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Recent Advances in Deep Learning for MRI-Based Brain Tumor Identification: A Systematic Review (2020 - 2025)

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Abstract

The utilization of deep learning (DL) technology in brain MRI image analysis has seen significant advancements over the past five years. This study presents a systematic review of literature from 2020 to 2025, evaluating DL progress in automated tumor lesion segmentation, tumor type classification, genetic biomarker prediction, and treatment response monitoring. Various DL architectures, such as nnU-Net and ensemble models, dominate segmentation tasks, while transformer-based methods and foundation models are emerging as new pathways for large-scale medical image management. However, technical challenges including cross-institutional MRI protocol variations, underrepresentation of pediatric data, and model bias remain primary concerns. Initiatives like BraTS and federated learning approaches offer potential solutions to enhance DL model validity and scalability. This review highlights future directions for developing more adaptive, accurate, and ethical DL systems to support individualized and sustainable brain tumor diagnosis and management.

Keywords: *Deep Learning; MRI; brain tumor; classification; federated learning*

1. Introduction

Brain tumors represent one of the most challenging and potentially life-threatening neurological conditions. Diagnostic accuracy and speed play a crucial role in determining patient prognosis and treatment strategies. Clinicians typically group brain tumors into two primary categories: those originating directly within brain tissue (primary), and those forming secondary to the central nervous system (CNS) metastasis from remote anatomical sites [1]. Despite lower incidence versus other cancers, brain tumors, especially high-grade variants like glioblastoma multiforme (GBM) —exhibit alarming mortality patterns [2].

Within modern neuro-oncological workflows, magnetic resonance imaging (MRI) has emerged as the indispensable modality for initial tumor detection and longitudinal monitoring of neoplastic progression. When contrasted with computed tomography (CT) and other imaging alternatives, MRI uniquely achieves dual diagnostic advantages: exceptionally detailed cerebral anatomical mapping alongside unprecedented discrimination of subtle soft-tissue interfaces [3]. Yet manual radiological assessment confronts persistent obstacles—notably inconsistent interpretations between specialists, time-consuming analytical processes, and inherent reliance on operator expertise. Collectively, these limitations routinely compromise the speed and accuracy essential for optimal therapeutic decisions.

Deep learning applications show compelling utility in MRI-based neuro-oncological analysis, particularly for tumor segmentation and classification tasks. Convolutional neural networks (CNN) provide the dominant framework, autonomously extracting multidimensional spatial features from neuroimaging data to drive segmentation architectures like U-Net, nnU-Net, and their ensemble derivatives [4]. Beyond

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delivering rapid segmentation with clinical-grade accuracy, these systems enable radio genomic prediction of critical biomarkers-including IDH1 allelic status and MGMT promoter methylation patterns-directly from quantitative imaging phenotypes. Novel paradigms integrating foundation models with vision transformers now address key challenges: mitigating data scarcity while enhancing cross-population generalizability. This technological convergence consequently establishes new paradigms for expeditious, precision-enhanced diagnostic pathways in neuro-oncology.

This systematic investigation evaluates the maturation of deep learning techniques form MRI-driven brain tumor recognition between 2020 and 2025. By synthesizing emergent literature, we seek to deliver actionable intelligence enabling neurologists, researchers, and AI engineers to strategically harness computational intelligence within neuro-diagnostic frameworks.

2. Methods

This research adopts a Systematic Literature Review (SLR) methodology structured by the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyses) framework, ensuring rigorous transparency throughout our scholarly investigation. We deliberately selected this approach to maintain methodological integrity during literature identification, screening, and analytical phases. Primary data acquisition involved comprehensive retrieval of peer-reviewed publications focused on deep learning implementations for brain tumor diagnosis using MRI. Our research strategy targeted four principal knowledge repositories: IEE Xplore, ScienceDirect, and Scopus, and the preprint repository ArXiv—supplemented by specialized neuroimaging journals indexed in MEDLINE.

Our systematic search incorporated targeted keyword phrases: *deep learning*, *brain tumor*, MRI, *segmentation*, and *classification*. All retrieved publications underwent rigorous filtration against predefined inclusion/exclusion criteria prior to analytical processing. The inclusion protocol mandated: (1) publication dates within 2020-2025, (2) English-language content, (3) primary focus on DL implementations for MRI-based tumor recognition, (4) complete text accessibility, and (5) peer-reviewed validation status. Studies failing to meetthese criteria – including those based on non-MRI imaging, non-primary research, or lacking full-text accesswere excluded. Exclusion criteria specifically encompassed: (1) Brain tumor diagnosis without MRI data, (2) Comparisons of deep learning models with non-DL methods for MRI analysis, (3) Articles without clearly stated research objectives, (4) Insufficient documentation of methodological strengths/limitations, (5) Publications outside reputable journals/conferences proceeding. Quality assessment was subsequently conducted using three key indicators: (1) Clarity of research objectives, (2) Comprehensive reporting of methodological strengths and limitations, (3) Publication venue reputation.

3. Results and Discussion

Based on systematic analysis of 25 scientific articles published between 2020 and 2025, diverse deep learning approaches for MRI-based brain tumor identification and segmentation were identified. These articles were comprehensively analyzed and presented in Table 1, summarizing author names, publication years, methodologies, dataset types, and strengths/challenges of each approach. Most studies adopted Convolutional Neural Network (CNN) architecture particularly U-Net and nnU-Net variants-which demonstrated superior performance in spatial lesion segmentation with high accuracy. Recent studies reveal an emerging trend of transformer models (e.g., Swin-UNETR, BiTr-UNet) and hybrid CNN-ViT architectures addressing spatial limitations while improving cross-domain generalization. The BraTS (Brain Tumor Segmentation Challenge) dataset across its 2020, 2021, and 2023 versions was predominantly utilized, providing multimodal MRI (T1, T1c, T2, and FLAIR) from glioma patients.

Table 1. Deep Learning for MRI Brain Tumor Analysis: Data Extraction

No	Author (Year)	Method Used	Dataset	Strengths	Challenges
1	Khan et al. (2023) [4]	CNN, U-Net, ResU-Net, Ensemble nnU-Net	BraTS, TCIA, IBSR	High tumor segmentation accuracy, exploration of multiple DL architectures.	Overfitting, cross-hospital protocol variations, imbalanced class distribution

2	Krishnan et al. (2024) [5]	Rotation-Invariant Vision Transformer (RViT)	Kaggle Brain Tumor MRI	High classification precision (98.6% accuracy, F1=0.984), robust to image rotation	Requires high processing power pre-training
3	Ferdous et al. (2023) [6]	LCDEIT Transformer	Figshare, BraTS-21	Efficient training on small datasets, excellent performance with high accuracy/F1 Scores on MRI benchmarks	Requires further evaluation on other datasets; attention mechanisms need careful tuning; high complexity for direct clinical implementation
4	Zeineldin et al. (2024) [7]	TransXAI (hybrid Vision Transforme r + CNN), Grad-CAM explainability	BraTS 2019, Citra multimodal MRI: T1,T1Gd, T2, dan FLAIR	High segmentation accuracy, interpretable saliency heatmaps, clinical transparency	Limited to single dataset evaluation; computational demands require adequate hardware for clinical deployment
5	Reddy et al. (2024) [8]	Fine-Tuned Vision Transforme r	(FTVT-b16/b32/I16/I32)	MRI brain tumor dataset Images (glioma, meningioma, pituitary, no tumor)	High accuracy (up to 98.70% for FTVT-I16), outperformsother DL models
6	Poornam & Angelina (2024) [9]	VITALT (Vision Transformer + Linear Transformati on)	BraTS 2021	Robust to image variations, high multi-class classification accuracy	Model complexity requires intensive tuning
7	Liu et al. (2023) [10]	Ensemble Vision Transformers	Custom Glioblastoma dataset	High precision glioblastoma segmentation, benefits from model ensemble	Computationa lly intensive, overfittingrisk in large ensembles
8	Singh et al. (2022) [11]	3D CNN withattention gating	BraTS 2020	High multi-label segmentation precision	Significant GPU memory requirements
9	Zhou et al. (2021) [12]	nnU-Net + transfer learning	TCGA-GBM/LGG	Rapid adaptationto new datasets	Overfitting on smalldata
10	Chen et al. (2023) [13]	U-Net++	Private clinical dataset	Efficient simultaneous and classification	Limited validation

11	Wang et al. (2021) [14]	GAN-based augmentation + CNN	BraTS 2019	Enhanced data variation, improved accuracy	Increased architectural complexity
12	Nguyen et al. (2024) [15]	Multi-view CNN	Kaggle Brain MRI	Superior accuracy compared to single-view approaches	Longer training times
13	Patel et al. (2022) [16]	Hybrid CNN-Transformer	TCIA	Combines strengths of CNN & transformer	Still in exploratory phase
14	Ghosh et al. (2021) [17]	EfficientNet + Squeeze-Excite	Private dataset	Lightweight and efficient, suitable for small clinics	Limited scalability
15	Yadav et al. (2023) [18]	Capsule Network	TCGA	Robust to noise and distortion	Complex training curve
16	Lee et al. (2022) [19]	Attention U-Net	BraTS 2021	Enhanced focus on tumor regions	Require detailed annotations
17	Ahmed et al. (2020) [20]	Deep Residual U-Net	TCGA-GBM	High glioblastoma segmentation accuracy	Require large datasets
18	Tang et al. (2021) [21]	Transformer encoder-decoder	Custom annotated MRI	Generalizable and flexible	Time consuming training
19	Bose et al. (2023) [22]	DenseNet + Attention	BraTS + ISLES	Combines segmentation & outcome prediction	Sharp training curve
20	Walia et al. (2021) [23]	Autoencoder - based segmentation	Open Access MRI	Efficient feature dimensionality	Reduced accuracy for small tumors
21	Tan et al. (2022) [24]	Dual-path CNN	TCIA + Private	High generalization capability	Difficult to implement in real-time
22	Sharma et al. (2023) [25]	GAN + Transformer	BraTS 2020	Effective augmentation and classificatio	GAN training stability issues

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23	Zhang et al. (2024) [26]	Vision Transformer with Self-supervised Learning	Unlabeled MRI	Reduces annotation dependency	Uneven effectiveness across tumor types
24	Iqbal et al. (2022) [27]	Multi-scale ResNet	TCIA	Detect tumors of various sizes	High processing complexity
25	Roy et al. (2023) [28]	Meta-learning CNN	BraTS 2021	Adaptive to new domains	Meta-parameter tuning challenges

The implementation of deep learning (DL) technology in brain MRI image analysis has demonstrated significant progress in recent years. In the medical field, particularly for brain tumor identification and segmentation, DL has driven rapid advancements in diagnostic accuracy and speed. Architecture such as CNN, U-Net, nnU-Net, and Vision Transformers (ViT) have proven effective in detecting and analyzing tumor lesions in MRI scans. However, like most technologies, DL-based MRI processing faces several challenges that must be overcome to achieve broader and more effective clinical adoption.

A primary challenge is the heterogeneity of MRI data across institutions, where differing imaging protocols can compromise mode generalizability. Models trained on one dataset often underperform on others due to technical variations. Initiatives like BraTS (Brain Tumor Segmentation Challenge) address this by providing multimodal MRI datasets for training and testing DL models in more representative context. These datasets include diverse MRI scans from glioma patients, enabling researchers to develop more accurate and reliable models.

Recent research also highlights transformer-based models (e.g., Swin-UNET, BiTr-UNet) excel in specific MRI processing tasks. These architectures handle spatial complexity in larger, more variable images effectively. The Rotation-Invariant Vision Transformer (RI-ViT) [4] illustrates a pivotal computational trade-off in neuroimaging: Its innovative rotation-correction mechanism substantially boosts tumor classification fidelity yet concurrently impose demanding processing requirements. Beyond such resource-intensity constraints, medical DL systems confront deeper epistemological challenges—while achieving remarkable diagnostic accuracy, their decision pathways remain fundamentally inscrutable. This opacity presents clinical hazards where diagnostic traceability constitutes an ethical imperative. Consequently, developing intrinsically interpretable frameworks (e.g., Grad-CAM activation mapping or convolutional feature visualization) becomes non-negotiable for pinpointing anatomically decisive regions in diagnostic judgments.

Data integrity persists as a critical concern in neuroimaging analytics. Although public repositories like BraTS remain prevalent research resources, constructing truly representative cohorts—spanning diverse tumor phenotypes, demographic variables, and imaging protocols—demands urgent attention. Federated learning presents a compelling alternative by facilitating collaborative model refinement without centralized data pooling, thereby preserving patient confidentiality while strengthening DL generalizability. When applied to MRI interpretation, deep learning methodologies demonstrate transformative capacity for expediting diagnostic pathways and personalizing neuro-oncological interventions. These systems establish adaptive diagnostic frameworks empowering clinicians to execute evidence-based decisions with unprecedented efficiency. Yet three persistent barriers—dataset heterogeneity, interpretability deficits, and computational scalability—necessitate dedicated solutions. Continuous methodological evolution positions DL architecture toward becoming indispensable, clinically embedded instruments for precision neuro-oncology.

While data variability and model interpretability present significant technical hurdles, a deeper challenge in developing deep learning (DL) models for MRI-based brain tumor analysis is the pronounced scarcity of data for rarer tumor types. Widely utilized public datasets like BraTS predominantly feature gliomas, inadvertently marginalizing may other clinically important brain tumor categories. This inherent data imbalance critically undermines a model's ability to generalize effectively across the diverse spectrum of brain tumors encountered in clinical practice. Consequently, a strategic imperative for the field involves actively expanding the breadth of available datasets to encompass a far wider variety of tumor pathologies.

Federated learning emerges as a strategic response to the constraints of institutionally siloed medical imaging data. This paradigm enables collaborative model development without transferring sensitive patient scans, intrinsically preserving privacy while complying with healthcare regulations. Crucially, models trained on distributed datasets from multiple institutions exhibit enhanced robustness and clinical validity due to inherent population diversity. Nevertheless, substantial implementation barriers persist, including heterogeneous system interoperability, cross-institutional coordination complexities, and the demanding infrastructure requirements for managing decentralized data workflows.

Self-supervised learning (SSL) methodologies integrated into vision transformers demonstrate significant potential to reduce annotation dependency in medical imaging. These approaches extract latent features from unlabeled MRI scans, potentially improving tumor detection performance by capturing intrinsic data relationships. Nevertheless, conclusive evidence of their efficacy demands comprehensive evaluation across diverse, clinically complex imaging cohorts to address domain-specific challenges.

The integrity of medical imaging data fundamentally governs deep learning model reliability. Within this study, variations in MRI quality – including resolution limitations, artifacts (e.g., motion blur, Gibbs ringing), noise (e.g., Gaussian, Rician), and inconsistencies in acquisition protocols (e.g., differing pulse sequence parameters, field strengths) – demonstrably degraded tumor segmentation accuracy and classification performance. Empirically, these data-centric limitations emerged as primary constraints on model generalizability and clinical utility. Consequently, advancing the robustness of medical AI necessitates a dedicated research focus on enhancing data acquisition standards, establishing rigorous quality control frameworks, and developing robust pre-processing pipelines specifically designed to mitigate these inherent image quality variations prior to model training.

In conclusion, deep learning demonstrates substantial efficacy in automating MRI-based brain tumor identification and segmentation, representing a critical evolution in diagnostic neuroimaging workflows. While persistent challenges—notably heterogeneity in multi-institutional data, limitations in dataset scale/diversity, and the opacity of complex model decisions—demand continued attention, emergent methodologies offer targeted pathways forward. Specifically, federated learning addresses data privacy and silo constraints, explainable AI (XAI) techniques enhance clinical trust through interpretable decision rationales, and self-supervised learning mitigates reliance on scarce expert annotations. Collective, these approaches provide a concrete framework for translating algorithmic potential into clinically robust, accountable tools.

4. Conclusion

This systematic review establishes that DL demonstrably enhances precision and workflow efficiency in brain tumor detection via MRI analysis. Key architectures—including CNNs, U-Net variants (notably nnU-Net), and Vision Transformers—have achieved validated performance in tumor segmentation and classification tasks. Critically, however, our analysis identifies institutional MRI data heterogeneity and insufficient dataset representativeness as primary barriers to model generalizability. To solve these constraints, we assert that: (1) curating multi-institutional datasets reflecting real-world demographic and technical diversity is imperative, and (2) federated learning architectures offer a clinically viable pathway to enhance model validity while ensuring data privacy. These approaches directly address scalability challenges in deploying DL system across diverse healthcare environments.

Clinically, the persistent opacity of deep learning decision-making remains a critical barrier to adoption in medical imaging, raising justifiable concerns about diagnostic reliability. To bridge this trust gap, we must pioneer clinically grounded explainable AI (XAI) frameworks that enable physicians to scrutinize prediction rationales and error boundaries. While current XAI methods represent progress, our review identifies three imperative research trajectories: (1) enhancing visual saliency maps for radiological relevance, (2) developing quantitative metrics for interpretability validation in clinical trials, and (3) creating real-time explanations system compatible with PACS workflows. These advances are non-negotiable prerequisites for deploying clinically accountable DL tools that oncologists and radiologists can ethically endorse.

In synthesis. While significant implementation barriers persist, deep learning constitutes a strategic priority for advancing neuro-oncology practice. Its demonstrable improvements in glioma classification precision, surgical planning accuracy, and treatment response assessment efficiency necessitate focused efforts toward clinical deployment. Realizing this potential requires a concerted effort to resolve core challenges in model interpretability, multi-institutional validation, and seamless integration into neurosurgical workflows.

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