# Federated learning-based machine learning for predicting brain tumor

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**Abstract.** The swift advancements in artificial intelligence (AI) and machine learning have profoundly impacted the realm of medical research, particularly in the realm of diagnosing and treating intricate conditions such as brain tumors. These tumors, characterized by unregulated cell proliferation, pose significant challenges. The complexities inherent in brain tumor diagnosis stem from the intricate nature of these tumors, symptom overlap with other ailments, and the inherent complexity of the brain itself. Nevertheless, the application of an advanced machine learning algorithm known as Federated Learning (FL) has demonstrated its potential to address data privacy concerns and enhance diagnostic accuracy in this context. This essay discusses the application of FL which is a decentralized training strategy in brain tumor research. FL allows multiple institutions to train the model collaboratively without data sharing. The key advancement includes the improved U-Net model implementation and the utilization of Convolutional Neural Network (CNN) Ensemble Architectures for brain tumor identification. This paper also discusses the potential of FL in optimizing weight sharing for model aggregation in heterogeneous data. Furthermore, it underscores the important role of FL in modern healthcare since FL also solves the privacy concern in smart healthcare. However, challenges such as communication lag, data heterogeneity, and computational cost still exist.

**Keywords:** Federated Learning, Smart Healthcare, Deep Learning.

## 1. Introduction

The landscape of medical research and treatment has been dramatically reshaped by the techniques of artificial intelligence and powerful machine learning algorithms. These sophisticated methods have achieved remarkable advancements in processing intricate medical data, delivering enhanced precision in analysis, and refining approaches to treatment. The advanced techniques in machine learning are expected to solve the problem of slow diagnosis rate and hit misdiagnosis rate of brain tumor.

Brain tumor is a serious disease and has a pretty high death rate. It as a disease that an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. Brain tumor is one of the most difficult tumors to cure, this is due to the brain complexity, heterogeneity, location and the diagnostic challenges. Most of the challenges are biological problems but the diagnostic challenges can be solved by machine learning algorithms and some other artificial intelligence techniques. Segmenting brain tumors from Magnetic

Resonance Imaging (MRI) scans continues to be a complex undertaking, primarily due to the subtle intensity variations in tumor-related image voxels that are hard to delineate.

Brain tumors can present with a variety of symptoms that overlap with other neurological conditions. This kind of complexity makes the early diagnosis and differentiation from other disorders a pretty hard task, which will also delay the timely intervention. Moreover, advanced algorithms can also help with complicated medical data to make the analysis process faster and reach a treatment with higher accuracy.

One of the widely used machine learning algorithms in brain tumor research area is federated learning. The main objective of automated brain tumor diagnosis is to gather medical information regarding the tumor's presence, its location, and its specific type [1]. Researchers applied the deep learning to do the state-of art brain tumor identification, but the results are less accurate. To address this challenge, federated learning is implemented to train the shared global model using data from multiple institutions, ensuring data privacy at the same time [1]. Federated learning effectively tackles privacy concerns by facilitating collaborative training of each data processor on localized data [2]. Recent studies indicate that FL-trained models can perform on par with those trained on centralized data repositories and even outperform models restricted to data from a single institution [3]. Additionally, Federated Averaging (FA) enables the Mobile Nodes (MNs) to train a communal machine learning model guided by a Parameter Server (PS). Generally, the PS communicates with medical devices via a network [4].

In the rest of the paper, this study will explore the approaches to resolve those challenges when applying federated learning in brain tumor research area. It will discuss the techniques that can be used to improve the models' performance to reach a higher accuracy which directly expedite the training process and optimize the communication latency. Furthermore, the concept of edge computing and asynchronous federated learning is also mentioned that introduces the potential for more streamlined communication processes, optimizing the balance between real-time insights and resource constraints. It is through the synergy of these measures that the concerns of data privacy and communication efficiency can be methodically addressed, creating an environment where the promises of federated learning in brain tumor research can be fully realized.

## 2. Method

### *2.1. U-Net Model combined with FL Adaptations*

To improve the accuracy and reduce the calculation efficiency of brain tumor segmentation, researchers applied federated learning models and metrics. The segmentation of brain tumors is one of the most fundamental steps in brain tumor diagnosis. The segmentation helps to evaluate the potential treatment [5] and that is why the segmentation is so important in the whole diagnosis process. In recent years, the U-Net models have gained a lot of traction due to their excellent performance. The U-Net model is separated into two segments:(1) The encoder which is responsible for drawing context from the images. (2) The decoder which is to identify the segmentation area. In this paper, it discusses the adaptation of the U-Net model which is to align more effectively with the context of FL. Compared to the original model, the modified version implements dropout layers to improve the model generalization process and avoid overfitting [6].

*2.1.1. Classification of Brain Tumors Using MRI Images.* Federated Learning (FL) enables the model to train without directly sharing data. The constitutions can also train the model on numerous decentralized devices and the data will be stored in the local server. This study mainly focuses on implementing federated learning through the establishment of a central server and the interaction with other clients. Figure 1 provides a federated learning-based framework for predicting brain tumor.

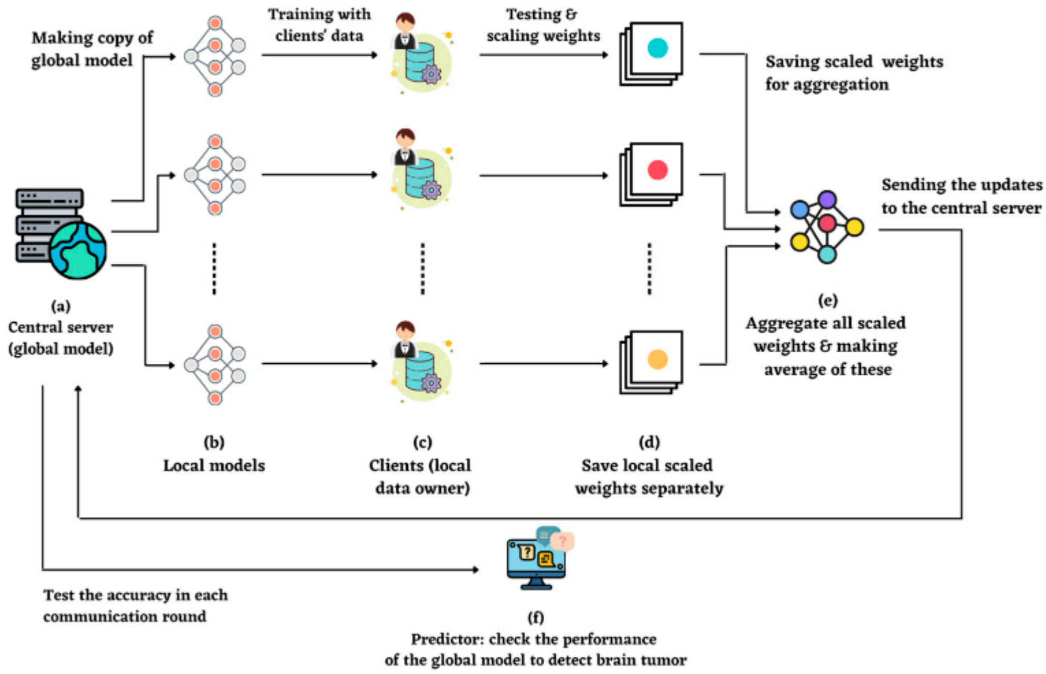


**Figure 1.** The model architecture: (a) Global model. (b) 50 copies of the global model. (c) Clients built with local data. (d) Training & testing. (e) Combining the diverse weights and calculating their mean, the revised weight is subsequently relayed to the central server. This procedure is repeated across five communication iterations. (f) Check the global model accuracy [1].

*2.1.2. Global Model.* In a study focused on Federated Learning and Convolutional Neural Network (CNN) Ensemble Architectures for Brain Tumor Identification via MRI Images [2], various CNN architectures were assessed. The evaluation included individual CNN models, the mean CNN model, and the voting ensemble. The most effective among them was chosen to construct a global model on the central server. Notably, the average model outperformed the other CNN configurations. Hence, the global model within the FL framework was built using the mean CNN model. The federated learning model takes into account the uneven distribution of data across clients. A scaling factor ensures clients with more data have greater influence during weight aggregation. Instead of transferring data, only local model weights are shared with the central server. These weights are scaled, aggregated, and used to update the global model, ensuring privacy and improved accuracy. The FL model's efficacy in detecting brain tumors is gauged across multiple communication rounds. With each round, as the global model aggregates insights from all clients, the model's accuracy on the test dataset is expected to increase, benefiting all users.

*2.1.3. Training of the FL Model.* The FL model was trained using an MRI dataset, ensuring it wasn't overfitting or underfitting. However, due to its decentralized nature, it encountered difficulties in delving into the deeper attributes of the dataset. The algorithm emphasized securing the data confidentiality and the global model solely obtained refreshed weights from the local models. The non-uniform distribution of data across clients led to biases. Though clients possessing larger datasets were assigned greater significance, this couldn't solve the issue of the biases. Moreover, variations in class distribution resulted in additional training challenges. Whereas, due to the accuracy improvement, it is clear that FL does have the potential in medical imaging and applications.

*2.1.4. Optimize Weight Sharing for Aggregation Model.* In another study about optimizing weight sharing for the aggregation model of federated learning [7], Federated Learning typically uses average weights for aggregating model parameters. However, this method is not ideal in heterogeneous environments since the data distribution is not uniform. To address this, a new aggregation method was proposed. This method ranks weights based on their percentage and the data size of each client. It considers a percentage of the shared weight for combination. This approach is designed for heterogeneous environments, and it will produce an accurate and efficient solution [7].

## 3. Application and discussion

Recent progress and the development in artificial intelligence have made it pretty clear to us that smart health and remote medical are realizable. Historically, AI methods relied on centralized data gathering and analysis. However, this kind of centralized data gathering is not possible in the real-world smart health setting since there are concerns about data privacy [8]. Federated Learning is attractive for smart healthcare since it will perfectly solve the privacy issue by training the data on local clients with no direct data sharing. The recent applications of FL in important healthcare areas include health data administration, distant health surveillance, medical image analysis, and detection of COVID-19.

However, there are still some things that can be improved in the field of smart healthcare. Medical sites often have insufficient datasets to train AI models for smart healthcare [9, 10], hindering the efficiency of AI solutions. Training AI models at a single medical site often fall short of achieving high accuracy, especially in tasks like brain tumor as discussed previously. This shortfall results from imbalances in data features and inadequate data sizes. While data augmentation techniques, like Generative Adversarial Networks (GANs), can help, they might not offer enough diversity for effective training. This lack of comprehensive datasets is a significant challenge in applying AI to healthcare. Recent studies have shown that there will be some trade-offs between the model performance and the cost of privacy protection [11]. Furthermore, traditional AI-based healthcare systems that offload health data to the cloud can be costly in terms of time and resources. Transferring large medical files, like audio or images, can lead to significant network latency and bandwidth consumption. As more devices are added, the risk of network congestion grows. Additionally, the offloading process demands high power from medical devices, presenting challenges for their battery life and hardware design.

FL will resolve the data privacy concern as the paper has discussed before and it will also lower the code of Health-data Training. By utilizing Federated Learning, which avoids transferring large data volumes to servers, communication costs such as latency and transmit power can be considerably reduced. This is because model gradients, used in FL, are typically smaller than the actual datasets. Consequently, FL also conserves network bandwidth and decreases the likelihood of congestion in extensive healthcare networks.

## 4. Conclusion

FL is a revolutionary presence in the field of medical research, offering an innovative approach to address data privacy concerns and fostering collaborative expertise in brain tumor research. Leveraging modified U-Net models and CNN architectures, FL has proven effective in enhancing the precision and efficiency of MRI image analysis and brain tumor segmentation. Nevertheless, several challenges persist, including communication latency, data heterogeneity, and computational cost constraints. Nevertheless, promising solutions through edge computing and FL algorithms are emerging, instilling optimism for future endeavors in this domain. Other than brain tumor research, FL also influences the reshape of modern smart health. Modern smart health also has a data privacy concern and FL provides a balance between data privacy, efficiency, and accuracy. FL also reduces the computation cost in smart healthcare to offer more opportunities for this industry to develop. As moving forward, it is crucial for the AI techniques and medical communities to work together and achieve more goals. With advanced techniques developing and more challenges coming, the full potential of FL in revolutionizing modern smart healthcare will be realized soon.

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