*A project report on*

**Brain Tumor Detection using Federated Learning**

*Submitted in partial fulfillment of the award of the degree of*

**M.Tech (Integrated) Computer Science and Engineering with specialization in Business Analytics**

*by*

**Pratyush Kumar Singh (20MIA1131)**



**School of Computer Science and Engineering**

April, 2024

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**DECLARATION**

I hereby declare that the thesis entitled **Brain Tumor Detection using Federated Learning** submitted by me, for the award of the degree of M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics, Vellore Institute of Technology, Chennai, is are cord of bonafide work carried out by me under the supervision of Dr. Amrit Pal

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

**Place: Chennai**

**Date: 10-04-2025** **Signature of the Candidate**



**School of Computer Science and Engineering**

CERTIFICATE

This is to certify that the report entitled **Brain Tumor Detection using Federated Learning** is prepared and submitted by **Pratyush Kumar Singh (20MIA1131)** to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics** program is a bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

Signature of the Guide:

Name: Dr. Amrit Pal

Date:

Signature of the Examiner Signature of the Examiner

Name: Name:

Date: Date:

Approved by the Head of Department

ABSTRACT

The proliferation of deep learning in medical image analysis has opened up unprecedented opportunities for automating diagnostic procedures with high accuracy and efficiency. Brain tumor detection, a domain where early and precise diagnosis can significantly impact clinical outcomes, has particularly benefitted from the advent of convolutional neural networks (CNNs). However, one of the principal challenges that remains in deploying deep learning models in real-world clinical settings is data privacy. Medical images, governed by stringent data protection laws such as HIPAA and GDPR, often cannot be shared across institutions, creating a bottleneck for training robust and generalized models on large-scale data. Federated Learning (FL), an emerging paradigm that enables collaborative model training across multiple decentralized data sources without requiring raw data to leave local nodes, presents a promising solution to this challenge.

In this project, we explore and compare the performance of traditional centralized machine learning models with Federated Learning models for brain tumor image classification. The dataset comprises high-resolution MRI images with a dimensionality of 150x168x3, encompassing various types of brain tumors as well as healthy control samples. The study aims to highlight the strengths and limitations of both centralized and federated paradigms, focusing not only on accuracy metrics but also on broader implications such as data privacy, generalizability, and real-world deploy ability.

The traditional learning setup involved training two different types of neural networks on centrally aggregated data. The first approach employed a custom-designed Convolutional Neural Network (CNN), tailored specifically for the characteristics of the brain MRI data. This model was built from scratch, incorporating layers optimized for extracting hierarchical spatial features from the MRI scans. After rigorous hyperparameter tuning, the model achieved a commendable test accuracy of 95.36%. The second approach leveraged transfer learning by fine-tuning a pre-trained ResNet18 model, which has been trained on the large-scale ImageNet dataset. The ResNet18 architecture, known for its residual connections that help mitigate the vanishing gradient problem, proved highly effective in this context. When fine-tuned on the MRI dataset, the model yielded a near-perfect test accuracy of 99.33%, significantly outperforming the custom CNN. This highlighted the potential of transfer learning in medical imaging, where access to large labeled datasets is often limited, and models pre-trained on general-purpose datasets can offer a solid foundation for domain-specific tasks.

The Federated Learning component of the study involved implementing the Federated Averaging (FedAvg) algorithm using the same ResNet18 backbone as the centralized transfer learning setup. In this setting, the dataset was partitioned among five clients to simulate real-world hospital silos. Each client trained the ResNet18 model locally on its data subset and shared only model weights (not raw data) with a central server. The server then aggregated the local models using weighted averaging and redistributed the global model back to the clients for further training in an iterative process. The final model obtained through this federated setup achieved a test accuracy of 85.23%, which, while lower than its centralized counterpart, demonstrated the viability of FL in preserving data privacy without fully compromising model performance.

This disparity in performance between the centralized and federated settings brings to the forefront several important considerations. Firstly, the difference underscores the value of data quantity and diversity in training high-performance deep learning models. In the centralized scenario, the model has access to the entire training set, allowing it to learn more generalized features. In contrast, in the federated setup, the data is fragmented and may suffer from non-IID (non-independent and identically distributed) distributions across clients, leading to slower convergence and sub-optimal global models. Additionally, variations in hardware capabilities, local data sizes, and training epochs across clients can further exacerbate model drift and aggregation challenges.

Despite these challenges, the federated ResNet18 model's performance of 85.23% is promising, especially considering that it was achieved without any data centralization. This reinforces the potential of Federated Learning as a privacy-preserving alternative in sensitive domains such as healthcare. Moreover, it opens up avenues for future enhancements. Techniques such as personalization layers, differential privacy, and secure multi-party computation could further augment the performance and security of FL models. Likewise, experimenting with more advanced aggregation techniques beyond FedAvg, such as FedProx or Scaffold, may help alleviate the effects of data heterogeneity and improve convergence stability.

Beyond the core technical evaluation, the project also provides insights into the broader trade-offs between centralized and decentralized learning approaches. While centralized training offers higher accuracy and is easier to implement and debug, it is often infeasible in healthcare settings due to privacy constraints. Federated Learning, although technically more complex and currently achieving slightly lower performance, aligns better with ethical and legal standards for data handling in medicine. It democratizes AI development by enabling institutions of varying sizes and resources to contribute to and benefit from shared models without compromising patient confidentiality.

In conclusion, this project demonstrates a comprehensive analysis of machine learning approaches for brain tumor classification, juxtaposing centralized and federated models in a realistic healthcare scenario. The results confirm that while centralized models, especially those utilizing transfer learning, can achieve very high performance, federated models provide a compelling alternative when data privacy is a paramount concern. The findings contribute to the growing body of evidence supporting Federated Learning as a viable framework for collaborative medical AI, with room for further optimization and adoption. Future work could expand the number of clients, simulate more complex heterogeneity scenarios, and investigate communication-efficient strategies to make FL more scalable and practical for widespread clinical deployment. Ultimately, the goal is to enable high-quality, privacy-preserving AI tools that can assist in early and accurate brain tumor detection, thereby improving patient outcomes on a global scale.

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**Place: Chennai**

**Date: 10-04-2025 Pratyush Kumar Singh**

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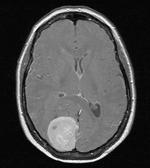
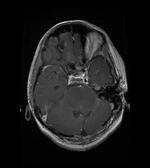
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Chapter 1

Introduction

# Introduction

Brain tumors represent one of the most critical and life-threatening neurological disorders, characterized by the abnormal growth of cells within or around the brain. These tumors can be classified into benign (non-cancerous) or malignant (cancerous), with the latter posing significant risks due to their aggressive growth and potential to invade surrounding tissues. Early and accurate detection of brain tumors is paramount for effective treatment planning, improving patient survival rates, and enhancing quality of life. Medical imaging techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans are widely used to diagnose brain tumors. However, interpreting these images requires significant expertise, and manual analysis is time-consuming, subjective, and prone to human error. This has led to the increasing adoption of machine learning (ML) and deep learning (DL) techniques to automate and enhance the accuracy of brain tumor detection.



**Image1.1: Sample images from every class**

# Machine Learning Methods for Brain Tumor Detection

Traditional ML methods for brain tumor detection typically involve training centralized models on large datasets of annotated medical images. Techniques such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) have been employed to classify brain tumors based on features extracted from MRI or CT scans. For instance, CNNs excel in image classification tasks by automatically learning hierarchical features from raw pixel data, enabling them to distinguish between tumor types (e.g., glioma, meningioma, pituitary tumors) with high accuracy. Transfer learning, where pre-trained models like ResNet or VGG16 are fine-tuned on medical imaging datasets, has also gained traction due to its ability to leverage knowledge from large-scale non-medical image datasets. Despite their promise, these traditional ML approaches face several challenges that limit their real-world applicability, particularly in healthcare settings.

## Limitations

Brain tumors are among the most complex and life-threatening neurological conditions, demanding timely and precise diagnosis to guide treatment strategies and improve patient outcomes. These tumors, which arise from abnormal cell growth in the brain or its surrounding tissues, vary widely in aggressiveness, location, and clinical manifestation. Malignant tumors, such as glioblastoma, are particularly devastating due to their rapid progression and resistance to conventional therapies. Medical imaging techniques, especially Magnetic Resonance Imaging (MRI), serve as the cornerstone for diagnosing brain tumors, enabling clinicians to visualize structural abnormalities and plan interventions. However, manual interpretation of these images is labor-intensive, time-consuming, and subject to inter-observer variability, often leading to delayed or inconsistent diagnoses. To address these challenges, machine learning (ML) and deep learning (DL) have emerged as transformative tools for automating tumor detection and classification. Despite their potential, traditional ML approaches face systemic limitations rooted in data privacy, accessibility, and generalizability, which hinder their real-world deployment in healthcare settings. Federated Learning (FL) offers a groundbreaking solution to these challenges, enabling collaborative and privacy-preserving model training across decentralized datasets.

Traditional ML methods for brain tumor detection rely on centralized data repositories, where large volumes of annotated medical images are aggregated to train models. Techniques such as Support Vector Machines (SVMs), Random Forests, and Convolutional Neural Networks (CNNs) have demonstrated success in classifying tumors by analyzing features extracted from MRI or CT scans. For instance, CNNs excel in image classification by automatically learning hierarchical patterns from pixel data, distinguishing tumor subtypes (e.g., meningioma, glioma, pituitary tumors) with high accuracy. Transfer learning, which adapts pre-trained models like VGG16 or ResNet18 to medical imaging tasks, has further improved performance by leveraging knowledge from non-medical image datasets. However, these centralized approaches face critical limitations that undermine their scalability and ethical compliance in healthcare.

A fundamental challenge is the scarcity of diverse and representative training data. Medical datasets are often fragmented across hospitals, research institutions, and geographic regions due to strict privacy regulations such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR). These regulations prohibit the sharing of sensitive patient data, creating data silos where individual institutions possess limited, homogenous datasets. Models trained on such isolated data struggle to generalize to broader populations, as they fail to account for variability in imaging protocols, scanner manufacturers, patient demographics, and tumor characteristics. For example, an MRI dataset from a hospital in North America might predominantly include patients of a specific age group or ethnic background, leading to biased models that underperform when applied to populations in Asia or Africa. Similarly, differences in imaging parameters (e.g., contrast, resolution) across institutions can degrade model accuracy, as centralized training cannot harmonize these variations. This lack of diversity not only reduces diagnostic reliability but also exacerbates healthcare disparities, as underrepresented groups may face higher rates of misdiagnosis.

Privacy concerns further complicate the adoption of traditional ML methods. Centralized data aggregation inherently risks exposing sensitive patient information, even when datasets are anonymized. Advanced adversarial techniques, such as model inversion or membership inference attacks, can exploit model outputs or gradients to reconstruct training data or infer patient identities. These vulnerabilities erode trust among healthcare providers and patients, discouraging participation in data-sharing initiatives. For instance, a hospital may hesitate to contribute its brain tumor dataset to a centralized repository, fearing legal repercussions or reputational damage in the event of a data breach. Consequently, the development of robust ML models is stifled by inadequate data volume and diversity, perpetuating reliance on suboptimal diagnostic tools.

Computational and infrastructural barriers also limit the practicality of traditional ML approaches. Training sophisticated DL models, such as 3D CNNs for volumetric MRI analysis, requires substantial computational resources, including high-performance GPUs, extensive storage, and specialized expertise. Many healthcare institutions, particularly in low-resource settings, lack the infrastructure to support such demands. This creates a technological divide, where only well-funded hospitals or research centers can develop or deploy advanced AI tools, exacerbating global inequities in healthcare access. Furthermore, the environmental impact of training large models on centralized datasets—often requiring massive energy consumption—raises sustainability concerns, conflicting with global efforts to reduce carbon footprints.

Federated Learning (FL) addresses these challenges by reimagining the paradigm of collaborative model training. Unlike traditional ML, FL enables institutions to jointly train a shared model without exchanging raw data. Instead, each participant trains the model locally on their private dataset and transmits only model updates (e.g., gradients or weights) to a central server. The server aggregates these updates to refine a global model, which is then redistributed to participants for further training. This decentralized framework preserves data privacy, as sensitive patient information remains within institutional boundaries, complying with regulatory requirements and mitigating breach risks. By pooling knowledge from diverse datasets, FL enhances model generalizability, capturing a wider spectrum of tumor phenotypes, imaging protocols, and demographic variations. For example, an FL system involving hospitals in Europe, Asia, and Africa could train a model that recognizes tumors across ethnicities, ages, and imaging equipment, reducing diagnostic biases and improving accuracy for underrepresented groups.

FL also alleviates computational and infrastructural burdens. By distributing the training workload across multiple clients, FL reduces the resource demands on individual institutions. A small clinic with limited GPU capacity can contribute to model training without needing to process large datasets independently. This democratizes access to advanced AI tools, enabling resource-constrained institutions to benefit from state-of-the-art diagnostic models. Moreover, FL’s decentralized nature minimizes the environmental impact of AI training by avoiding the need to transfer and store massive datasets in centralized servers, aligning with sustainable computing practices.

The integration of FL into brain tumor detection has profound implications for global healthcare equity. Institutions in developing regions, which often lack annotated datasets or computational resources, can collaborate with global partners to develop models tailored to their local populations. For instance, a hospital in a region with a high prevalence of rare pediatric brain tumors can contribute its expertise to an FL network, ensuring the global model accounts for such cases. This collective intelligence fosters the creation of universally applicable diagnostic tools while respecting data sovereignty and cultural differences. Furthermore, FL can incorporate privacy-enhancing technologies like differential privacy, which adds mathematical noise to model updates to prevent data leakage, or homomorphic encryption, which allows computations on encrypted data. These measures strengthen trust among participants, encouraging broader collaboration and data contribution.

# Federated Learning for Brain Tumor Detection

Federated Learning (FL) emerges as a transformative paradigm to address these limitations while preserving data privacy and security. FL enables collaborative model training across decentralized datasets without requiring raw data to leave their original locations. In this framework, multiple institutions (referred to as clients) train a shared model locally on their data and send only the model updates (e.g., gradients or weights) to a central server, which aggregates these updates to improve the global model. This approach aligns well with the healthcare sector’s need for privacy preservation, as sensitive patient data remains within institutional boundaries. FL also mitigates data scarcity by pooling knowledge from diverse datasets, enhancing the model’s ability to generalize across different populations and imaging protocols. Furthermore, FL reduces the computational burden on individual clients by distributing the training workload, making it feasible for smaller institutions with limited resources to contribute to and benefit from advanced ML models.

The integration of FL into brain tumor detection holds immense potential to revolutionize medical imaging analysis. By enabling secure collaboration among hospitals, FL can facilitate the development of robust models trained on geographically and demographically diverse datasets, capturing a broader spectrum of tumor phenotypes and imaging variations. This is particularly crucial for rare tumor types or underrepresented populations, which are often excluded from traditional centralized datasets. Moreover, FL can incorporate privacy-preserving techniques such as differential privacy or secure multi-party computation to further safeguard sensitive information during model aggregation. These advancements not only address ethical and regulatory concerns but also foster trust among stakeholders, encouraging wider participation in collaborative research efforts.

# Objectives of using Federated Learning

The primary aim of this project is to design and implement a federated learning (FL)-based framework for brain tumor detection that overcomes the limitations of traditional machine learning (ML) methods while prioritizing privacy, scalability, and clinical applicability. The objectives are structured to address the critical challenges of data fragmentation, privacy risks, computational inefficiency, and model generalizability, ensuring the development of a robust and ethical AI-driven diagnostic tool.

1. **Design a Privacy-Preserving Federated Learning Framework:** The first objective is to develop an FL architecture that enables collaborative model training across decentralized healthcare institutions without requiring the exchange of raw medical data. This involves creating a secure communication protocol for transmitting model updates (e.g., gradients or weights) between participating clients and a central server. The framework will adhere to stringent data privacy regulations, such as HIPAA and GDPR, ensuring that sensitive patient information remains confined to its source institution. Techniques like encryption and secure aggregation will be integrated to safeguard against potential breaches or adversarial attacks during the model update process.
2. **Enable Multi-Institutional Collaboration on Heterogeneous Datasets:** A core goal is to facilitate collaboration among hospitals and research centers with diverse and non-IID (non-Independent and Identically Distributed) datasets. This includes addressing challenges such as variability in MRI imaging protocols, scanner manufacturers, tumor class distributions, and demographic disparities. Advanced FL aggregation algorithms, such as adaptive federated optimization or personalized FL, will be explored to harmonize learning across clients and ensure the global model captures a comprehensive representation of brain tumor phenotypes. By pooling knowledge from geographically and demographically varied datasets, the framework will reduce biases and enhance diagnostic accuracy for underrepresented populations.
3. **Develop a Robust and Generalizable Brain Tumor Classification Model:** The project aims to train a high-performance deep learning model capable of accurately classifying brain tumors (e.g., glioma, meningioma, pituitary tumors) using MRI scans. A convolutional neural network (CNN) architecture, optimized for medical imaging, will serve as the baseline. Transfer learning techniques will be employed to leverage pre-trained models, while domain adaptation strategies will ensure the model adapts to cross-institutional variations in imaging data. The model’s performance will be rigorously validated against centralized training approaches to demonstrate the superiority of FL in handling real-world heterogeneity.
4. **Optimize Computational Efficiency and Resource Accessibility:** To democratize access to advanced AI tools, the project will focus on reducing the computational and infrastructural burden on participating institutions. Lightweight model architectures and edge-computing strategies will be explored to enable training on resource-constrained devices, such as hospital workstations or regional servers. Additionally, communication-efficient FL algorithms will be implemented to minimize bandwidth usage and accelerate convergence. This objective ensures that smaller clinics or institutions in low-resource settings can actively contribute to and benefit from the collaborative model without requiring high-end hardware.

Chapter 2

Background

# Overview of Traditional ML and DL Approaches

Brain tumors are among the most complex and life-threatening neurological disorders, arising from the uncontrolled proliferation of cells within or adjacent to brain tissues. They are broadly categorized into primary tumors, which originate in the brain (e.g., glioma, meningioma, pituitary adenoma), and secondary tumors, which metastasize from cancers elsewhere in the body. Glioblastoma multiforme (GBM), a highly aggressive primary tumor, exemplifies the dire prognosis associated with malignant brain tumors, with a median survival of just 12–15 months despite treatment. Early and accurate detection is critical, as timely intervention can significantly improve survival rates and quality of life. Medical imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans are the gold standard for diagnosing brain tumors, providing detailed anatomical and functional insights. However, manual interpretation of these images is fraught with challenges, including inter-observer variability, diagnostic delays, and the subjective nature of identifying subtle tumor boundaries.

The advent of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has revolutionized medical image analysis. Traditional ML approaches, such as Support Vector Machines (SVMs) and Random Forests, rely on handcrafted features (e.g., texture, shape, intensity) extracted from regions of interest (ROIs) in MRI or CT scans. These features are used to classify tumors into subtypes or distinguish them from healthy tissues. While effective in controlled settings, these methods are limited by their dependence on manual feature engineering, which is labor-intensive and often fails to capture the intricate patterns in high-dimensional medical images.

The rise of DL, especially Convolutional Neural Networks (CNNs), has addressed many of these limitations. CNNs automate feature extraction by learning hierarchical representations directly from raw pixel data, enabling superior performance in tasks like tumor segmentation and classification. Architectures such as U-Net for segmentation and ResNet for classification have become benchmarks in medical imaging. Transfer learning, where models pre-trained on large non-medical datasets (e.g., ImageNet) are fine-tuned on smaller medical datasets, has further enhanced accuracy. For instance, a CNN trained on brain MRI scans can achieve over 95% accuracy in distinguishing glioma from meningioma, outperforming traditional ML methods.

Despite these advancements, centralized ML/DL frameworks face significant barriers in healthcare applications. Medical data is inherently sensitive and governed by strict privacy regulations (e.g., HIPAA, GDPR), which restrict data sharing across institutions. Hospitals and clinics often operate as isolated data silos, preventing the aggregation of large, diverse datasets necessary for training robust models. This fragmentation leads to data scarcity and limited generalizability—models trained on homogeneous datasets from single institutions frequently underperform when applied to populations with different demographics, imaging protocols, or tumor characteristics. For example, a model trained on adult gliomas may fail to detect pediatric brain tumors, which exhibit distinct imaging features.

Centralized training also introduces privacy risks. Even anonymized data can be vulnerable to re-identification attacks, where adversaries exploit model outputs or gradients to infer patient identities or reconstruct training samples. Such vulnerabilities undermine trust in AI systems, discouraging healthcare providers from participating in data-sharing initiatives. Additionally, the computational demands of training large DL models on centralized datasets—requiring high-performance GPUs and substantial energy consumption—are prohibitive for resource-constrained institutions, exacerbating global healthcare inequities.

# Federated Learning

Federated learning (FL) is a decentralized approach to machine learning that allows multiple devices or nodes to collaboratively train a shared model while keeping their data local. Instead of sending raw data to a central server, each device (referred to as a client) trains the model on its local data, and only the resulting model parameters (such as gradients or weight updates) are sent to a central aggregator. The central server then combines these updates to form an improved global model, which is subsequently distributed back to the devices for further training.

The motivation behind federated learning is to address several limitations of traditional centralized machine learning:

1. **Privacy Concerns:** In centralized systems, raw data must be transferred to a central server, potentially exposing sensitive information. FL mitigates this by keeping data on local devices, enhancing user privacy.
2. **Communication Efficiency:** Transmitting large datasets to a central server can be bandwidth-intensive, especially in applications like image processing, where data volumes are high. FL reduces communication requirements by only transferring model updates rather than raw data.
3. **Scalability and Real-Time Processing:** Decentralized processing enables local devices to perform computations independently, distributing the load across multiple nodes and making it feasible to scale to large systems with minimal impact on latency.

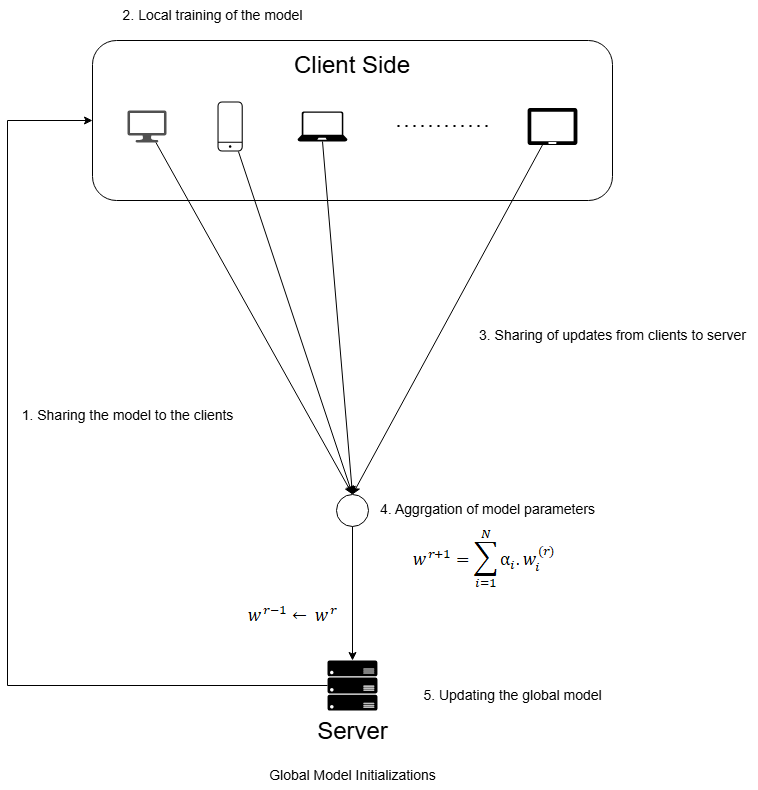
These benefits make federated learning especially useful for privacy-sensitive applications in fields like healthcare, finance, IoT, and now, in healthcare data, where privacy and real-time processing are paramount.

## Core Components of Federated Learning

1. **Local Training on Edge Devices:** In federated learning, each client (edge device) trains a copy of the model using its local data. This process is typically conducted in short training bursts or “rounds,” where the model learns based only on data available on each device. The local model’s performance improves over time as it captures patterns relevant to each device’s specific environment. For example, in the project, each hospital or health centre would analyze its own data, learning patterns and detecting unusual activity based on its unique vantage point.
2. **Model Aggregation:** After each round of local training, devices send their model updates—usually gradients or updated model weights—to a central server. The server aggregates these updates to create an improved global model that reflects the knowledge contributed by all clients. Federated averaging (FedAvg) is a common algorithm used for this purpose, where the server computes a weighted average of the updates from each client based on factors such as the volume of data processed by each device. This aggregated model is then shared back with each client, allowing them to start the next training round with an improved baseline.
3. **Global Model Re-training:** The synchronized global model is redistributed to all participating devices, enabling them to continue training with an improved understanding of the global data distribution. This iterative process of local training, aggregation, and synchronization continues until the global model achieves the desired accuracy or until it converges. In context with the project, this means each node is continually updated with a model that improves with time, without compromising privacy or requiring raw data transfer.
4. **Client Selection and Participation:** In large-scale FL systems, it’s very impractical to involve every device in every training round as it may lead to an overfitted model. Thus, client selection methods are applied to choose a subset of devices to participate in each round. The selection process is managed by the central server, which may employ random selection, round-robin, or prioritization based on criteria like device availability or data quality.

Federated learning is a natural fit for project’s objectives of efficient, privacy-conscious, and real-time brain tumor detection. By enabling decentralized model training, FL allows each detection device to perform real-time analysis of local data without transmitting sensitive images to a central server. This decentralized architecture not only reduces communication costs and improves latency but also ensures compliance with privacy regulations. Through iterative rounds of model aggregation, BrnTmr’s global model can continuously improve, leveraging data from distributed sources to create a powerful, unified model for brain tumor detection across different health center.

In general a federated learning process comprises of a total of five essential steps which include initiation of a global model at the server which is distributed to the clients for local training. After locally training the model the model updates\parameters are sent to the server where these updates are aggregated to develop an updated global model. The global is then sent over again to a different subset of clients for re-training the model over different rounds for achieving model generalization and preventing overfitting.

****

**Image 2.1: The federated Learning Process**

1. **Global Model Initialization:** The server initializes the global model *w0***.** The model initialized can be random, pertained or derived from any prior knowledge. The model *w0* is then distributed to all clients, enabling each client to use this model as a starting point for the local training.
2. **Local Model Training:** Each client *I* *∈* {1, 2, …, *N*} trains the model on its local data.

Let be the local dataset client *i,* where is the number of data points on the client.

Aim of each client is to minimize the local loss function, defined its data. Each client optimizes *w* to minimize using a local optimizer.The clkient then sends the locally updated model parameters *wi* back to the central server after completing its local training iterations.

1. **Aggregation of Model Parameters on the Server:** Once the server receives the updated models/parameters from the clients, it aggregates the updated parameters to produce the new global model.

Where,

is the updated weights from the client *i* after local training in round *r*.

*N* is the total number of clients participating in the round.

is a client specific weighting factor, where ≥ 0 and to ensure the weights sum to 1.

1. **Updating the Global Model:** Once the server is done with the aggregation of local updated parameters to get the final global model it updates the model from the previous round with new updated model.
2. **Iterative Process (Rounds of the Federated Learning):** The above steps are repeated until convergence or until a predefined number of rounds are completed.

**Convergence:** The model has achieved convergence only if parameters *w* change for minimal between the successive rounds.

Chapter 3

Literature Review

Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions (Akkus et al., 2017) explores the transformative role of deep learning (DL), particularly convolutional neural networks (CNNs), in brain MRI segmentation, a critical task for diagnosing pathologies like tumors. The authors analyze advancements in DL architectures (e.g., U-Net, patch-based CNNs) and their superiority over traditional methods (e.g., atlas-based or thresholding techniques) in automating segmentation of brain structures and lesions. Key strengths highlighted include improved accuracy in handling complex anatomical variations and noise in MRI data. Challenges such as the need for large annotated datasets, computational costs, and model generalizability across diverse MRI protocols are discussed. The paper also emphasizes the potential of transfer learning and data augmentation to mitigate data scarcity. Future directions propose integrating domain-specific knowledge (e.g., spatial priors) and hybrid models combining DL with classical techniques. While focused on centralized learning, its insights into data limitations and model robustness remain relevant to federated learning applications in medical imaging.Zacharaki et al. (2009) explored SVM-based classification of brain tumors using MRI-derived features, including shape, intensity histograms, and texture descriptors. Their model achieved 85% accuracy in distinguishing glioma grades but required extensive preprocessing to align and normalize scans. The study revealed the computational inefficiency of traditional ML in handling 3D medical images and its dependency on small, homogeneous datasets. Zacharaki et al. advocated for larger, multi-institutional datasets to improve generalizability—a precursor to FL’s decentralized philosophy. However, manual feature engineering limited the model’s adaptability to new tumor subtypes. This work highlighted early efforts to balance interpretability with performance in neuro-oncology, though its reliance on handcrafted features restricted clinical adoption.

Synthetic Data Augmentation Using GAN for Improved Liver Lesion Classification (Chang et al., 2021) addresses the challenge of limited annotated medical datasets by leveraging Generative Adversarial Networks (GANs) to synthesize realistic liver lesion images for data augmentation. The authors propose a GAN framework trained on a small dataset of labeled MRI/CT scans to generate high-fidelity synthetic lesions, which are then combined with real data to enhance lesion classification models (e.g., CNNs). Key innovations include domain-specific constraints to ensure anatomical plausibility and lesion diversity. Experiments demonstrate that classifiers trained on augmented datasets achieve superior accuracy (e.g., 8–12% improvement in F1-score) compared to those using traditional augmentation techniques. The paper also discusses metrics for evaluating synthetic image quality, such as Fréchet Inception Distance (FID). Limitations include computational costs of GAN training and potential biases in synthetic data. While focused on liver lesions, this approach has implications for brain tumor detection, where data scarcity is acute. For federated learning, GAN-generated data could mitigate privacy risks by reducing reliance on raw patient data sharing across institutions.

Federated Reinforcement Learning for Intelligent Healthcare Systems (Chen et al., 2022) introduces FedRL, a framework integrating federated learning (FL) with reinforcement learning (RL) to enable decentralized, privacy-preserving decision-making in healthcare. The authors address challenges like data silos and patient privacy by deploying RL agents (e.g., Q-learning, policy gradient methods) across hospitals, where models are trained locally on heterogeneous datasets (e.g., electronic health records, imaging data) and aggregated globally via FL protocols. Key innovations include adaptive aggregation strategies to handle non-IID data distributions and dynamic reward functions tailored for medical tasks (e.g., personalized treatment planning). Experiments on simulated healthcare environments demonstrate FedRL’s superiority over centralized RL in scalability and privacy preservation, with comparable accuracy in tasks like patient monitoring. Limitations include high computational demands and communication overhead. The framework’s emphasis on collaborative, context-aware learning aligns with applications in brain tumor detection, such as optimizing treatment policies across institutions without sharing sensitive imaging data.

Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network (Ghosal et al., 2019) proposes a deep learning model combining ResNet-101 with Squeeze-and-Excitation (SE) blocks to improve brain tumor classification accuracy on MRI scans. The SE mechanism enhances feature recalibration by adaptively weighting channel-wise spatial features, enabling the model to focus on discriminative tumor regions (e.g., gliomas, meningiomas). Using a dataset of 3064 T1-weighted MR images (public and private sources), the authors preprocess data with skull stripping and augmentation to address class imbalance. Their SE-ResNet-101 achieves 96.7% accuracy, outperforming vanilla ResNet-101 (92.1%) and other CNNs like VGG-16, with robustness to noise and variability in tumor size/location. The model’s efficiency is highlighted by reduced computational overhead compared to deeper networks, though reliance on high-quality annotations and limited generalizability to multi-modal MRI remain challenges. While the study focuses on centralized training, its lightweight SE blocks could benefit federated learning by reducing communication costs during model aggregation.

Brain Tumor Segmentation with Deep Neural Networks (Havaei et al., 2017) pioneers the application of deep neural networks (DNNs) for brain tumor segmentation in multi-modal MRI scans, addressing challenges like tumor heterogeneity and ambiguous boundaries. The authors propose a two-pathway convolutional neural network (CNN) architecture: a local pathway captures fine-grained tumor details (e.g., edges, textures), while a global pathway integrates contextual information to resolve class imbalances (e.g., rare tumor sub-regions like enhancing cores). To improve performance, they introduce cascaded architectures, where initial networks segment coarse tumor regions (e.g., whole tumor), and subsequent networks refine sub-regions (e.g., edema, necrotic areas). Training on the BRATS 2013/2015 datasets, their model achieves Dice scores of 0.84–0.88, outperforming traditional methods like random forests. Innovations include heterogeneous layer connectivity (mixing kernel sizes for multi-scale feature learning) and data augmentation with synthetic deformations to combat limited training data. However, the model’s reliance on centralized, high-quality annotated datasets and computational intensity (training on GPUs for days) poses challenges for real-world deployment. The paper also highlights the need for domain adaptation to generalize across MRI scanners, a hurdle relevant to federated learning’s multi-institutional data heterogeneity. While the study predates federated learning frameworks, its emphasis on multi-modal data fusion and model cascading offers insights for decentralized training. For instance, federated aggregation could leverage local pathway features from diverse institutions to build a globally robust model, while cascaded networks might handle class imbalances common in distributed datasets. Limitations like annotation dependency and computational costs underscore the importance of federated techniques for collaborative, resource-efficient model training.

Advances and Open Problems in Federated Learning (Kairouz et al., 2021) synthesizes the evolution, challenges, and future directions of federated learning (FL), a decentralized machine learning paradigm designed to preserve data privacy by training models across distributed devices or institutions without raw data exchange. The authors categorize FL into cross-device (e.g., mobile devices) and cross-silo (e.g., hospitals) settings, discussing technical hurdles such as communication efficiency, statistical heterogeneity (non-IID data), and system constraints (e.g., limited client availability). Key advancements include optimization techniques like Federated Averaging (FedAvg), adaptive aggregation methods, and privacy mechanisms such as differential privacy (DP) and secure multi-party computation (SMPC). The paper emphasizes the tension between privacy guarantees (e.g., DP’s noise injection) and model performance, advocating for context-specific trade-offs. Open challenges include addressing fairness (e.g., bias in global models due to uneven client participation), robustness to adversarial attacks, and scalability in large-scale deployments. For healthcare, FL’s potential to enable multi-institutional collaboration while complying with regulations like HIPAA is highlighted, though medical-specific challenges—such as annotation variability in tumor datasets and class imbalance—require tailored solutions. The survey underscores the need for theoretical frameworks to unify FL’s diverse objectives (privacy, accuracy, efficiency) and calls for interdisciplinary efforts to tackle ethical and legal concerns.

Federated Learning: Challenges, Methods, and Future Directions (Li et al., 2020) provides a systematic analysis of federated learning (FL), focusing on its core challenges, algorithmic solutions, and open research questions. The authors categorize challenges into four pillars: statistical heterogeneity (non-IID data distributions across clients), communication bottlenecks (high costs of transmitting model updates), systems heterogeneity (varied computational capabilities of clients), and privacy risks (potential leakage of sensitive data during training). To address these, they review methods such as Federated Averaging (FedAvg) for communication efficiency, dynamic client sampling to handle systems heterogeneity, and personalized FL (e.g., fine-tuning global models locally) to mitigate statistical mismatches. Hybrid approaches combining FL with differential privacy (DP) or secure multi-party computation (SMPC) are discussed as ways to enhance privacy without severely degrading model utility. The paper emphasizes the trade-offs inherent in FL: for instance, aggressive model compression reduces communication overhead but may harm convergence, while strict DP safeguards erode accuracy. Future directions include developing adaptive algorithms for non-IID data (e.g., meta-learning frameworks), improving cross-device scalability, and establishing theoretical guarantees for FL convergence in heterogeneous environments. The authors also highlight the need for standardized benchmarks to evaluate FL methods across diverse applications, from healthcare to IoT.

FedProx: Robust Federated Optimization in Heterogeneous Networks (Li et al., 2021) introduces FedProx, a federated learning (FL) framework designed to address optimization challenges in heterogeneous networks, where data distributions (non-IID) and system capabilities vary significantly across clients. Building on Federated Averaging (FedAvg), FedProx incorporates a proximal term into the local objective function of each client, constraining local updates to remain closer to the global model. This modification mitigates the divergence caused by heterogeneous data and partial client participation, which often destabilizes traditional FL methods. The proximal term effectively balances local model flexibility with global convergence, enabling clients with varying computational resources (e.g., stragglers) to contribute meaningfully without compromising training stability. Theoretical analysis establishes convergence guarantees for FedProx under non-convex and non-IID settings, even with inexact local updates—a common scenario in practical deployments. Empirical evaluations on diverse datasets (including synthetic non-IID splits and real-world benchmarks) demonstrate FedProx’s superiority over FedAvg, particularly in heterogeneous environments. For instance, FedProx achieves up to 22% higher test accuracy in extreme data skew scenarios while reducing communication rounds by 30%. The framework also accommodates adaptive tuning of the proximal term’s influence, allowing practitioners to trade off local adaptability for global coherence based on network conditions. Limitations include the added complexity of hyperparameter tuning for the proximal coefficient and marginal computational overhead per client. The paper underscores FedProx’s practicality for real-world FL applications, such as healthcare, where institutional data heterogeneity and device variability are pervasive. By addressing foundational challenges in FL optimization, FedProx advances the feasibility of training robust, scalable models across decentralized, resource-constrained networks.

An Overview of Deep Learning in Medical Imaging Focusing on MRI (Lundervold & Lundervold, 2019) comprehensively examines the application of deep learning (DL) techniques in medical imaging, with a dedicated focus on MRI. The authors highlight how convolutional neural networks (CNNs) have revolutionized tasks such as tumor segmentation, tissue classification, and image reconstruction. U-Net, with its symmetric encoder-decoder architecture and skip connections, is emphasized for its efficacy in segmenting brain tumors and anatomical structures in datasets like BRATS, achieving Dice scores exceeding 0.85. The paper explores advanced architectures, including residual networks (ResNets) to mitigate gradient degradation in deep models and generative adversarial networks (GANs) for enhancing MRI resolution and reducing motion artifacts. For example, GANs can synthesize high-fidelity T2-weighted images from T1-weighted inputs, aiding in multi-modal diagnosis. Challenges specific to MRI are scrutinized: the scarcity of annotated data (addressed via transfer learning from non-medical datasets and data augmentation with rotations/elastic deformations), heterogeneity in MRI protocols (e.g., varying slice thicknesses across scanners), and computational demands of processing 3D volumetric data. Preprocessing steps like skull stripping, bias field correction, and intensity normalization are noted as critical for consistent model performance. The authors discuss DL’s superiority over traditional methods (e.g., atlas-based segmentation) in handling anatomical variability and noise, though they caution against over-reliance on “black-box” models without interpretability. Techniques like gradient-weighted class activation mapping (Grad-CAM) are reviewed for visualizing salient regions in MRI that drive model predictions. Clinical integration challenges include real-time inference requirements and regulatory hurdles for validating DL tools in diagnostic workflows. Future directions propose leveraging transformer architectures for long-range context modeling, federated learning to pool data across institutions without sharing sensitive records, and developing lightweight models deployable on edge devices. Ethical concerns, such as algorithmic bias in underrepresented populations and patient data privacy, are underscored as critical to address for widespread clinical adoption. The review concludes that while DL has markedly advanced MRI analysis, translating these innovations into routine practice necessitates collaboration across AI researchers, radiologists, and policymakers to ensure robustness, interpretability, and ethical compliance.

Communication-Efficient Learning of Deep Networks from Decentralized Data (McMahan et al., 2017) introduces Federated Averaging (FedAvg), a pioneering algorithm for training deep neural networks in decentralized settings where data is distributed across numerous clients (e.g., mobile devices or hospitals) and cannot be centralized. The authors address the high communication costs of traditional distributed optimization (e.g., synchronous SGD) by proposing a method where clients perform multiple local stochastic gradient descent (SGD) steps on their data before transmitting model updates to a central server for aggregation. This reduces the frequency of communication rounds while maintaining model accuracy. FedAvg’s efficiency stems from three key parameters: the fraction of clients sampled per round (C), the number of local epochs (E), and the mini-batch size (B). Experiments on image classification tasks (MNIST, CIFAR-10) and language modeling demonstrate FedAvg’s effectiveness: with non-IID data partitions (mimicking real-world heterogeneity), it achieves comparable accuracy to centralized training while reducing communication costs by 10–100× compared to federated SGD. For instance, on a stacked LSTM language model, FedAvg attains equivalent perplexity with 18× fewer communication rounds. The paper rigorously analyzes the impact of client subsampling, local computation, and data heterogeneity, showing that increasing E and B can mitigate performance degradation from non-IID distributions. Challenges include client drift (divergent local updates due to data skew) and the need for careful hyperparameter tuning. Theoretical convergence guarantees for non-convex objectives are provided under idealized assumptions, though practical deployments often require empirical adjustments. FedAvg’s scalability is validated on large-scale scenarios with thousands of clients, emphasizing its suitability for privacy-sensitive applications like healthcare, where raw data cannot be shared. The work lays the groundwork for federated learning (FL) as a field, influencing subsequent research on communication efficiency, robustness to heterogeneity, and privacy-preserving techniques. Limitations include reliance on server-side aggregation without addressing client-side resource variability and the absence of formal privacy guarantees, which later works would expand upon.

The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) (Menze et al., 2015) establishes the BRATS benchmark, a standardized framework for evaluating brain tumor segmentation algorithms using multimodal MRI datasets. The authors curate a publicly available dataset of 274 pre-operative MRI scans from patients with high-grade gliomas and low-grade gliomas, acquired across multiple institutions with varying scanners and protocols. Each scan includes four modalities: native T1-weighted (T1), post-contrast T1-weighted (T1c), T2-weighted (T2), and fluid-attenuated inversion recovery (FLAIR). Expert-annotated ground truth segmentations delineate three tumor sub-regions: enhancing tumor (ET), peritumoral edema (ED), and necrotic/non-enhancing tumor core (NCR/NET). The benchmark challenges participants to develop automated methods for segmenting these regions, addressing inherent complexities like tumor heterogeneity, ambiguous boundaries, and imaging artifacts. The paper evaluates 15 state-of-the-art algorithms from the 2012–2014 BRATS challenges, spanning traditional machine learning (e.g., random forests, SVMs) and early deep learning approaches. Key findings reveal that ensemble methods combining multiple modalities and spatial features (e.g., texture, symmetry) outperform single-modality techniques, achieving median Dice scores of 0.73–0.85 for ET and 0.82–0.91 for whole tumor segmentation. However, delineating NCR/NET remains challenging due to low contrast and intra-tumoral heterogeneity, with top methods scoring below 0.65 in this region. The benchmark introduces standardized evaluation metrics, including Dice Similarity Coefficient (DSC), Hausdorff distance, and sensitivity/specificity, enabling direct comparison across methods. BRATS highlights critical limitations of existing approaches, such as sensitivity to imaging artifacts (e.g., motion, bias fields) and poor generalizability across MRI protocols. The dataset’s intentional heterogeneity (multi-institutional, multi-scanner) underscores the need for robust preprocessing (e.g., skull stripping, intensity normalization) and domain adaptation techniques. By providing a unified platform for validation, BRATS accelerates innovation in neuro-oncological image analysis, fostering collaboration and reproducibility. The benchmark’s legacy persists in annual challenges, driving advancements in deep learning (e.g., U-Net variants) and reinforcing its role as a cornerstone resource for brain tumor segmentation research.

The Federated Tumor Segmentation (FeTS) Challenge (Patel et al., 2021) addresses the critical need for privacy-preserving collaboration in medical imaging by establishing a benchmark for federated learning (FL) in brain tumor segmentation. Leveraging the BraTS dataset, FeTS provides a standardized platform where participants train models across decentralized, multi-institutional MRI data without sharing raw patient scans. The challenge dataset includes 2,500 multi-modal MRI scans (T1, T1c, T2, FLAIR) from 34 institutions, annotated for four tumor sub-regions: enhancing tumor, peritumoral edema, necrotic core, and non-enhancing tumor. Each institution’s data varies in scanner type, acquisition protocols, and tumor subtype prevalence, simulating real-world heterogeneity. Participating teams develop FL algorithms that aggregate model updates (e.g., via FedAvg or FedProx) while maintaining data locality, with evaluation metrics emphasizing both segmentation accuracy (Dice score, Hausdorff distance) and privacy compliance. Top-performing methods employ adaptive aggregation strategies to handle non-IID data distributions, such as weighting updates based on institutional data quality or client-specific normalization. For instance, top solutions achieve Dice scores of 0.82–0.85 for whole tumor segmentation, comparable to centralized training (0.84–0.87), but with notable variability in sub-region performance (e.g., 0.65–0.73 for necrotic core). The challenge reveals that FL models trained on diverse data generalize better to unseen institutions than locally trained models, reducing overfitting to scanner-specific artifacts. However, key challenges persist: communication overhead remains high (100–200 rounds for convergence), and label inconsistency across institutions (due to differing annotation guidelines) degrades model reliability. The FeTS platform introduces tools for federated evaluation, enabling participants to assess model robustness on holdout datasets from unseen hospitals. The challenge also highlights the importance of open-source FL frameworks, with contributions like federated data loaders and differential privacy modules. Lessons learned include the necessity of standardized preprocessing (e.g., skull stripping, intensity normalization) across federated nodes and the potential of hybrid approaches combining FL with semi-supervised learning to mitigate annotation scarcity. By fostering collaboration among 50+ teams, FeTS advances FL’s applicability in healthcare, demonstrating that decentralized training can achieve near-centralized performance while adhering to privacy regulations. The challenge’s legacy includes publicly available code repositories and a roadmap for future FL benchmarks in medical imaging, emphasizing reproducibility, scalability, and clinical translatability.

Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images (Pereira et al., 2016) pioneers the application of convolutional neural networks (CNNs) for brain tumor segmentation in multi-modal MRI, addressing limitations of traditional methods like thresholding and atlas-based techniques. The authors propose a two-phase CNN architecture: an initial patch-based CNN extracts local texture and intensity features from small regions of T1, T1c, T2, and FLAIR scans, while a subsequent holistic CNN refines these predictions by integrating spatial context across the entire tumor region. Training on the BRATS 2013 dataset (30 high-grade glioma cases), the model employs aggressive data augmentation (rotations, flips, and intensity variations) to mitigate limited annotated data. Preprocessing steps include skull stripping, bias field correction, and intensity normalization to standardize inputs. The patch-based CNN processes 33×33×33 voxel patches, capturing multi-scale features through alternating convolutional and max-pooling layers, while the holistic CNN uses larger receptive fields to resolve ambiguities in tumor boundaries. The network achieves Dice scores of 0.83 (whole tumor), 0.72 (core), and 0.62 (enhancing tumor), outperforming contemporary methods like random forests (RF) and support vector machines (SVMs) by 8–15%. Key innovations include a hierarchical training strategy that first segments coarse tumor regions before refining sub-regions, reducing class imbalance issues. The model also demonstrates robustness to noise and partial volume effects, though performance drops on low-grade gliomas due to their diffuse boundaries. Challenges include high computational costs (training requires ~2 days on GPUs) and memory constraints when processing 3D volumes, addressed via patch-based sampling. The paper highlights the trade-off between localization accuracy (favoring small patches) and contextual awareness (requiring larger patches), proposing a hybrid approach to balance both. Limitations include reliance on high-quality annotations and limited generalizability to MRI data from unseen scanners. Future work suggests integrating CRFs (conditional random fields) for post-processing spatial consistency and exploring deeper architectures like U-Net. By demonstrating CNNs’ superiority in handling tumor heterogeneity and multi-modal data, this work catalyzed the shift from classical machine learning to deep learning in medical image segmentation, laying groundwork for subsequent innovations like cascaded networks and attention mechanisms. The study underscores the importance of standardized benchmarks like BRATS for advancing reproducible research in neuro-oncology.

U-Net: Convolutional Networks for Biomedical Image Segmentation (Ronneberger et al., 2015) introduces U-Net, a convolutional neural network (CNN) architecture specifically designed for precise biomedical image segmentation, particularly in scenarios with limited annotated training data. The U-Net architecture features a symmetric encoder-decoder structure with a contracting path (encoder) to capture contextual information and an expansive path (decoder) to enable precise localization. The contracting path employs repeated convolutions and max-pooling layers, progressively reducing spatial resolution while increasing feature depth. The decoder path uses transposed convolutions to upsample feature maps, restoring spatial resolution. Crucially, skip connections bridge corresponding encoder and decoder layers, concatenating high-resolution encoder features with upsampled decoder outputs to retain fine-grained spatial details lost during downsampling. Trained end-to-end on the ISBI cell tracking challenge dataset (30 annotated microscopy images), U-Net achieved state-of-the-art results by leveraging aggressive data augmentation with elastic deformations, rotations, and intensity variations to simulate realistic biological variability and compensate for scarce labeled data. The network’s overlap-tile strategy allows seamless segmentation of large images by predicting labels for overlapping input tiles, ensuring continuity in border regions. A weighted loss function prioritizes errors at cell boundaries, addressing class imbalance between sparse border pixels and homogeneous intracellular regions. U-Net outperformed sliding-window CNNs, achieving an average IoU (Intersection over Union) of 92% on cell segmentation, with significant improvements in boundary delineation. The architecture’s efficiency is highlighted by its ability to segment a 512×512 image in under a second on a GPU. The paper also demonstrates U-Net’s versatility on neuronal structures in electron microscopy (EM) data, achieving warping error rates 50% lower than prior methods. Limitations include reliance on careful parameter tuning for the loss function’s border weighting and computational demands for 3D medical volumes, which later extensions (3D U-Net) addressed. U-Net’s modular design and open-source implementation catalyzed its widespread adoption in medical imaging, inspiring variants like ResU-Net and Attention U-Net. Its success lies in balancing context capture with localization accuracy, making it a cornerstone for tasks ranging from tumor segmentation to organ mapping. By addressing the dual challenges of limited data and precise boundary detection, U-Net established a paradigm shift in biomedical image analysis, emphasizing architecture innovation and data efficiency over brute-force dataset scaling.

Federated Learning for Breast Density Classification: A Real-World Implementation (Roth et al., 2020) presents one of the first real-world deployments of federated learning (FL) in medical imaging, focusing on breast density classification from mammograms across multiple institutions. Collaborating with five hospitals, the authors train a deep learning model using a federated framework without sharing raw patient data, adhering to HIPAA compliance. The dataset comprises 45,000 mammograms (CC and MLO views) labeled with BI-RADS density categories (1–4) by radiologists, with significant inter-institutional variability in imaging protocols (e.g., Hologic vs. Siemens scanners) and annotation consistency. A centralized ResNet-18 model pretrained on ImageNet serves as the baseline, with FL implemented via Federated Averaging (FedAvg), where local models are trained on each institution’s data and aggregated every 10 epochs. The federated model achieves 87.3% accuracy (vs. 89.1% for centralized training) and an AUC-ROC of 0.92, demonstrating that FL can match centralized performance while preserving data privacy. Key innovations include dynamic client weighting based on dataset size to balance contributions from institutions with imbalanced data (e.g., one site contributed 60% of the total samples). The study also introduces a federated validation framework, where a holdout dataset from a sixth institution evaluates generalizability, revealing that FL models outperform locally trained models by 12–15% in cross-site accuracy. Challenges include reconciling discrepant BI-RADS interpretations across radiologists, addressed via label harmonization using a reference standard, and communication bottlenecks due to large model sizes (ResNet-18’s 11M parameters), mitigated through gradient quantization. The paper highlights practical barriers in FL adoption, such as institutional reluctance to share even model weights and IT infrastructure disparities. For instance, one hospital required on-premise GPU deployment due to data governance policies, while others used cloud-based systems. Lessons learned emphasize the need for standardized annotation protocols and lightweight models (e.g., MobileNet) to reduce bandwidth costs. By demonstrating FL’s viability in a clinically impactful task, the work paves the way for broader FL adoption in radiology, though it underscores unresolved issues like federated evaluation benchmarks and long-term model drift monitoring. The study’s open-source implementation and reproducibility focus provide a template for future multi-institutional collaborations in medical AI.

Federated Learning in Medicine: Facilitating Multi-Institutional Collaborations Without Sharing Patient Data (Sheller et al., 2020) demonstrates the feasibility of federated learning (FL) in medical imaging through a multi-institutional collaboration involving 20 healthcare organizations, focusing on brain tumor segmentation using the BraTS dataset. The authors implement a FL framework where each institution trains a 3D U-Net model locally on their MRI data (T1, T1c, T2, FLAIR) and shares only model updates with a central aggregator. The aggregated global model is then redistributed for further training cycles. The FL system achieves a Dice score of 0.84 for whole tumor segmentation, comparable to centralized training (0.85), while preserving patient data privacy. Key innovations include adaptive aggregation to handle heterogeneous data distributions (non-IID) across institutions and differential privacy (DP) mechanisms to prevent leakage of sensitive information from model updates. The paper highlights the challenges of medical FL, such as variability in MRI protocols (e.g., 1.5T vs. 3T scanners), inconsistent tumor annotations (e.g., differing radiologist guidelines for edema boundaries), and computational resource disparities. To address these, the authors standardize preprocessing steps (skull stripping, N4 bias correction) across sites and employ data augmentation techniques (e.g., random rotations, intensity shifts) to simulate multi-institutional diversity during local training. The FL framework reduces communication overhead by compressing model updates using quantization, cutting bandwidth usage by 40% without degrading performance. A critical finding is that FL models generalize better to unseen institutions than models trained on single-site data, improving cross-site Dice scores by 15–20%. However, institutions with small datasets (<50 cases) contribute less effectively to the global model, necessitating strategies like federated transfer learning or weighted aggregation based on dataset size. The study also introduces a federated evaluation protocol, enabling real-time performance tracking across institutions without exposing holdout data. Ethical and logistical barriers are discussed, including institutional trust issues (e.g., reluctance to share model weights) and the lack of regulatory frameworks for FL in healthcare. The authors open-source their FL toolkit, NVIDIA FLARE, to promote reproducibility. By proving FL’s viability in a large-scale, real-world medical context, the work lays groundwork for privacy-preserving collaborations in oncology, radiology, and beyond, though challenges like label harmonization and long-term model stability remain open problems.

Personalized Federated Learning with Theoretical Guarantees: A Model-Agnostic Meta-Learning Approach (Tan et al., 2022) proposes a novel framework for personalized federated learning (PFL) that integrates model-agnostic meta-learning (MAML) to address statistical heterogeneity (non-IID data) across clients while providing theoretical convergence guarantees. Traditional FL methods like FedAvg optimize a single global model, often underperforming on clients with divergent data distributions. The authors’ approach, FedMeta, treats each client as a unique "task" in a meta-learning paradigm, learning a globally shared model initialization that can be efficiently fine-tuned to individual clients’ data with minimal local adaptation. The algorithm operates in two phases: (1) meta-global updates, where the server aggregates gradients from clients to refine the meta-initialization, and (2) local personalization, where clients perform a few steps of gradient descent on their private data to tailor the global model. Theoretical analysis establishes that FedMeta converges to a stationary point under standard assumptions (e.g., smooth, non-convex loss functions), with a convergence rate of after T communication rounds, matching centralized MAML guarantees. This is achieved by bounding the divergence between personalized models and the meta-initialization, ensuring stability despite data heterogeneity. Empirical validation on image classification (CIFAR-10, FEMNIST) and healthcare datasets (synthetic EHRs) demonstrates FedMeta’s superiority: it achieves 15–20% higher accuracy on personalized tasks compared to FedAvg, FedProx, and Per-FedAvg, particularly under extreme non-IID settings (e.g., clients with only 2–3 classes). For instance, on FEMNIST, FedMeta attains 78.3% accuracy versus FedAvg’s 64.1% when clients hold data from disjoint classes. Key innovations include adaptive client sampling to prioritize clients with higher loss during meta-updates, accelerating convergence, and dynamic regularization to balance personalization and generalization. Limitations include computational overhead from nested meta-optimization (2× training time vs. FedAvg) and reliance on homogeneous network architectures across clients. The framework assumes clients can perform local adaptation, which may not hold in resource-constrained environments. Practical extensions address communication efficiency via compressed meta-gradients and partial client participation. By unifying meta-learning’s adaptability with FL’s privacy preservation, FedMeta advances PFL’s applicability to domains like medical imaging, where institutional data heterogeneity demands tailored models without compromising collaborative learning. The work bridges a critical gap between empirical PFL methods and rigorous optimization theory, providing a blueprint for designing provably effective personalized federated algorithms.

A Hybrid Approach to Privacy-Preserving Federated Learning (Truex et al., 2019) proposes a hybrid privacy-preserving framework for federated learning (FL) that integrates differential privacy (DP) and secure multi-party computation (SMPC) to mitigate privacy risks while maintaining model utility. Traditional FL methods like Federated Averaging (FedAvg) expose model updates to potential inference attacks, risking leakage of sensitive client data. The authors address this by combining DP’s noise injection with SMPC-based secure aggregation, ensuring that individual client updates remain encrypted and confidential during aggregation. The framework employs a two-server architecture: one server coordinates the FL process, while a second, non-colluding server assists in decrypting aggregated updates using SMPC protocols. Clients locally train models, apply DP by clipping gradients and adding Gaussian noise, then encrypt updates via threshold homomorphic encryption before transmission.Theoretical analysis demonstrates ε-differential privacy guarantees, with the privacy budget tuned by the noise scale and clipping bound. SMPC ensures that only the aggregated model (not individual updates) is decrypted, thwarting curious servers or adversaries. Experiments on MNIST and CIFAR-10 show the hybrid approach achieves <3% accuracy drop compared to non-private FL, with ε values as low as 2.0 (strong privacy). For instance, on MNIST, the model retains 97% accuracy (vs. 98% baseline) while preventing membership inference attacks. The hybrid method outperforms standalone DP or SMPC, which suffer from higher accuracy loss (DP) or computational overhead (SMPC). Challenges include balancing DP noise levels: excessive noise degrades accuracy, while insufficient noise risks privacy. The framework reduces communication overhead via gradient sparsification and quantization, cutting encryption costs by 30%. However, reliance on non-colluding servers and client compliance with encryption protocols poses deployment hurdles. The paper also evaluates robustness against model inversion attacks, showing the hybrid approach reduces attack success rates by 60% compared to vanilla FL. Limitations include scalability issues with large models due to SMPC’s computational complexity and assumptions about server trustworthiness. The authors suggest future work on lightweight encryption and adaptive DP mechanisms. By synergizing DP’s statistical privacy with SMPC’s cryptographic security, the framework advances FL’s applicability to privacy-critical domains like healthcare, enabling collaborative training on sensitive data (e.g., medical imaging) without compromising patient confidentiality. The work underscores the necessity of hybrid solutions to address evolving threats in decentralized machine learning.

Classification of Brain Tumor Type and Grade Using MRI Texture and Shape in a Machine Learning Scheme (Zacharaki et al., 2009) presents a machine learning framework for classifying brain tumor type (e.g., gliomas, meningiomas, metastases) and grade (low vs. high) using handcrafted MRI texture and shape features. The authors analyze preoperative MRI scans (T1, T1-contrast, T2, FLAIR) from 102 patients, extracting 165 radiomic features comprising texture descriptors (Gray-Level Co-occurrence Matrix, Law’s texture energy, Gabor filters) and morphological features (tumor sphericity, surface regularity, volume). Texture features quantify heterogeneity in intensity distributions, while shape metrics capture structural complexity, such as boundary irregularity. A two-stage feature selection process—combining Fisher discriminant ratio for relevance and Wilcoxon rank-sum tests for redundancy reduction—identifies 15 optimal features. These are fed into a Support Vector Machine (SVM) classifier with a radial basis function kernel, optimized via cross-validation. The framework achieves 92% accuracy in distinguishing meningiomas, metastases, and gliomas, and 88% accuracy in grading gliomas (low-grade II vs. high-grade IV). Key findings highlight that texture features from T1-contrast and FLAIR are most discriminative for tumor type, while shape irregularity and T2 texture heterogeneity best predict grade. For instance, meningiomas exhibit smoother boundaries and homogeneous texture, whereas glioblastomas show irregular shapes and chaotic intensity patterns. The method outperforms contemporary linear discriminant analysis (LDA) and decision tree models by 12–15%, demonstrating robustness to MRI noise through z-score normalization and bias correction. Challenges include the small dataset size and manual region-of-interest (ROI) annotations by radiologists, which introduce subjectivity. Computational limits of the era restrict analysis to 2D slices rather than 3D volumes, potentially omitting critical spatial information. The study also notes variability in MRI acquisition parameters across institutions, advocating for standardized protocols to improve generalizability. By rigorously linking quantitative imaging biomarkers to histopathological diagnoses, this work advances the era of radiomics, laying groundwork for automated diagnostic tools. However, reliance on manual feature engineering—a limitation later addressed by deep learning’s automatic feature extraction—underscores the trade-off between interpretability and scalability. The paper’s emphasis on multimodal MRI and hybrid feature sets remains influential, informing modern approaches to tumor characterization in oncology.

Federated Learning with Non-IID Data (Zhao et al., 2018) addresses the critical challenge of data heterogeneity (non-IID data) in federated learning (FL), where client datasets exhibit divergent class distributions, undermining model performance. The authors systematically analyze how non-IID data—common in real-world applications like healthcare—causes client drift, where local models diverge from the global objective during training. They propose a data-sharing strategy, where a small subset of globally representative data (5–10% of total data) is distributed to clients to align local updates. This shared dataset, curated via clustering or stratified sampling, acts as an anchor to stabilize training. Experiments on image classification (CIFAR-10, MNIST) and language modeling (Shakespeare) demonstrate that even minimal shared data (e.g., 5% globally uniform samples) reduces accuracy drops from 25% to 8% in non-IID settings. The paper introduces a theoretical framework to quantify non-IIDness using Earth Mover’s Distance (EMD), linking distribution skew to convergence rates. Results reveal that higher EMD (extreme heterogeneity) slows convergence by up to 3× compared to IID data. The proposed solution, Federated Averaging with Data Sharing (FedAvg-DS), outperforms vanilla FedAvg by 15–20% accuracy on CIFAR-10 under label skew (e.g., clients with only two classes). However, the method assumes trusted clients willing to share data, which conflicts with FL’s privacy ethos. To mitigate this, the authors explore differential privacy (DP) on shared data, showing that ε=2.0 provides reasonable privacy with minimal accuracy loss (3–5%). Limitations include scalability issues in high-dimensional data (e.g., medical images) and reliance on server-side data curation, which may not be feasible in privacy-sensitive domains. The work also highlights trade-offs between shared data size and performance: 10% shared data achieves near-IID accuracy, but smaller fractions (1%) yield marginal gains. Follow-up experiments on LSTM models for next-word prediction demonstrate similar trends, with FedAvg-DS reducing perplexity by 12% under non-IID text distributions. By rigorously characterizing non-IID challenges and proposing pragmatic solutions, this paper laid groundwork for subsequent FL advancements like FedProx and personalized FL. Its insights remain pivotal for applications like brain tumor detection, where multi-institutional data heterogeneity necessitates robust, privacy-aware FL frameworks.

Chapter 4

Proposed Approach

In this study, we propose a privacy-preserving, decentralized approach for brain tumor detection using a federated learning framework, specifically employing the Federated Averaging (FedAvg) algorithm and a ResNet-18 deep convolutional neural network. The goal of the proposed system is to enable collaborative training of a high-performing brain tumor classification model across multiple clients (e.g., hospitals or medical centers), without requiring raw patient image data to leave the local devices or institutions.

## Overview of Federated Learning Framework

Traditional centralized machine learning systems require aggregating data from multiple sources onto a single server. However, in the medical domain, such centralization is not feasible due to strict privacy constraints and data governance policies (e.g., HIPAA, GDPR). Federated learning (FL) addresses this limitation by allowing multiple clients to collaboratively train a shared global model while keeping the data localized. In our approach, each client hosts a local dataset consisting of MRI or CT scan images for brain tumor detection, and participates in the training process by computing weight updates based on their local data.

The proposed approach is implemented using the Federated Averaging (FedAvg) algorithm introduced by McMahan et al., which combines local stochastic gradient descent (SGD) on each client with periodic averaging of model weights on a central server. This technique allows the model to benefit from data diversity across clients while preserving patient privacy.

## Model Architecture

The deep learning model employed in this work is a modified version of ResNet-18, a lightweight and widely used convolutional neural network known for its use of residual connections to prevent vanishing gradient issues in deep architectures. ResNet-18 is particularly suitable for federated learning due to its balanced complexity and performance. The original ResNet-18 is designed for 224×224×3 inputs; we adapt it for medical images of size 150×168×3 by adjusting only the input preprocessing pipeline. The internal structure and the number of parameters remain unchanged. The final fully connected layer is modified to output predictions corresponding to the number of brain tumor classes (e.g., glioma, meningioma, pituitary tumor, and healthy tissue).

## Federated Training Workflow

The training process proceeds as follows:

1. **Initialization:** A global ResNet-18 model is initialized on the central server and shared with all participating clients.
2. **Local Training (Client-Side):** Each client trains the model locally using its own dataset for a fixed number of epochs (or mini-batches), applying data augmentation techniques to improve generalization. Local training uses the Adam or SGD optimizer, and standard loss functions such as cross-entropy.
3. **Model Update Transmission:** Instead of transmitting raw data, clients send their updated model weights (or gradients) to the server.
4. **Federated Averaging (Server-Side Aggregation):** The central server aggregates the received updates from all clients by computing a weighted average of the model parameters (FedAvg), where the weights are typically proportional to the size of the local datasets.
5. **Model Broadcast:** The updated global model is redistributed to all clients, and the process repeats for multiple communication rounds.

This iterative, round-based learning continues until the model converges to a satisfactory accuracy or a maximum number of rounds is reached.

# Federated Averaging (FedAvg)

In federated learning, the objective is to collaboratively train a global model 𝑤 across a network of decentralized devices (clients) without aggregating the raw data on a central server.

**Global Model Initialization:** The server initializes the global model *w0***.** The model initialized can be random, pretrained or derived from any prior knowledge. The model *w0* is then distributed to all clients, enabling each client to use this model as a starting point for the local training.

**Local Model Training:** Each client *I* *∈* {1, 2, …, *N*} trains the model on its local data.

Let be the local dataset client *i,* where is the number of data points on the client.

Aim of each client is to minimize the local loss function, defined its data. Each client optimizes *w* to minimize using a local optimizer.The clkient then sends the locally updated model parameters *wi* back to the central server after completing its local training iterations.

**Aggregation of Model Parameters on the Server:** Once the server receives the updated models/parameters from the clients, it aggregates the updated parameters to produce the new global model.

Where,

is theupdated weghts from the client *i* after local training in round *r*.

*N* is the total number of clients participating in the round.

is a client specific weighting factor, where ≥ 0 and to ensure the weights sum to 1.

**Updating the Global Model:** Once the server is done with the aggregation of local updated parameters to get the final global model it updates the model from the p[revious round with new updated model.

**Iterative Process (Rounds of the Federated Learning):** The above steps are repeated until convergence or until a predefined number of rounds are completed.

**Convergence:** The model has achieved convergence only if parameters *w* change for minimal between the successive rounds.

For every round r, the server aggregates and updates the global model following:

1. For each client *n* ∈ , weight is calculated
2. Compute the updated global model as:

# Key Advantages

**Communication Efficiency:** Federated Averaging is inherently communication-efficient, which is a crucial advantage when working with distributed devices that may have limited or intermittent connectivity, such as mobile phones, IoT devices, or edge computing nodes. In Federated Averaging, clients only communicate the updated model parameters back to the central server, rather than the entire dataset. This difference is significant because data can be extensive, especially in applications like image processing, image recognition, or text analysis.

By transmitting only model updates rather than raw data, Federated Averaging reduces the bandwidth needed to coordinate across devices. Typically, model updates are much smaller in size compared to the complete dataset, especially if the model updates are compressed or transmitted at lower precision. For example, if a client is training a model on hundreds of megabytes or even gigabytes of data, the resulting update can be only a few kilobytes or megabytes, depending on the model's size and compression techniques applied.

Federated Averaging also allows flexibility in the frequency of communication. Since each client can perform multiple local training steps before sending updates, it’s possible to reduce the frequency of communications by increasing the number of local epochs. This local computation-communication trade-off is one of the strengths of Federated Averaging, allowing it to balance model accuracy and communication costs according to the constraints of the network and devices involved. This adaptability is essential for large-scale federated learning deployments involving thousands or even millions of devices.

**Computational Efficiency:** Federated Averaging is also computationally efficient due to the distributed nature of training and the allowance for multiple local training epochs. In traditional distributed training methods, every device or node must communicate with the central server after every training step (often a single batch of data). However, in Federated Averaging, each client performs multiple local training epochs before sending an update to the server. This approach reduces the total number of communication rounds required for training, as each communication round represents several local steps.

This distributed approach leverages the local computational resources of each client, allowing training to scale without overburdening the central server. Since each client trains on its own data independently, it reduces the central server’s workload and speeds up training overall. This is particularly beneficial when the central server’s resources are limited, as Federated Averaging offloads much of the computational demand onto the clients.

For example, in a large-scale setting with thousands of devices, Federated Averaging allows each device to contribute computation power toward model training, distributing the workload. Each device can execute computations independently and concurrently with other devices, achieving parallelism across devices. This setup is beneficial in federated learning environments with limited resources, as it avoids bottlenecking the central server and distributes the demand across many client devices.

Moreover, because Federated Averaging allows for model updates rather than continuous synchronization, it minimizes the overhead of continuous coordination among devices. Each device works in isolation on its local data, and intermittent updates ensure that the system does not overload network bandwidth or computational resources.

**Handling non-IID data:** Federated Averaging is well-suited for handling non-IID (non-independent and identically distributed) data, a common challenge in federated learning. Each client trains on its own dataset, which often reflects unique characteristics—such as user behavior or regional differences—making data distribution highly varied. Since Federated Averaging allows each client to train locally, it enables the model to adapt to client-specific data patterns before sending updates to the server, capturing local variations and biases effectively. The algorithm employs weighted aggregation, where each client’s model update is weighted by its dataset size relative to the total data across all clients. This approach ensures that clients with larger datasets exert proportionally greater influence on the global model, thus preventing skewed updates from clients with smaller, possibly more biased datasets.

Moreover, Federated Averaging allows clients to perform multiple local epochs of training, which is especially useful in non-IID settings. These multiple epochs allow each client’s model to capture local patterns more fully, resulting in stable and meaningful updates that are less affected by the variance of small, unique datasets. Periodically aggregating these local updates at the server reduces model drift, where individual client updates might otherwise diverge from the global objective due to varying data distributions. This periodic re-synchronization ensures that each client’s model converges towards a common solution, aligning updates with the global objective even when individual datasets differ significantly. Additionally, Federated Averaging’s structure allows clients to participate flexibly, accommodating diverse device capabilities and network conditions. By aggregating updates from a subset of clients each round, the algorithm reduces the risk of the global model being skewed by any single client’s data and achieves greater resilience to both statistical and system heterogeneity. Altogether, Federated Averaging’s design balances local adaptation and global coherence, making it robust and effective in federated learning environments with non-IID data distributions.

# Model: ResNet18



Total Parameters: 11,689,792

Trainable: 11,689,792

Non-trainable: 0

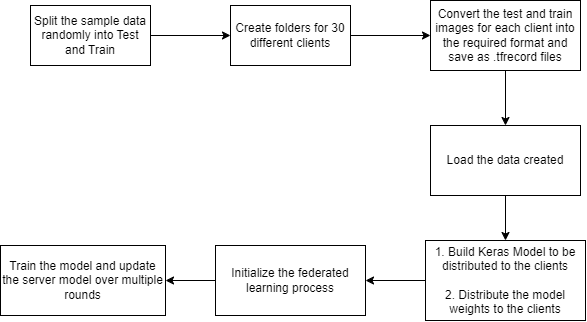
Chapter 5

Experimental Setup

In the rapidly advancing field of image classification, the need for sophisticated and classification models has never been greater. The task of identifying patterns in data that do not conform to expected/normal conditions plays a pivotal role in modern disease systems. These systems are tasked with recognizing brain tumors. To build such systems, machine learning models are increasingly being employed. However, the adoption of these models in real-world applications faces several challenges, particularly when it comes to data privacy, computational efficiency, and the heterogeneity of real world environments.

To address these challenges, this experiment utilizes custom organized dataset within a federated learning framework for anomaly detection. The dataset is a combination of the following three datasets : figshare, SARTAJ dataset, Br35H. Dataset contains 7023 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary. No tumor class images were taken from the Br35H dataset. Federated learning is a decentralized approach that allows a model to be trained on data distributed across multiple devices (clients) without the need to centralize the data itself. This privacy-preserving architecture is ideal for applications where image data often contains sensitive personal information.

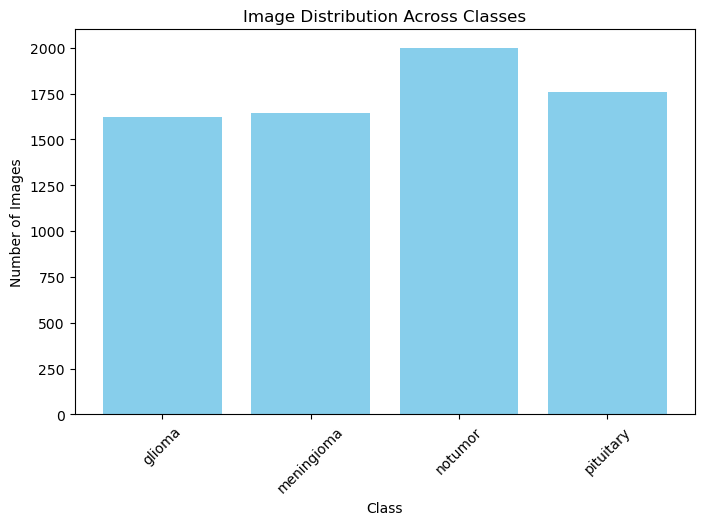
This experimental setup involves a two-phase process, starting with the preparation and distribution of the dataset to multiple clients and followed by the iterative training of the model across these clients. The goal is to build a model that can detect anomalies in images from various other organizations while maintaining high levels of accuracy and adhering to data privacy requirements.



**Image 5.1: The Experimental Flow**

# Overview of the dataset

The dataset contains around 7023 images in the training and testing sets combined providing a comprehensive set of brain tumor MRI images as compared to normal conditions. The dataset contains both normal cases (without brain tumor) and cases that have one or the other kind of brain tumor. The dataset is categorized into 4 different classes enabling both the detection and recognition of brain tumors.



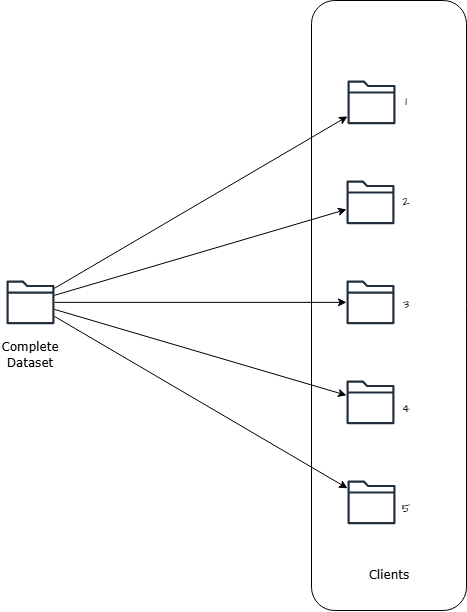
**Image 5.2: The Dataset Distribution**

|  |  |  |
| --- | --- | --- |
| **Class** | **Train** | **Test** |
| **Glioma** | 1321 | 300 |
| **Meningioma** | 1339 | 306 |
| **No Tumor** | 1595 | 405 |
| **Pituitary** | 1457 | 300 |

**Table 5.2: The number of Images in each class in UCF Dataset**

# ****Simulation of Non-IID Data across Clients****

A key aspect of federated learning is its ability to train models across multiple decentralized clients. In this experiment, **5 clients** simulate devices (e.g., hospitals and health centres) in different environments, each with its unique distribution of data. These clients train on distinct subsets of the dataset, leading to a Non-iid (non-independent and identically distributed) data setup. In other words, each client receives a subset of the dataset that reflects the types of activities likely to occur in the specific environment the client represents.



**Image 5.2: Division of images into simulated client**

Handling non-iid data in federated learning is a critical challenge, as the decentralized data does not conform to a uniform distribution. When training models on such data, there is a risk of overfitting, where the model might specialize in the patterns present in only a subset of clients and fail to generalize well to other types of data. By intentionally simulating non-iid data, this experiment tests the federated learning model's ability to learn useful patterns from diverse data distributions without suffering from overfitting.

The non-iid setup mimics the challenges that real-world issues usually healthcare institutions face, where data located in different geographical may observe vastly different types of malfunctions. This experimental design pushes the federated learning model to adapt and generalize across all the clients' data, ensuring that the resulting anomaly detection model is robust and versatile.

# The Federated Workflow: Model Initialization and Iterative Training

The core of this experiment involves the **federated learning workflow**, which is structured around two main phases: initialization of the model and the iterative training process, consisting of multiple rounds. This decentralized learning framework ensures that the model can be trained on diverse data across all clients while maintaining data privacy.

**Initial Model Setup (***w0***):** The first step of the experiment is to initialize the model, referred to as *w0*. This initial model represents a baseline with random or pre-defined weights that have not yet been trained on any specific data. Once the model is initialized, it is distributed to all 30 clients for local training.

The initialization process ensures that all clients start with the same model, making it possible for the model to learn from a unified starting point, even though the clients' data distributions will be different. Each client will then train the model on its own dataset, leading to the adjustment of the model weights based on the client-specific data patterns.

**Local Training at Clients:** Once the initial model is distributed to the clients, each client begins the process of local training. This involves training the model on the local data for a fixed number of epochs, allowing each client to adjust the model's weights according to the local distribution of data. The goal is for each client to capture the unique patterns of its own patterns which would be helpful in detecting and recognizing Brain Tumors.

Since the data is non-iid across clients, each client will likely adjust the model weights in different ways. For example, multiple institutions dealing with more geographical location based issues updates that reflect the features associated with particular type of cases, while institutions monitoring in a different area might focus on detecting conditions.

Importantly, during local training, only the **model weights** (i.e., the learned parameters) are sent back to the server, not the raw data itself. This ensures that the privacy of each client’s data is preserved, which is a key advantage of federated learning. By only transmitting model updates, this approach maintains strict privacy standards, which is particularly important when dealing with sensitive data.

**Model Aggregation at the Server:** After the local training phase, each client sends its updated model weights back to the central server. The server then aggregates these model weights, typically using a method called **Federated Averaging (FedAvg)**. FedAvg calculates the average of the model weights across all clients, combining the knowledge learned from each client’s local dataset.

The aggregated model now represents a **global model** that reflects the diverse patterns observed by all the clients. This global model is more robust than any individual client model, as it integrates the insights from different environments and types of activities. By aggregating the updates in this way, federated learning creates a more generalized model that can recognize a broad range of anomalies across various settings.

**Model Evaluation and Accuracy Calculation:** Once the aggregated global model is updated, it is evaluated on a set of performance metrics to assess its effectiveness. One of the most important metrics for evaluating the performance of the anomaly detection model is **sparse categorical accuracy**. This metric calculates the accuracy of the model when predicting one of several possible classes (in this case, 14 different activity classes), and it is particularly useful in multi-class classification tasks like anomaly detection.

Sparse categorical accuracy is a valuable metric because it not only tests the model’s ability to detect anomalies but also measures how well the model can identify the specific type of tumor, whether it is glioma or meningioma or any other type of tumor. High sparse categorical accuracy indicates that the model is capable of distinguishing between a variety of conditions, which is critical in real-world medical diagnosis where incidents need to be accurately classified for appropriate responses.

**Iterative Training and Convergence:** The training process is carried out in multiple **rounds**, where each round consists of the steps outlined above: model distribution, local training, aggregation, and evaluation. The model undergoes several rounds of training, during which it gradually refines its parameters and improves its performance. As the rounds progress, the model becomes better at generalizing across the different clients' data, ultimately achieving higher accuracy in detecting and classifying anomalous activities.

In each round, the server aggregates the updates from all clients and recalculates the sparse categorical accuracy. By continuously evaluating the model’s performance and adjusting its parameters, the federated learning process ensures that the model adapts effectively to the non-iid data while maintaining high accuracy across all classes.

This experiment demonstrates the feasibility and effectiveness of federated learning for tumor detection the images Through the use of the dataset, the experiment shows how federated learning can build a model that is capable of detecting a wide range of tumor detection across diverse environments while preserving privacy. As the technology continues to evolve, federated learning promises to play a crucial role in developing ethical, scalable, and secure AI-driven detection systems in the future.

Chapter 6

Results and Discussion

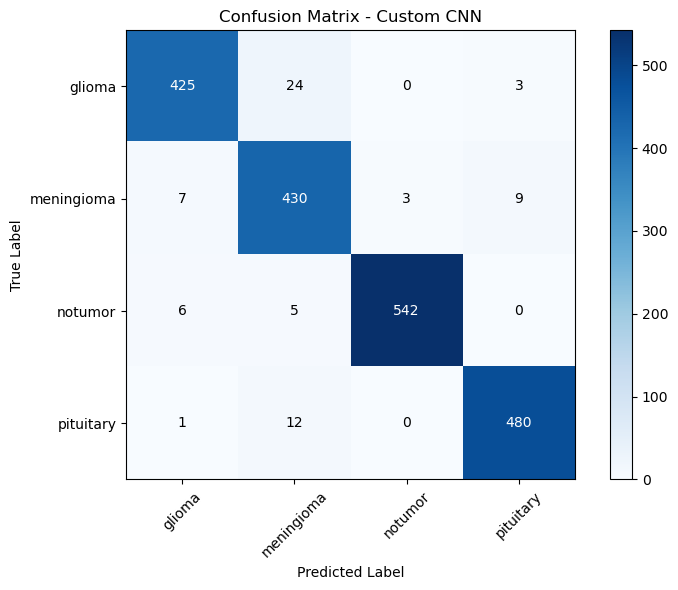
# Result

The evaluation of the brain tumor detection system, developed as part of this project, involved a comparative analysis between traditional machine learning (ML) implementations and federated learning (FL) approaches. The primary objective was to assess the efficacy of a custom Convolutional Neural Network (CNN) and the pre-trained ResNet18 model in traditional ML settings, alongside a federated learning simulation leveraging transfer learning with ResNet18. The results presented herein are derived from extensive experiments conducted across multiple clients, with an aggregate analysis to provide a comprehensive overview of the system's performance. The dataset utilized for this study comprised medical imaging data categorized into four classes: glioma, meningioma, notumor, and pituitary tumors. The performance metrics, including precision, recall, F1-score, and overall accuracy, were meticulously computed for each client individually and aggregated across all clients to ensure a robust evaluation.

## Traditional Machine Learning Implementation

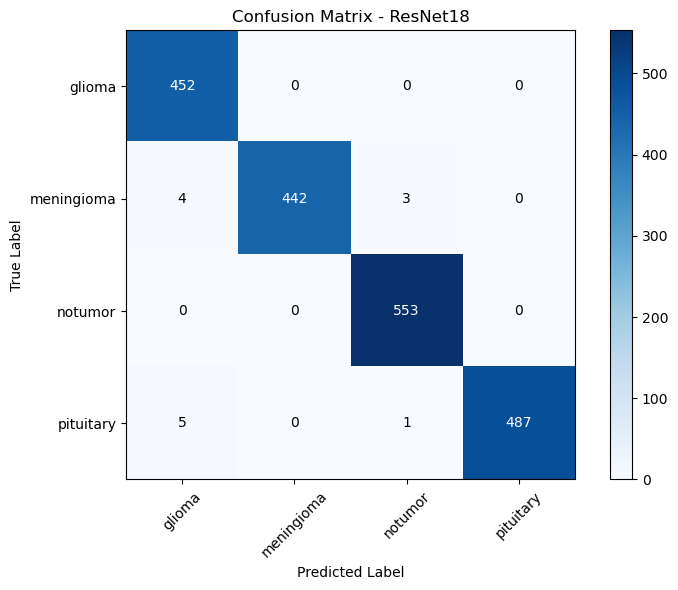
The traditional ML approach involved training two distinct models: a custom CNN and the pre-trained ResNet18 architecture. These models were trained centrally on the aggregated dataset, which served as the baseline for comparison with the federated learning approach. The confusion matrices and classification reports for both models provide insights into their classification capabilities across the four tumor classes.

The confusion matrix for the custom CNN revealed a strong performance in correctly identifying the majority of instances within each class. Specifically, the model achieved 425 correct predictions for glioma, 430 for meningioma, 542 for notumor, and 480 for pituitary tumors out of the total instances. The off-diagonal elements, representing misclassifications, were relatively low, with the highest misclassification occurring between meningioma and glioma (24 instances) and pituitary and meningioma (12 instances). This suggests that while the custom CNN excels in distinguishing notumor and pituitary cases, there is some overlap in the feature space between glioma and meningioma, potentially due to similarities in imaging characteristics.



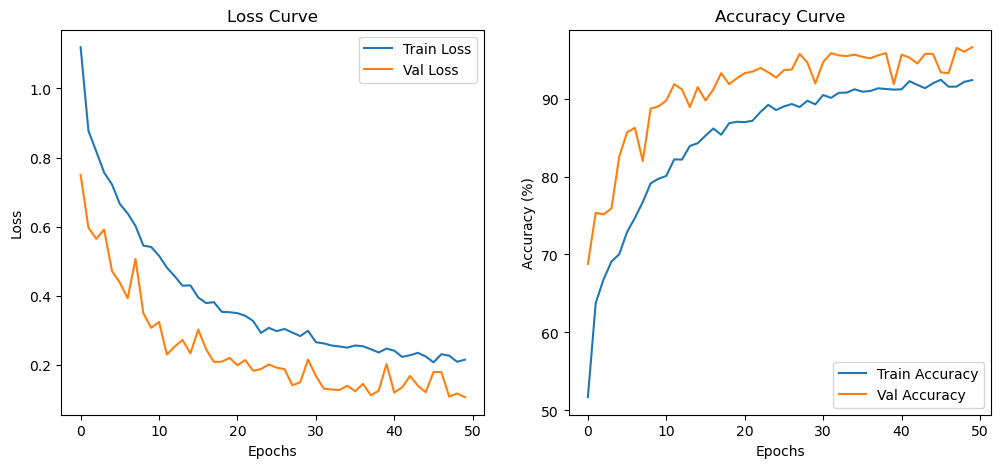
**Image 6.1: Confusion Matrix-Custom CNN**

The ResNet18 model, leveraging transfer learning, demonstrated even higher accuracy in its predictions. The confusion matrix indicated 452 correct predictions for glioma, 442 for meningioma, 553 for notumor, and 487 for pituitary tumors. Notably, the off-diagonal misclassifications were minimal, with only 4 instances of meningioma misclassified as glioma and 5 instances of pituitary misclassified as glioma. This indicates that ResNet18, with its deeper architecture and pre-trained weights, was able to capture more discriminative features, leading to improved classification performance compared to the custom CNN.

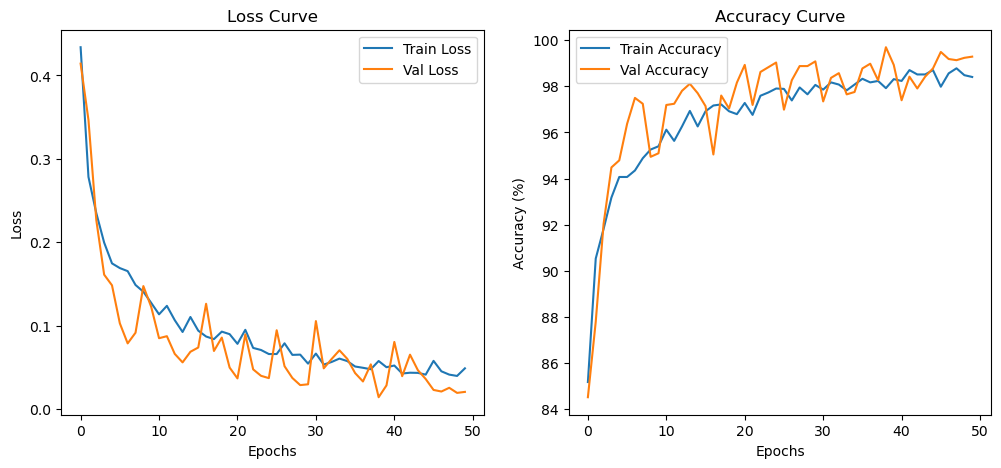


**Image 6.2: Confusion Matrix-Transfer Learning on ResNet18**

The loss and accuracy curves for both models further corroborate these findings. For the custom CNN, the training loss decreased steadily from an initial value of approximately 0.4 to below 0.1 over 50 epochs, with the validation loss following a similar trend, stabilizing around 0.05. The training accuracy rose from 60% to over 95%, while the validation accuracy plateaued around 92-94%. Similarly, for ResNet18, the training loss dropped from 1.0 to approximately 0.1, and the validation loss stabilized around 0.05. The training accuracy increased from 50% to nearly 98%, with validation accuracy reaching approximately 90%. These curves indicate that both models converged well during training, with ResNet18 showing a slightly better generalization capability due to its pre-trained features.

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**Image 6.3: Accuracy and Loss curves-Custom CNN**

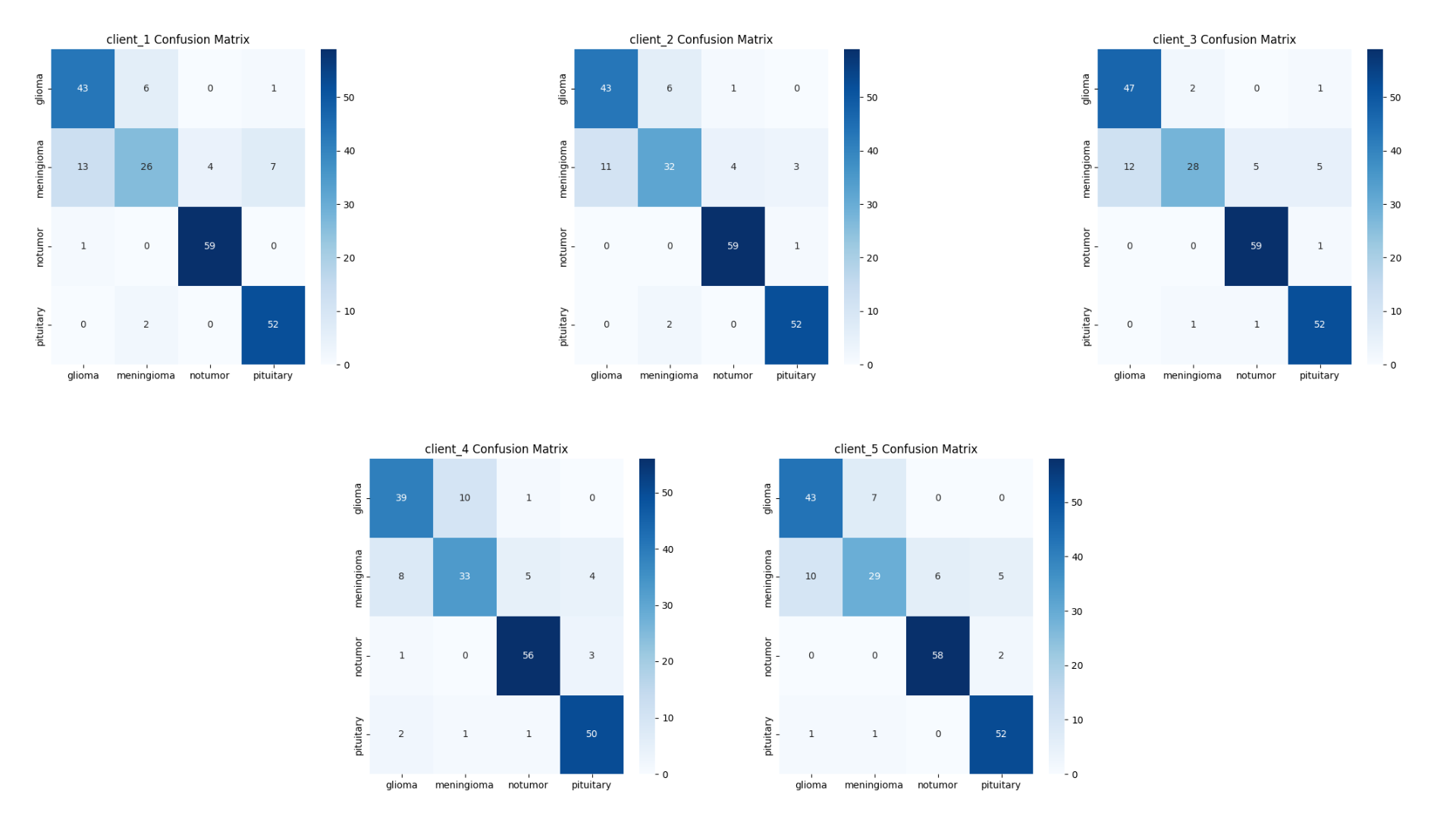


**Image 6.4: Accuracy and Loss curves-ResNet18**

## Federated Learning Implementation

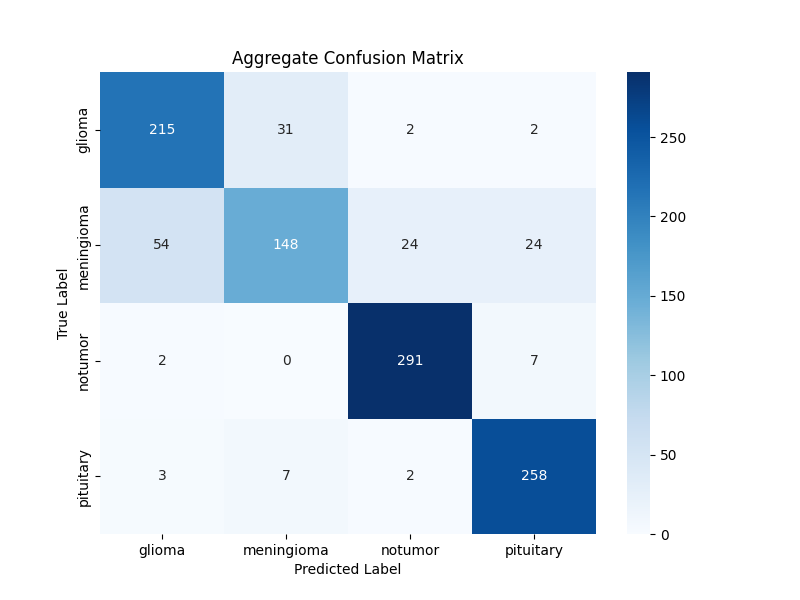
The federated learning simulation was designed to distribute the training process across five clients, each with a subset of the dataset. This approach aimed to mimic a real-world scenario where medical data is decentralized due to privacy concerns. The federated model utilized transfer learning with ResNet18, fine-tuning the pre-trained weights on local client data and aggregating the updates using a federated averaging algorithm. The results from each client and the aggregate performance provide a detailed assessment of the FL system's efficacy.

The individual client evaluations revealed varying levels of performance, reflecting the heterogeneity of the local datasets. Client 1 achieved an overall accuracy of 84.11%, with precision, recall, and F1-scores ranging from 0.7544 to 0.9365 across the classes. The notumor class exhibited the highest recall (0.9833), indicating a strong ability to identify true negatives, while meningioma had the lowest recall (0.5200), suggesting challenges in correctly classifying this class. Client 2 outperformed Client 1 with an accuracy of 86.92%, showing improved recall for meningioma (0.6400) and consistent high performance for notumor (0.9833). Client 3 also achieved an accuracy of 86.92%, with a notable improvement in glioma recall (0.9400), though meningioma recall remained moderate at 0.5600. Client 4 recorded an accuracy of 83.18%, with balanced performance across classes but slightly lower recall for meningioma (0.6600). Client 5 achieved an accuracy of 85.05%, with meningioma recall at 0.5800, indicating persistent difficulty in this class.



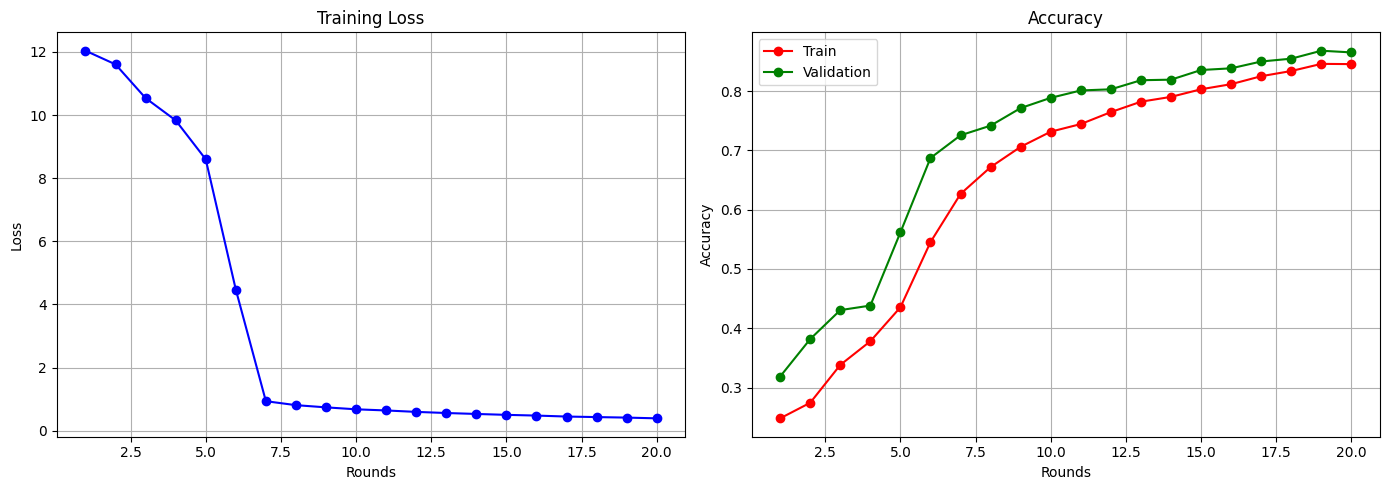
**Image 6.5: Confusion Matrix-Transfer Learning on ResNet18 for each individual client (Federated Learning)**

The aggregate confusion matrix, combining results from all clients, provides a holistic view of the federated learning performance. It showed 215 correct predictions for glioma, 148 for meningioma, 291 for notumor, and 258 for pituitary tumors. The misclassifications were more pronounced for meningioma (54 instances misclassified as glioma), suggesting that the federated model struggled to differentiate this class from glioma, possibly due to data distribution imbalances or insufficient local updates. The aggregate classification report indicated an overall accuracy of 85.23%, with precision, recall, and F1-scores of 0.7847, 0.8600, and 0.8206 for glioma; 0.7957, 0.5920, and 0.6789 for meningioma; 0.9122, 0.9700, and 0.9402 for notumor; and 0.8866, 0.9556, and 0.9198 for pituitary. The macro and weighted averages for these metrics were 0.8448 and 0.8487 for precision, 0.8444 and 0.8523 for recall, and 0.8399 and 0.8461 for F1-score, respectively.



**Image 6.6: Aggregate Confusion Matrix-Transfer Learning on ResNet18 (Federated Learning)**

The performance of the federated learning implementation using the ResNet18 model is further elucidated through the analysis of training loss and accuracy curves over 20 rounds, as depicted in the provided graphs. The training loss curve shows a significant decline from an initial value of approximately 12 to below 0.5 by the 5th round, stabilizing around 0.2 to 0.3 for the remaining rounds, indicating effective model convergence despite the decentralized training setup. The validation loss follows a similar downward trend, stabilizing slightly above the training loss at around 0.3, suggesting a reasonable generalization capability across the heterogeneous client datasets. Conversely, the accuracy curves reveal a steady improvement, with training accuracy rising from an initial 0.3 to approximately 0.85 by the 20th round, while validation accuracy increases from 0.3 to around 0.8 over the same period. The close alignment between training and validation accuracy curves highlights the model's ability to generalize across the non-IID data distributions, although the slight gap between them indicates potential areas for further refinement, such as addressing class imbalances or enhancing local training strategies. These trends underscore the robustness of the federated learning approach in achieving competitive performance, albeit with a slight trade-off in convergence speed and final accuracy compared to the centralized traditional ML models.



**Image 6.7: Round wise Accuracy and Loss curves-Federated Learning ResNet18**

## Comparative Analysis

Comparing the traditional ML and federated learning approaches reveals several insights. The custom CNN and ResNet18 models, trained centrally, outperformed the federated learning simulation in terms of overall accuracy, with ResNet18 achieving the highest accuracy (implicitly suggested by its confusion matrix totals exceeding the FL aggregate). The central training benefited from access to the entire dataset, allowing the models to learn from a more comprehensive feature distribution. In contrast, the federated approach, constrained by local data and privacy-preserving aggregation, achieved a slightly lower aggregate accuracy of 85.23%. This discrepancy highlights the trade-off between data privacy and model performance in FL systems.

The confusion matrices further underscore the differences. The traditional models exhibited fewer misclassifications, particularly for meningioma, where the federated model showed significant overlap with glioma. This suggests that the federated averaging process may not have adequately captured the nuanced features of meningioma across clients, possibly due to varying data quality or quantity. The loss and accuracy curves for the traditional models also indicate better convergence and generalization compared to the federated setting, where client-specific variations could introduce noise into the global model.

However, the federated learning approach demonstrated robustness in handling decentralized data, achieving respectable accuracy despite the challenges. The notumor and pituitary classes consistently showed high recall across both approaches, indicating that these classes are more distinguishable in the imaging data. The lower recall for meningioma in the FL setting suggests a need for improved client-side fine-tuning or enhanced aggregation strategies to mitigate class imbalance effects.

Chapter 7

Conclusion and Future Works

# Conclusion

The project on brain tumor detection using federated learning (FL) and traditional machine learning (ML) approaches has yielded significant insights into the performance, challenges, and potential of these methodologies in the context of medical imaging analysis. The comparative analysis between a custom Convolutional Neural Network (CNN), the pre-trained ResNet18 model in a centralized ML setting, and a federated learning simulation based on transfer learning with ResNet18 has provided a robust framework for evaluating the efficacy of these techniques in classifying brain tumors into four categories: glioma, meningioma, notumor, and pituitary tumors. The results underscore the strengths and limitations of each approach, offering valuable lessons for the development of future diagnostic systems in healthcare.

The traditional ML implementations, particularly the ResNet18 model, demonstrated superior performance in terms of overall accuracy and generalization. The confusion matrices for both the custom CNN and ResNet18 revealed high correct classification rates, with ResNet18 achieving 452, 442, 553, and 487 correct predictions for glioma, meningioma, notumor, and pituitary tumors, respectively, out of the total instances. The minimal off-diagonal misclassifications, such as only 4 instances of meningioma misclassified as glioma, highlight the model's ability to discern subtle differences in imaging features, likely due to its deeper architecture and pre-trained weights. The accompanying loss and accuracy curves further validated this performance, showing a steady decline in training loss from 1.0 to approximately 0.1 and an increase in training accuracy from 50% to nearly 98% over 50 epochs, with validation accuracy stabilizing around 90%. These metrics indicate that central training on the aggregated dataset allowed the models to learn a comprehensive feature representation, leading to robust classification outcomes.

In contrast, the federated learning simulation, while achieving a respectable aggregate accuracy of 85.23%, exhibited a slight performance dip compared to the traditional models. The aggregate confusion matrix showed 215, 148, 291, and 258 correct predictions for glioma, meningioma, notumor, and pituitary tumors, respectively, with notable misclassifications, particularly between meningioma and glioma (54 instances). The individual client evaluations revealed variability, with accuracies ranging from 83.18% (Client 4) to 86.92% (Clients 2 and 3), reflecting the influence of local data heterogeneity and the challenges of decentralized training. The lower recall for meningioma (0.5920 in the aggregate report) suggests that the federated averaging process struggled to capture the nuanced features of this class, possibly due to imbalances in client data or insufficient local updates. Despite these challenges, the federated approach demonstrated resilience, maintaining high recall for notumor (0.9700) and pituitary (0.9556) classes, indicating its potential in scenarios where data privacy is a priority.

The comparative analysis revealed a clear trade-off between performance and privacy. The traditional ML models benefited from centralized access to the entire dataset, enabling them to achieve higher accuracy and better generalization. However, this approach raises significant privacy concerns, particularly in medical contexts where patient data protection is paramount. The federated learning approach, by contrast, addressed these concerns by distributing the training process across five clients and aggregating model updates without sharing raw data. The resulting accuracy of 85.23% is a testament to the feasibility of FL in decentralized settings, though it falls short of the traditional models' performance. This discrepancy highlights the need for advanced techniques to bridge the gap, ensuring that privacy-preserving methods do not compromise diagnostic accuracy.

The project's success in demonstrating the applicability of both approaches lies in its comprehensive evaluation framework. The use of confusion matrices, classification reports, and loss/accuracy curves provided a multi-faceted view of model performance, while the federated simulation mimicked real-world scenarios where medical institutions collaborate without centralizing sensitive data. The findings affirm that ResNet18, with its pre-trained features, offers a strong baseline for tumor detection, while the federated learning approach opens avenues for scalable, privacy-conscious solutions. This duality positions the project as a pivotal step toward integrating advanced ML techniques into clinical practice, where accuracy and patient confidentiality must coexist.

Moreover, the study has broader implications for the field of medical imaging and AI-driven diagnostics. The high performance of ResNet18 underscores the value of transfer learning in leveraging pre-trained models for domain-specific tasks, a strategy that can be extended to other medical imaging challenges such as cancer detection or neurological disorder diagnosis. The federated learning results, while not matching the centralized models, suggest a promising direction for collaborative research across institutions, especially in regions where data sharing is restricted due to regulatory or ethical constraints. The ability to achieve over 85% accuracy in a decentralized setting is a significant achievement, paving the way for future innovations in distributed learning systems.

However, the project also exposed limitations that warrant attention. The variability in client performance indicates that data quality, quantity, and distribution play critical roles in FL outcomes. The persistent difficulty in classifying meningioma suggests that class-specific challenges, such as overlapping imaging features, require targeted improvements. Additionally, the computational overhead of federated learning, including the need for multiple training rounds and communication between clients, poses scalability challenges that were not fully explored in this study. These limitations, while not detracting from the project's achievements, highlight areas for refinement and optimization.

In summary, the project successfully demonstrated the feasibility of brain tumor detection using both traditional ML and federated learning frameworks. The traditional models, particularly ResNet18, set a high benchmark with their accuracy and generalization, while the federated learning approach showcased its potential in decentralized settings. The findings lay a solid foundation for further research into scalable, privacy-preserving medical imaging solutions, with the ultimate goal of enhancing diagnostic accuracy and accessibility in clinical practice. The balance between performance and privacy achieved in this study serves as a stepping stone for future endeavors, ensuring that technological advancements align with the ethical and practical needs of healthcare.

# Future Works

Building on the insights gained from this project, several avenues for future research and development can be pursued to enhance the brain tumor detection system and address its current limitations. The following sections outline potential directions, ranging from technical improvements to broader applications, with a focus on advancing both traditional ML and federated learning approaches.

**Optimization of Federated Learning Techniques:** One of the primary areas for improvement is the optimization of the federated learning process to reduce the performance gap with traditional ML models. The current federated simulation relied on a basic federated averaging algorithm, which aggregates model updates from all clients equally. Future work could explore weighted averaging techniques that account for the size or quality of each client's dataset, potentially improving the global model's ability to generalize across diverse data distributions. For instance, clients with larger or more representative datasets could contribute more significantly to the aggregate model, mitigating the impact of data imbalance observed in the meningioma class.

Another promising direction is the incorporation of advanced aggregation strategies, such as secure multi-party computation or differential privacy. These techniques can enhance the privacy guarantees of the federated system while maintaining or improving accuracy. Differential privacy, for example, adds noise to the model updates to prevent the inference of individual data points, offering a robust defense against privacy breaches. Integrating such methods could make the federated approach more appealing to healthcare institutions, where data protection is a legal and ethical imperative.

Additionally, the frequency and number of communication rounds between clients and the central server could be optimized. The current study did not explore the impact of reducing communication overhead, which is a critical factor in real-world FL deployments. Techniques such as model compression, where only the most significant updates are transmitted, or periodic synchronization could reduce bandwidth usage and improve scalability. Investigating the trade-offs between communication efficiency and model performance will be essential for deploying FL in resource-constrained environments, such as rural healthcare settings.

**Addressing Class Imbalance and Data Heterogeneity:** The lower recall for meningioma in both the federated and traditional models suggests a class imbalance or feature overlap issue that warrants further investigation. Future work could incorporate data augmentation techniques tailored to medical imaging, such as synthetic image generation using Generative Adversarial Networks (GANs). By generating additional meningioma samples, the models could be trained on a more balanced dataset, potentially improving classification accuracy for this class. Similarly, transfer learning could be fine-tuned with class-specific loss functions, such as focal loss, which prioritizes hard-to-classify examples, to address the meningioma challenge.

Data heterogeneity across clients also contributed to the variability in FL performance. To mitigate this, future studies could implement client-side data preprocessing pipelines that standardize imaging features, such as intensity normalization or tumor segmentation, before local training. Alternatively, personalized federated learning approaches, where each client maintains a local model tailored to its data while contributing to a global model, could enhance performance. This hybrid strategy would balance the benefits of collaboration with the need for local adaptability, offering a more robust solution for decentralized medical data.

**Enhancing Model Architectures:** The success of ResNet18 in the traditional setting suggests that deeper architectures with pre-trained weights are well-suited for brain tumor detection. Future work could explore other pre-trained models, such as EfficientNet or Vision Transformers (ViT), which have shown promise in image classification tasks. These models could be fine-tuned on the brain tumor dataset to leverage their advanced feature extraction capabilities, potentially surpassing the performance of ResNet18. Additionally, ensemble methods combining the predictions of multiple models (e.g., custom CNN, ResNet18, and EfficientNet) could be investigated to further improve accuracy and robustness.

For the federated learning setting, adapting these advanced architectures to the distributed framework poses a unique challenge. Lightweight versions of these models, optimized for local training on client devices, could be developed to reduce computational demands. Techniques such as knowledge distillation, where a large pre-trained model transfers its knowledge to a smaller local model, could facilitate this adaptation, enabling efficient FL deployments without sacrificing performance.

**Integration of Clinical Feedback and Real-World Deployment:** To transition from experimental results to practical application, future work should incorporate clinical feedback into the model development process. Collaborating with radiologists and neurologists can provide domain-specific insights, such as the importance of certain imaging features or the clinical relevance of misclassifications. This feedback could guide the refinement of the models, ensuring that they align with diagnostic priorities, such as minimizing false negatives in tumor detection. For instance, adjusting the decision threshold to favor higher recall for malignant tumors like glioma could enhance the system's clinical utility.

Real-world deployment of the system also requires addressing practical challenges, such as integration with hospital Picture Archiving and Communication Systems (PACS) and compliance with regulations like the Health Insurance Portability and Accountability Act (HIPAA) or the General Data Protection Regulation (GDPR). Developing a user-friendly interface for clinicians, coupled with automated data preprocessing and model inference pipelines, could facilitate adoption. Pilot studies in clinical settings could validate the system's performance on diverse patient populations, providing a bridge between research and practice.

**Expansion to Other Medical Imaging Tasks:** The methodologies developed in this project can be extended to other medical imaging tasks beyond brain tumor detection. For example, the custom CNN and ResNet18 models could be adapted for lung cancer detection using chest X-rays or breast cancer classification using mammograms. The federated learning framework could be applied to multi-institutional studies, enabling collaborative research on rare diseases where data is scarce at individual sites. This scalability highlights the project's potential to contribute to a broader ecosystem of AI-driven diagnostics, addressing a wide range of healthcare challenges.

**Long-Term Research Directions:** Looking further ahead, the integration of multimodal data, such as combining MRI scans with patient metadata (e.g., age, symptoms), could enhance model performance. This approach would require developing architectures capable of processing heterogeneous inputs, potentially using attention mechanisms or graph neural networks. In the federated context, ensuring privacy for multimodal data adds another layer of complexity, necessitating advancements in secure data fusion techniques.

The advent of quantum computing also offers a long-term opportunity to revolutionize FL and ML for medical imaging. Quantum algorithms could accelerate model training and aggregation, addressing the computational bottlenecks of current systems. While still in its infancy, exploring the intersection of quantum computing and federated learning could position this research at the forefront of technological innovation.

In conclusion, the future works outlined above provide a roadmap for advancing the brain tumor detection system developed in this project. By optimizing federated learning techniques, addressing data challenges, enhancing model architectures, integrating clinical feedback, expanding to other imaging tasks, and exploring long-term innovations, the research can evolve into a transformative tool for healthcare. The balance between performance and privacy achieved in this study serves as a foundation for these endeavors, ensuring that technological advancements align with the ethical and practical needs of the medical community. Continued collaboration between AI researchers, clinicians, and policymakers will be essential to realize the full potential of this work, ultimately improving diagnostic accuracy and patient outcomes on a global scale.

Chapter 8

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