Enhancing Brain Tumor Segmentation through Federated Learning under Non-IID Constraints

Paramkusam Sriharsha, Yelipe Gowtham, Geda Tejesh Chowdary, Meena Belwal
Dept. of Computer Science and Engineering,
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India
bl.en.u4cse22141@bl.students.amrita.edu, bl.en.u4cse22163@bl.students.amrita.edu,
bl.en.u4cse22114@bl.students.amrita.edu, b_meena@blr.amrita.edu

***Abstract*—Brain tumor segmentation in medical settings demands accurate results to achieve proper diagnosis together with treatment planning and prediction of patient outcomes. The centralized deep learning approaches encounter several obstacles because of data privacy rules and institutional data variations and regulatory restrictions. FL (Federated Learning) delivers privacy-protecting training that lets medical facilities develop models together while maintaining individual patients' raw information private. The study conducts an evaluation of different federated aggregation algorithms which function for brain tumor segmentation within non-IID (non-independent and identically distributed) data environments. Non-IID situations created by demographic divergences and different imaging parameters and acquisition instrument variations create major obstacles that hinder model generalization and convergence success. A detailed analysis evaluates how aggregation strategies affect segmentation performance by using Dice Similarity Coefficient (DSC) as one of the key metrics. The research investigates FL aggregation strategies that deliver high accuracy and protect privacy in order to enhance the medical image analysis capabilities of federated learning systems.**

***Index Terms*—Brain tumor, Segmentation, Federated Learning, Dice Similarity Coefficient, Non-IID, Aggregation.**

I. Introduction

The uncontrolled cell developments inside brain tissues and its neighboring regions represents one of the most fatal brain cancer manifestations. The problem with these brain tumors stems from both their multiple biological forms and their changing dimensions and site distributions through irregular patterns that create medical difficulties during diagnostic and treatment planning. Brain tumor detection at an early stage with precision stands as an essential element because it leads to better treatments together with enhanced survival rates for patients [1].

Workers in medical image analysis make use of recent advances in Artificial Intelligence (AI) and its deep learning branch for transformative success. The combination of AI models using Magnetic Resonance Imaging (MRI) incorporates the capacity to detect and classify tumors along with segmenting tumors' shapes through automatic processes. The new technology helps reduce analysis procedures that depend on manual work and are both error-prone and slow which empowers radiologists to make better and speedier clinical choices [1], [2].

The successful execution of AI models heavily depends on obtaining extensive and diverse annotated datasets which medical institutions often cannot access due to strict data protection measures and institution-to-institution data-sharing boundaries. Federated Learning (FL) stands as the essential solution for this situation. The FL system enables distributed AI model training in separate medical institutions since institutions keep their patient data private. The system conducts exchanges of encrypted model updates as a privacy measure that obeys healthcare regulations [1], [3]. FL allows institutions to work together while improving model awareness through collective efforts and enables comprehensive AI system development without disclosing patient information [3], [4].

Medical image analysis depends heavily on segmentation because it enables doctors to precisely locate tumor areas through precise area segmentation therefore it assists professionals in diagnosis planning and ongoing medical observation. The pixel-level data from segmentation generates superior information which helps medical professionals make clinical decisions [1].

The key contributions in this work include:

- The research evaluates different aggregating method implementations during brain tumor segmentation tasks utilizing decentralized medical image collections from real-life environments.
- The performance evaluation of algorithms operated on non-IID data includes real-world elements which include differences in imaging protocols combined with scanner variability and patient demographic variations [1], [4].
- This study examines federated aggregation schemes by utilizing Dice Similarity Coefficient alongside practical evaluations for client unbalanced populations combined with heterogeneous medical data and efficient communication within federated learning frameworks.

II. Related Works

Kumar et al. [1] developed a federated learning platform with blockchain components to deliver protected brain tumor segmentation while achieving better accuracy and reliability than basic approaches. Giri et al. [2], introducedthe Federated ResUHybridNet for federated systems which blends ResNet deep learning capabilities with U-Net segmentation expertise to resolve accuracy and privacy concerns. Yahiaoui et al. [3], in this paper, introduced a privacy-preserving federated learning method employing a 3D U-Net model with differential privacy mechanisms to overcome issues of data confidentiality and segmentation performance in multi-institutional brain tumor diagnosis of MRI scans. Naeem et al. [4], performed a systematic review of the literature on deep and federated learning for brain tumor diagnosis and pointed out prevailing methods such as FCNs, pre-trained models, and overcoming issues such as dataset diversity and privacy.

In this work, Ahamed et al. [5], contributed a literature review on segmentation of brain tumors via deep and federated learning with focus on convolutional techniques, cascaded and ensemble networks, multimodal data, and introducing client-based federated methods for improved performance without compromising data privacy. In this work, Ullah et al. [6], designed an efficient federated learning algorithm using a U-Net-inspired architecture for segmentation of brain tumors, focusing on preservation of privacy, decentralized training in institutions, and achieving performance over the baseline CNN and RNN models. Chen et al. [7] introduce GCML, a federated learning architecture that is decentralized for improving medical image segmentation using gossip-based contrastive mutual learning to successfully resolve personalization, heterogeneity in data, privacy, and communication issues across hospitals. Gopal et al. [8] introduce a lightweight deep learning framework integrating adaptive data augmentation and efficient compact neural networks for brain tumor segmentation and classification with high accuracy and efficiency for clinical environments with limited resources.

Wakili et al. [9] propose FedMEMA, a federated learning solution employing modality-specific encoders and multimodal anchors to compensate for inter-modal heterogeneity of brain tumors to obtain better personalization and accuracy without compromising privacy. Manthe et al. [10] offer a detailed benchmarking of global, personalized, and hybrid federated learning brain tumor segmentation methods with the FeTS2022 dataset, documenting performance trade-offs in privacy-preserving decentralized training paradigms. Khan et al. [11] developed a reliable NNMF-based recommendation system that improves medical image segmentation performance by resolving the cold start situation along with task outsourcing optimization. Le et al. [12] did comparison of FedAvg and FedSGD aggregation algorithms against different clients and data distribution patterns revealed better results for FedAvg.

Zhang et al. [13] used a federated migration learning framework in which individual centers train local models and exchange partial parameters with a central server for aggregation to improve brain tumor detection accuracy and generalization. Yahiaoui et al. [14] applied a 3D U-Net-based federated semantic segmentation model to the BraTS 2020 dataset with competitive Dice scores and Hausdorff distances similar to centralized models for brain tumor segmentation. Zhou et al. [15] proposed Fed-MUnet, a new federated learning framework with multi-modal MRI for brain tumor segmentation, with better accuracy and lower model complexity and outperforming state-of-the-art segmentations.

III. Proposed Method

A. Dataset Details

The dataset employed for this project is named ”MRI Brain Tumor Segmentation.” [16] With a total of 3064 samples the dataset presents a pair of MRI image together with its binary segmentation mask. The binary mask clearly shows tumor areas so it can be used effectively for supervised learning in segmentation applications. The medical image analysis model employs this dataset which presents well-developed structure to handle deep learning techniques.

The necessary preprocessing procedures were used to maintain consistency throughout the process before starting training. The model training benefit from uniform image resizing because this technique maintains data structure while reducing computational complexity. The preprocessing pipeline included normalization as well as contrast enhancement and noise removal (when needed) because these operations enhanced the quality of the input images. Standards in the data become adopted by the pipeline as it makes sure the dataset becomes proper for effective model creation.

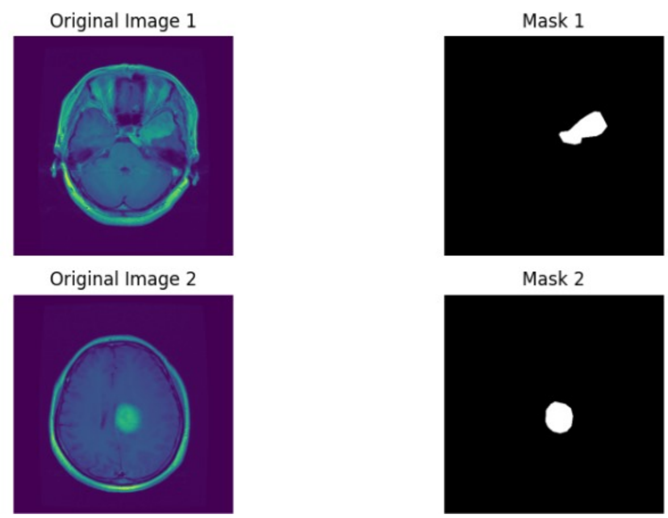

Fig. 1. Sample Dataset.

B. System Architecture

An overview of the federated brain tumor segmentation system architecture appears in Fig. 2. Multiple medical institutions serve as clients through which the data consisting of MRI scans and their truth masks are distributed. Each client executes preprocessing directly on its site to normalize features before conducting model development from private medical information. The data remains within the hosting facility at

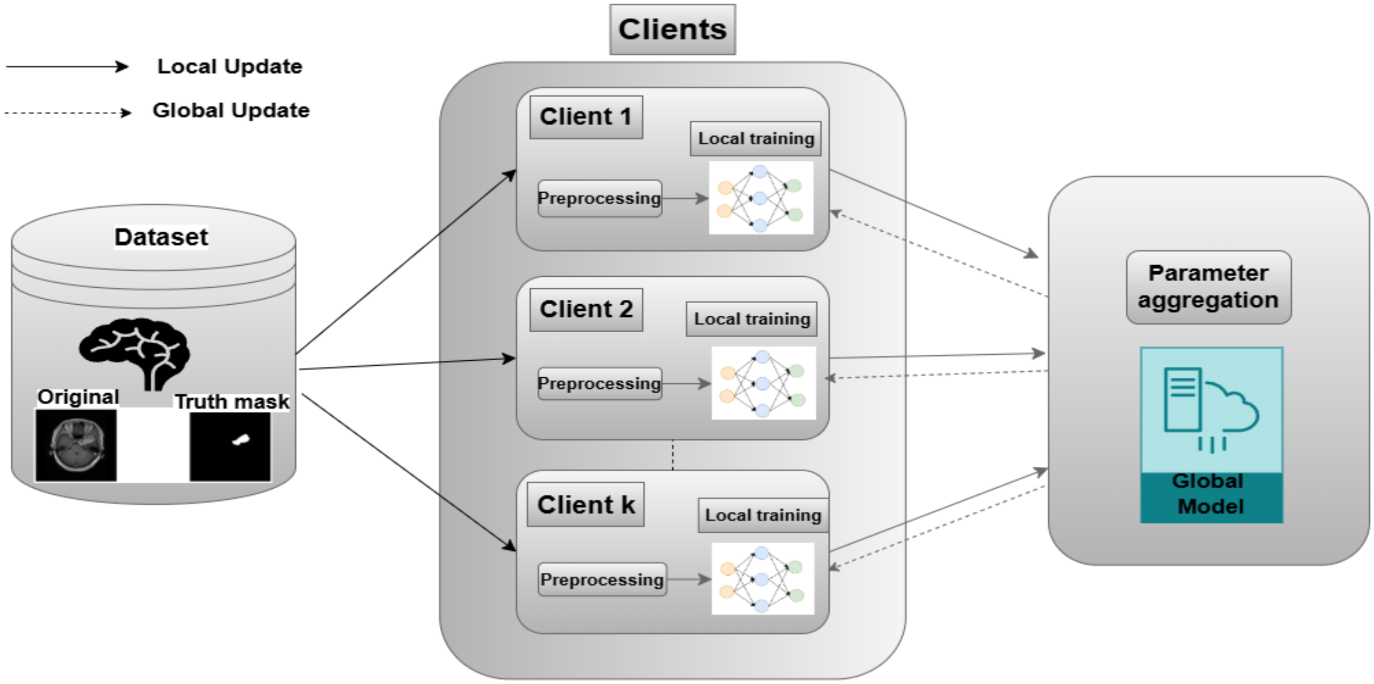

Fig. 2. Architecture Diagram

all times which protects patient privacy integrity for the entire training process.

The trained model parameters send from individual locations to a central storage point for combined use. All local model parameters sent from clients to the server are used to produce a unified global model through averaging or parameter combination procedures. The clients obtain this global model before starting the subsequent training cycle. The training sequence between local model updates and global aggregation repeats until the training stops. The system design allows multiple data types along with optimized distributed training capabilities when working with non-IID distributed data.

C. Federated Aggregation Techniques

The research uses three different federated aggregation methods including FedAvg, FedProx, to study systematically what model update strategies achieve in terms of federated learning performance. Standard averaging methods as well as regularization-based approaches and dynamic optimization schemes form an encompassing evaluation framework because they allow researchers to compare convergence behavior and accuracy while testing robustness to non-iid data between decentralized client models.

1) FedAvg: Federated Averaging (FedAvg) represents the cornerstone algorithm of Federated Learning which utilizes central server oversight of multiple client devices that train universal models through data-locked procedures. Local models undergo training based on individual client data which gets transmitted to the server for parameter aggregation. The server applies weighted averaging to these parameters using data points as weighting factors. Repetitions of this technique must run until the process achieves convergence. FedAvg provides better privacy benefits while lowering communication expenses and performs effectively on data formats that are non-IID (non-independent and identically distributed). This method finds vast use within decentralization-based training systems.

Algorithm 1 Federated Averaging (FedAvg)

```
Initialize: Global model w_0
for each round t = 1, 2, ... do
    Sample a subset of clients S_t
    for each client k ∈ S_t in parallel do
        Download global model w_t from server
        Update local model: w_k ← Train(w_t, D_k)
        Send w_k to server
    end for
    Aggregation:
    w_{t+1} ← Σ_{k∈S_t} (n_k/N) w_k
end for
```

$$w_{t+1} \leftarrow \sum_{k \in \mathcal{S}_t} \frac{n_k}{N} w_k$$

2) FedProx: The FedProx framework operates as a solution to resolve machine learning modeling difficulties when executed within federated learning environments. FedProx introduces a proximal term to the objective function to solve the problems associated with traditional federated learning specifically when devices have different data distributions. Local models maintain closeness to the global model through this change which enables them to adapt to local datasets. A random collection of devices transfers new data to an aggregator as each device performs suboptimal target function optimization. The non-iid data distribution receives enhanced stability and convergence through FedProx through its ability to maintain close relationships between local and global model updates.

Algorithm 2 FedProx

Input: Number of clients K, total rounds T, proximal term coefficient μ, learning rate γ, initial model w_0, total clients N, client sampling probability p_k, for $k = 1, \ldots, N$

for each round $t = 0, 1, \ldots, T-1$ **do**

  Server samples a subset of clients S_t (each client k is chosen with probability p_k)

  Server sends global model w^t to all selected clients

  for each client $k \in S_t$ in parallel **do**

    Compute updated model w_k^{t+1} as a γ_k^t-inexact minimizer of:

$$w_k^{t+1} \approx \arg\min_w F_k(w) + \frac{\mu}{2}\|w - w^t\|^2 \tag{1}$$

    Send updated model w_k^{t+1} to server

  end for

  Aggregation: Server updates global model:

$$w^{t+1} = \frac{1}{|S_t|} \sum_{k \in S_t} w_k^{t+1} \tag{2}$$

end for

D. Metrics of Evaluation

The research employs Dice Similarity Coefficient and Intersection over Union to determine the performance of brain tumor segmentation models operating through federation. The metrics measure prediction-observation area alignment for assessing classifier performance regarding its accuracy in identifying tumor regions throughout decentralized non-independent and identically distributed client data sets.

1) Dice Similarity Coefficient (DSC): The DSC functions as a statistical metric which serves as a standard assessment for measuring image segmentation outcomes. The DSC assessment provides information about how well a predicted mask matches the true ground truth labeling area. The measurement score of segmentation precision increases when DSC values demonstrate higher numbers. The method to determine DSC measurement requires the usage of this mathematical expression:

$$\text{DSC} = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{1}$$

where the model identifies correctly detected tumor pixels (TP) and simultaneously registers wrong tumor pixels as false positives (FP) and missed tumor pixels as false negatives (FN).

2) Intersection over Union (IoU): The IoU functions as a fundamental metric for evaluating segmentation and object detection models under its formal name of Jaccard Index. The metric analyzes the corresponding relationship of predicted segmentation areas to reference areas through their shared spatial zones. The formula for IoU is:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{2}$$

The Intersection over Union (IoU) measure provides an accurate performance assessment method that evaluates model tumor detection accuracy through concomitantly calculated spatial measures.

IV. Implementation

V. Results and Discussion

VI. Conclusion and Future Work

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