B. Tech. Project

Title : Federated Learning on Medical Data Imaging

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GOAL :

1. Develop a privacy-preserving federated learning framework for brain tumour segmentation.
2. Achieve comparable accuracy than centralized training while ensuring data remains decentralized.

MOTIVATION :

1. Medical imaging datasets contain sensitive patient information. Centralized training models require sharing raw data, raising ethical and legal concerns.
2. Hospitals/research centers hesitate to share data due to privacy risks, creating silos that hinder advancements in medical AI.

Privacy-Preserving

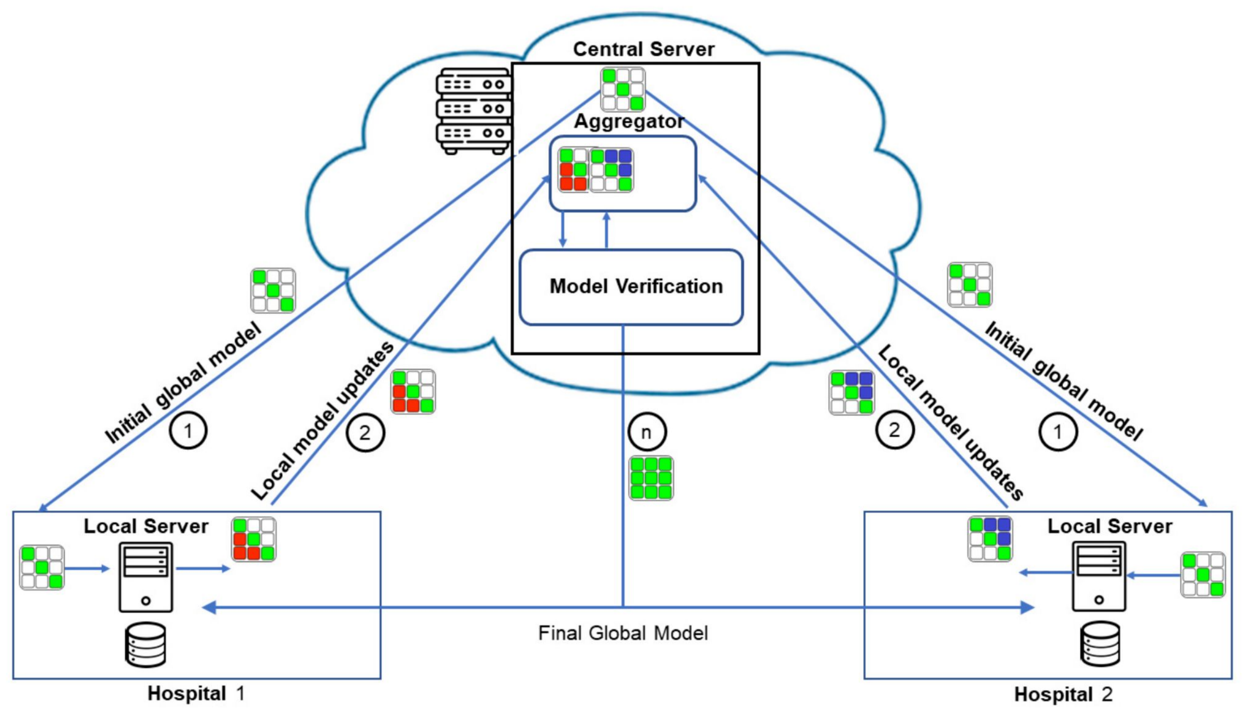
Keeps data secure.

Collaborative

Enables model training.

Technical Foundations of Federated Learning

Federated Learning is a decentralized machine learning paradigm where multiple parties collaboratively train a shared model without exchanging raw data. Instead only model updates are shared and aggregated centrally.

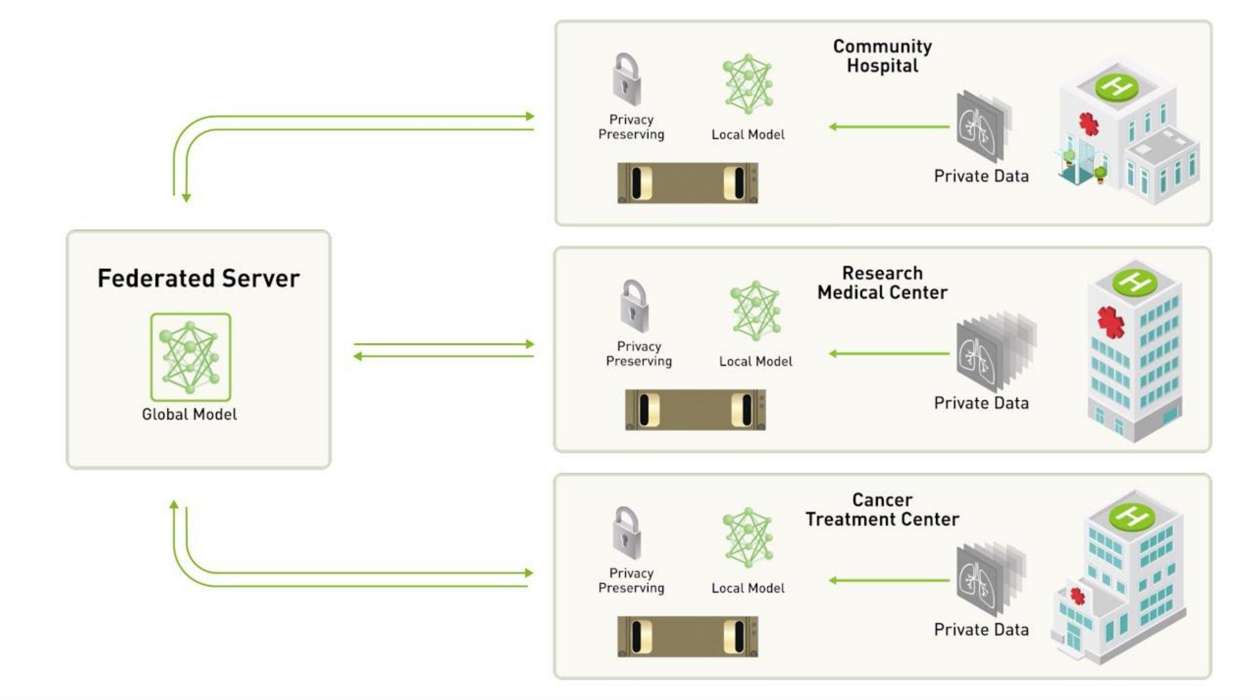


Local Training

Models trained on local devices.

Parameter Aggregation

Updates combined securely using FedAvg Algorithm.



Differential Privacy

Enhanced data protection.

BraTS-2020 Dataset

Multi-institutional benchmark dataset for brain tumor segmentation using MRI.

Organised by MICCAI (Medical Image Computing and Computer-Assisted Intervention Society).

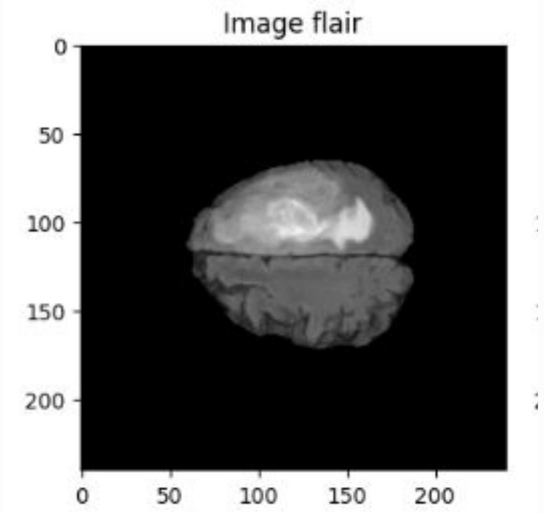
Four channels of information - 4 different volumes of the same region.

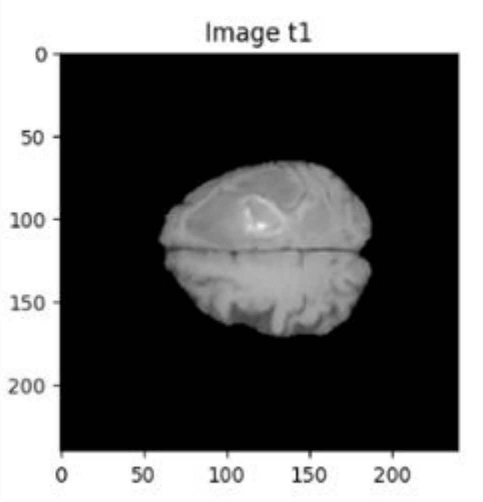
1. Native (T 1)
2. Post-contrast T 1 - weighted (T1 CE)
3. T2 - weighted (T 2)
4. T2 Fluid Attenuated Inversion Recovery (FLAIR) volumes

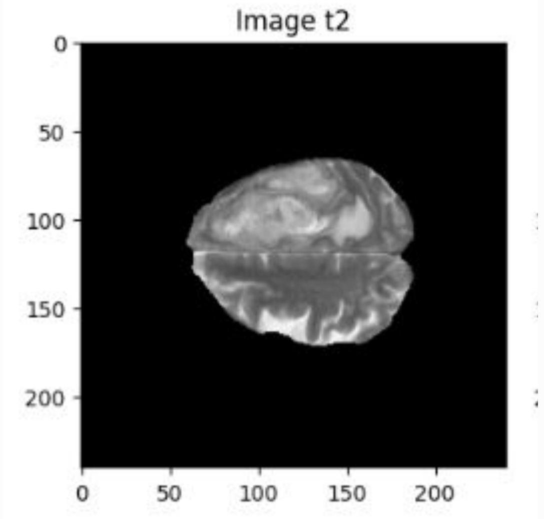
All the imaging datasets have been segmented manually and were approved by experienced neuro-radiologists.

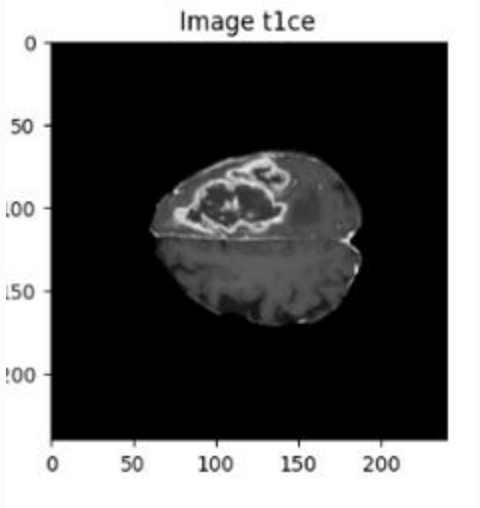
Annotations :

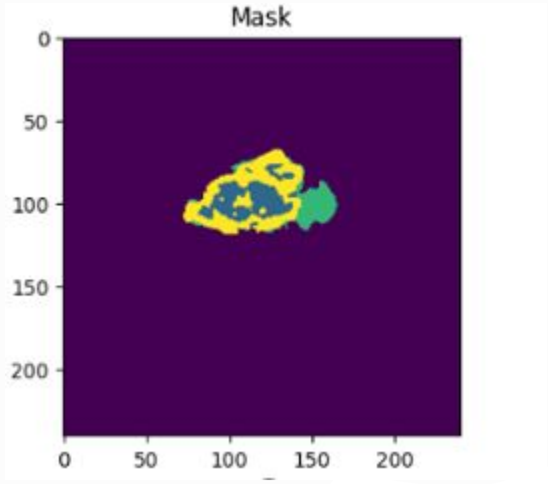
- Label 0 : Unlabeled Volume
- Label 1 : Necrotic and Non-enhancing tumor core.
- Label 2 : Peritumoral Edema
- Label 3 : GD Enhancing Tumor











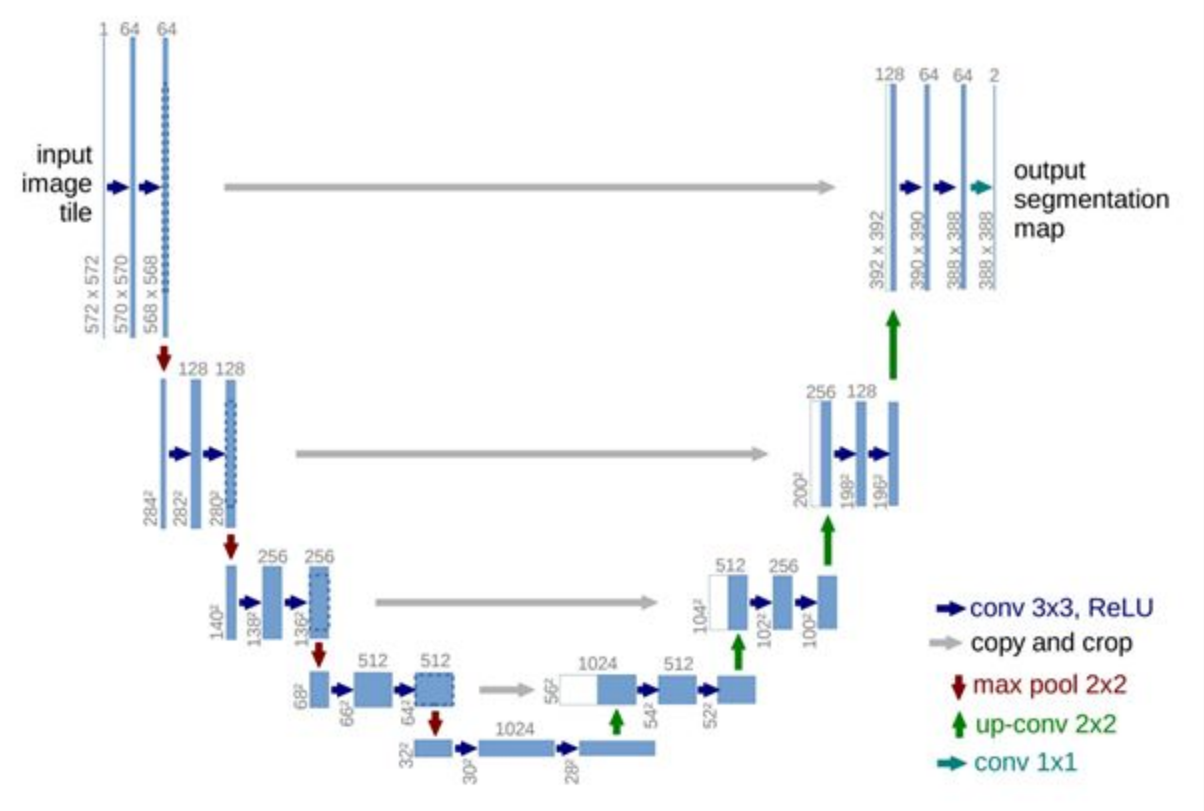
Simple U-Net

Designed for precise biomedical image segmentation (eg. tumours).

Encoder (Contracting Path): Extracts features via convolutional layers and max-pooling (down sampling).

Decoder (Expanding Path): Reconstructs segmentation maps via upsampling and transposed convolutions.

Skip Connections: Bridges encoder and decoder to retain spatial details (critical for small tumors).



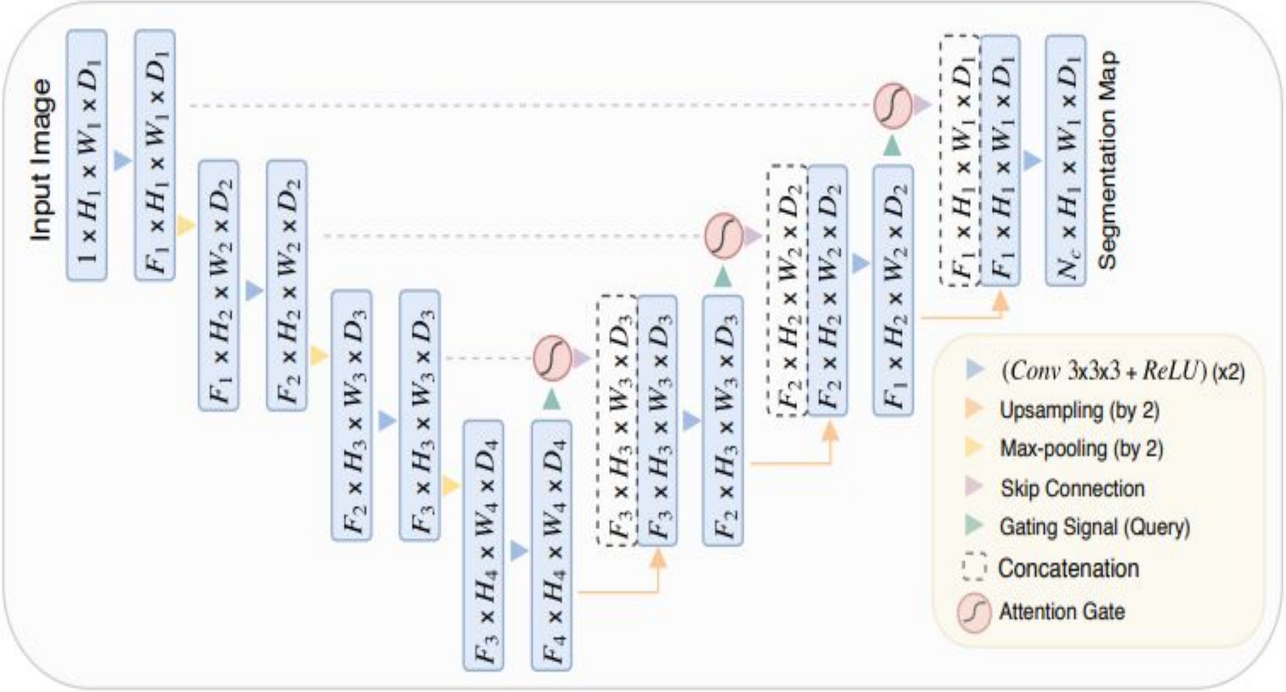
Attention U-Net

Improves segmentation accuracy by focusing on relevant regions (e.g., tumor areas).

Key Innovation : Attention Gates

Function : Dynamically highlight salient regions (e.g., tumors) and suppress irrelevant background.

Placement : Integrated into skip connections to filter encoder features before merging with the decoder.



Advantages Over Standard U-Net:

Reduced False Positives: Suppresses noise in MRI scans (e.g., healthy tissue).

Handles Class Imbalance: Focuses on small lesions (common in brain tumors).

Federated Learning

5 Clients - Each with 50 images to train.

FedAvg Algorithm :

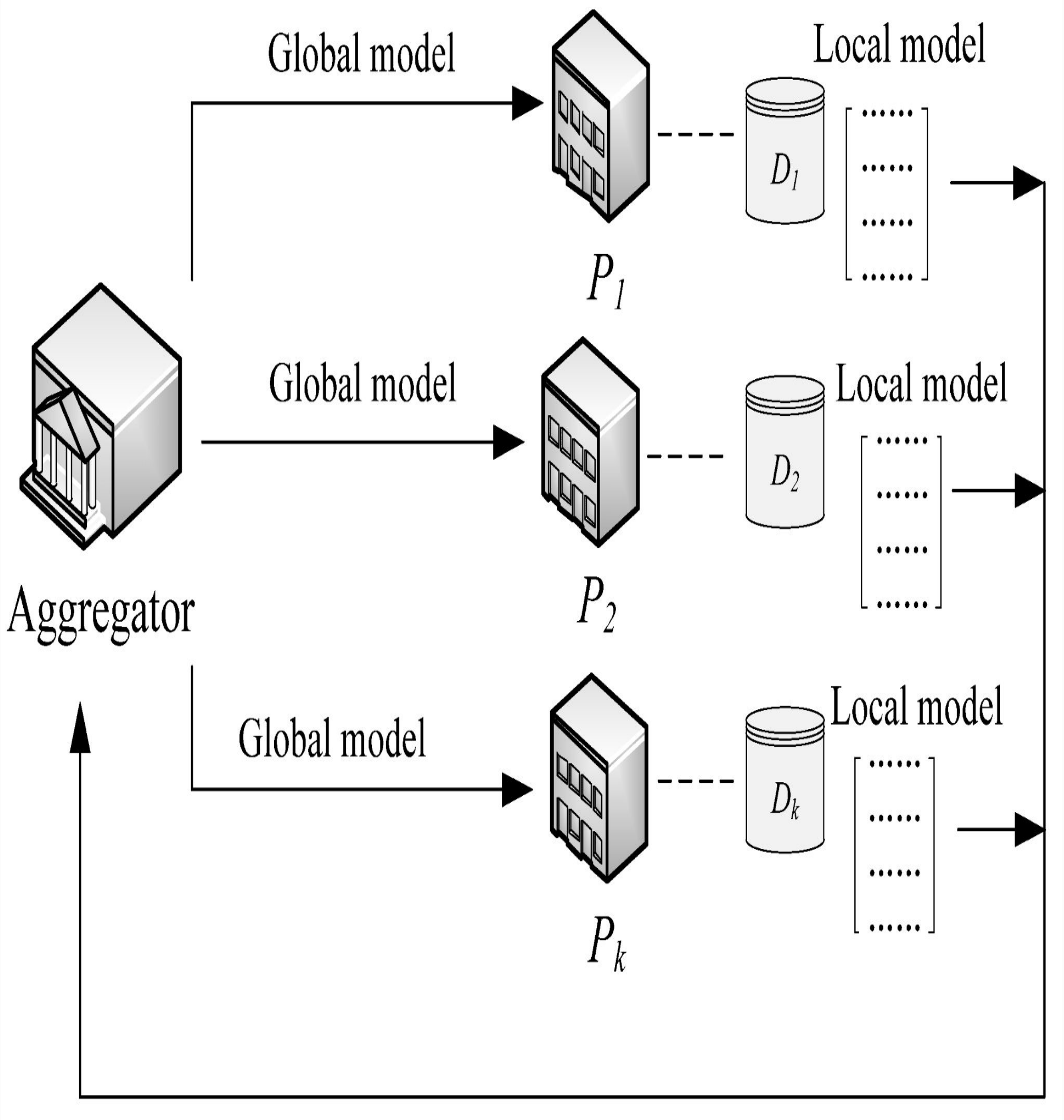
1. Server Initialization: A global model is initialized on the central server.

2. Client Selection: A subset of clients (hospitals) is selected for training in each communication round.

3. Local Training: Each client trains the global model on its local data for E epochs.

4. Parameter Aggregation: The server averages the model parameters/weights from all clients to update the global model.

5. Repeat: Steps 2-4 are repeated for T communication rounds.



	Centralised Model		Federated Learning Model	
	Simple U-Net	Attention U-Net	Simple U-Net	Attention U-Net
Mean Dice	0.3651	0.4143	0.2903	0.3407
Mean Jaccard	0.2873	0.3708	0.2496	0.2698
Class Wise Dice - Whole Tumour (1+2+3)	0.5304	0.5762	0.4332	0.4622
Class Wise Dice- Tumour Core (1+3)	0.3344	0.3791	0.2701	0.3345
Class Wise Dice- Enhancing Tumour (3)	0.2306	0.2878	0.1677	0.2254

Phase II - Future Directions

In the next phase, we will focus on minimising the number of rounds.

Objective : *Accelerate convergence while reducing communication overhead in federated learning (FL) to enable efficient deployment in resource-constrained medical environments.*

References

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