Federated Learning in Brain Tumor Imaging: A Review of Privacy-Preserving Techniques in Medical Diagnosis

Mahamodul Hasan Mahadi[1], Nousheen Jahan[2], Yamlick Abdullah[3], Mohammad Nazmus Saquib[4], Dardina Sara Narisha[5], and Rajarshi Roy Chowdhury[6]
[1,2,3,4,5,6]Department of Computer Science, American International University-Bangladesh
Dhaka, Bangladesh
Email: [1,2,3,4,5][24-93530-3, 25-93648-1, 25-93663-1, 24-93425-2, 25-93820-2]@student.aiub.edu
[6]rajarshi@aiub.edu

***Abstract*—Diagnosing brain tumors remains a complex task due to the variability in tumor characteristics and institutional imaging practices, coupled with the sensitive nature of patient data. While centralized deep learning models have shown promise, they often compromise data privacy. Federated Learning offers a secure alternative by enabling institutions to collaboratively train models without sharing raw data. This review presents a comprehensive analysis of FL-based approaches applied to brain tumor imaging, focusing on their effectiveness, privacy strategies, model architectures, and preprocessing techniques. The survey evaluates models such as FL-CNN, GoogLeNet-FL, and ResCapFed-Net, which are frequently paired with data normalization, augmentation, and segmentation methods. The identified challenges include uneven data distributions, communication overhead, limited model transparency, and practical deployment issues. The review emphasizes the importance of improving personalization, incorporating interpretability tools, and adopting secure and efficient aggregation methods. By highlighting current progress and open research problems, this study contributes to the development of scalable, privacy-aware, and clinically viable federated learning solutions for brain tumor diagnosis.**

***Index Terms*—federated learning, medical imaging, EfficientNet, ResNet, privacy preserving**

I. Introduction

Brain tumors constitute a significant global health challenge due to their diverse types and varying degrees of malignancy, requiring precise and early diagnosis to enable effective treatment strategies. Accurate diagnosis of brain tumors is complicated by their inherent complexity and heterogeneity. Traditional diagnostic approaches often involve manual analysis of magnetic resonance imaging (MRI) scans, methods which are labor-intensive, subjective, and can yield inconsistent results. Such limitations highlight the necessity for advanced computational approaches capable of providing reliable, objective, and timely assessments [1].

In recent years, artificial intelligence, particularly deep learning (DL) methods, has substantially enhanced automated tasks such as feature extraction, segmentation, and classification within medical imaging. Techniques such as Convolutional Neural Networks (CNN), U-Net architectures, and Generative Adversarial Networks (GAN) have demonstrated significant promise in diagnosing brain tumors accurately, facilitating clinical decision-making, and potentially improving patient prognoses. CNN specifically have emerged as essential tools in medical imaging, capable of autonomously learning intricate patterns from extensive datasets, thereby improving diagnostic accuracy and efficiency. GAN and Autoencoders have also contributed by generating synthetic training data and effectively reducing image noise, improving the robustness of diagnostic models. Despite these advances, conventional DL approaches typically depend heavily on centralized data, raising substantial concerns regarding data privacy and security. This issue becomes particularly significant in medical imaging due to strict regulations concerning the sharing of sensitive patient information across institutions. In response, Federated Learning (FL) has emerged as a viable privacy-preserving solution, allowing collaborative training of robust artificial intelligence models on decentralized datasets without compromising patient confidentiality [2].

FL facilitates collaborative model training across multiple institutions, utilizing insights from geographically dispersed and diverse data sources while ensuring that sensitive patient data remains secure locally. This approach preserves both patient privacy and enables the development of generalized models capable of addressing heterogeneous data distributions common in real-world medical imaging scenarios. Studies such as FL-PedBrain [3], focused on pediatric posterior fossa brain tumors, illustrate that FL achieves performance levels comparable to centralized methods, providing improved generalizability and resilience to data variability. Additionally, an integrated FL approach employing transfer learning and a modified VGG16 architecture, as proposed by Albalawi and colleagues, demonstrated notably high accuracy, substantially outperforming traditional methods.

While these advancements showcase considerable potential, FL's application in medical imaging, specifically brain tumor imaging, remains relatively nascent. Comprehensive systematic evaluations of existing FL methodologies in this context are currently limited. Previous literature reviews have

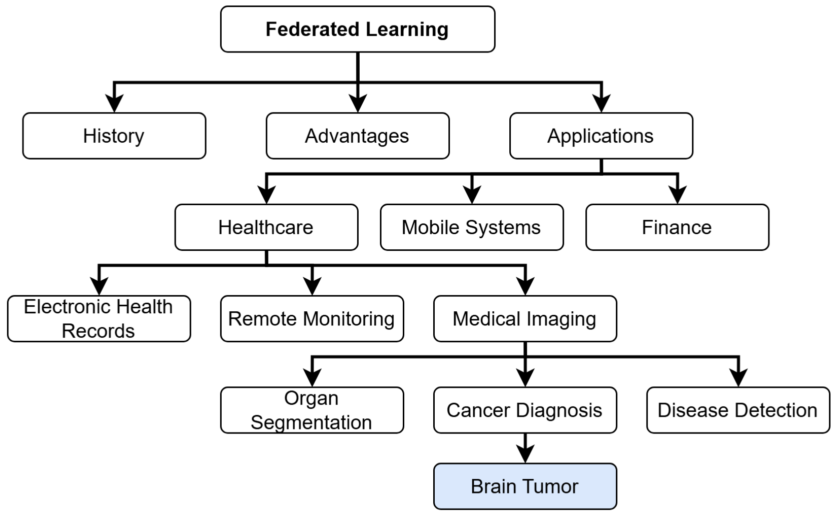

Fig. 1. Progressive narrowing of research focus from FL to its application in brain tumor diagnosis.

identified the critical need for thorough exploration and evaluation of FL and DL methodologies, emphasizing addressing existing research gaps and suggesting structured pathways for future research. Recent analyses have also pointed out specific challenges associated with DL models, such as the requirement for extensive annotated datasets, limited generalizability to new data, and significant concerns regarding data privacy. These challenges underscore the importance of FL, which can address these issues by enabling cooperative training without direct data sharing [4]. Additionally, the fields of Explainable Artificial Intelligence and model interpretability have gained increasing attention for their potential to improve transparency and trustworthiness in clinical decision-making, aspects crucial for the broader adoption of artificial intelligence solutions in healthcare.

This systematic literature review aims to critically evaluate FL methodologies specifically applied to brain tumor imaging. The review assesses current privacy-preserving FL methods, exploring their effectiveness, associated challenges, and feasibility for clinical integration. By comprehensively evaluating current methodologies and identifying potential areas for future research, this study aspires to contribute to the development of more effective, reliable, and ethically responsible artificial intelligence solutions, ultimately enhancing patient care and outcomes in brain tumor diagnosis and management.

This systematic literature review offers the following key contributions to the field of privacy-preserving FL in brain tumor imaging:

- Analyzes recent FL techniques used in brain tumor imaging, highlighting architectures, datasets, and aggregation methods.
- Evaluates the privacy-preserving techniques applied in FL and their trade-offs with performance and communication overhead.
- Identifies major technical challenges in privacy-preserving FL deployments, including data heterogeneity, infrastructure limitations, and lack of interpretability.
- Suggests future research directions to improve model robustness, security, and clinical integration.

The paper is structured as follows: Section II outlines foundational concepts of FL and its role in medical imaging. Section III details the methodology used for study selection and data analysis. Section IV presents a synthesis of recent research findings. Section V discusses existing limitations and technical barriers. Section VI proposes directions for future investigation, and Section VII offers concluding remarks.

II. Background Study

FL supports joint model development across distributed data sources while maintaining local data privacy. Its application in healthcare has gained attention due to the constraints around patient data sharing. Among healthcare tasks, medical imaging is a key area where FL can offer practical benefits. Fig. 1 illustrates the structured progression of this research, beginning with the general framework of FL and narrowing the scope through its advantages and applications, eventually focusing on brain tumor diagnosis as the specific area of interest.

A. Federated Learning

FL is a decentralized learning technique that enables multiple participants to train a shared machine learning model without exchanging their local data. In contrast to conventional centralized systems where all data is collected in one location, FL keeps data within its source environment and shares only model updates with a central aggregator. This approach reduces privacy risks and complies with legal restrictions, which is especially valuable in areas like healthcare and finance [5]. Fig. 2 outlines the process followed in the FL setup. A global model, initialized using EfficientNetB3, is sent to several local nodes. Each node trains the model on its own data and returns parameter updates. These updates are combined using the

Federated Averaging (FedAvg) method to refine the global model, which is then shared again for the next cycle.

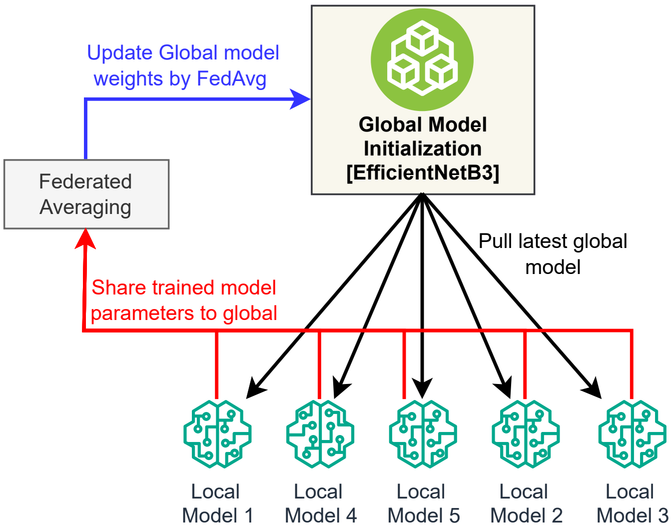

Fig. 2. Federated Learning working principle.

B. Historical Perspective

FL was first introduced by McMahan et al. in 2016 to solve privacy issues in mobile environments [5]. The initial application aimed to improve mobile keyboard suggestions by training models directly on user devices while keeping the personal data local. The proposed FedAvg algorithm became the foundational approach for FL and has since been adapted for broader use in institutional and cross-device settings.

C. Advantages and Applications

One of the key benefits of FL is its ability to preserve privacy while enabling collaborative model development. It allows organizations to comply with regulations like the General Data Protection Regulation and the Health Insurance Portability and Accountability Act [6]. Additionally, FL improves model generalization by using diverse data from different sources, minimizes communication costs by sharing only necessary updates, and supports training across devices with varying computational power. FL has been successfully applied in mobile applications, financial services, and particularly in healthcare. In mobile systems, it supports on-device learning for personalized services. In the financial sector, it enables fraud detection models without exposing customer data. In the healthcare domain, FL is gaining momentum for training diagnostic models using medical data that cannot be shared due to privacy constraints.

D. Medical Imaging and Federated Learning

Medical imaging provides essential insights for disease diagnosis and includes modalities such as MRI, computed tomography (CT), and X-rays. Developing accurate diagnostic models using these images requires large datasets, which are often restricted to single institutions due to privacy and policy barriers. FL addresses this issue by allowing institutions to contribute to model training without transferring images outside their secure environments. Several FL techniques have shown strong performance in medical imaging tasks. Techniques such as FL-CNN, GoogLeNet-FL, and ResCapFed-Net have been used to classify and segment medical images effectively while maintaining privacy standards [7], [8].

E. Cancer Detection using Federated Learning

Cancer is one of the most significant health concerns globally, and early detection is critical for improving patient outcomes. Medical imaging plays a central role in identifying tumors and monitoring their progression. However, training robust cancer detection models is challenging due to the limited availability of large, labeled datasets across institutions. FL enables collaborative model development across multiple centers, allowing for the use of diverse datasets without compromising patient confidentiality. Research has shown that FL can be successfully applied to several cancer types, including breast, lung, and brain cancers, resulting in accurate and secure diagnostic models [9].

F. Brain Tumor Diagnosis: A Case Study

Among various types of cancer, brain tumors present a particularly difficult challenge due to their structural complexity and high variability. MRI is the most commonly used imaging method for brain tumor detection. However, differences in equipment, imaging protocols, and patient demographics across institutions limit the effectiveness of traditional centralized learning models. FL offers a solution by allowing decentralized training on MRI data collected from different hospitals. Mastoi et al. developed an interpretable federated model that achieved high classification accuracy for brain tumor detection [7]. Similarly, Albalawi et al. incorporated transfer learning with FL and reported strong performance improvements [8]. Awotunde et al. also demonstrated the effectiveness of CNN in federated settings for multi-center brain tumor classification [9].

These studies confirm that FL is a secure method for handling sensitive medical data and a practical approach to building high-performance diagnostic models for brain tumor detection.

III. Methodology

This section describes the approach used to conduct the review. A systematic search was carried out across several scientific databases to identify studies focusing on FL techniques applied to brain tumor imaging. Predefined criteria were used to include only high quality and relevant publications. The aim was to examine recent trends, evaluate methodological frameworks, and highlight significant contributions in the field of privacy-aware medical diagnostics. This review systematically explores FL approaches for brain tumor detection, utilizing the PRISMA guideline to guide the study selection process (see Figure 3).

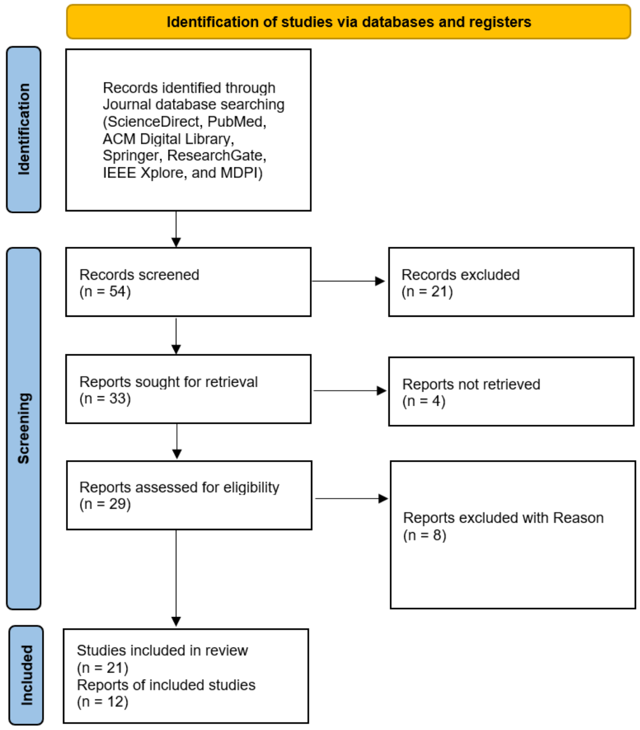

Fig. 3. PRISMA flowchart illustrating the process of identifying, screening, and selecting studies included in this scoping review.

A. Search Strategy

A detailed analysis was conducted to find relevant studies that employ algorithms that process FL techniques in medical imaging to detect cancer or classify different types of cancer. These databases, especially ScienceDirect, PubMed, ACM Digital Library, Springer, ResearchGate, IEEE Xplore, and MDPI, are utilized. The following boolean string combination search criteria were employed to search in databases.

- (”federated learning”) AND
- (”cancer detection” OR ”cancer classification” OR ”tumor classification” OR ”oncology”) AND
- (”MRI” OR ”X-ray” OR ”CT scan” OR ”Ultrasound”) AND
- (”deep learning” OR ”machine learning” OR ”AI” OR ”artificial intelligence”)

B. Screening Process

Using particular inclusion criteria, a thorough screening and selection process was conducted to identify pertinent studies on federated learning in medical imaging. Only English-language publications were taken into account; these included research papers; especially, journal articles that were released during 2020-August 2025. The exclusion of research studies on FL on medical imaging in foreign languages was further highlighted by inclusion criteria. It was also necessary that the chosen publications come from reputable conferences and journals. The inclusion and exclusion criteria were applied consistently throughout this procedure, and disagreements were settled by general agreement.

The following requirements must be met for inclusion:
- The research must be presented at good conferences or in reputed journals.
- Articles submitted for consideration must have appeared in English between January of 2020 and July of 2025.
- The main focus should be on FL in medical imaging, using models or algorithms to detect, classify cancer.

Exclusion Criteria:
- Articles that use FL without suggesting or utilizing federated setup or model aggregation techniques would not be accepted.
- Papers published in languages other than English would not be reviewed.

IV. Discussion and Findings

FL is becoming a valuable approach for brain tumor detection by enabling collaborative model training across different medical institutions while keeping patient data private. Based on the performance results shown in Table II, models such as ResCapFed-Net and Multi-site FL-CNN have achieved very high accuracy, precision, and recall, often exceeding 98 percent. These outcomes suggest that combining DL with FL frameworks can lead to highly effective diagnostic tools.

The model structures summarized in Table III reveal a wide range of architectural choices. While some studies use basic FL-CNN models, others employ more complex designs such as GoogLeNet-FL, ResNet-based architectures, or Siamese networks. These advanced models are designed to handle variability across different institutions and improve overall generalization. However, most of these evaluations are conducted in simulated settings rather than in real-world clinical environments, which limits our understanding of how these models would perform under practical deployment.

Pre-processing techniques play a key role in improving model stability and accuracy in FL systems. As detailed in Table I, common strategies include intensity normalization, resizing or resampling to uniform shapes, and skull stripping to remove non-brain tissues. These steps help reduce inconsistencies across imaging sources and are essential for ensuring that federated training remains effective despite non-uniform data. Augmentation techniques and filtering methods also contribute to better tumor localization and generalization.

Even though these models show strong performance, there are some gaps. Interpretability features are often missing, making it difficult for medical professionals to fully trust and understand the predictions. Furthermore, few studies include external validation or report performance per institution, which are important for measuring reliability across diverse healthcare settings.

In conclusion, the evidence from the reviewed studies shows that FL-based models, supported by effective pre-processing (Table I) and robust architecture choices (Table III), can deliver high performance in brain tumor detection (Table II). However, further efforts are needed to improve transparency, clinical validation, and deployment in real healthcare systems.

V. Challenges and Limitations

FL offers a compelling paradigm for multi-institutional collaboration in brain tumor detection using MRI and CT data. However, analysis of recent studies reveals several persistent limitations and challenges that hinder clinical translation. These issues are grouped into four major themes: performance and data heterogeneity, infrastructure and orchestration, privacy and security, and clinical validation and interpretability.

A. Performance Degradation and Data Heterogeneity

A consistent observation across the literature is that FL models often underperform when compared to centralized counterparts trained on pooled data. Studies on both segmentation and classification report accuracy gaps, even when employing techniques such as regularization, transfer learning, and ensemble methods [10], [17], [19]. These performance differences, while sometimes small in absolute terms, can have important implications for clinical decision-making where precision is critical.

A key factor contributing to this performance gap is the heterogeneity of data across participating sites. Institutions vary in imaging equipment, acquisition protocols, demographic distributions, and annotation practices, creating non-identically distributed (non-IID) data. This results in biased global models that favor dominant clients and struggle to generalize to underrepresented sites [4], [12], [15]. Task and modality heterogeneity further compound the problem, as federated models are often required to support a mix of imaging sequences and diagnostic targets. Approaches such as modality union inputs and dropout strategies have been proposed by Wagner et al. [18], but challenges remain when new combinations or rare pathologies are introduced.

Annotation quality and availability also present a fundamental limitation. While some datasets offer a large number of slices, they often lack diversity in patient populations [17]. Moreover, differences in labeling protocols across institutions introduce inconsistencies that impair model training and evaluation. In unsupervised pipelines, the absence of lesion-level labels places further strain on model robustness, especially when scanner-specific artifacts are misinterpreted as anomalies [11].

B. Systemic and Infrastructural Limitations

From a systems perspective, FL imposes substantial orchestration and communication overhead. Repeated synchronization between client sites and central servers increases wall-clock time and bandwidth usage. These issues are exacerbated by the addition of integrity layers or audit mechanisms [13]. In practice, variation in network reliability across hospitals leads to client dropout, partial participation, and asynchronous updates, all of which impact model convergence [15], [21].

Hardware constraints also influence participation and fairness. Many FL experiments utilize resource-intensive models such as 3D CNNs, capsule networks, or Siamese architectures, which are not practical for deployment at smaller clinics lacking GPU resources [13], [15]. This results in biased learning signals that disproportionately reflect well-equipped sites.

C. Privacy, Security, and Stability Concerns

Although FL reduces direct exposure of raw medical data, it does not inherently guarantee privacy. Multiple studies highlight potential vulnerabilities such as membership inference, gradient inversion, and adversarial poisoning [11]. Existing defense mechanisms, including secure aggregation and blockchain-based audit trails [13], can improve security but also introduce latency, complexity, and scalability concerns [21].

The optimization dynamics of FL are also fragile under heterogeneous data conditions. Simple FedAvg has been shown to oscillate or diverge in practice [19]. Stability-enhancing techniques such as proximal terms, gradient clipping, and adaptive weighting have been proposed, but outcomes remain sensitive to local training parameters, aggregation intervals, and client selection schedules [15]. This sensitivity complicates reproducibility and clinical reliability.

D. Clinical Integration, Interpretability, and Evaluation Gaps

Many reviewed studies place emphasis on model accuracy but provide limited support for interpretability and clinical review. Transparent decision-making is essential in medical contexts, yet few FL frameworks include mechanisms for explainability. Notable exceptions integrate saliency maps or Grad-CAM visualizations to guide clinician trust [16], but these remain isolated efforts.

A further limitation lies in the lack of rigorous external validation and benchmarking. Most experiments are conducted in simulated federated environments [10], without prospective multi-institutional trials or standardized evaluation protocols [17]. Recommendations across studies emphasize the need for site-wise reporting, calibration analysis, and decision-curve metrics before FL systems can be deployed in clinical workflows [4].

VI. Future Directions and Recommendations

Insights from the reviewed literature highlight emerging priorities for advancing FL in neuroimaging applications. These are organized around five focal areas: model generalization, system security, communication efficiency, label scarcity, and deployment governance.

A. Advancing Model Robustness and Personalization

Addressing data and task heterogeneity continues to be central in the development of FL strategies. The literature reflects an increasing emphasis on personalization techniques, such as client-specific fine-tuning, partial model aggregation, and grouping of similar clients based on task or data characteristics [15], [19]. Aggregation mechanisms that incorporate

TABLE I
DATA–PREPROCESSING TECHNIQUES FOR BRAIN TUMOR DETECTION USING FL

Technique	Brief description	Ref.
Intensity normalisation	Every voxel is rescaled to a common range—typically $[0, 1]$ or $[-1, 1]$—to offset scanner-specific gain differences. A common formula is $I' = \dfrac{I - \min(I)}{\max(I) - \min(I)}$.	[10]–[13]
Uniform resizing / resampling	All slices or volumes are interpolated (e.g., bicubic) to a fixed matrix such as 128×128 pixels or an isotropic $1\,\mathrm{mm}^3$ grid, ensuring equal tensor shapes across the batch.	[10], [12], [14], [15]
Data augmentation	Synthetic samples are generated via random rotations, flips, zooms and brightness/contrast jitter, expanding the dataset and reducing over-fitting.	[10], [12], [16], [17]
Skull stripping	Morphological operations or dedicated tools (e.g., ROBEX) remove non-brain tissue, leaving intracranial content for analysis.	[13], [18]
Anisotropic diffusion filtering	A PDE-based smoother $\partial I/\partial t = \nabla\cdot(c\nabla I)$ attenuates noise while preserving edges, clarifying tumour boundaries.	[13]
Frost filter	An adaptive, exponentially weighted kernel suppresses speckle noise by favouring nearby pixels of similar intensity.	[14]
3-D $\rightarrow$ 2-D slice extraction	3-D volumes (e.g., NIfTI) are decomposed into 2-D PNG slices so that standard 2-D CNNs can be trained.	[17], [19]

TABLE II
PERFORMANCE COMPARISON OF FL APPROACHES FOR BRAIN TUMOR DETECTION

Ref.	Classifier	Accuracy	Precision	Recall / Sens.	Specificity	F1-score	Dataset
[16]	**FL-CNN**	0.96	0.97	0.97	-	0.97	BT-large-3c MRI
[14]	**Multi-site FL-CNN**	0.998	0.999	0.999	1.000	1.000	3 064 CE-MRI
[13]	**ResCapFed-Net**	0.9907	0.9854	0.9982	0.9879	0.9955	1600 CT + 800 synthetic MRI images
[20]	**FedSPD**	0.9972	-	0.9687	0.9899	-	Brain-Tumor MRI (7 023 imgs)
[10]	**FL-CNN**	0.98	0.97	0.99	-	0.98	Private multi-centre MRI
[16]	**GoogLeNet-FL**	0.9424	0.9374	0.9389	-	0.9380	CE-MRI
[15]	**Hybrid FL (FedAvg/FedProx)**	0.9719	0.9725	0.9719	-	0.9718	Brain Tumor MRI Dataset
[21]	**SiCNN (P2P-FL)**	0.9711	0.9603	0.9589	-	0.9639	3-class Brain MRI
[17]	**CNN-Ensemble FL**	0.9322	0.94	0.93	-	0.93	Brain MRI

TABLE III
SUMMARY OF FL MODELS FOR BRAIN TUMOR DETECTION: ARCHITECTURES, ALGORITHMS, AND DATASETS

Ref.	Model Architecture	Model Name	Aggregation Method	Dataset
[16]	4-layer CNN	FL-CNN	FedAvg	BT-large-3c
[14]	CNN ensemble	FL-CNN (multi-site)	FedAvg	3,064 CE-MRI
[13]	ResNet-50 + Capsule	ResCapFed-Net	Blockchain-secured FedAvg	CT + synthetic MRI
[20]	ResNet-18 encoder	FedSPD	Semi-param. distillation (FedSPD)	Brain-Tumor MRI (7,023)
[10]	CNN	FL-CNN	FedAvg	Private MRI
[16]	Inception + GoogLeNet	GoogLeNet-FL	FedAvg	CE-MRI
[15]	Hybrid CNN	-	FedAvg + FedProx	Brain Tumor MRI Dataset
[21]	Siamese-CNN	SiCNN	Peer-to-Peer FL	3-class Brain MRI
[17]	6 backbone CNNs	CNN-Ensemble FL	FedAvg	Brain MRI

public validation or model uncertainty have been proposed to balance contributions from clients with unequal data volumes. Furthermore, shared encoders combined with task-specific heads offer a practical approach to handling multi-task and multi-modality settings, as discussed by Wagner *et al.* [18].

Explainability is also gaining prominence. Integrating interpretability tools such as Grad-CAM and uncertainty overlays has been shown to support clinician engagement and model auditing, and may serve as a foundation for federated active learning loops [16].

B. Reinforcing Security and Privacy Foundations

Although FL reduces data centralization, privacy concerns remain. Studies recommend the application of secure aggregation protocols, differential privacy with quantifiable budgets, and homomorphic encryption for highly sensitive environments [13]. Auditing mechanisms that balance transparency with computational overhead such as hash-based integrity chains or trusted execution environments are gaining attention as scalable alternatives to full blockchain architectures [11]. There is also a noted need for consistent formulation and testing of formal threat models, which are currently under reported in most experimental setups.

C. Improving Communication and Computational Efficiency

Scalability of FL in resource-diverse clinical environments depends on reducing both communication and computation costs. Literature suggests the adoption of compressed update mechanisms, lightweight local models, and asynchronous aggregation frameworks. Such approaches aim to minimize client overhead while preserving convergence behavior and model quality [14], [15]. Additionally, reporting infrastructure-related metrics such as bandwidth usage and energy consumption is encouraged for comprehensive benchmarking.

D. Enhancing Label Efficiency Through Unsupervised and Semi-Supervised Learning

Given the difficulty and cost associated with labeling brain tumor images, there is a clear focus on integrating weakly supervised learning approaches into FL. Techniques such as federated pseudo-labeling, self-supervised pretraining of encoders, and consistency-based training are being explored to exploit unlabeled data at the client level. Bercea *et al.* provide an example of unsupervised anomaly detection using disentangled representation learning, which avoids reliance on lesion masks while maintaining diagnostic utility [11].

E. Benchmarking, Clinical Validation, and Governance Readiness

Establishing FL benchmarks for medical imaging is an area of shared concern among researchers. Recommended elements include standardized non-IID partitions, multi-pathology scenarios, and missing modality setups. Performance evaluation frameworks are expected to include both accuracy metrics and calibration scores, confidence intervals, and decision-curve analysis [17], [18]. Clinical deployment further requires transparent consent handling, site-specific monitoring, rollback safety, and identity management, particularly in peer-to-peer configurations [21]. For CT-based pipelines, radiation governance and quality control protocols are necessary for regulatory alignment [13].

VII. Conclusion

FL presents a promising approach for improving brain tumor diagnosis by enabling secure collaboration across medical institutions while preserving patient confidentiality. This review explored current FL techniques, showcasing a variety of architectures and strategies that enhance diagnostic performance without compromising data privacy. However, challenges such as uneven data distribution, system inefficiencies, and limited interpretability still hinder widespread clinical adoption. Overcoming these issues will require advancements in model personalization, lightweight frameworks, and the integration of interpretable AI mechanisms. Additionally, establishing unified benchmarks and conducting real-world clinical trials will be vital for validating FL systems in practical healthcare settings. By synthesizing the current progress and outlining key areas for development, this study aims to support the evolution of trustworthy and scalable FL solutions for brain tumor imaging.

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