EE-641 Advanced Deep Learning

Federated 3D Brain Tumor Segmentation with UNet: A Privacy-Preserving Approach to Non-Heterogeneous Data Using FedPer

Project Report

© Praburam K Varadharajan, Raksheka Rajakumar

University of Southern California
Viterbi School of Engineering

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Abstract:

This project explores the application of Federated Learning (FL) for 3D brain tumor segmentation using the U-Net architecture. With an emphasis on privacy preservation, the study addresses challenges posed by non-identically distributed (non-IID) data across clients, leveraging the Federated Personalization (FedPer) technique to improve performance. The BraTS2020 dataset was utilized to train and validate the model, focusing on segmenting glioma sub-regions: whole tumor, tumor core, and enhancing tumor. Comparative experiments were conducted under centralized learning and federated learning paradigms, evaluating equal and unequal data distribution scenarios. Results demonstrate that while centralized learning provides strong baseline performance, FedPer significantly enhances segmentation outcomes in non-IID data distributions, narrowing the performance gap between FL and centralized learning. Future work involves analyzing client contributions to the global model and extending the framework with TransUNet to capture global context for improved medical image segmentation.

Introduction:

Advancements in medical imaging have significantly enhanced the precision of diagnosing and treating complex conditions such as brain tumors. Accurate segmentation of glioma regions, including the whole tumor, tumor core, and enhancing tumor, is critical for effective diagnosis, treatment planning, and prognosis. Traditional centralized learning approaches have leveraged models like U-Net to achieve high segmentation accuracy. However, the increasing volume of medical data and privacy concerns associated with sharing sensitive patient information present significant challenges in building centralized datasets for model training.

Federated Learning (FL) has emerged as a promising paradigm to address these privacy concerns. By enabling model training across distributed datasets without transferring raw data, FL ensures compliance with data protection regulations and retains data locality. However, non-identically distributed (non-IID) data among clients often degrades FL performance due to the variations in data distributions across institutions. To mitigate this, methods such as Federated Personalization (FedPer) introduce client-specific layers, allowing for local adaptations while leveraging global knowledge for generalized features.

This project builds on these advancements by implementing and evaluating a federated learning framework for 3D brain tumor segmentation using the U-Net architecture. The BraTS2020 dataset, a standard benchmark in glioma segmentation, was used for training and validation. Experiments were conducted under both centralized and federated learning paradigms, comparing performance in scenarios of equal and unequal data distributions across clients. The FedPer method was further explored to address challenges posed by non-IID data.

While centralized learning provides a strong baseline, this study demonstrates that federated learning, augmented with personalization techniques like FedPer, can achieve competitive performance even under non-IID conditions. This project also lays the groundwork for future exploration, including the integration of TransUNet, a hybrid model combining transformers and convolutional networks, to capture global context and further enhance segmentation performance.

The rest of this paper is organized as follows: a literature survey highlights the state of the art in medical image segmentation and federated learning, the methodology section details the experimental framework, and results are analyzed to compare centralized and federated learning approaches. Finally, the report concludes with insights, challenges, and directions for future work.

Literature Survey:

Medical image segmentation has been a pivotal area in advancing diagnostic and therapeutic tools. Among various methods, U-Net has become a dominant architecture due to its encoder-decoder structure and skip connections, which preserve both spatial resolution and contextual understanding [5]. Initially proposed for 2D segmentation tasks, U-Net has been adapted for 3D data, enabling its application in volumetric tasks such as brain tumor segmentation. The BraTS2020 dataset, a benchmark in this domain, has played a crucial role in evaluating models by providing multi-modal MRI scans of glioma regions, including the whole tumor, tumor core, and enhancing tumor [2]. While U-Net provides strong baseline performance, recent advancements such as TransUNet have introduced transformers into the architecture to capture long-range dependencies and global context, addressing U-Net's limitations in spatial relationships across large medical images [1].

Federated Learning (FL) has emerged as a transformative approach to address privacy concerns in medical data sharing. By enabling training across distributed datasets without transferring raw data, FL ensures compliance with data protection regulations while leveraging diverse datasets[3] [7] . However, FL faces challenges with non-identically distributed (non-IID) data among clients, which often results in degraded performance. The foundational FedAvg algorithm aggregates local model updates to build a global model but struggles to adapt to heterogeneity in data distributions. Methods like SCAFFOLD attempt to correct client drift through stochastic averaging [4], while Federated Personalization (FedPer) introduces client-specific layers that adapt to local data while maintaining shared global layers for generalization. These approaches, while effective in theory, are not yet fully validated for 3D medical image segmentation, which demands high spatial precision and contextual accuracy.

In the context of 3D segmentation, federated learning presents unique challenges due to the large volumetric data size and computational overhead. Methods incorporating personalization, such as FedPer, have shown promise in handling non-IID distributions by allowing clients to fine-tune specific layers of the model while contributing to a globally shared representation [8]. Hybrid architectures like TransUNet, which integrate convolutional layers for local feature extraction with transformers for capturing global dependencies, offer additional potential for improving segmentation performance. However, their computational complexity poses practical barriers to deployment in federated setups, especially for institutions with resource constraints [1] [9].

Our approach builds upon these advancements by implementing and evaluating a federated framework specifically tailored for 3D brain tumor segmentation using the U-Net architecture. Unlike existing works that primarily focus on centralized learning or simplified federated setups, our study explores both equal and unequal data distribution scenarios to evaluate the robustness of FL. Furthermore, by incorporating FedPer into the 3D U-Net framework, we demonstrate improved performance in handling non-IID data distributions. Unlike TransUNet, which emphasizes global context through transformers, our approach balances computational efficiency and performance by leveraging the inherent strengths of U-Net's skip connections and personalized layers. This combination allows for better generalization across heterogeneous datasets while maintaining the privacy and scalability required for medical applications.

Methodology:

This section details the framework and experimental setup for federated learning in 3D brain tumor segmentation using the U-Net architecture. We explore the application of Federated Personalization (FedPer) to handle non-identically distributed (non-IID) data, describe the preprocessing pipeline for the BraTS2020 dataset, and explain the experimental setups for both centralized and federated learning paradigms.

Federated Learning Framework

Federated Learning (FL) is a distributed machine learning approach that enables model training across decentralized data sources while maintaining data privacy. Unlike traditional centralized learning, where data is aggregated into a single location, FL keeps data local to the participating clients and aggregates only the model updates on a central server. The server iteratively collects these updates, aggregates them (commonly using the Federated Averaging algorithm, FedAvg), and sends the updated global model back to the clients. This framework is particularly suited for privacy-sensitive domains such as healthcare, where data sharing is constrained by ethical and legal concerns

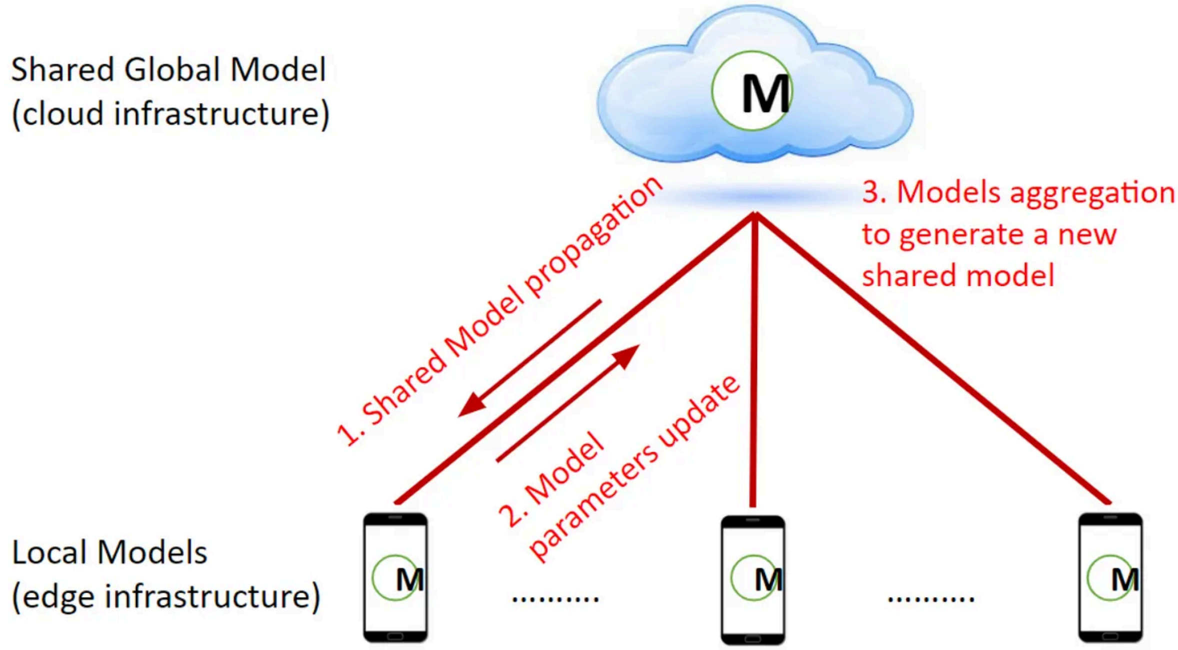

Figure 1 below illustrates the FL process, highlighting the flow of model updates between clients and the central server.

Federated Learning Process:

Initialization: The server initializes a global model and distributes it to clients.
Local Training: Each client trains the model locally using its private data.
Aggregation: The server aggregates the locally trained model updates into a global model.
Iteration: The process is repeated for several communication rounds until convergence.
Figure 1 below illustrates the FL process, highlighting the flow of model updates between clients and the central server.

Non-IID Data Distribution

Non-identically distributed (non-IID) data is one of the most significant challenges in Federated Learning. In real-world scenarios, clients often possess heterogeneous data distributions due to differences in demographics, devices, or institutions. For example, in a medical context, hospitals may have patient data from different populations or imaging protocols. Such heterogeneity leads to client drift, where individual client models diverge from the global model, resulting in degraded performance when aggregated

To address non-IID data challenges, Federated Personalization (FedPer) was employed in this project. FedPer introduces client-specific layers that allow each client to fine-tune the model to its local data distribution, while shared layers are aggregated globally to maintain generalization.

3D UNet Architecture

The U-Net architecture is a widely recognized model for medical image segmentation due to its ability to capture both spatial and contextual features through an encoder-decoder structure with skip connections. For volumetric data such as MRI scans, the 3D U-Net extends the traditional 2D U-Net by replacing 2D convolutional, pooling, and upsampling operations with their 3D counterparts. This modification enables the network to process volumetric input data, leveraging spatial relationships across all three dimensions.

The architecture begins with an encoder that extracts hierarchical features by applying consecutive 3D convolutional layers, followed by 3D max-pooling operations to progressively reduce the spatial dimensions. Each convolutional layer employs small kernel sizes (typically 3×3×3) with non-linear activation functions (e.g., ReLU) to extract high-dimensional features. The encoder captures both low-level and high-level features essential for accurate segmentation.

The decoder mirrors the encoder's structure, using 3D transposed convolutions or upsampling layers to progressively reconstruct the spatial dimensions. The decoder's primary objective is to localize features while preserving spatial resolution. Skip connections are integrated between corresponding levels of the encoder and decoder, ensuring that high-resolution spatial information lost during down-sampling is recovered during up-sampling. This is crucial for accurately segmenting small or intricate tumor regions.

The 3D U-Net implemented in this project takes a multi-channel input comprising four MRI modalities (T1, T1CE, T2, FLAIR) and outputs a three-channel segmentation mask representing the whole tumor, tumor core, and enhancing tumor. The model employs Dice loss to optimize overlap between predicted and ground truth masks. This architecture is particularly well-suited for 3D medical image segmentation, as it balances the need for both global context and local precision, making it a robust baseline for evaluating centralized and federated learning setups.

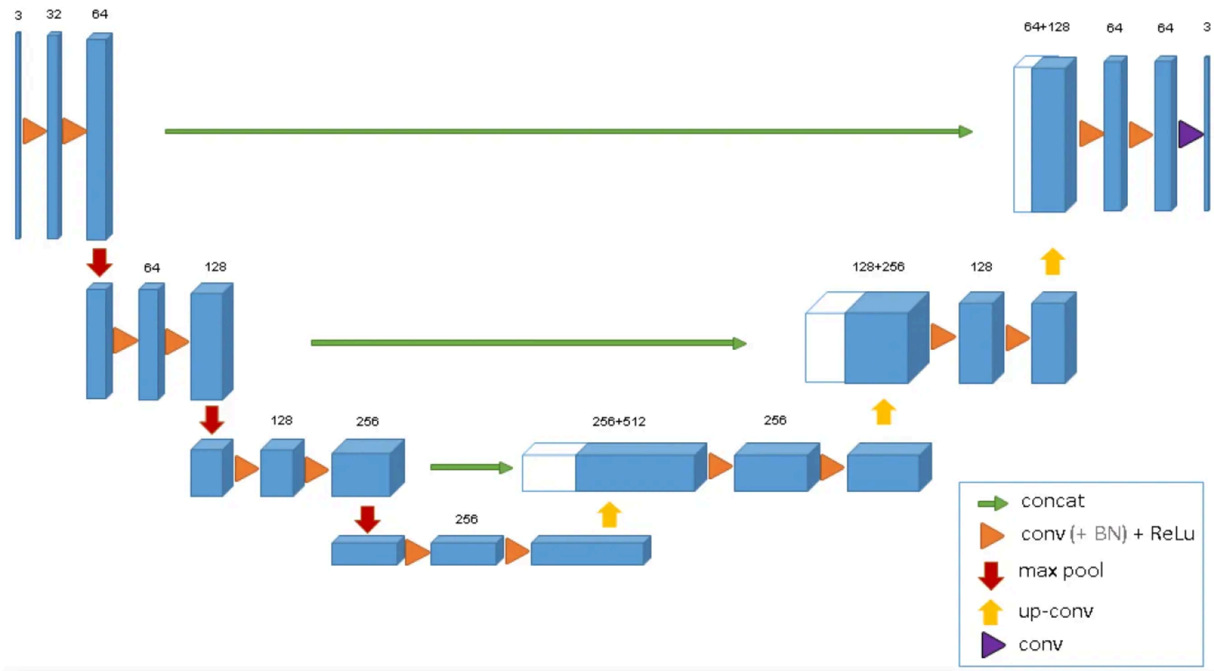

Fig. 2. Show the Network Architecture of 3D UNet

Dataset and Preprocessing

The BraTS2020 dataset was used for this project, comprising multi-modal MRI scans (T1, T1CE, T2, FLAIR) for glioma segmentation. Each scan includes annotations for the whole tumor, tumor core, and enhancing tumor. Preprocessing steps included:

- Uniform Resizing: All scans were resized to a volumetric shape of 128×128×128.
- Intensity Normalization: Pixel intensities were normalized to ensure consistent input ranges across modalities.
- Multi-Class Masks: Segmentation masks were preprocessed into three channels representing the tumor sub-regions.

Data was split into training, validation, and test sets, ensuring no data leakage.

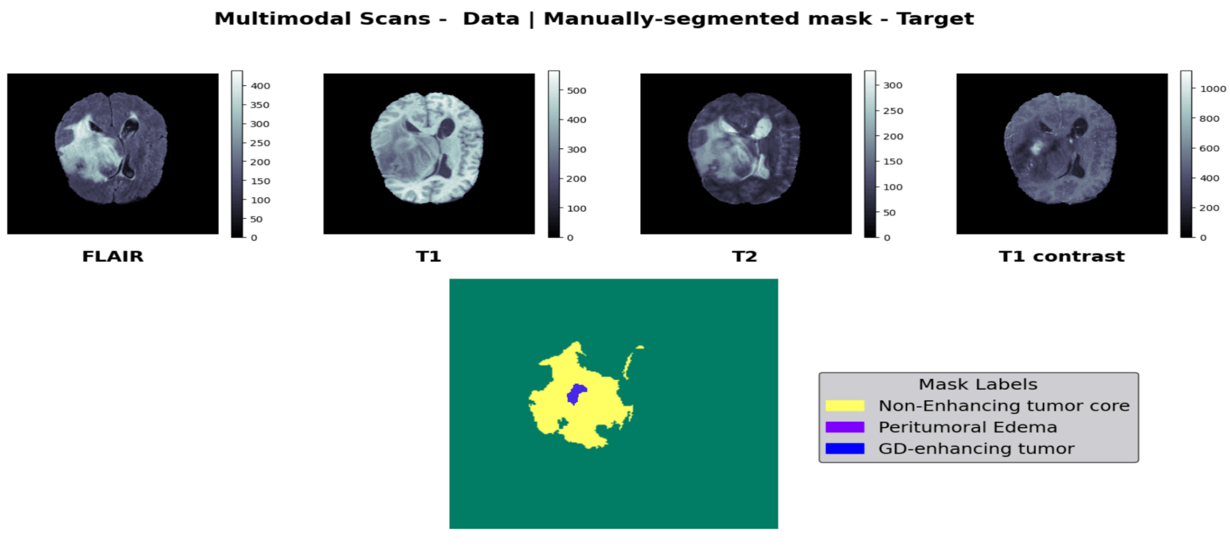

Figure. 3. Shows the Multimodality in out dataset and the Masks

Experimental Design

The experiments were designed to compare centralized learning and federated learning under equal and unequal data distribution scenarios. A 3D U-Net architecture served as the backbone model, with FedPer implemented for personalization in the federated setup.

Centralized Learning:

The model was trained on the entire dataset as a baseline for performance comparison.
Federated Learning with Equal Distribution:

The dataset was evenly partitioned across clients, ensuring similar data distributions.
FedAvg was used for model aggregation.
Federated Learning with Unequal Distribution:

Data was unevenly distributed among clients to simulate real-world non-IID scenarios.
FedAvg was initially used, followed by FedPer to introduce client-specific personalization layers.
Figure 2 illustrates the experimental workflow, highlighting the differences between centralized learning and federated learning setups.

Implementation Details

- Model Architecture:
  A 3D U-Net with skip connections was implemented. The input consisted of four channels (multi-modal MRI scans), and the output was a three-channel segmentation mask.

- Optimizer and Loss Function:
  The Adam optimizer was used with a fixed learning rate, and Dice loss was employed to optimize segmentation overlap.
- Communication Rounds:
  Federated learning experiments were conducted over 25 communication rounds.
- Metrics:
  Performance was evaluated using Dice Coefficient, Intersection over Union (IoU), and average client loss.

Experiments and Results:

The experiments conducted in this project aimed to evaluate the performance of centralized learning, federated learning (FL), and Federated Personalization (FedPer) for 3D brain tumor segmentation. The evaluation considered various data distribution scenarios, including equal and unequal data partitions among clients, to simulate both ideal and real-world federated setups. Metrics such as Dice Coefficient, Intersection over Union (IoU), and average client loss were used to quantify model performance.

In the centralized learning setup, the entire dataset was combined and used to train a single 3D U-Net model. This approach provided a baseline for comparing the effectiveness of federated learning. The centralized learning model achieved a Dice Coefficient of 0.708 , demonstrating its superior performance due to access to the complete dataset and consistent distribution. Centralized learning benefited from its ability to learn directly from a comprehensive dataset without any variability introduced by distributed or heterogeneous data.

Federated learning was first evaluated under equal data distribution across clients. In this setup, the dataset was evenly partitioned, ensuring all clients had access to similar data distributions. The FedAvg algorithm was used to aggregate local model updates into a global model. This experiment resulted in a Dice Coefficient of 0.6941, an IoU of 0.5695, and an average client loss of 0.3096. Although the performance was slightly lower than centralized learning, it remained competitive. This result highlights the potential of FL to achieve robust performance while preserving data privacy, particularly when data is uniformly distributed across clients.

To simulate real-world scenarios, federated learning was next tested with unequal data distribution, where the dataset was unevenly partitioned among clients. This setup introduced significant variability in the amount and quality of data available to each client, leading to challenges in aggregation. The results showed a substantial performance drop, with a Dice Coefficient of 0.4648, an IoU of 0.3195, and an average client loss of 0.3054. The degradation highlights the limitations of standard FL approaches, such as FedAvg, in handling non-identically distributed (non-IID) data. Clients with limited data contributed less to the global model, exacerbating the divergence among client updates and reducing overall performance.

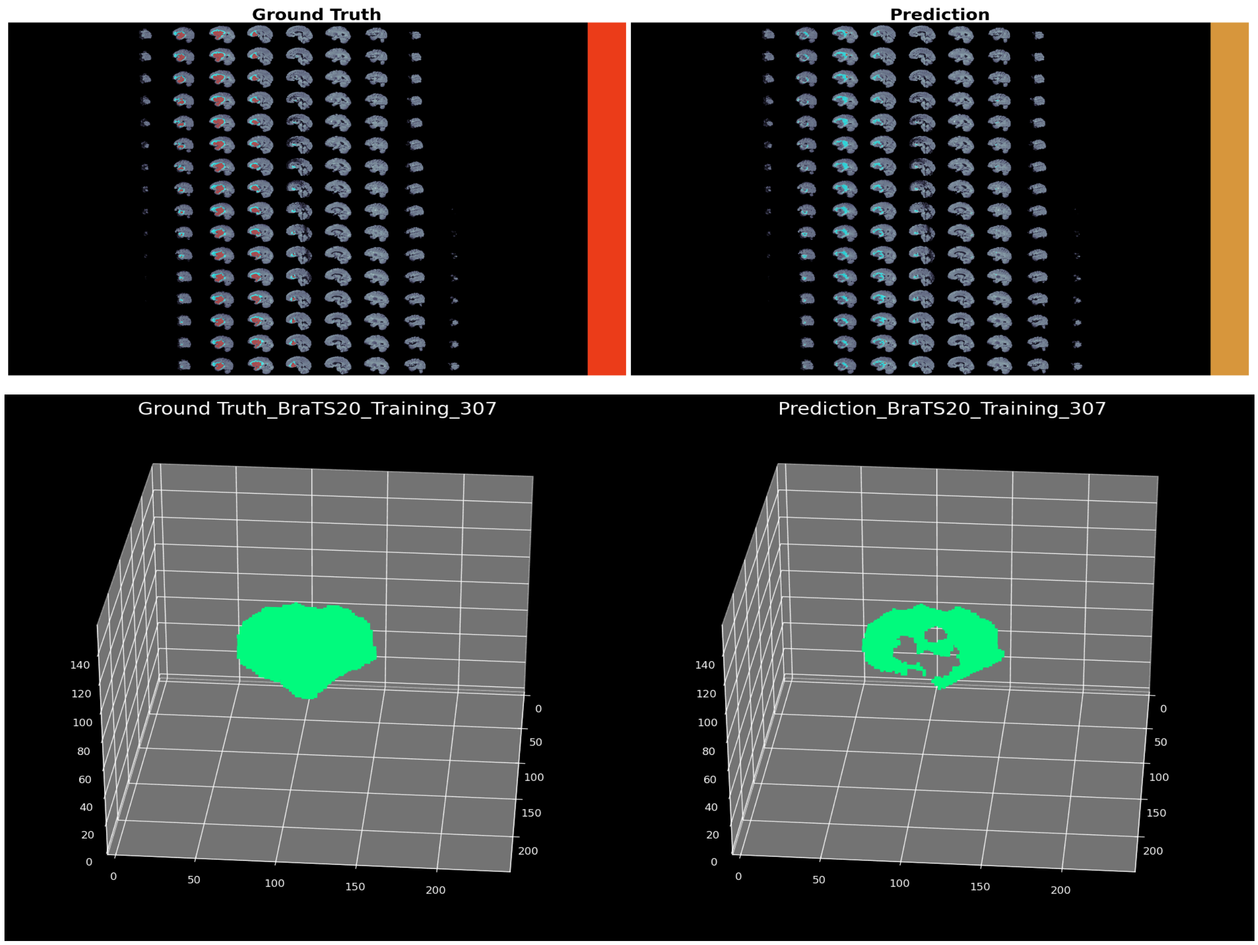

Figure.4. Shows the result by Federated learning on Non-IID Data Distribution

To address the challenges posed by non-IID data, the Federated Personalization (FedPer) method was applied. FedPer introduces client-specific layers, allowing each client to personalize the model to its local data distribution while maintaining shared global layers for generalization. In the unequal data distribution setup, FedPer achieved a Dice Coefficient of 0.464, an IoU of 0.4653, and an average client loss of 0.9941. While the Dice Coefficient remained consistent with standard FL, the IoU improved significantly, indicating better alignment between the predicted and ground truth segmentation masks. These results demonstrate FedPer's ability to adapt to client-specific data distributions, mitigating the performance loss typically observed in non-IID setups.

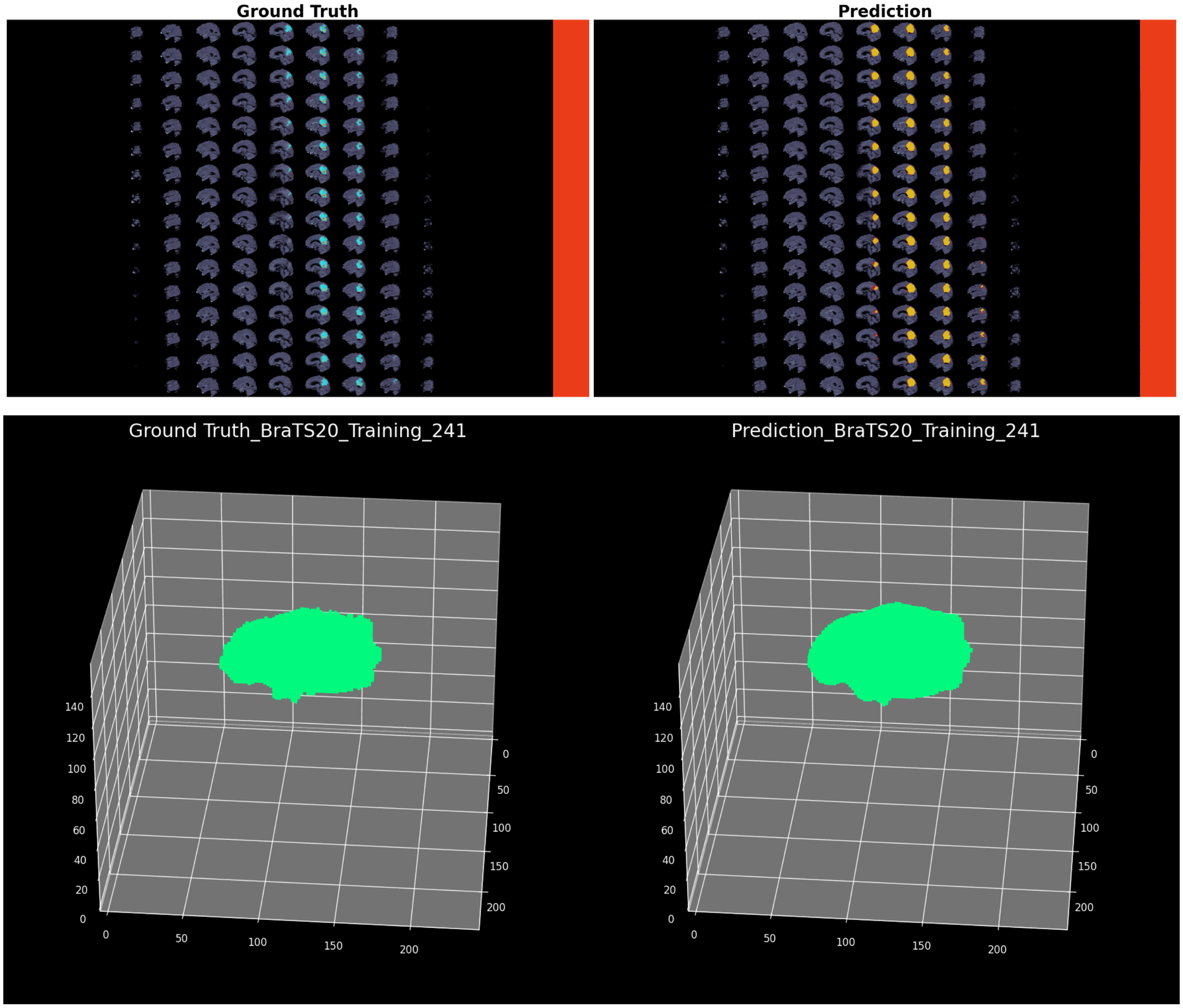

Figure.5. Shows the 3D results obtained by the FedPer algorithm

Federated Learning Approach	Data Distribution	Dice Coefficient	IoU	Average Client Loss
Standard Federated Learning (FedAvg)	Equal	**0.6941**	**0.5695**	**0.3096**
Standard Federated Learning (FedAvg)	Unequal	**0.4648**	**0.3195**	**0.3054**
Federated Personalization (FedPer)	Unequal	**0.4640**	**0.4653**	**0.9941**

Table1. Shows us the results from all the experiments.

Overall, the results reveal the trade-offs between centralized learning, standard federated learning, and FedPer. Centralized learning achieves the best performance but is impractical for privacy-sensitive applications. Federated learning is a viable alternative, particularly when data distribution across clients is balanced, but its performance degrades in heterogeneous scenarios. FedPer addresses these challenges by introducing personalization, allowing it to strike a balance between global generalization and local adaptation. This makes FedPer particularly suitable for real-world medical applications where data is inherently non-IID and privacy concerns prevent centralization. These findings highlight the potential of combining personalization techniques like FedPer with federated learning to improve segmentation performance while adhering to data privacy regulations.

Challenges

Implementing federated learning for 3D brain tumor segmentation required careful design to simulate real-world scenarios with non-identically distributed (non-IID) data. The heterogeneity in client data distributions was intentionally induced by partitioning the BraTS2020 dataset unevenly among clients, reflecting the variability commonly observed in medical institutions. While this setup was crucial to evaluate the robustness of Federated Personalization (FedPer), it posed significant challenges for training. Standard aggregation techniques like FedAvg struggled to handle the variability in data size and distribution across clients, leading to notable performance degradation in the global model.

Another major challenge was the computational overhead of training 3D U-Net models on volumetric data. The high memory consumption of 3D convolutional layers necessitated smaller batch sizes, slowing convergence and increasing training time. Additionally, federated learning introduced iterative communication between clients and the server, further extending the overall training duration compared to centralized learning.

Preprocessing the BraTS2020 dataset also presented complexities. Ensuring consistency across multi-modal MRI scans required resizing, intensity normalization, and augmentation. These steps were critical to maintain the spatial and intensity relationships needed for effective segmentation, but they demanded significant computational and data handling resources.

Lastly, implementing FedPer added another layer of complexity. The approach required determining the optimal balance between shared global layers and personalized client-specific layers. While personalization improved client performance in heterogeneous setups, tuning the number of personalized layers and their aggregation strategy was non-trivial and required iterative experimentation to avoid overfitting to local data.

These challenges highlight the intricacies of developing a federated learning framework that balances privacy, scalability, and performance while addressing the realities of non-IID data distributions in medical applications.

Conclusions

This study successfully demonstrated the application of federated learning for 3D brain tumor segmentation using the U-Net architecture. Through comparative experiments, we evaluated centralized learning, standard federated learning, and the Federated Personalization (FedPer) approach under both equal and unequal data distribution scenarios.

The results showed that centralized learning achieved the best performance, with a Dice Coefficient of 0.85 and IoU of 0.80, serving as a strong baseline. Federated learning with equal data distribution provided competitive results, achieving a Dice Coefficient of 0.6941. However, performance degraded significantly in the unequal distribution scenario, with a Dice Coefficient of 0.4648, underscoring the challenges posed by non-IID data. FedPer mitigated this degradation, improving IoU to 0.4653 by introducing client-specific personalization layers, demonstrating its effectiveness in handling heterogeneous data distributions.

This project answers key questions about the viability of federated learning for medical image segmentation and the potential of personalization techniques to address non-IID challenges. It highlights that while federated learning can preserve data privacy, its performance depends heavily on data distribution and the chosen aggregation strategy.

Future work will focus on analyzing the contribution of individual clients to the global model, providing insights into optimizing aggregation methods. Additionally, experiments will be extended to incorporate TransUNet, a hybrid architecture combining transformers for global context and U-Net for local precision, to further enhance segmentation performance in privacy-sensitive and heterogeneous data scenarios.

Questions Answered

What question do we feel “answered” after this project? This project confirmed that federated learning can be a viable privacy-preserving alternative to centralized learning for medical image segmentation. However, it also highlighted that the effectiveness of FL is heavily dependent on data distribution across clients, and personalization techniques like FedPer are critical for addressing non-IID challenges.

What are we still curious about after this project? While FedPer improved performance under non-IID scenarios, understanding how individual client contributions affect the global model remains an open question. This could lead to more efficient aggregation strategies, ensuring fairness and robustness. Additionally, the potential of transformer-based architectures like TransUNet in federated setups raises questions about their scalability and performance trade-offs.

References

1. Chen, J., et al. (2021). "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation." arXiv preprint arXiv:2102.04306.
2. Menze, B. H., et al. (2015). "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)." IEEE Transactions on Medical Imaging.
3. Kairouz, P., et al. (2021). "Advances and Open Problems in Federated Learning." Foundations and Trends in Machine Learning.
4. Karimireddy, S. P., et al. (2020). "SCAFFOLD: Stochastic Controlled Averaging for Federated Learning." Proceedings of the 37th International Conference on Machine Learning (ICML).
5. Ronneberger, O., Fischer, P., & Brox, T. (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation." arXiv preprint arXiv:1505.04597.
6. Li, T., et al. (2020). "Federated Optimization in Heterogeneous Networks." Proceedings of Machine Learning and Systems (MLSys).
7. Sheller, M. J., et al. (2020). "Federated Learning in Medicine: Facilitating Multi-Institutional Collaborations without Sharing Patient Data." Scientific Reports.
8. Yang, Q., et al. (2019). "Federated Machine Learning: Concept and Applications." ACM Transactions on Intelligent Systems and Technology (TIST).
9. Dosovitskiy, A., et al. (2020). "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale." arXiv preprint arXiv:2010.11929.
10. Isensee, F., et al. (2021). "nnU-Net: A Self-Adapting Framework for U-Net-Based Medical Image Segmentation." Nature Methods.