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Artificial Intelligence for Brain Tumor Segmentation: A Review of 3D MRI-Based Models and Clinical Applications

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Abstract

Artificial intelligence (AI) has significantly advanced the field of brain tumor segmentation by enabling accurate and automated analysis of volumetric magnetic resonance imaging (MRI) data. Traditional manual segmentation is labor-intensive and subject to inter-observer variability, necessitating robust computational approaches. Recent developments in deep learning, particularly 3D convolutional neural networks, U-Net variants, and transformer-based architectures, have demonstrated superior capability in capturing complex spatial and contextual features of brain tumors. Benchmark initiatives such as the Brain Tumor Segmentation Challenge (BraTS) have facilitated standardized evaluation and accelerated innovation in this domain. These models have shown promising results in clinical applications, including tumor detection, treatment planning, and disease monitoring. However, challenges such as data heterogeneity, computational demands, and limited interpretability remain barriers to widespread clinical adoption. This review critically examines recent advancements in 3D MRI-based AI models and their translational potential in neuro-oncology.

Keywords: Artificial Intelligence, Brain Tumor Segmentation, 3D MRI, Deep Learning, Clinical Applications

Introduction

Brain tumor segmentation is a critical task in neuro-oncology, enabling accurate diagnosis, treatment planning, and longitudinal monitoring of disease progression. Brain tumors, particularly gliomas, exhibit high heterogeneity in shape, size, and intensity, making manual delineation from magnetic resonance imaging (MRI) both time-consuming and prone to inter-observer variability. Advanced imaging techniques such as multi-modal MRI—including T1-weighted, contrast-enhanced T1 (T1c), T2-weighted, and FLAIR sequences—provide complementary information about tumor subregions like edema, necrotic core, and enhancing tumor tissue. However, extracting clinically meaningful insights from these high-dimensional volumetric datasets necessitates automated and reliable computational methods. In recent years, artificial intelligence (AI), particularly deep learning, has revolutionized medical image analysis by enabling data-driven feature extraction and high-precision segmentation. Architectures such as 3D convolutional neural networks (CNNs), U-Net variants, and transformer-based models have demonstrated remarkable performance in capturing both local spatial features and global contextual dependencies within 3D MRI volumes. Unlike traditional machine learning approaches that rely on handcrafted features, these models learn hierarchical representations directly from data, significantly improving segmentation accuracy and robustness. Publicly available benchmark datasets such as the Brain Tumor Segmentation Challenge (BraTS) have further accelerated research by providing standardized data and evaluation metrics. Despite these advancements, challenges remain, including data scarcity, class imbalance, high computational requirements, and limited interpretability of deep learning models, which hinder their widespread clinical adoption. Moreover, integration into real-world clinical workflows requires validation across diverse patient populations and imaging protocols. This review aims to systematically analyze the evolution of AI-based techniques for brain tumor segmentation, with a particular focus on 3D MRI-based models and their clinical applications. It also highlights current limitations and outlines future research directions to bridge the gap between experimental performance and practical deployment in healthcare systems.

Scope of the Study

This study focuses on reviewing and synthesizing recent advancements in artificial intelligence (AI) techniques for brain tumor segmentation using 3D magnetic resonance imaging (MRI). It primarily examines deep learning-based architectures, including 3D convolutional neural networks, U-Net variants, and transformer-based models, with an emphasis on their ability to process volumetric data and improve segmentation accuracy. The scope includes analysis of publicly available benchmark datasets such as the Brain Tumor Segmentation Challenge (BraTS), commonly used preprocessing techniques, and standard evaluation metrics. Additionally, the study explores clinical applications such as tumor detection, treatment planning, and monitoring.

Background of Brain Tumors

Brain tumors are abnormal growths of cells within the brain or central nervous system that can be broadly classified as primary tumors, originating in the brain, or secondary (metastatic) tumors that spread from other parts of the body. Among primary tumors, gliomas are the most common and aggressive, with subtypes such as astrocytomas, oligodendrogliomas, and glioblastomas, the latter being associated with poor prognosis and high mortality rates. Other types include meningiomas, which are typically benign and arise from the meninges, and pituitary tumors, which affect hormonal regulation. The classification and grading of brain tumors are standardized by the World Health Organization (WHO) based on histopathological and molecular characteristics, ranging from low-grade (slow-growing) to high-grade (highly malignant) forms. Brain tumors present diverse symptoms depending on their size and location, including headaches, seizures, cognitive impairments, and neurological deficits. Magnetic resonance imaging (MRI) plays a pivotal role in detecting and characterizing these tumors due to its superior soft tissue contrast and ability to provide multi-modal information. However, the heterogeneity of tumor regions—such as enhancing tumor, necrotic core, and surrounding edema—poses significant challenges for accurate delineation. Early and precise diagnosis is critical for effective treatment planning, which may involve surgery, radiotherapy, and chemotherapy.

Importance of MRI in Neuroimaging

Magnetic resonance imaging (MRI) is a cornerstone of modern neuroimaging due to its exceptional soft tissue contrast, non-invasive nature, and ability to provide detailed anatomical and functional information about the brain. Unlike computed tomography (CT), MRI does not use ionizing radiation, making it safer for repeated imaging, which is crucial for monitoring disease progression and treatment response in neurological conditions, particularly brain tumors. MRI employs strong magnetic fields and radiofrequency pulses to generate high-resolution images, allowing precise visualization of brain structures and pathological changes. Multi-modal MRI sequences—such as T1-weighted, contrast-enhanced T1 (T1c), T2-weighted, and fluid-attenuated inversion recovery (FLAIR)—offer complementary insights into different tumor components, including enhancing tumor regions, edema, and necrotic tissue. This multi-parametric capability significantly enhances diagnostic accuracy and supports clinicians in distinguishing between tumor types and grades. Advanced MRI techniques, such as diffusion-weighted imaging (DWI), perfusion imaging, and functional MRI (fMRI), further provide information on tissue cellularity, blood flow, and brain activity, respectively. These features are particularly valuable in pre-surgical planning and assessing tumor aggressiveness. MRI serves as the primary imaging modality in datasets like the Brain Tumor Segmentation Challenge (BraTS), which are widely used to develop and validate artificial intelligence models for automated segmentation.

Need for Automated Segmentation

Automated segmentation of brain tumors has become essential in modern neuroimaging due to the limitations of manual delineation and the increasing complexity of medical imaging data. Traditionally, radiologists and clinicians manually outline tumor regions on magnetic resonance imaging (MRI) scans, a process that is not only time-consuming but also highly subjective, leading to significant inter- and intra-observer variability. With the growing volume of high-resolution, multi-modal MRI data generated in clinical practice, manual segmentation is no longer scalable or efficient. Automated segmentation techniques, particularly those based on artificial intelligence (AI), provide a consistent, objective, and reproducible alternative by rapidly identifying and delineating tumor subregions such as enhancing tumor, necrotic core, and peritumoral edema. These precise segmentations are crucial for accurate diagnosis, treatment planning, surgical navigation, and radiotherapy targeting, where even minor inaccuracies can impact patient outcomes. Automated systems enable quantitative analysis of tumor size, shape, and progression over time, supporting longitudinal monitoring and personalized treatment strategies. Benchmark platforms such as the Brain Tumor Segmentation Challenge (BraTS) have demonstrated the effectiveness of AI-driven models in achieving high segmentation accuracy comparable to expert annotations.

Literature Review

The early development of artificial intelligence (AI) techniques for brain tumor segmentation in 3D magnetic resonance imaging (MRI) was largely influenced by the transition from conventional machine learning to deep learning paradigms. Initial approaches relied on handcrafted features and statistical learning, which often struggled to capture the complex heterogeneity of tumor structures. The work of Andriy Myronenko (2018) marked a significant advancement by introducing a 3D convolutional neural network with autoencoder-based regularization, which improved segmentation performance by enforcing structural consistency in latent representations. This approach demonstrated strong results on benchmark datasets such as the Brain Tumor Segmentation Challenge (BraTS), highlighting the importance of volumetric learning and regularization in handling limited annotated data. Similarly, Hamghalam et al. (2019) explored synthetic data generation for enhancing 3D multimodal MRI segmentation, addressing the critical issue of data scarcity. Their work emphasized the integration of multiple MRI modalities to improve model generalization and segmentation accuracy. Fernando and Tsokos (2021) provided a comprehensive overview of both deep and statistical learning approaches, reinforcing the superiority of deep learning methods while acknowledging the complementary role of statistical models in feature interpretation. Collectively, these studies established the foundational shift toward data-driven, end-to-end learning frameworks capable of handling complex medical imaging tasks.

The expansion of deep learning applications in medical imaging further accelerated during the early 2020s, with research focusing on improving model robustness and adaptability. Ahsan et al. (2020), although primarily centered on COVID-19 diagnosis, demonstrated the broader applicability of deep learning techniques in medical image analysis, emphasizing their potential for rapid and accurate disease detection. This cross-domain success reinforced confidence in applying similar architectures to neuroimaging tasks. Concurrently, Montaha et al. (2023) advanced the field by implementing U-Net-based architectures for 3D MRI brain tumor segmentation, achieving high accuracy through efficient encoder–decoder structures and skip connections. Their findings underscored the effectiveness of U-Net in preserving spatial information while enabling precise localization of tumor regions. Gitonga (2023) further enhanced this approach by incorporating attention mechanisms into a 3D U-Net framework, allowing the model to focus on relevant tumor regions while suppressing background noise. This innovation significantly improved segmentation performance, particularly in cases with complex tumor boundaries and low contrast. These studies collectively demonstrate the evolution of deep learning architectures toward more sophisticated and adaptive frameworks capable of addressing key challenges in medical image segmentation.

Recent literature has increasingly focused on refining and optimizing U-Net variants to achieve higher accuracy and generalization. Yang et al. (2025) conducted a comprehensive survey of U-Net-based architectures, highlighting the diversity of modifications such as residual connections, dense blocks, and attention modules. Their analysis revealed that hybrid architectures combining multiple enhancements consistently outperform baseline models, particularly in handling multi-class segmentation tasks involving different tumor subregions. Similarly, Saleh et al. (2025) provided an extensive review of segmentation techniques, tracing the progression from traditional methods to advanced 3D U-Net architectures. Their study emphasized the critical role of volumetric data processing in capturing spatial continuity and improving segmentation reliability. Both studies highlighted the importance of standardized datasets like the Brain Tumor Segmentation Challenge (BraTS) in enabling fair comparison and benchmarking of models. Additionally, these reviews pointed out that while U-Net variants dominate the field, emerging architectures such as transformers and hybrid CNN-transformer models are gaining traction due to their ability to capture long-range dependencies and global context.

Despite significant advancements, the literature consistently identifies several persistent challenges that limit the clinical translation of AI-based brain tumor segmentation models. Data scarcity and class imbalance remain major issues, as annotated medical datasets are limited and tumor regions often occupy a small portion of the image. Furthermore, variability in MRI acquisition protocols across institutions introduces inconsistencies that can affect model generalization. While techniques such as data augmentation and transfer learning have been proposed to mitigate these issues, they do not fully address the underlying limitations. Another critical concern is the lack of interpretability in deep learning models, which hinders trust and adoption in clinical settings. Although attention mechanisms and visualization tools have been introduced to improve explainability, further research is needed to develop transparent and reliable systems.

Fundamentals of Brain Tumor Segmentation

1. Types of Brain Tumors

- **Glioma**

Gliomas are the most common primary brain tumors, originating from glial cells that support and protect neurons. They include subtypes such as astrocytomas, oligodendrogliomas, and glioblastomas, with glioblastoma being the most aggressive and associated with poor survival rates. These tumors are highly infiltrative, often spreading into surrounding brain tissue, which complicates surgical removal and increases the likelihood of recurrence. Gliomas are typically classified into low-grade and high-grade categories based on their malignancy and growth rate.

- **Meningioma**

Meningiomas arise from the meninges, the protective membranes covering the brain and spinal cord. They are generally benign, slow-growing tumors and are often discovered incidentally during imaging. However, some meningiomas can be atypical or malignant, leading to more aggressive behavior. Depending on their size and location, they may cause symptoms such as headaches, seizures, or neurological deficits due to pressure on adjacent brain structures.

- **Pituitary Tumors**

Pituitary tumors develop in the pituitary gland and are usually benign adenomas. Despite their non-cancerous nature, they can significantly impact hormonal regulation, leading to disorders such as hypersecretion or hyposecretion of hormones. Symptoms may include vision problems, fatigue, and metabolic imbalances. The classification and grading of these tumors are standardized by the World Health Organization (WHO), ensuring consistent diagnosis and treatment approaches.

2. MRI Modalities (T1, T1c, T2, FLAIR)

Magnetic resonance imaging (MRI) employs multiple imaging sequences to capture complementary information about brain tissue and tumor characteristics. T1-weighted imaging provides high-resolution anatomical detail and is useful for visualizing normal brain structures.

Contrast-enhanced T1 (T1c) involves the administration of gadolinium-based contrast agents, which highlight regions with a disrupted blood–brain barrier, making it particularly effective for identifying active tumor regions. T2-weighted imaging is sensitive to fluid content and is commonly used to detect edema and pathological changes in tissue. Fluid-attenuated inversion recovery (FLAIR) suppresses cerebrospinal fluid signals, enhancing the visibility of lesions located near fluid-filled spaces and improving detection of peritumoral edema. These modalities are extensively utilized in datasets such as the Brain Tumor Segmentation Challenge (BraTS), enabling comprehensive analysis of tumor subregions through multi-modal integration.

3. Manual vs Automated Segmentation

Manual segmentation involves expert radiologists delineating tumor regions slice-by-slice from MRI scans, which, although accurate, is time-intensive and subject to inter- and intra-observer variability. In contrast, automated segmentation leverages artificial intelligence (AI), particularly deep learning models, to perform rapid and consistent tumor delineation. Automated methods significantly reduce human effort, improve reproducibility, and enable large-scale data processing. They are especially valuable in clinical workflows where time efficiency and precision are critical. While manual methods remain the gold standard for validation, automated approaches are increasingly achieving comparable or superior performance, particularly when trained on standardized datasets like the Brain Tumor Segmentation Challenge (BraTS).

4. Challenges in Tumor Segmentation

- **Heterogeneity of Tumor Regions**

Brain tumors exhibit significant variability in shape, size, texture, and intensity across different patients and even within the same tumor. Subregions such as enhancing tumor, necrotic core, and edema have distinct imaging characteristics, making accurate delineation complex for both manual and automated systems.

- **Noise and Variability in MRI Scans**

MRI images are often affected by noise, intensity inhomogeneity, and variations in acquisition protocols across different scanners and institutions. These inconsistencies can degrade model performance and hinder generalization across datasets.

- **Class Imbalance and Limited Datasets**

In most MRI datasets, tumor regions occupy a much smaller volume compared to healthy tissue, leading to class imbalance issues that bias model training. Additionally, the availability of large, well-annotated medical datasets is limited due to privacy concerns and the need for expert labeling, posing a challenge for developing robust AI models.

Literature Review

The application of artificial intelligence (AI), particularly deep learning, in brain tumor segmentation using three-dimensional magnetic resonance imaging (3D MRI) has evolved into a highly specialized and impactful research domain. Early contributions laid the groundwork by introducing volumetric learning strategies capable of exploiting spatial dependencies inherent in 3D medical images. Myronenko (2018) proposed a pioneering framework that integrated autoencoder regularization with convolutional neural networks (CNNs), significantly improving segmentation accuracy while mitigating overfitting in limited medical datasets. Similarly, Hamghalam et al. (2019) explored synthetic segmentation techniques using multimodal MRI data, demonstrating the importance of combining different imaging modalities—such as T1, T2, and FLAIR—to enhance tumor boundary delineation. Fernando and Tsokos (2021) further expanded this perspective by integrating statistical learning with deep neural networks, highlighting how hybrid approaches can improve robustness and interpretability in biomedical imaging. These foundational studies collectively emphasize that 3D MRI segmentation benefits substantially from architectures capable of capturing volumetric context, thereby outperforming traditional 2D slice-based approaches. Moreover, Ahsan et al. (2020), although focused on COVID-19 imaging, provided transferable insights into the scalability of deep learning frameworks in medical diagnostics, reinforcing the adaptability of CNN-based models across different disease domains. This early body of work established critical methodological principles, including multimodal data fusion, volumetric feature extraction, and regularization strategies, which continue to underpin contemporary segmentation frameworks.

Subsequent research has been dominated by the rapid advancement and widespread adoption of U-Net-based architectures, which have become the de facto standard for medical image segmentation tasks. Montaha et al. (2023) demonstrated the effectiveness of 3D U-Net models in segmenting brain tumors from volumetric MRI scans, achieving high accuracy through encoder–decoder structures with skip connections that preserve spatial information. Gitonga (2023) extended this paradigm by incorporating attention mechanisms into 3D U-Net architectures, enabling the model to focus selectively on relevant tumor regions while suppressing background noise. The evolution of U-Net variants is comprehensively reviewed by Yang et al. (2025) and Saleh et al. (2025), who highlight innovations such as residual connections, dense blocks, and multi-scale feature extraction. These enhancements address key challenges such as class imbalance, heterogeneous tumor morphology, and varying image resolutions. A major breakthrough in this domain is the development of the nnU-Net framework by Isensee et al. (2021/2022), which automates configuration processes including preprocessing, architecture design, and hyperparameter tuning. This self-configuring capability significantly reduces the need for expert intervention, making high-performance segmentation more accessible and reproducible. Collectively, these studies demonstrate that U-Net-based models, particularly when augmented with attention and automation mechanisms, provide a robust and scalable solution for brain tumor segmentation in 3D MRI datasets.

In parallel with the refinement of convolutional architectures, recent literature has witnessed the emergence of transformer-based models and hybrid frameworks that integrate global contextual learning with local feature extraction. Hatamizadeh et al. (2022) introduced UNETR, a novel architecture that replaces traditional CNN encoders with transformers, enabling the model to capture long-range dependencies across volumetric data. This represents a significant shift from purely convolutional approaches, addressing limitations related to receptive field size and contextual awareness. Tang et al. (2022) further advanced this direction by employing self-supervised pre-training of Swin Transformers for 3D medical image analysis, demonstrating improved generalization in scenarios with limited labeled data—a common challenge in medical imaging. Zhou et al. (2023) contributed to architectural innovation through UNet++, which incorporates nested and dense skip pathways to enhance feature propagation and reduce semantic gaps between encoder and decoder layers. Wang et al. (2024) proposed cascaded anisotropic convolutional neural networks, which optimize computational efficiency by processing different spatial dimensions separately while maintaining high segmentation accuracy. These developments collectively illustrate a paradigm shift toward hybrid and transformer-driven models that combine the strengths of CNNs and attention mechanisms. Such architectures are particularly well-suited for handling the complexity and variability of brain tumor structures in 3D MRI data, offering improved performance in both segmentation accuracy and computational scalability.

Despite these significant advancements, the literature consistently identifies several challenges and future research directions that must be addressed to fully realize the clinical potential of AI-based brain tumor segmentation. One of the primary concerns is the generalizability of models across diverse datasets and clinical environments. Variations in MRI acquisition protocols, scanner types, and patient demographics can lead to performance degradation when models are deployed outside their training domain. The requirement for large annotated datasets remains a critical bottleneck, as manual segmentation by medical experts is time-consuming and resource-intensive. While approaches such as self-supervised learning and data augmentation have shown promise, further research is needed to develop more efficient annotation strategies. Another significant challenge is the interpretability of deep learning models, particularly transformer-based architectures, which are often perceived as “black boxes” in clinical settings. Ensuring transparency and explainability is essential for gaining the trust of healthcare professionals and facilitating regulatory approval. Furthermore, computational complexity and resource requirements pose practical limitations for real-time clinical deployment, especially in resource-constrained environments. Future research is expected to focus on lightweight models, federated learning for privacy-preserving data sharing, and integration with clinical decision support systems.

3D MRI-Based Deep Learning Architectures

Three-dimensional (3D) deep learning architectures have become the dominant paradigm for brain tumor segmentation due to their ability to process volumetric MRI data and capture rich spatial context. Unlike 2D models that operate on individual slices, 3D models analyze entire volumes, enabling improved continuity and anatomical consistency in segmentation. Advances in architectures—ranging from convolutional neural networks to transformer-based models—have significantly enhanced performance on benchmark datasets such as the Brain Tumor Segmentation Challenge (BraTS). This section outlines key architectural families and their contributions.

1. Convolutional Neural Networks (CNNs)

- **3D CNN Fundamentals**

3D convolutional neural networks extend traditional 2D CNNs by applying convolutional kernels across three spatial dimensions (height, width, depth). This allows the model to learn volumetric features directly from MRI scans, preserving inter-slice dependencies. Each convolutional layer captures spatial hierarchies, while pooling operations reduce dimensionality and improve computational efficiency. These models are particularly effective in modeling structural continuity in brain anatomy.

- **Feature Extraction Capabilities**

3D CNNs excel at automatic feature extraction, learning low-level features such as edges and textures in early layers and progressively capturing high-level semantic representations of tumor regions in deeper layers. This hierarchical learning enables precise differentiation between tumor subregions, including enhancing tumor, necrotic core, and edema. Their ability to integrate multi-modal MRI inputs further strengthens feature representation and segmentation accuracy.

2. U-Net and Its Variants

- **3D U-Net**

The 3D U-Net architecture is an extension of the original U-Net, specifically designed for volumetric data. It follows an encoder–decoder structure, where the encoder captures contextual information and the decoder reconstructs spatial details. Skip connections between corresponding layers preserve fine-grained features, improving localization accuracy.

- **Residual U-Net**

Residual U-Net incorporates residual connections into the U-Net framework, allowing gradients to flow more effectively during training. This helps mitigate the vanishing gradient problem and enables deeper architectures, leading to improved performance and stability.

- **Attention U-Net**

Attention U-Net integrates attention mechanisms that enable the model to focus on relevant regions of the input, suppressing irrelevant background information. This is particularly beneficial in brain tumor segmentation, where tumor boundaries may be subtle and difficult to distinguish.

U-Net-based architectures remain dominant due to their efficient encoder–decoder design, ability to capture both global and local context, and consistently high segmentation accuracy across diverse datasets.

3. Transformer-Based Models

- **Vision Transformers (ViT)**

Vision Transformers (ViT) introduce a novel approach by modeling long-range dependencies using self-attention mechanisms rather than convolution operations. In medical imaging, ViT-based models divide input images into patches and process them as sequences, enabling global context understanding that is often limited in CNNs.

- **3D Transformer Architectures**

3D transformer models extend this concept to volumetric data, allowing attention mechanisms to operate across all spatial dimensions. These architectures are particularly effective in capturing global relationships within MRI volumes, improving segmentation of complex and heterogeneous tumor regions. Hybrid models that combine CNNs with transformers leverage the strengths of both local feature extraction and global context modeling, representing a promising direction in advanced medical image segmentation.

Conclusion

Artificial intelligence (AI) has fundamentally transformed the landscape of brain tumor segmentation, particularly through the development of advanced 3D MRI-based deep learning models. This review highlights how the transition from traditional machine learning techniques to sophisticated architectures such as 3D convolutional neural networks, U-Net variants, and transformer-based models has significantly improved segmentation accuracy, robustness, and efficiency. By leveraging volumetric data, these models effectively capture complex spatial relationships and heterogeneous tumor characteristics, enabling precise delineation of tumor subregions such as enhancing tumor, necrotic core, and edema. Benchmark datasets like the Brain Tumor Segmentation Challenge (BraTS) have played a crucial role in standardizing evaluation and accelerating innovation in this domain. Despite these advancements, several challenges persist, including data scarcity, class imbalance, variability in imaging protocols, high computational requirements, and limited interpretability of deep learning models. These issues continue to hinder the seamless integration of AI systems into routine clinical practice. Furthermore, the need for large, annotated datasets and rigorous validation across diverse populations remains a critical concern. Nonetheless, the clinical potential of AI-driven segmentation is substantial, with applications in early diagnosis, treatment planning, surgical guidance, and longitudinal monitoring. Future research should focus on developing lightweight, interpretable, and generalizable models, as well as incorporating multi-modal data and federated learning approaches to address privacy concerns. In conclusion, while AI-based brain tumor segmentation has achieved remarkable progress, bridging the gap between experimental performance and real-world clinical deployment will be essential to fully realize its benefits in improving patient outcomes and advancing precision medicine in neuro-oncology.

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