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Advances In Deep Learning-Based Brain Tumor Classification Using Mri

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Abstract

Brain tumor diagnosis using magnetic resonance imaging (MRI) is a critical step in clinical decision-making. In recent years, deep learning, particularly convolutional neural networks (CNNs), has revolutionized the landscape of automated medical image analysis. This review presents an extensive synthesis of state-of-the-art deep learning techniques employed in brain tumor classification using MRI. The discussion encompasses foundational CNN architectures, advanced models incorporating attention mechanisms, transformer-based designs, and emerging paradigms such as Capsule Networks and hybrid CNN-transformer frameworks. Emphasis is placed on understanding how model complexity, interpretability, and modality integration affect diagnostic performance. The review also covers key MRI modalities including T1, T2, FLAIR, and DWI, and their significance in accurate tumor delineation. Furthermore, it highlights major datasets, performance benchmarks, evaluation metrics, and clinical validation strategies. Challenges such as data scarcity, generalization, interpretability, and deployment constraints are thoroughly analyzed. Lastly, the paper outlines future directions including multimodal learning, explainable AI, and federated learning to bridge the gap between research prototypes and real-world clinical adoption. This review aims to guide researchers, clinicians, and developers in understanding the current landscape, identifying challenges, and exploring innovations that can lead to more robust and interpretable diagnostic systems for brain tumor classification.

Keywords: Brain Tumor, MRI, Deep Learning, CNN, Classification, Medical Imaging

1. Introduction

1.1. Background on Brain Tumors and Their Clinical Impact

Brain tumors, whether malignant or benign, pose a severe threat due to their impact on critical brain functions and high mortality rates. These tumors are often characterized by abnormal growth of brain tissue, leading to symptoms like headaches, cognitive dysfunction, and motor impairment. Malignant forms such as glioblastomas have particularly poor prognoses, emphasizing the need for timely detection and intervention (Misu, 2023). According to the World Health Organization, accurate classification of tumor type, grade, and location is crucial for determining treatment plans (Kokila et al., 2021). The growing incidence of brain tumors globally, alongside limited access to expert radiologists, underscores the urgency of improving diagnostic pathways. As these tumors may progress rapidly and can be difficult to treat in advanced stages, early and reliable diagnosis remains a key challenge in modern neuro-oncology (Al-Jammas et al., 2024).

1.2. Importance of Early and Accurate Diagnosis Using MRI

Magnetic Resonance Imaging (MRI) is considered the gold standard for non-invasive brain tumor detection due to its high-resolution, multi-dimensional imaging capabilities. Accurate interpretation of MRI scans is critical for identifying tumor characteristics like size, location, and heterogeneity, which directly influence clinical decisions. However, manual analysis can be subjective and time-consuming, leading to delays or inconsistencies in diagnosis (Srinivasarao et al., 2024). Automated techniques that enhance early-stage detection can drastically improve patient outcomes by enabling faster intervention and personalized treatment planning (Jaiswal et al., 2023). Additionally, the use of MRI reduces the need for invasive procedures like biopsies when used effectively in diagnosis pipelines (Romaisa' et al., 2023). Thus, enhancing MRI-based diagnostics with advanced analytical tools is central to modern neuro-oncology.

1.3. Emergence of Artificial Intelligence and Deep Learning in Medical Imaging

Artificial intelligence (AI), particularly deep learning, has revolutionized the medical imaging landscape. Convolutional Neural Networks (CNNs) and other deep learning architectures now facilitate automated image analysis, achieving diagnostic performance comparable to expert radiologists. These methods can learn complex patterns in MRI data, enabling high-accuracy tumor detection and classification (Peng & Liao, 2023). Transfer learning models like ResNet50 and EfficientNet further enhance diagnostic precision by leveraging pre-trained networks on large datasets (Misu, 2023). The ability of AI to provide rapid, objective, and reproducible insights is transforming clinical workflows, especially in resource-constrained settings where expert radiologists are scarce (Sharma et al., 2023). As computational power and data availability increase, AI-driven diagnostics are expected to become standard practice in neuroimaging and beyond.

1.4. Motivation for Reviewing Current Deep Learning Techniques

Given the rapid advancements in deep learning applications for brain tumor diagnosis, there is a pressing need to systematically review and synthesize existing methodologies. While many CNN-based architectures have demonstrated promising results, challenges remain in generalizability, interpretability, and clinical integration (Bhuvaneswari et al., 2024). Models trained on limited or biased datasets may underperform in real-world scenarios, necessitating careful evaluation and cross-institutional validation (Aykat, 2024). Moreover, interpretability remains a major hurdle for clinical adoption, as medical practitioners require explainable outputs to trust AI-generated insights (Bhatt et al., 2024). This review aims to bridge these gaps by critically analyzing the state-of-the-art in deep learning for brain MRI analysis, highlighting both successes and limitations, and outlining future directions for research and clinical translation.

Despite significant progress in deep learning-based brain tumor classification, existing models often suffer from limited generalizability, inadequate interpretability, and reliance on small or imbalanced datasets. Few studies address multi-institutional validation or real-world deployment challenges, underscoring the need for clinically-aligned, explainable, and scalable diagnostic systems. The objective of this review is to comprehensively evaluate and synthesize deep learning approaches used in MRI-based brain tumor classification, highlighting advancements, comparing model architectures, and analyzing diagnostic performance across modalities, while identifying gaps and future directions for enhancing clinical integration, interpretability, and diagnostic robustness.

This review was conducted through a comprehensive and structured analysis of peer-reviewed literature published between 2016 and 2025 across major scientific databases including IEEE Xplore, PubMed, Scopus, and ScienceDirect. Search terms such as “brain tumor classification,” “MRI,” “deep learning,” “CNN,” “transformer,” and “medical image analysis” were employed to curate relevant studies. Inclusion criteria focused on studies that used MRI as the imaging modality and applied deep learning techniques—ranging from traditional CNNs to advanced hybrid models. Articles were selected based on methodological rigor, clinical relevance, innovation, and reported performance metrics. Key aspects reviewed included model architecture, dataset characteristics, evaluation methods, and practical limitations. Findings were organized thematically into architecture types, learning strategies, data modalities, and clinical applicability. Emphasis was placed on comparing shallow versus deep networks, 2D versus 3D models, and interpretability tools, to provide a critical evaluation of current capabilities and limitations in AI-driven brain tumor diagnostics.

2. Brain Tumor Imaging and Clinical Background

2.1. Overview of Brain Tumor Types (Glioma, Meningioma, Pituitary, etc.)

Primary brain tumors are typically categorized into gliomas, meningiomas, and pituitary adenomas—each with distinct pathological and clinical features. **Gliomas** originate from glial cells and range from low-grade to highly malignant forms like glioblastoma, which are aggressive and often fatal (Gupta, 2024). **Meningiomas** arise from the meninges and are mostly benign, though their growth can compress brain tissue and lead to serious neurological symptoms (Mahesh & Yogesh, 2024). **Pituitary tumors**, located at the base of the brain, frequently disrupt hormonal regulation and vision due to their anatomical position (Gorenshtein et al., 2024). These tumor types differ not only in clinical presentation but also in prognosis and treatment strategies. Automated classification systems using MRI data and deep learning have shown strong results in identifying these three major tumor types (Hafeez et al., 2022), (Yıldırım et al., 2023). Understanding these types is essential for tailored treatment planning and effective patient management.

2.2. MRI Modalities Used in Diagnostics (T1, T2, FLAIR, DWI)

Magnetic Resonance Imaging (MRI) is the primary tool in brain tumor diagnosis due to its superior soft-tissue contrast and non-invasive nature. Different MRI modalities serve unique diagnostic roles. **T1-weighted imaging** is excellent for anatomical detail and post-contrast enhancement, helping detect tumor borders and blood-brain barrier disruptions. **T2-weighted** and **FLAIR (Fluid-Attenuated Inversion Recovery)** images highlight edema and tumor-induced fluid accumulation, essential for identifying tumor extent (Gupta, 2024), (Mahesh & Yogesh, 2024). **Diffusion Weighted Imaging (DWI)** aids in differentiating high-grade tumors from non-neoplastic conditions like abscesses by measuring the movement of water molecules (Yan et al., 2016). Additionally, modern techniques like **contrast-enhanced MRI** and **semi-automated segmentation** help in better defining tumor morphology (Thias et al., 2019), (Zhu et al., 2022). Combining these modalities offers a comprehensive view, enhancing diagnostic confidence and surgical planning.

2.3. Clinical Challenges in Interpretation and Diagnosis

Despite MRI's capabilities, the **interpretation of brain tumor images** presents significant challenges. Tumors such as gliomas, meningiomas, and pituitary adenomas may share overlapping radiological features, making differentiation difficult without histopathological confirmation (Yan et al., 2016), (Chouksey et al., 2021). Manual MRI interpretation is time-consuming and vulnerable to inter-observer variability, especially in large-scale screening settings. Subtle lesions or tumors in complex regions like the brainstem may be overlooked or misclassified (Gorenshtein et al., 2024). Additionally, accurate pre-surgical planning requires a clear understanding of tumor margins and adjacent structures, which is often difficult with conventional MRI alone (Thias et al., 2019). The increasing complexity of imaging data has led to the growing integration of AI systems that provide consistent and reproducible insights to support clinical decision-making (Zhu et al., 2022), (Hafeez et al., 2022). These tools are vital in reducing diagnostic uncertainty and enhancing patient outcomes.

3. Deep Learning in Medical Imaging

3.1. Evolution of Deep Learning in Radiology

The integration of deep learning (DL) into radiology has transformed medical image interpretation, enabling faster, more accurate, and scalable diagnostic tools. Initially driven by Convolutional Neural Networks (CNNs), DL rapidly replaced traditional handcrafted feature extraction with data-driven methods. These models showed promising results in classifying, segmenting, and detecting anomalies in modalities like MRI, CT, and X-ray (Willemink et al., 2022), (Ahmed, 2025). Over time, architectures evolved from CNNs to hybrid models and now include Transformer-based frameworks, offering improvements in capturing long-range dependencies and context in images (Gejji et al., 2024), (Reddy & Kothinti, 2024). This shift was further empowered by increasing computational capabilities and large datasets. Despite its success, challenges remain—including data scarcity, annotation requirements, and ethical concerns. Nevertheless, DL's adaptability has cemented its role in radiology as it continues to evolve through collaborative initiatives and foundational model development (Khan, 2024).

3.2. Core Techniques: CNNs, RNNs, Transformers in Medical Applications

Deep learning in medical imaging employs three major architectures: CNNs, RNNs, and Transformers. **CNNs** are the most widely used, excelling in spatial feature extraction and classification tasks for MRI, CT, and X-ray images (Wang & Huang, 2018), (Reddy & Kothinti, 2024). **RNNs**, particularly LSTMs, handle sequential medical data such as patient records or time-series signals, though less common in image analysis. Recently, **Transformers** have gained popularity due to their attention mechanisms, outperforming CNNs in several vision tasks when enough data is available (Willemink et al., 2022), (Gejji et al., 2024), (Kranthi et al., 2024). Hybrid models combining CNNs and Transformers are now being explored to improve diagnostic performance and interpretability in tasks like tumor detection and disease progression analysis (Reddy & Kothinti, 2024).

3.3. Role of Supervised vs Unsupervised Learning

Supervised learning remains dominant in medical imaging due to its high accuracy in labeled environments. Models like CNNs are trained on annotated datasets to perform classification or segmentation. However, the manual labeling process is time-intensive and requires domain expertise. In contrast, **unsupervised learning** methods, such as autoencoders and Generative Adversarial Networks (GANs), learn representations without labeled data, offering a scalable solution when annotations are limited (Shafana & Senthilselvi, 2022), (Ahn et al., 2020), (Hussein et al., 2018). Emerging **self-supervised** techniques now bridge the gap by pretraining models using unlabeled data before fine-tuning them on small labeled sets, offering performance comparable to fully supervised methods (Yan et al., 2022). These paradigms are particularly promising in low-resource or privacy-sensitive clinical environments.

3.4. Pretraining, Transfer Learning, and Federated Learning

To overcome the limitations of small datasets, medical AI increasingly relies on **transfer learning** and **pretraining**. Transfer learning leverages models trained on large, generic datasets (e.g., ImageNet) and fine-tunes them for medical applications, significantly reducing the need for labeled data while improving performance (Bruno et al., 2020), (Willemink et al., 2022). **Federated learning** (FL) has emerged as a solution to data-sharing limitations by enabling decentralized training across institutions while preserving patient privacy (Lonia et al., 2024), (Jindal et al., 2023). Recent advances in **self-supervised federated learning** further combine privacy preservation with powerful representation learning, particularly in highly heterogeneous datasets (Yan et al., 2022), (Kranthi et al., 2024). Together, these methods are crucial in advancing AI-based healthcare while addressing ethical and logistical constraints.

4. Deep Learning Approaches for Brain Tumor Classification

4.1. Convolutional Neural Networks (CNNs)

4.1.1. Basic Architectures and Their Applications

Convolutional Neural Networks (CNNs) are the foundation of deep learning in medical image classification. Their architecture, which mimics visual processing in the brain, allows for hierarchical feature extraction from MRI scans. CNNs have proven exceptionally effective for brain tumor classification by learning spatial hierarchies of features directly from image data, eliminating the need for manual feature engineering. Basic CNN models designed from scratch for specific brain tumor datasets have achieved high accuracy while maintaining computational efficiency (Khan & Auvee, 2024), (Chowdhury & Srivastava, 2024). These architectures are tailored to the task and have shown promising performance even on multi-class tumor datasets.

Some studies have also combined CNNs with attention mechanisms or used ensemble methods to improve classification accuracy and robustness (Taher & Anan, 2023), (Fabian & Vancea, 2024). Additionally, tools like Grad-CAM or LIME have been employed to make CNN decisions interpretable for clinical use (Jha et al., 2024). CNNs not only automate tumor identification but also provide saliency maps to help clinicians understand model decisions. Despite being simple in structure, basic CNNs are a critical entry point into deep learning-based tumor diagnostics.

4.1.2. Shallow vs Deep Models (Custom CNNs vs ResNet, VGG, DenseNet)

A major trend in brain tumor classification is the comparison between shallow, custom CNNs and deeper, pre-trained networks like ResNet, VGG, and DenseNet. **Custom CNNs** often offer fast training, reduced overfitting, and require fewer computational resources. Despite their simplicity, many custom models have shown competitive or even superior results to deep architectures when properly optimized (Khan & Auvee, 2024), (Masab et al., 2024). However, **deep models**—particularly ResNet and DenseNet—are favored for their residual connections and feature reuse, enabling the training of very deep architectures without vanishing gradients (Mao et al., 2025), (Fabian & Vancea, 2024), (Mukeshkumar & Sankar, 2024).

VGG, while simpler, often underperforms compared to newer architectures but still serves as a useful baseline. Studies report DenseNet121 achieving accuracy up to 99%, outperforming custom models in large-scale scenarios (Masab et al., 2024). Hybrid models, incorporating features from multiple CNN types, have also emerged as effective tools for boosting diagnostic confidence (BeebiNaseeba et al., 2023). The tradeoff between computational efficiency and diagnostic accuracy remains central to model selection in clinical settings.

4.1.3. 2D vs 3D CNNs

In brain tumor classification, **2D CNNs** are the most common due to their compatibility with slice-based MRI data. They offer high speed and work well with limited data. However, 2D models may lose contextual information across adjacent slices, which can be crucial for accurate diagnosis. As an alternative, **3D CNNs** process volumetric data and can learn inter-slice spatial relationships, offering better tumor localization and classification in some scenarios (Singh & Dyrba, 2023), (Das & Goswami, 2024).

For example, DenseNet and ResNet have both been adapted to 3D form and show enhanced performance in detecting Alzheimer's and brain tumors from MRI data (Mao et al., 2025). Still, these models are resource-intensive and may overfit when data is scarce. Some researchers have proposed hybrid 2D-3D networks or feature fusion strategies that combine the best of both approaches (Seetha & Raja, 2019). While 3D CNNs offer theoretical advantages, their adoption is still limited due to computational demands and lack of annotated volumetric datasets. Therefore, 2D CNNs remain dominant, particularly when combined with preprocessing and data augmentation techniques to simulate 3D context.

4.2. Hybrid and Attention-Based Models

4.2.1. CNN with Attention Mechanisms

Attention-enhanced CNNs improve performance by helping models focus on the most relevant regions of MRI scans. These models integrate attention gates or residual attention blocks to emphasize tumor features while suppressing irrelevant background. This leads to improved segmentation and classification accuracy, especially for small or complex tumor regions. For example, Residual Attention U-Nets have demonstrated significant performance boosts in tumor segmentation by capturing fine-grained spatial details (Taher & Anan, 2023). Other hybrid designs like BiTr-Unet combine CNNs with transformer modules, leveraging local feature extraction from CNNs and global contextual awareness from transformers (Jia & Shu, 2021). Furthermore, models like DRTFNet fuse residual CNNs with dual-shuffled attention and Swin Transformer modules to achieve highly accurate tumor type classification (Wang et al., 2024). These hybrid attention models show that integrating focused spatial information with broader contextual data enhances diagnostic precision.

4.2.2. Capsule Networks

Capsule Networks (CapsNets) offer an alternative to CNNs by modeling spatial hierarchies and pose relationships between features, making them highly suitable for medical imaging. CapsNets are inherently resistant to transformations such as rotations and scaling—common challenges in MRI data. Unlike CNNs that use max-pooling, CapsNets preserve spatial relationships through dynamic routing, which improves classification of complex patterns like brain tumors (Afshar et al., 2018). More recent work shows CapsNets outperform CNNs in low-data scenarios and exhibit greater robustness to image orientation changes (Raythatha & V.M., 2023). Surveys have highlighted CapsNet's potential as a CNN replacement in critical medical tasks, particularly where data scarcity and rotation invariance are vital concerns (Akinyelu et al., 2022), (Bhagat & Pandian, 2024). Although not yet mainstream, CapsNets remain a promising avenue, especially for interpretable and geometrically aware classification tasks.

4.2.3. Transformer-Based Architectures (e.g., Vision Transformer)

Transformers, especially Vision Transformers (ViTs), are revolutionizing medical imaging by capturing global context through self-attention mechanisms. ViTs outperform CNNs in learning long-range dependencies, making them ideal for analyzing tumor shape, size, and location across the brain. Studies show that ViTs pre-trained on large datasets and fine-tuned on MRI scans achieve exceptional performance—up to 99% accuracy in some cases (Ali, 2024), (Mzoughi et al., 2024), (Khaniki et al., 2024). Comparative research shows ViTs outperform traditional models like VGG and ResNet in both binary and multi-class tumor classification (Zhang, 2025), (Simon & Briassouli, 2022). Hybrid models that combine CNNs and ViTs—such as BiTr-Unet and iResNet-ViT—leverage the best of local and global feature extraction, further boosting classification accuracy (Jaffar, 2024). As computational resources grow, transformer-based architectures are expected to play a central role in future clinical diagnostic systems.

4.3. Ensemble Learning and Multi-Modal Fusion

4.3.1. Combining Multiple Architectures for Robustness

Ensemble learning enhances classification robustness by integrating the strengths of multiple models, reducing individual weaknesses, and increasing predictive stability. In brain tumor diagnosis from MRI, combining different deep learning architectures—such as CNNs, ResNets, and EfficientNet—through ensemble methods like voting, stacking, or averaging, has shown to significantly boost diagnostic performance. A study using ensemble learning with DenseNet121 and EfficientNet-B0 achieved a remarkable accuracy of 99.67%, outperforming standalone models (Hun et al., 2024). Another approach using weighted average fusion of VGG19, CNN with augmentation, and CNN without augmentation reported improved F1 scores and better generalization on real-world MRI data (Anand et al., 2023).

Additionally, stacking ensemble models—such as combining predictions from VGG19 and EfficientNetB3 with Random Forest classifiers—demonstrated enhanced classification accuracy of up to 93% (Shaikh & Shaikh, 2024). A more advanced hybrid framework, known as DBFS-EC, merges deep-boosted CNN features with traditional classifiers to capture both static and dynamic tumor characteristics, reaching over 99% accuracy (Zahoor et al., 2022). Similarly, a 2024 ensemble approach combining DenseNet and InceptionV3 integrated with explainable AI (e.g., Grad-CAM) achieved over 99% accuracy while also increasing clinician trust (Hosny et al., 2024). These methods highlight the practical advantage of combining complementary architectures to capture diverse image features, leading to higher accuracy, resilience to noise, and clinical relevance. Ensemble techniques are now a cornerstone in developing robust brain tumor classifiers in real-world medical imaging workflows.

4.3.2. Integrating Multimodal MRI Sequences and Clinical Data

Multimodal fusion integrates various MRI sequences—such as T1, T2, FLAIR—and clinical metadata (e.g., age, symptoms, genetic markers), improving tumor characterization beyond what any single input can provide. Fusing imaging modalities at early, intermediate, or late stages allows models to leverage complementary spatial and contextual information. For example, an ensemble-based fusion of multimodal MRI and PET imaging achieved 98.1% accuracy using models like VGG19, ResNet50, and DenseNet121 in a weighted voting ensemble (Karthik et al., 2024).

Similarly, hybrid learning frameworks that combine deep features from CNNs with structured clinical data have shown superior classification performance. DRIFA-Net, for instance, introduces a dual-attention mechanism to blend multimodal medical inputs, including MRI, CT, and clinical data, resulting in superior generalization and performance (Dhar et al., 2024). Another study successfully fused Brain MRI features with demographic and histological data using multi-objective optimization and achieved state-of-the-art survival prediction in glioma patients (Caruso et al., 2022). Further advancements include using GANs and CNNs together for enhanced multimodal image fusion, preserving both high-resolution spatial features and semantic details for more effective classification (Maseleno et al., 2023). The inclusion of temporal and physiological signals in addition to MRI images has also been explored, indicating a broader trend toward holistic diagnostic modeling. These strategies underscore that multimodal fusion is essential for comprehensive tumor assessment, offering improved accuracy, interpretability, and clinical decision support over unimodal approaches.

5. Conclusion

The integration of deep learning into MRI-based brain tumor classification has yielded transformative results, enabling high-accuracy, automated diagnostics that are increasingly approaching expert radiologist performance. This review critically evaluated a wide spectrum of architectures, from custom CNNs and deep pretrained models like ResNet and DenseNet, to emerging transformer-based frameworks and capsule networks. CNNs remain foundational, particularly for their efficiency and adaptability in clinical settings. However, deeper models and hybrid architectures are showing superior performance in complex classification tasks and multimodal fusion. Performance metrics across studies indicate that accuracies above 90 percent are increasingly common, with some models achieving near-perfect classification when trained on large, curated datasets. Transformer models, in particular, are demonstrating promising generalization and context-awareness due to their global feature extraction capabilities. Attention mechanisms further enhance model precision by focusing on tumor-relevant regions.

Despite these advancements, significant challenges persist. Data scarcity, especially for rare tumor types, limits model robustness. Model interpretability is still insufficient for clinical decision-making, underscoring the need for explainable AI techniques like Grad-CAM and SHAP. Generalizability across diverse patient populations and imaging protocols also remains a concern, particularly for deployment in real-world healthcare systems. Future research must focus on expanding annotated datasets, improving domain adaptation, and integrating clinical metadata for personalized diagnostics. Federated learning and privacy-preserving frameworks can facilitate collaborative model training without compromising patient confidentiality. Ultimately, bridging the gap between algorithmic performance and clinical trust will determine the success of deep learning in neuro-oncology. This review underscores the potential and the pathway for deep learning models to become indispensable tools in brain tumor diagnosis, offering accuracy, speed, and reproducibility in clinical radiology.

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