A techno-analytical insight on federated learning methodologies towards diagnosis of brain tumor

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ABSTRACT

Artificial intelligence (AI) has made rapid progress in addressing complex medical challenges, including life-threatening conditions such as brain tumors. Recent years have witnessed significant contributions from machine learning (ML) and deep learning (DL), yet practical deployment remains limited due to privacy concerns, data heterogeneity, and lack of collaborative training. Federated learning (FL) offers a promising alternative by enabling distributed training across institutions without data sharing, thereby improving detection accuracy while preserving patient privacy. This paper systematically reviews FL in the context of brain tumor diagnosis, with a focus on its mathematical foundations, core modelling approaches, and emerging research trends. The analysis highlights that while FL demonstrates strong potential in enhancing classification, detection, and segmentation tasks, major gaps remain in handling non-independent and identically distributed (non-IID) data, cross-modal integration, scalability, and real-world deployment. The key insight of this study is that future progress will rely on hybrid FL systems, fairness-aware aggregation, and security-enhanced frameworks to achieve clinically viable, equitable, and scalable diagnostic solutions.

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1. INTRODUCTION

Brain tumors are medical conditions characterized by abnormal cell growth within the central spinal cord or brain. The presence of a brain tumor potentially impacts a person's quality of life, neurological function, and health [1]. Furthermore, even small tumors can cause seizure activity, vision and hearing problems, speech and communication, and memory or cognition. Imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) scans are commonly used to diagnose brain tumors. Despite this, there is currently a potential trend in the healthcare sector to explore the adoption of artificial intelligence (AI) for diagnostic purposes, for several reasons: early detection, increased accuracy, increased speed and automation, accessibility within limited resources, multimodal integration, and improved tumor classification and prognosis. Currently, various research is being conducted adopting machine learning (ML) and deep learning (DL) as two of the most integral components of AI for brain tumor diagnosis. Various related works have been studied to understand the potential of intelligent systems in brain tumor diagnosis. Khalighi *et al*. [2] reviewed various AI approaches towards integrating genomics, histopathology, and imaging techniques for glioma detection. Cè *et al*. [3]

reviewed radiomics and DL frameworks under multimodal images for molecular marker prediction, surgical planning, lesion characterization, and prognosis. Chukwujindu *et al*. [4] discussed various ML and DL approaches for detecting glioma and non-glioma related tumors. Kaifi [5] have systematically reviewed various AI-driven methods associated with feature engineering, transfer learning, DL, ML towards segmentation and classification. Amin *et al*. [6] have discussed quantum ML, transfer learning, feature extraction techniques, and conventional segmentation towards investigating the effectiveness of various AI-methods for diagnosis of brain tumor. Various research problems have been noted after reviewing the existing AI-based approaches viz: i) only few number of AI models have actually been subjected to rigorous assessment in practical world parameters, ii) existing studies have not discussed much solutions about intratumorally heterogeneity and is characterized by boundary ambiguity, iii) although there are various DL models being implemented but they being resource-intensive are not practically assessed for their applicality on real-world scenario, and iv) there is no report of any distributed, decentralized, and highly structured system connected various healthcare center to facilitate enriched information towards brain tumor detection. This is exactly where federated learning (FL) plays a crucial role by connected a pipeline of all the hospital which facilitates analysis of brain tumor without much dependency on raw data. FL approach offers data privacy as models learns locally where training is carried out without moving the original data. However, there is no publication of any review work to understand the implication of FL approaches and its methodologies towards addressing various problems associated with brain tumor detection.

The proposed study aims to assess the current practices of FL methods for brain tumor diagnosis. Particular emphasis is placed on understanding the mathematical modeling perspective of frequently adopted FL methods. The value-added contributions of this paper are: i) a simplified and generalized mathematical approach to the current state of FL models is presented; ii) a comprehensive trend analysis is performed, contributing to a global picture of the current adoption process toward solving the challenges of brain tumor diagnosis; and iii) the study also highlights some unique unresolved issues that have no potential research work to address. The manuscript is organized as follows: section 2 briefly discusses the adopted method, while section 3 provides a detailed discussion of the results obtained. Lastly, overall work is concluded in section 4.

2. METHOD

The proposed work is a systematic review of the literature (SRL) to evaluate and synthesize the growing body of literature on FL for brain tumor analysis. The method adopted in the proposed is based on the analytical approach and conducted in accordance with preferred reporting items for systematic reviews and meta-analyses (PRISMA-style) framework. The methodology involves four main steps: i) formulating research questions (RQs) and defining keywords, ii) data collection from multiple scholarly sources, iii) screening and duplicate removal, and iv) application of inclusion and exclusion criteria to arrive at the final set of studies. Figure 1 illustrates entire work-flow of methodology adopted for SLR.

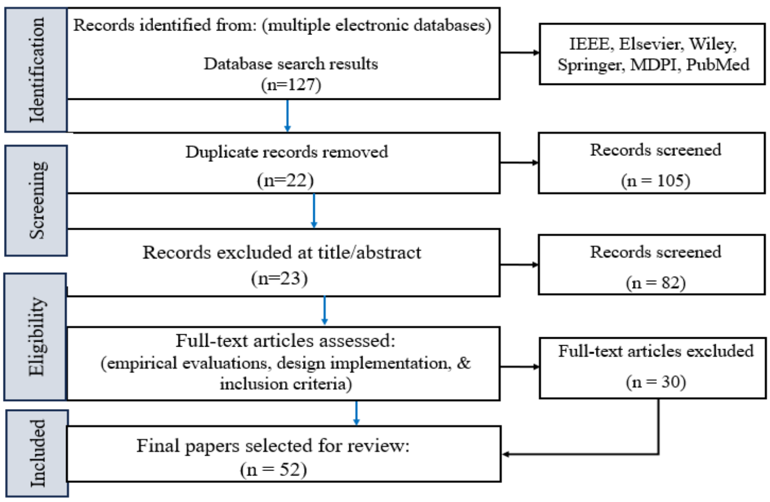

Figure 1. Adopted method in the proposed work

2.1. Research questions

The primary objective of this study is to investigate the role of FL methodologies in enhancing the diagnosis of brain tumors in the context of decentralized data environments and medical privacy constraints. This study seeks to understand how various FL techniques perform under real-world constraints such as data heterogeneity, limited communication bandwidth, and compliance with privacy regulations. To achieve these goals, the following RQs were formulated:

- RQ1: how effectively do current FL approaches address challenges such as data heterogeneity, communication overhead, and privacy in real-world clinical settings?
- RQ2: how has FL been applied to brain tumor detection, classification, and segmentation in medical imaging studies?
- RQ3: what datasets, methodologies, and model architectures have been most frequently adopted in FL-based brain tumor research?
- RQ4: what are the key limitations, challenges, and future opportunities identified in the literature regarding the use of FL for privacy-preserving and robust brain tumor diagnosis?

2.2. Keyword formulation

In order to ensure a comprehensive retrieval of relevant literature, a structured keyword formulation strategy was adopted, driven by the RQs and the scope of this review. The search keywords are categorized into three complementary domains. The first domain addressed the clinical context, with terms such as "Brain Tumor," "Glioma," "Glioblastoma," "Medical Imaging." The second domain represented the computational paradigm like "Federated Learning," "Distributed Learning," and "Collaborative Learning." The third domain expanded to task-specific methods that includes "Artificial Intelligence," "Machine Learning," "Deep Learning," "Segmentation," "Classification," and "Detection." During search process Boolean operators were employed to combine these terms of search results.

- "Brain Tumor" AND "Federated Learning"
- "Glioma" OR "Glioblastoma" AND "Federated Learning"
- "Brain Tumor Diagnosis" AND ("Federated Learning" OR "Distributed Learning")
- "Brain Tumor" AND ("Segmentation" OR "Classification") AND "Federated Learning"
- "MRI" OR "CT" AND "Federated Learning" AND "Brain Tumor"

2.3. Data sources

To obtain a comprehensive and reliable set of studies, multiple well-established scientific databases were systematically searched. The primary sources included IEEE Xplore, SpringerLink, ScienceDirect (Elsevier), Wiley Online Library, Nature (Scientific Reports), BMC Journals, MDPI, and PubMed. These databases were selected due to their wide recognition in publishing peer-reviewed research across computer science, medical imaging, and healthcare informatics. The search was conducted for articles published between 2021 and 2025. Conference proceedings, opinion pieces, and review articles were excluded to focus on original, high-impact research. Both open-access and subscription-based publications were considered to reduce publication bias and ensure broad coverage. Only peer-reviewed articles written in English were included. The preprints from platforms such as arXiv were screened separately and included only if they presented substantial technical contributions and met the inclusion criteria.

2.4. Screening and final selection

The proposed study adopts a multi-stage screening process which involves duplicate removal, application of predefined inclusion and exclusion criteria, and final eligibility assessment. The initial database search yielded 127 records. After removing 22 duplicates, 105 unique studies remained. Titles and abstracts were reviewed to assess relevance. At this stage, 23 studies were excluded for reasons such as lacking a focus on brain tumor diagnosis, not using FL, or missing methodological clarity. Full texts of the remaining 82 studies were then reviewed. Another 30 were excluded for not meeting one or more inclusion criteria, such as limited methodological detail or insufficient alignment with FL objectives. In total, 52 studies were included in the final review.

3. RESULTS

FL approach is an integral part of DL methods in AI and is well-suited for streamlining the synchronization of incoming traffic of data from various clients to carry out its predictive or analytical operations. However, the biggest dilemma found from reviewing existing research articles is that voluminous segment of existing work is focused on detection and classification problems using FL approaches while only a fraction of research work has emphasized on practical part of realization of FL models in healthcare units towards diagnosing of brain tumor. Hence, this section highlights the findings of the study related to only FL models used for diagnosis of brain tumor along with contribution of trends and open challenges.

3.1. Assessing current mathematical foundation

The implementation of FL in form of mathematical formulation towards diagnosis of brain tumor is based on ideation of training and learning a shared global framework over different decentralized servers (diagnostic center and hospital) without the need to share any raw data. This section details about varied form of essential mathematical foundation towards implementing FL with core agenda to analyze their convergence behaviour. Following are the core models deployed with FL:

3.1.1. Modelling focusing on objective foundation

Unlike centralized learning, FL based approaches are meant for preserving the data locality by sharing only model parameters, which is important in healthcare, where privacy regulations prevent direct data exchange between institutions. However, to ensure that local model updates effectively contribute to the global model while maintaining data privacy, a global optimization objective formulation is necessary to maintain an effective collaborative training process across distributed clients. In FL, the global objective function is defined by aggregating local client losses into a single empirical risk function [7]–[10], numerically expressed as (1):

$$\min_{w} f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \tag{1}$$

Where, w denotes the global model parameters, K is the number of clients n_k is the sample size at client k, and $n = \sum_{k=1}^{K} n_k$ is the total number of training samples at all clients. For each client, the local empirical risk is:

$$F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} l\left(w; x_i^{(k)}, y_i^{(k)}\right) \tag{2}$$

Where, $l(\cdot)$ represents the loss function, and $a = \left(x_i^{(k)}, y_i^{(k)}\right)$ denotes the input MRI scan and its corresponding label. This process minimizes a weighted average of local losses, and ensures that each client's contribution is proportional to its dataset size, which hospitals to collaboratively train robust diagnostic models for brain tumor detection without violating privacy constraints. It also encourages model generalization by integrating heterogeneous datasets from diverse patient populations.

3.1.2. Modelling focusing on federated averaging

Federated averaging (FedAvg) is one of the most widely adopted algorithms in FL to solve this optimization problem discussed above to update the global model by computing a weighted average of locally trained models. It was introduced to address the challenge of coordinating learning in environments where data remains distributed due to privacy or regulatory constraints [11]-[13]. The global model update at communication round $t + 1$ is numerically expressed as (3):

$$w^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^{(t+1)} \tag{3}$$

Where, $w^{(t+1)}$ denotes the local model parameters at client k after local training, n_k is the sample size at client. The local updates are performed using optimizer which can be ADAM, SGD, and RMSprop. The FedAvg reduces communication overhead by allowing multiple local training steps before synchronization. It also supports heterogeneity in both data distributions and hardware across clients. However, its performance can degrade under non-independent and identically distributed (non-IID) data, which is common in medical applications. In such cases, the local updates may diverge, and often lead to slower or unstable convergence of the global model.

3.1.3. Modelling focusing on heterogeneity and drifting

One of the major challenges in medical FL context is statistical heterogeneity due to the variations in patient demographics, imaging protocols, annotation practices, and tumor classifications often result in non-independent and non-IID datasets across institutions [14], [15]. This heterogeneity can lead to divergence in local model updates, which slows down or destabilizes the convergence of the global model. The degree of client drift can be quantified by measuring the dissimilarity between the gradient of the local objective and the global gradient, expressed as (4):

$$Drift_k = || \Delta F_k(w) \, \Delta f(w)||^2 \tag{4}$$

Where, $\Delta F_k\ (w)$ denotes the gradient update at client k and $\Delta f(w)$ is the global gradient. A higher drift value indicates stronger non-IID effects, which may lead to oscillations during training and suboptimal convergence. To mitigate this issue federated proximal (FedProx) an extension of the FedAvg is often adopted, which introduces a proximal term into the local objective, numerically given as (5):

$$w_k^{(t+1)} = \arg\min_{w} \left[F_k(w) + \frac{\mu}{2}\left||w - w^{(t)}|\right|^2\right] \tag{5}$$

where μ is the proximal coefficient that penalizes deviations from the global model and $||\cdot||$ represents L_2 norm to incorporate stability over the heterogeneous datasets. The proximal term acts as a regularize that penalizes large deviations from the global model. This process encourages local solutions to remain closer to the global model trajectory, which improves convergence stability across heterogeneous clients, thereby making FL more robust in real-world clinical scenarios.

3.1.4. Modelling focusing on convergence analysis

There are several studies that have focused on understanding the convergence behavior of FL models trained under distributed and communication-constrained environments [16]–[18]. Unlike centralized approach that does not account for communication constraints, FL focuses on balancing the model performance with real-world limitations such as local computation capacity and bandwidth. However, the convergence rate of an FL model depends on different hyperparameters such as number of local epochs E, the number of clients K, and the learning rate η. The expected convergence rate of the global loss can be obtained considering the standard assumptions of convexity and bounded variance σ^2, as (6):

$$E[f(w^{(t)}) - f(w^*)] \leq \frac{C}{\sqrt{t}} + O\left(\frac{\sigma^2}{t}\right) \tag{6}$$

Where, $f(w^*)$ represents the optimal global loss, t is the number of communication rounds, and C is a constant based on the initial distance from the optimal solution. Although increasing the number of local updates E can reduce the frequency of communication, but it also increases the risk of client drift in the higher heterogeneous contexts. Therefore, an adequate tuning of FL parameters is needed to achieve an efficient trade-off between communication efficiency and model stability.

3.1.5. Modelling focusing on communication cost

The communication is one of the most critical factors that influences the practicality of FL in healthcare applications such as brain tumor diagnosis, where timely and reliable model updates can directly affect clinical outcomes [19]–[21]. Unlike conventional centralized learning models that often dependent on complex and large network architecture which requires large computational resources and place significant burden on communication channels with limited bandwidth. The total communication cost C_{tot} in FL can be expressed as (7):

$$C_{tot} = T.K.|w| \tag{7}$$

Where, $|w|$ denotes the size of the model parameters, T and K represent quantity of communication attempts/rounds and clients respectively. For an optimal modelling, it is essential to compress w or minimize T using quantization and local training respectively. In the context of brain tumor detection, efficient communication modelling ensures that FL systems are scalable and highly responsive towards enabling hospitals with varying network capacities to collaborate without overwhelming infrastructure resources.

3.1.6. Modelling focusing on injection of differential noise

Apart from reducing communication cost or latency, ensuring privacy is also one of the basic requirements in the context of medical FL [22]. It is noted that majority of existing system adopted differential noise injection technique to prevent unintended data leakage during training [23]. In this process instead of sharing raw gradients or parameters, a noise is added to obscure individual contributions yet still enabling effective global learning. The process of noise-injected local update at client k is expressed as (8):

$$\widetilde{w}_k^{(t+1)} = w_k^{(t+1)} + N(0, \sigma^2 \mathrm{I}) \tag{8}$$

Where, $\widetilde{w}_k^{(t+1)}$ denotes the local model update after training, and $N(0, \sigma^2 I)$, represents multivariate Gaussian noise with zero mean and variance σ^2, which controls the balance between privacy and accuracy. The larger value more the privacy, and smaller values higher accuracy but weaker privacy guarantees.

3.1.7. Modelling focusing on fairness and weighting client contribution

The fairness is an important consideration in FL where hospitals and clinics may differ significantly in terms of dataset size, quality, and diversity. Most of the conventional FL approaches assigns weight proportional to client dataset sizes, which can lead to biased the global model toward larger institutions [24]-[26]. The analysis of the recent works showed that few studies have considered dynamic weighting approach for facilitating clients with more quality-enriched data for better modelling. It was also noted that certain studies have implemented this metric of client contribution and one commonly used strategy is based on Shapley values, which quantify a client's marginal contribution to overall model performance. The fairness-based aggregation scheme is defined as (9):

$$\alpha_k = \frac{score_k}{\sum_{j=1}^{K} score_j},\ w^{(t+1)} = \sum_{k=1}^{K} \alpha_k w_k^{(t+1)} \tag{9}$$

Where, $score_k$ denotes the performance of client k on a held-out validation set, α_k represents the normalized contribution weight, $w_k^{(t+1)}$ is the local model from client k and $w^{(t+1)}$ is the updated global model. In the context of brain tumor diagnosis, fairness-driven FL ensures balanced contributions from both large and small institutions, mainly important for smaller hospitals that may handle rare or complex cases often overlooked in standard aggregation schemes. Therefore, by prioritizing contribution quality over quantity, fairness-aware FL improves generalization and supports equitable model performance across diverse clinical settings. The above discussed modelling approaches are summarized in Table 1 with their objectives, advantages, limitations, and clinical implications in brain tumor diagnosis.

Table 1. Highlights of mathematical models in FL for the medical context

Model type	Objective	Pros	Cons	Clinical implications
Global loss minimization (1) and (2)	Minimize global empirical risk via weighted local losses; preserves data locality	Strong privacy; integrates heterogeneous data	Sensitive to imbalance across clients	Enables secure collaborative diagnosis without raw data exchange
FedAvg (3)	Aggregate local updates through weighted averaging; assumes IID or near-IID	Scalable; reduces communication	Prone to client drift under non-IID data	Practical for multi-hospital training with modest datasets
FedProx/drift control (4) and (5)	Add proximal term to stabilize updates in heterogeneous data	Improves stability and convergence	Extra computation overhead	Robust under diverse MRI protocols and patient demographics
Convergence analysis (6)	Balance accuracy vs. communication	Helps tune training–communication trade-off	Risk of drift if local epochs too high	Supports efficient FL in bandwidth-limited hospital networks
Communication cost (7)	Quantify bandwidth=rounds×clients× model size	Estimates resource needs; supports compression	High overhead for large models	Guides deployment in hospitals with limited infrastructure
Differential privacy noise (8)	Inject Gaussian noise into updates for privacy	Protects sensitive patient data	Accuracy–privacy trade-off	Ensures compliance with GDPR/HIPAA without compromising collaboration
Fairness/weighted contribution (9)	Weight client updates based on contribution (Shapley score)	Promotes inclusivity and equity	Needs reliable scoring mechanism	Prevents bias; ensures smaller hospitals' rare cases influence model

3.2. Research trend

In order to understand the current research trend and progress, numerous recent works [27]-[52] between 2021 and 2025 have been reviewed on FL for brain tumor detection, classification, and segmentation, with some extending to related domains such as traumatic brain injury (TBI) and multiple sclerosis (MS). Table 2 and Figure 2 highlight the trends of current research work adopting FL towards diagnosis of brain tumor. The analysis reveals several emerging trends:

– Shift toward privacy-preserving methods: integration of blockchain, homomorphic encryption, and differential privacy is increasingly seen to enhance trust in clinical settings [31], [42], [52].
– Diverse model integration: CNNs, U-Net variants, and hybrid FL approaches have been extensively applied to tackle heterogeneity, communication cost, and limited datasets [27], [30], [45], [49].
– Emphasis on segmentation and diagnosis tasks: many studies demonstrate strong performance on segmentation benchmarks (e.g., Dice scores ~0.89–0.93) and high classification accuracy (>99%), highlighting the promise of FL in brain tumor diagnosis [33], [41], [42], [51].
– Challenges in clinical translation: despite experimental success, scalability, generalization across institutions, and robustness to real-world heterogeneity remain unresolved issues [29], [36], [47].

Table 2. Highlights of recent research trends in FL for brain tumor diagnosis

Author	Method	Dataset	Contribution	Observation
[27]	FL (FedAvg+FedProx)	Kaggle MRI	Improved robustness; higher accuracy vs. centralized.	Scalability unproven.
[28]	ML and DL	BraTS and Kaggle	Analyzed different algorithms and datasets.	No FL validation.
[29]	Decentralized FL and U-Net	Multi-site MRI	Real-time FL; analyzed accuracy–latency trade-offs.	Small-scale, limited diversity.
[30]	FKD-Med (FL+KD)	2 segmentation sets	Cut communication cost with minimal accuracy loss.	Gains modest; no clinical validation.
[31]	FL-CNN-Blockchain	CT datasets	Higher accuracy; blockchain-secured updates.	Complex; blockchain overhead.
[32]	Transfer learning	Kaggle MRI	Higher accuracy.	Centralized; no FL.
[33]	CNNs/FCNs with multichannel MRI	203 subjects	Improved accuracy and Dice score.	Not clinically integrated.
[34]	MobileNetV2	6 Kaggle sets	Higher detection for binary task.	Centralized; risk of overfit.
[35]	Transfer learning+ensemble ML	5,712 MRIs	Stacking model achieved higher AUC score	Single-modality and lacks novelty
[36]	3D FL (EtFedDyn)	TCGA, US, and MICCAI	FL accuracy close to centralized.	Moderate acc.; limited sets.
[37]	FL with migration learning	Independent MRI	Outperformed centralized; boosted collaboration.	No effective benchmarking.
[38]	FedCNN for TBI prediction	CQ500, RSNA and CENTER-TBI	Higher accuracy; privacy-preserving TBI classification.	Generalization to brain tumor not shown.
[39]	FL+transfer learning	Open MRI (4 classes)	FL outperformed pretrained; edge-suited.	Limited dataset diversity.
[40]	FL+compression	Simulated MRI	Significant reduction in communication cost.	No effective benchmarking
[41]	FL for SRS tumor delineation	Multi-institution MRI	FL Dice, comparable to CL; standardization improved results.	CL better in some cases.
[42]	FL+U-Net for segmentation	Multi-institution MRI	Improved Dice (0.89) and specificity (0.96).	Tested only on simulated FL lacks extensive validation.
[43]	FL for MGMT methylation prediction	BraTS2021 (MRI)	FL matched centralized quality after 300 rounds.	Requires large rounds; tested only on BraTS, needs more validation study.
[44]	CNN+Grad-CAM	MRI (unspecified)	~98% acc.; interpretable via Grad-CAM.	Small datasets.
[45]	GAN+EfficientNet	Gazi, BraTS, and Br35H	Augmented data improved accuracy.	Relies on synthetic data.
[46]	FL with DL classifiers	BT-small-2c and BT-large-3c	Achieved modest accuracy.	Limited datasets; modest accuracy on 2-class set.
[47]	FL for MS lesion segmentation (nnU-Net)	512 MRIs and 3 sites	Feasible FL; Dice 0.66–0.80 across different sites.	Varied performance due to heterogeneity.
[48]	FL+CNN+transfer learning	Multi-client MRI	FL improved privacy-preserving classification.	Dataset details scarce.
[49]	FL-CNN+GAN	Synthetic+real MRI	Solved privacy+data scarcity.	GAN realism questionable.
[50]	FL+U-Net	Multicenter MRI	FL for MRI-to-CT; SSIM 0.89, PSNR 26.6.	Tested in 5 centres; moderate perf.
[51]	EfficientNetB7+UNet	MRI data (unspecified)	Mostly suitable for centralized approach.	Centralized; not much suitable for FL.
[52]	FL+blockchain	Healthcare EHR+imaging	Secure FL framework with privacy and integrity.	Conceptual; no real dataset test.

3.3. Identification of unsolved research problems

Despite many progresses in the literature, it has been identified that the existing FL methods remain inadequate in handling domain-shifted, diverse, and imbalanced brain MRI datasets, where performance often declines under extreme heterogeneity [29], [36], [47]. There is also a lack of benchmarked cross-modal FL frameworks capable of integrating asynchronous and multi-source data streams (e.g., genomics, MRI, CT, and clinical reports), which limits their real-world applicability. Another unresolved issue lies in the generalization to rare tumor types (e.g., ependymoma and craniopharyngioma), where few-shot or zero-shot cases pose unique challenges [43]. Moreover, existing studies rarely explore long-term, continuously updating FL systems, which are essential for clinical scalability and adapting to evolving patient cohorts. Finally, the absence of hybrid FL architectures that combine hospital-centered models with edge-based devices restricts translation into personalized care settings [52]. The future research work needs to address these gaps with RQs: how can FL be adapted to cross-modal and rare-case scenarios? What strategies support lifelong FL for dynamic clinical datasets? How can hospital-level FL be integrated with edge intelligence to achieve patient-centered precision diagnosis?

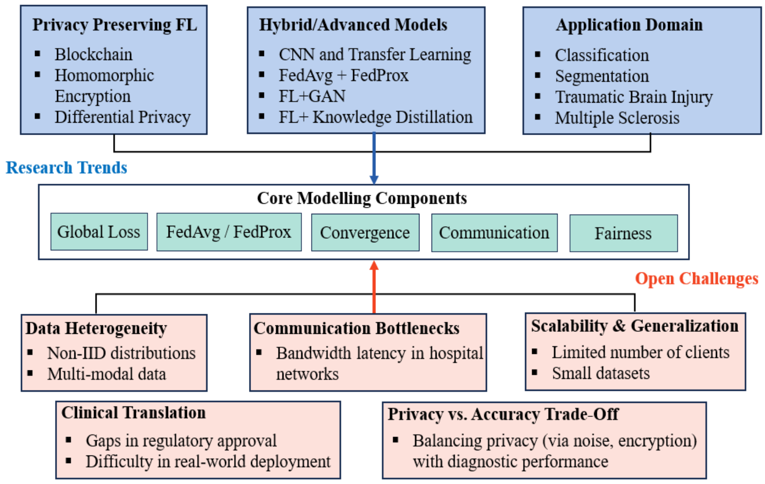

Figure 2. Current research trends, core modelling components, and open challenges in FL for brain tumor diagnosis

4. CONCLUSION

This paper systematically reviewed the application of FL in brain tumor diagnosis, with emphasis on its mathematical foundations, recent research trends, and open challenges. The review highlights that although FL demonstrates promising results in accuracy and privacy preservation, its limitations remain evident in handling data heterogeneity, rare tumor types, cross-modal integration, and scalability to real-world hospital networks. The future research must focus on hybrid FL systems that integrate centralized, decentralized, and edge-based models, alongside robust strategies for data heterogeneity mitigation such as adaptive weighting, multi-modal fusion, and fairness-aware aggregation. Moreover, there is a critical need for lifelong FL frameworks that can continuously adapt to dynamic clinical datasets, as well as security-enhanced approaches capable of resisting adversarial perturbations while maintaining diagnostic reliability. Future research should prioritize including security module and ensure robustness against adversarial attacks along with optimization in the communication latency. Addressing these gaps is essential for translating FL into a clinically viable and equitable paradigm for brain tumor diagnosis.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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