Federated Learning of Privacy-Preserving Brain Tumor Detection with MRI Image: A Comparative Study

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***Abstract*—One of the most important challenges in clinical diagnosis is the identification of brain tumors from MRI scans, and early discovery greatly improves the patient's prognosis. In terms of autonomous segmenting and classifying brain tumors, deep learning techniques have recently produced exceptional results. However, collecting sensitive medical data is necessary for traditional model training using a centralized method, which poses serious concerns regarding data security, privacy, and legal issues. Federated learning, which has recently emerged as a possible decentralized learning paradigm, is one of the ways through which many institutions can cooperate using train models without sharing raw patient data. We provide a comparative study of deep learning models, which are based on the work of federated learning to detect brain tumors on MRI images without violating privacy [1].The proposed study evaluates the effectiveness of federated optimization us- ing the Federated Averaging (FedAvg) algorithm in a multi-client setting, simulating distributed healthcare institutions with non-identically distributed (non-IID) data.Lightweight and pre- trained convolutional neural network architectures are utilized, balancing both the computational efficiency with diagnostic accuracy for resource-constrained environments. Experimental analysis reveals competitive performance with federated training while granting data locality and confidentiality. Further, expected trade-offs with respect to centralized learning are noted. The convergence behavior across different communication rounds real-world deployment of federated learning for medical im-age analysis in healthcare [2]. Moreover, challenges including communication efficiency, heterogeneity in systems, and model generalization have been discussed with interpretations from the recent works in federated learning. The obtained results firmly establish FL as a practical and privacy-oriented solution for collaborative brain tumor detection and create a base for further research related to scalable and secure medical imaging.**

***Index Terms*—Federated Learning, Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Privacy-Preserving Deep Learning**

I. INTRODUCTION

One of the most dangerous and potentially fatal neurological conditions is a brain tumor. Patient survival and treatment planning depend on an accurate and timely diagnosis. Due to its non-invasive nature and ability to provide better soft tissue delineation, magnetic resonance imaging (MRI) has been extensively used in clinical practice [1]. Particularly, convolutional neural network (CNNs) have of late been suc- cessful in automatically detecting and localizing brain cancers using MRI data. Radiologists' workloads have significantly decreased as a result, and clinical decision-making has become more consistent [2],[3].

Even with these improvements, most current deep learning methods still use centralized training paradigms, which means that large medical datasets have to be stored on a central server. Centralized methods like these make people very worried about patient data privacy, following the law, and who owns the data, especially when healthcare laws are strict like HIPAA and GDPR [3], [4]. Hospitals and other medical facilities often can't or won't share sensitive patient information. This makes datasets incomplete and makes it harder to create strong, generalizable diagnostic models.

Federated Learning (FL) has become a viable decentralized learning model that can solve these issues by allowing collab- orative model training without direct interaction of data [5]. In federated learning where the training of models is carried out locally at enrolled universities, the changes in models alone are transmitted to a central server where the

changes are aggregated. This model significantly reduces privacy threats while enabling several institutions to benefit from collaborative learning. FL is gaining popularity in many domains, including digital health, mobile systems, and large-scale distributed optimization [6], [7].

Federated learning provides a workable solution for coop- erative brain tumor analysis across institutions while main- taining data confidentiality in the context of medical imaging. However, new issues like statistical heterogeneity (non-IID data), system heterogeneity, communication overhead, and convergence instability are brought about by federated learning in medical image analysis [8], [9]. These problems are espe- cially noticeable when working with deep neural networks and complicated medical imaging tasks.

Inspired by these difficulties, this paper compares federated learning methods for MRI image-based privacy-preserving brain tumor detection. The study focuses on evaluating deep learning architectures and federated learning techniques in decentralized data environments. The given work tries to provide practical information on the feasibility of federated learning to the real-life diagnosis of brain tumors by evaluating the performance of federated learning in accuracy.

II. LITERATUR REVIEW

When federated learning was first introduced as a communication-efficient framework for training deep neural networks on decentralized data, the Federated Averaging (Fe- dAvg) algorithm was proposed as a basic aggregating method [1]. By averaging locally updated model parameters at a central server, FedAvg eliminates the need to distribute raw data, enabling numerous clients to collaborate to train a global model.This method reduces communication overhead by a large factor and is a common methodology to most federated learning systems, although as communication between clients is not identically and independently distributed (non-IID) (as is common in real-world deployments, such as healthcare sys- tems), FedAvg exhibits unstable convergence behavior and can be observed to significantly degrade performance in practice [9].

Heterogeneous data setting suggests a large number of adap- tive and optimized federated learning algorithms suggested in the literature to address the shortcomings of FedAvg. Adap- tive federated optimization strategies, like FedAdam, FedYogi and FedAdagrad extend the existing server-side optimization systems to include the variation in the gradient among clients by examining client adaptive learning rate schemes [10]. It is found that these methods result in converged faster and more stable when using skewed data distributions. The federated op- timization in heterogeneous networks has also been examined in the context of the interactions between the statistical and system heterogeneity of various computational capabilities and communication delays, and the overall model performance. These investigations encourage the creation of more resilient aggregation techniques that can manage practical deployment settings [11].

Because medical data is sensitive, the use of federated learning in healthcare has received a lot of attention lately. According to surveys on federated learning applications, pri- vacy preservation is a crucial requirement in fields like digital health, medical imaging, and clinical decision support systems [6], [7]. Federated learning is in line with ethical and regu- latory frameworks in the healthcare industry by facilitating collaborative model training without direct data exchange. Federated learning can enable large-scale collaborative med- ical image analysis across hospitals and research institutions while upholding strict data confidentiality, as several studies have shown [12].

Many federated deep learning techniques have been pro- posed for MRI-based tumor detection and segmentation tasks in the particular context of brain tumor analysis. While main- taining patient data localization at individual institutions, fed- erated CNN-based frameworks have demonstrated promising performance in classifying various types of brain tumors [13], [14]. More sophisticated methods combine federated learning with transfer learning and lightweight deep neural network architectures to further improve performance, allowing effec- tive training under constrained computational resources and data availability [15]. Furthermore, the efficiency of utilizing various MRI modalities across institutions to enhance segmen- tation accuracy and robustness in brain tumor analysis has been shown by multi-modal and multi-institutional federated learning frameworks, such as

Fed-MUNet [16].

Recent research has concentrated on the enhancement of communication efficiency in federated learning for the purpose of classifying brain tumors. Among the proposed techniques, ensemble knowledge distillation and communication-efficient aggregation mechanisms stand out as they allow the reduction of the quantity of model updates sent, at the same time maintaining the performance of the classification in non-IID settings [17]. These methods are especially important in the context of medical imaging, where the models are usually very large and the communication bandwidth might be very low. Furthermore, the extensive reviews of privacy-preserving tech- niques in federated learning have pointed out the necessity of secure aggregation protocols, differential privacy mechanisms and the resilience to adversarial attacks in medical image analysis systems as the main issues [18].

Authoritative research work has been performed showing that federated learning has the capability of being used as a technique for brain tumor diagnosis, yet the matter is not entirely solved and the challenges still exist. The questions of data heterogeneity regarding convergence, communication costs, and the performance of various deep learning archi- tectures are still being actively researched. This publication which is based on previous studies, offers comparing federated learning-driven deep learning models designed for brain tumor detection and emphasizes the performance evaluation under decentralized, privacy-preserving data settings.

III. METHOD

A. Dataset Description and Preparation

The model training and evaluation was carried out using an MRI brain tumor dataset that comprised 3,096 labeled images. The four categories included in the dataset were glioma tumor, meningioma tumor, pituitary tumor, and normal brain images. JPEG format was used for all MRI scans, which had a maximum resolution of 256×256 pixels. The dataset was structured in a way that each class was given a separate directory, making it possible to load data efficiently with directory-based data pipelines.

To ensure that all the models are similar across the board so that the trained models can be used, the size of the images was reduced to 224x224 pixels. The data was separated into two sections, i.e. training, and validation based on the 80:20 ratio through random selection. By normalizing the pixel values, it was aimed that the training convergence would be with a higher stability. The TensorFlow tf.data API was used in combination with prefetching for the loading and batching of data to achieve maximal GPU utilization and minimize the latency of the input pipeline.

B. Federated Learning Framework

Federated Learning (FL) ensured the confidentiality of the data during the model training process, thus, it was adopted. The training dataset was divided among several simulated clients—representing independent medical institu- tions—rather than bringing all MRI images to a central server for processing. For this research, five federated clients were assigned a share of the training data based on a stratified index- based partitioning technique which guaranteed that every client got a different portion of the training samples.

Let w stand for the global model parameters and N for the total number of clients that take part. Each client i uses its private dataset D_i to locally optimize its model. Only the model parameters are sent to the central server following local training [11]. Using the Federated Averaging (FedAvg) technique, which is described as follows, the server aggregates these parameters:

$$w^{(t+1)} = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{j=1}^{N} |D_j|} w_i^{(t)} \quad (1)$$

where $w^{(t)}$ represents the locally updated weights from client i at communication round t. For the subsequent training cycle, the revised global model is redistributed to every client. Until convergence, this procedure is continued over several communication rounds.

C. Deep Learning Model Architectures

Two pretrained convolutional neural network models, Mo- bileNetV2 and EfficientNet-B0 were utilised to evaluate the performance of federated learning in different topologies. The reason behind selecting these designs is that they provide a good trade-off between classification accuracy and computa- tional efficiency; they are suitable in applications that need

distributed and resource-constrained environments [15].

To use transfer learning, ImageNet pretrained weights were used to initialize the convolutional basic layers of both archi- tectures and were frozen throughout the training process. It was represented by a global average pooling layer, followed by a fully connected dense layer with ReLU activation and a final softmax layer, which represented the four tumor classes [14]. Multi-class classification was based on the loss function that was categorical cross-entropy, and Adam optimizer was employed to optimize it [16].

D. Federated Training Procedure

At the beginning of federated training, the global model weights were set and matched across all clients models. At every round of communication, each client applied its own dataset in one epoch of local training. Client models uploaded their learnt weights to the central server upon completion of local updates.

To update the global model, the server used the FedAvg algorithm for parameter aggregation. Before the subsequent communication cycle, all clients received a redistribution of the modified global weights. Several iterations of this federated training cycle were carried out until the validation accuracy stabilized, signifying convergence.

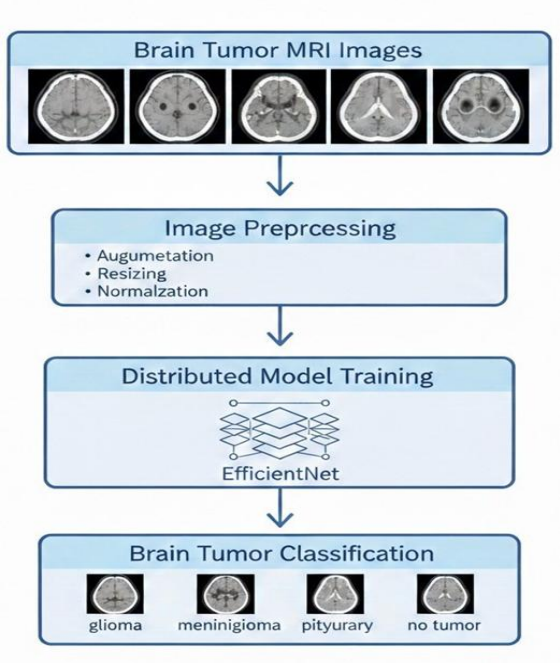

Fig. 1. workflow

E. Performance

The performance of the models was evaluated using ac- curacy, precision, recall, and F1-score, which was calculated with the use of macro-averaging to compensate against class imbalance in the dataset, in particular, the lower representation of normal MRI pictures than the tumor classes [18]. This was so to prevent the unequal contribution of every class in spite of

its sample size. After every federated communication round, the accuracy of validation was noted to investigate the stability of training and convergence behavior. These measurements have allowed a comprehensive comparison of the performance of federated learning and traditional centralized training tech- niques.

Table I indicates that in all the evaluated topologies, fed- erated learning provides similar performance to centralized training. Since centralized models are able to access the complete dataset, their accuracy is marginally better than their federated counterparts which only marginally underperform. This is a small price to pay considering the high levels of privacy ensured by federated learning, in which no sensitive medical information is ever transmitted outside of the local client environment.

Both in centralized and federated cases, pretrained models such as MobileNetV2 and EfficientNet-B0 excel over the Simple CNN among the evaluated models. This proves that transfer learning can be effective in situations where medical picture interpretation is required, particularly when the training data is scattered and only limited to particular customers.

F. Federated Learning Convergence Analysis

The convergence trend of the EfficientNet-B0 model during federated training was investigated in order to further char- acterize federated learning behavior. ”Fig. 1” shows how the number of federated communication rounds affects validation accuracy. The FedAvg aggregation approach was used to train the model for up to 20 communication rounds.

During early communication rounds, the federated EfficientNet-B0 model shows quick accuracy improvement, suggesting efficient knowledge aggregation from dispersed clients. The rate of improvement steadily declines as training goes on, and the model converges after about 15 to 20 cycles.

The stability and efficacy of federated learning for deep neural networks in decentralized medical imaging contexts are demonstrated by this convergence tendency.

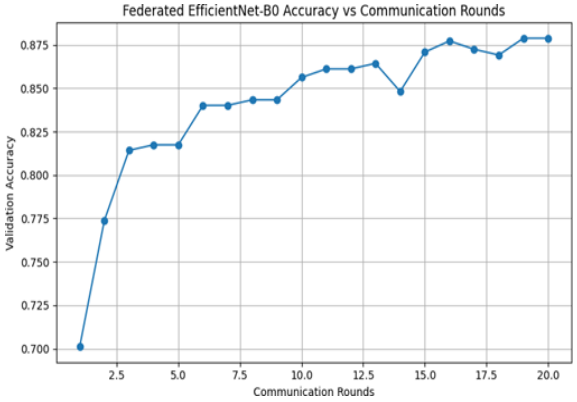

Fig. 2. Validation accuracy versus communication rounds for federated EfficientNet-B0.

IV. CONCLUSION

This study utilized federated learning as a decentralized training paradigm to present a proposal of a privacy pre- serving framework of brain tumor diagnosis through appli- cation of magnetic resonance imaging (MRI) [7]. The sug- gested methodology allows training three models on several clients without providing them with their personal medical information through the combination of the Federated Av- eraging (FedAvg) algorithm and deep learning models. An experimental study has demonstrated that federated learning significantly enhances the data security and data privacy and also performs as well as centralized training. The success of pretrained lightweight models, in particular, EfficientNet-B0 and MobileNetV2, in realizing high classification accuracy in a distributed learning model is further indicated by the comparative analysis conducted between a series of convolutional neural network architectures in centralized and federated configuration. The outcome confirms federated learning as a practical method to analysis of medical pictures with privacy concerns [8].

Although it is a great performance, there are a number of issues that need additional research. Seeing that non-IID data distribution may affect the convergence property and the generalization of the model as a whole, the data heterogeneity in federated clients remains a pressing concern. In order to increase the resilience of heterogeneous data conditions, any future research will concentrate on analyzing more sophis- ticated federated optimization strategies and customization strategies. The scaling requirements and the usefulness will also necessitate to scale up the proposed framework to larger, more diversified multi-institutional datasets as well as test its applicability on more challenging segmentation tasks. Among the locations where future research can be performed is combining improved privacy features, aggregation techniques that are communication-efficiency, which will enable the use of federated learning on clinical decision-support systems.

TABLE I COMPARISON OF PERFORMANCE OF CENTRALIZED AND FEDERATED LEARNING MODELS

Model	Training	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Simple CNN	Centralized	84	84	86	85
Simple CNN	Federated	77	76	79	77
MobileNetV2	Centralized	87	88	88	88
MobileNetV2	Federated	86	87	87	87
EfficientNet-B0	Centralized	90	91	91	91
EfficientNet-B0	Federated	88	89	89	89

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