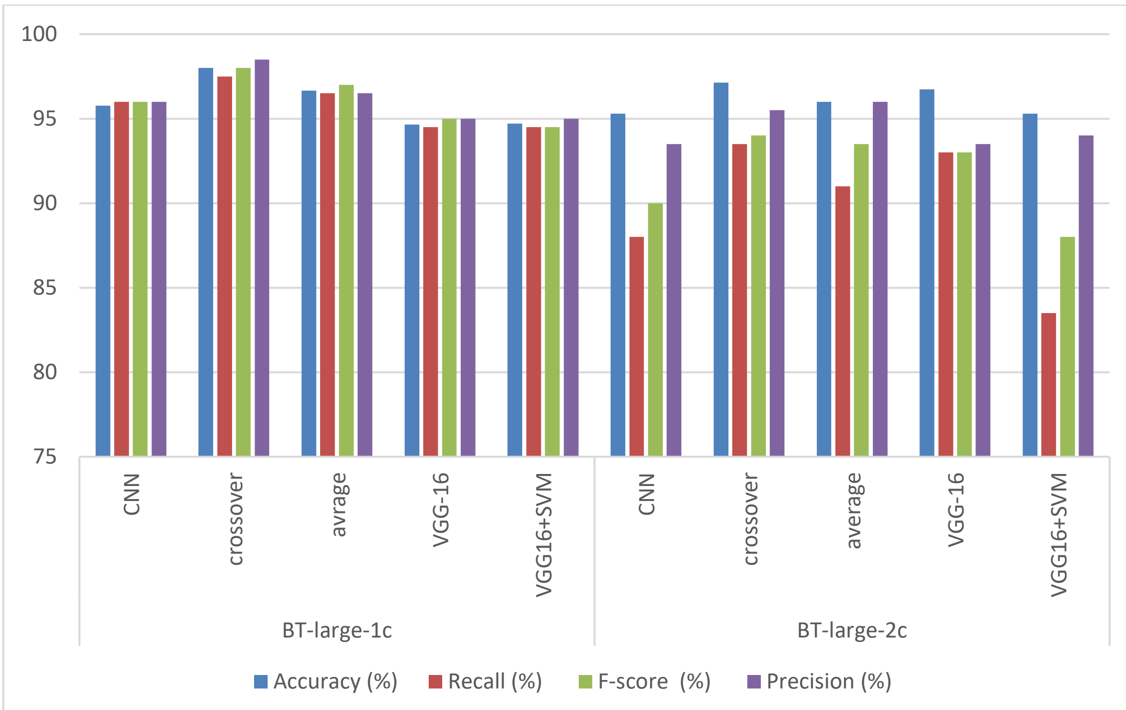


Fig. 7 comparison of ranking weight with other techniques.

The result obtained by applying FL using the proposed crossover for training parameters aggregation method recorded the highest accuracy percentage in the approach, reaching 98% and 97.14% on(BT-large-1c) and (BT-large-2c datasets), respectively.

5. Conclusion

In summary, we presented new aggregation method based on ranking concept of weights in federated learning environment to optimize sharing weights in brain tumor classification. Federated learning reveals a robust heuristic technique and addresses the gap between deep learning and data accessing for artificial intelligence applications. Nevertheless, for language model neural networks, there are still unsolved issues, especially communication costs, to be solved. This ranking weight method allows us to use adaptive aggregation to achieve high-accuracy models. Experimental results among two datasets demonstrate that our proposed ranking weight percentage approach provides better performance and considerable improvements due to using the same parameters in the aggregation model.

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