

CNN-Based Image Segmentation Approach in Brain Tumor Classification: A Review [†]

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Abstract: This study explores the application of Convolutional Neural Networks (CNNs) for brain tumor segmentation, leveraging their ability to automatically extract hierarchical features from medical images. CNN architectures like U-Net, V-Net, and ResNet have shown significant promise in brain tumor classification, offering high precision in detecting tumor boundaries and classifying tumor types. Various benchmark datasets, such as BraTS, TCIA, Harvard, and Kaggle, provide annotated MRI images to evaluate these models. Performance metrics including Dice Similarity Coefficient (DSC), Intersection over Union, and accuracy are employed to assess the models' effectiveness. The results demonstrate that CNN-based models, particularly U-Net, perform exceptionally well, with DSC scores exceeding 0.90 in most cases. However, challenges such as data imbalance, the need for large datasets, and high computational demands persist. Despite these limitations, CNNs, when combined with advanced techniques like transfer learning and data augmentation, offer robust solutions for brain tumor segmentation, showing promise for real-time clinical deployment. Further advancements are necessary to address generalization issues and enhance model efficiency, ensuring broader applicability in clinical settings.

Keywords: brain tumor classification; convolution neural network; image segmentation



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1. Introduction

Brain tumors present significant medical challenges due to their complex nature and potential to cause serious complications [1]. Precise and prompt diagnosis is crucial for optimizing the effectiveness of treatment approaches to enhance patient outcomes. Medical imaging techniques such as magnetic resonance imaging (MRI), is required for the identification, diagnosis, and classification of brain malignancies [2]. MRI provides comprehensive data on the dimensions, position, and structure of the tumor, which is crucial for making well-informed decisions on medical treatment. However, the manual analysis of brain tumor images is a time-consuming and error-prone process, leading to variations in diagnosis and treatment results [3]. The classification of brain tumors presents significant challenges due to the diverse composition of the tumor, similarities in visual characteristics among various tumor forms, and the distinction between malignant regions and normal tissues. In order to address this challenge, it is necessary to develop advanced technologies that can assist radiologists in precisely classifying and segmenting brain tumors from medical images [4].

Convolutional neural networks (CNNs) are very efficient for tasks involving image segmentation, particularly in the field of medical imaging. Convolutional neural networks (CNNs) are specifically designed to automatically adapt the feature space layer of the input image [5]. They are particularly effective in difficult image processing tasks, such as separating brain tumors. CNNs utilize deep learning to effectively identify complex patterns and variations in medical images without relying on manually crafted algorithms or simple categorization algorithms. CNN-based algorithms have demonstrated superior accuracy in the diagnosis and classification of brain tumors compared to conventional methods [6]. These attributes arise from their capacity to collect information from extensive datasets, their ability to adjust to varying tumor shapes, and their aptitude for intricate and precise differentiations. CNNs enhance the precision of tumor detection and accuracy, making them a suitable approach for diagnosing brain tumors in the medical field [7]. The primary objective of this review is to provide a comprehensive examination of the most recent CNN-based algorithm employed in the classification and segmentation of brain tumors. This includes evaluating their Peak Signal-to-Noise Ratio, Mean Square Error, time, accuracy, and precision in the clinical identification [8]. The review also aims to determine the current limitations associated with this approach on MRI images. The requirement for a comprehensive dataset that has been thoroughly evaluated, as well as the accuracy of the CNN model, are very important [9] in ensuring dependable and accurate classification and segmentation of brain tumors, which are crucial for optimal diagnostic and treatment planning. Furthermore, the research proposes to investigate prospective methods to enhance the brain tumor classification using CNN algorithms. These algorithms involve the creation of hybrid approaches and the enhancement of deep learning techniques to address unpredictability. The current advancement in CNN algorithms has the potential to fundamentally transform the field of brain tumor diagnosis and identification.

2. Brain Tumor Image Segmentation

Image segmentation is a key technique in medical imaging that involves segmenting an image into distinct regions or parts to streamline or transform its representation, increase its significance, and provide analysis [10]. Segmentation plays a crucial role in precisely defining tumor boundaries, in imaging modalities such as MRI and computed tomography (CT) scans, especially in the context of brain tumor diagnosis [11]. Precise segmentation is crucial for multiple reasons: it enables accurate measurement of tumor size, facilitates the identification of tumor sites, and assists in evaluating the tumor's effect on neighboring brain structures [12]. This comprehensive information is essential for making informed decisions regarding treatment planning, surgical intervention, and radiation therapy [13].

2.1. CNN Based Algorithm

Image segmentation plays a pivotal role in medical imaging, particularly in brain tumor diagnosis, by accurately defining tumor boundaries in MRI and CT scans [10]. CNNs have become a dominant approach due to their ability to extract complex features directly from data [14]. CNNs, like U-Net and V-Net, have been extensively employed for brain tumor segmentation. U-Net is an encoder-decoder architecture that effectively captures both global and local context through skip connections, making it suitable for precise tumor delineation [15,16]. V-Net, designed for 3D data, leverages 3D convolutions to capture spatial context in all three dimensions, making it highly efficient for volumetric segmentation tasks [17]. While CNNs, particularly U-Net, offer outstanding segmentation accuracy, challenges such as tumor variability and noisy artifacts can still affect their performance [18]. Moreover, computational demands are high, especially in 3D models, limiting their application in clinical settings with time constraints [19,20]. Hybrid methodologies combining

CNNs with classical algorithms or probabilistic models have been proposed to enhance reliability and interpretability in clinical environments [21]. The Table 1 highlights various CNN architectures employed for brain tumor segmentation, comparing their strengths and limitations based on accuracy, computational efficiency, and generalization capabilities.

Table 1. CNN Architectures for Brain Tumor Segmentation.

Reference	Year	Segmentation Algorithm	Strength	Limitation
[1]	2020	DCU-Net	Multi-scale feature extraction.	Computationally intensive resources.
[2]	2021	DFP-ResUNet	Fine and coarse capture.	Computationally demanding, struggles with diverse datasets.
[3]	2020	3D FCN	Multi-pathway integration.	Memory-intensive, struggles with heterogeneity.
[4]	2022	ResNet	High accuracy, scalability, efficient deployment.	Dataset dependency, modality generalization challenges.
[5]	2022	UNETR-SwinBTS	Global-local feature capture.	Large dataset dependency.
[11]	2024	Swin V-net	Enhanced feature learning, context-aware, improved segmentation.	High computational cost, resource-intensive.
[14]	2024	3D CNN and U-Net	Enhanced segmentation, multi-scale integration, robust classification.	High complexity, computational demands.
[15]	2024	MedSegDiff-V2	Diffusion models, transformer-based, enhanced accuracy.	High computational cost, generalization challenges.
[22]	2017	AlexNet	Efficient, Robust, Generalized.	Small data challenge, limited granularity.
[23]	2023	3D-UNet, V-Net	Platform optimization, improved accuracy, deep learning impact.	Environment limitations, task-specific, generalization challenges.
[24]	2024	Batch Normalization	Stability, robustness, efficiency.	Overfitting, computational cost.
[25]	2024	RCSF-CNN	Efficient, accurate, feature fusion.	Complexity reduction, generalization issues.
[26]	2024	U-Net and VGG-Net	Improved accuracy, hybrid approach, transfer learning.	Specialized datasets, computational complexity.
[27]	2024	PrinciResNet16	Multimodal fusion, improved accuracy, enhanced robustness.	Computational complexity, generalization challenges.
[28]	2024	VGG-Net	Pre-trained model, improved accuracy, efficient feature extraction.	Limited adaptability, high computational demand.

The analyzed algorithms exhibit a range of strengths and limitations in the segmentation of brain tumors. DCU-Net [1] stands out due to its ability to extract features at multiple scales, which greatly improves segmentation accuracy, positioning it among the top-performing models. Nonetheless, the computational requirements render it less practical for real-time applications, a frequent constraint observed in numerous CNN-based

algorithms. Moreover, the dependence on extensive datasets presents a common obstacle for numerous models, constraining their performance on smaller, less varied datasets.

Other powerful algorithms such as SwinVNet [11] and VGG-Net [29–31] provide effective feature learning, particularly when utilizing pre-trained models and context-aware mechanisms. These models greatly enhance segmentation accuracy; however, they also encounter the challenge of high computational demands and resource intensity. Although these models perform exceptionally well in specific tasks, their reliance on extensive and varied datasets poses challenges in practical clinical environments where immediate processing or constrained data availability might be necessary.

A significant constraint observed in many CNN-based algorithms is their difficulties with generalization and the associated computational expenses. While these models excel in segmentation and classification, they often face challenges with heterogeneity across datasets and generalizing across modalities, which limits their adaptability to new or diverse tumor types. Furthermore, as demonstrated by algorithms such as Batch Normalization and MedSegDiff-V2 [15], although there are enhancements in stability and accuracy, these improvements are accompanied by the downside of greater processing time and resource demands, which can impede their scalability for routine application in clinical settings.

2.2. Benchmark Datasets

Benchmark datasets are crucial for evaluating the effectiveness of image segmentation algorithms in the context of brain tumor diagnosis. These datasets provide annotated images that allow researchers to train, test, and compare segmentation models in a standardized manner. Some of the most widely used datasets include BraTS and TCIA, each with distinct characteristics that contribute to the development of robust segmentation algorithms.

The Brain Tumor Segmentation Challenge (BraTS) dataset is one of the most well-known and frequently used for brain tumor segmentation research [1,3,24,25,32]. It contains MRI images of gliomas (a type of brain tumor) and provides annotations for different tumor sub-regions such as the enhancing tumor, edema, and necrotic core. BraTS includes various MRI modalities, such as T1, T2, FLAIR, and contrast-enhanced T1 (T1-Gd), which are essential for accurate tumor delineation. This dataset is used annually in the BraTS Challenge, where researchers present their segmentation algorithms, and performance is evaluated using standard metrics like Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) [19–21,33–39].

The TCIA (The Cancer Imaging Archive) provides a comprehensive repository of medical images [40], including those for brain tumor segmentation. It includes both MRI and CT scans, covering a wide variety of tumor types and providing valuable datasets for general tumor analysis. TCIA's dataset also includes clinical data, which can be useful for developing models that not only segment tumors but also make predictions about tumor progression and patient outcomes.

These benchmark datasets are essential for the evaluation of segmentation algorithms, allowing for comparison of different methods across common challenges in brain tumor detection. The standard metrics used to evaluate segmentation performance, such as Dice Similarity Coefficient (DSC) and Intersection over Union (IoU), provide consistent and reliable ways to assess the effectiveness of different algorithms on these datasets. Table 2 summarizes key benchmark datasets commonly used in brain tumor research detailing the tumor class/type, segmentation technique and performance metrics.

The summary highlights that techniques employing CNN architectures like DCU-Net and U-Net are used for segmenting BraTS datasets while DSC being the predominant evaluation metric. This focus on tumor subtypes enables precise segmentation crucial for

clinical applications. Other datasets, such as Harvard and TCIA, typically employ accuracy as the primary performance metric, reflecting a more generalized approach to tumor type compared to BraTS dataset.

Table 2. Benchmark Datasets for Brain Tumor Segmentation.

Ref.	Dataset	Class	Segmentation Technique	Performance Metric					
				Accuracy	IoU	Recall	Precision	DSC	F1-Score
[1]	BraTS ¹ 2018	WT, CT, ET	DCU-Net	-	-	-	-	0.91	-
[2]	BraTS 2018	WT, CT, ET	DFP-ResUNet	-	-	-	-	0.91	-
	BraTS 2019							0.90	
[3]	BraTS 2018	WT, CT, ET	3D FCN	-	-	-	-	0.90	-
	BraTS 2019							0.89	
[4]	BraTS 2017–2020	WT, CT, ET	ResNet	96.0	0.77	-	-	0.91	-
[5]	BraTS 2019	WT, CT, ET	UNETR-SwinBTS	-	0.82	-	-	0.82	-
	BraTS 2020							0.82	
	BraTS 2021							0.87	
[11]	BraTS 2021	WT, CT, ET	Swin V-net	-	-	-	-	0.91	-
[14]	TCIA MRI dataset	Tumor, Normal	3D CNN and U-Net	98.5	-	96	87.45	0.92	-
[15]	AMOS2022	WT, CT, ET	MedSegDiff-V2	-	-	-	-	0.91	-
	REFUGE-2				0.89			0.97	
	BraTs-2021				0.83			0.91	
	ISIC				0.93			0.93	
	TNMIX				0.82			0.89	
[22]	³ MICCAI 2014	Normal Cancer	AlexNet	97.5	-	-	-	-	-
	Brain CRC			84.0				-	
[23]	BraTS, Harvard ² , RIDER, ISLES	Glioma, Normal	3D-UNet, V-Net	98.7	-	-	-	-	-
[24]	BraTS 2019	Tumor, Normal	Batch Normalization	99.55	-	98	98	-	-
	BraTS 2020			99.80		99	99	-	99
	BraTS 2021			99.29		99.15	99.3	-	99.78
[25]	BraTS 2015	Tumor, Normal	RCSF-CNN	98.99	-	-	-	-	-
[26]	Cheng et al.	Glioma, Pituitary, Menin- gioma	U-Net and VGG-Net	98.95	-	98	98.33	-	98.33
[27]	Kaggle ² Medharvard	Tumor, Normal	PrinciResNet16	99	-	95	-	-	-
[28]	BraTS 2018	WT, CT, ET	VGG-Net	99.6	-	99	93	99.53	99

¹ BraTS: MRI Images; ² Kaggle and Harvard: CT-Images; ³ MICCAI: Histopathology Images, WT: Whole Tumor, CT: Core Tumor, ET: Enhanced Tumor.

Overall, the BraTS series remains the gold standard for brain tumor segmentation, offering comprehensive annotations across multimodal MRI data. High DSC scores confirm its effectiveness in evaluating segmentation methods. However, datasets like TCIA and Cheng's stand out for classification, demonstrating near-perfect accuracy but focusing on simpler binary tasks. This indicates that segmentation tasks are inherently more challenging due to the complexity of tumor morphology and heterogeneity. These datasets collectively support diverse algorithmic evaluations, from segmentation to classification, with performance metrics tailored to specific applications.

CNN-based segmentation methods have revolutionized brain tumor detection by providing reliable, precise, and efficient solutions compared to traditional techniques [13,41,42]. Architectures like U-Net and V-Net [11,43,44] excel due to their ability to capture both global and local features, with U-Net's skip connections ensuring spatial information preservation and V-Net's 3D convolutions enhancing volumetric data analysis. These models are particularly effective in complex tumor boundary delineation. However, challenges such as computational intensity and sensitivity to heterogeneous datasets persist, limiting their feasibility in real-time or resource-constrained environments.

Hybrid methodologies are emerging to address these limitations, combining CNNs with traditional methods or probabilistic models to improve generalization and interpretability [14,45–47]. While CNNs like U-Net are highly accurate for intricate segmentation tasks, traditional methods offer simplicity and transparency, making them suitable for less complex scenarios. The hybrid approach balances these strengths, providing a promising pathway to improve accuracy, resource efficiency, and clinical applicability in brain tumor segmentation [6,48]. Further research and optimization are needed to address existing computational and dataset dependency challenges, ensuring broader adoption in medical imaging. An illustration of image segmentation techniques from 2013–2024 [2–5,21,22,29,35,37,48–54] can be seen in Figure 1.

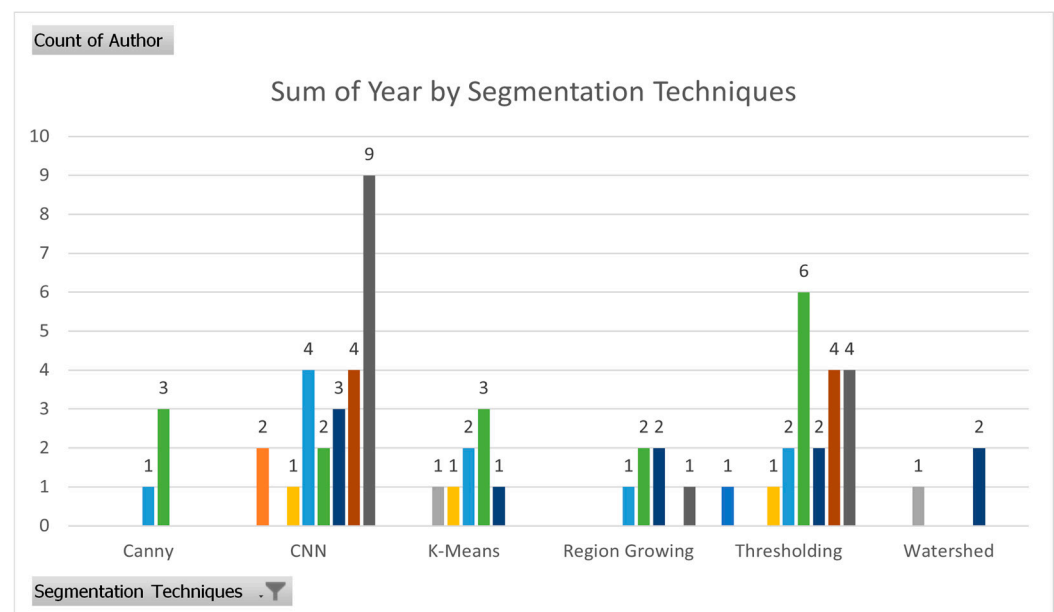


Figure 1. Segmentation Techniques from 2013–2024.

Almost half of the articles published from 2013 to 2024 have employed Convolutional Neural Networks for image segmentation in brain tumor classification. This is followed by the thresholding method, which is known for its simplicity of use. Convolutional Neural Networks are favored for their effectiveness in processing complex medical images. Other methods are not preferred because of their limitations in effectively addressing the complexities of medical imaging. Based on the trend, it is highly probable that Convolutional Neural Networks will continue to be at the forefront of this field, possibly through the use of hybrid methods. Convolutional Neural Networks are extensively employed to classify brain tumor images, and their performance is assessed using a variety of metrics that offer insights into various aspects of model efficacy. Accuracy [49–51] is a critical metric that quantifies the percentage of images correctly classified, serving as a fundamental indicator of the model's overall performance. The disparity between predicted and true values is represented by Loss [2,52], with smaller values indicating improved model performance.

The Intersection over Union (IoU) metric evaluates the extent of overlap between the predicted and actual tumor regions, thereby establishing a spatial alignment metric [36,53]. The model's capacity to accurately identify true positives and reduce false positives is assessed by Recall and Precision, respectively [51,54]. The Dice coefficient [1,55] provides an alternative measure of overlap by quantifying the similarity between predicted and actual tumor regions. Error Rate and Mean Squared Error [32,35] offer a comprehensive understanding of the prediction errors, with lower values indicating more precise predictions. Time measures the computational efficiency of the model, emphasizing its practicality in real-world applications. The Hausdorff Distance [2] evaluates the quality of boundary delineation by measuring the spatial resemblance between predicted and true tumor boundaries. The model's accuracy in identifying non-tumor regions is determined by Specificity, which complements the evaluation of positive tumor identification. The F1-Score is a comprehensive evaluation of model performance that integrates precision and recall into a single metric, thereby balancing the trade-off between false positives and false negatives.

3. Recent Advances and Future Directions

Image segmentation is a crucial task in medical brain tumor analysis. Significant advancements in the techniques used for brain tumor segmentation were published, especially with the advent of deep learning methods and improved imaging technologies. These advances provide basis for future work in research on brain tumor image segmentation.

3.1. Recent Advances

Advancements in CNNs have significantly improved brain tumor segmentation, with techniques such as transfer learning, which enables fine-tuning of pre-trained models for medical imaging tasks, thereby reducing dependency on large, labeled datasets. Attention mechanisms, including self-attention and transformers, enhance segmentation by focusing on critical image features. 3D CNNs extend traditional 2D methods by capturing spatial context in volumetric data, essential for MRI analysis [24,49,56]. The U-Net architecture, with its encoder-decoder framework and skip connections, remains a foundational approach, excelling in precise tumor boundary delineation.

Hybrid methods integrate CNNs with other frameworks to address segmentation challenges. Hybrid CNNs with graph neural networks (GNNs) incorporate structural details for better tumor connectivity [57,58]. Generative models like GANs aid in creating synthetic labeled datasets, boosting robustness, while RNNs capture temporal dependencies [59,60], enabling accurate segmentation in sequential imaging. Data augmentation now includes advanced synthetic generation methods, addressing dataset limitations and enhancing generalizability across heterogeneous data, reducing overfitting risks. Fusion networks in multi-modal imaging integrate complementary data from MRI modalities (T1, T2, FLAIR), enabling accurate segmentation and providing a holistic view crucial for precise diagnostics and treatment planning.

3.2. Future Work

Future work in brain tumor segmentation should prioritize addressing data imbalance, a significant challenge caused by the underrepresentation of rare tumor types. Advanced data augmentation, synthetic dataset creation using GANs) and balanced sampling techniques can help improve model performance across diverse tumor categories [61]. Enhancing generalization is also critical, as models need to perform consistently across heterogeneous datasets and imaging modalities [62]. Robust architectures and domain

adaptation strategies should be developed to minimize performance degradation when applied to unseen or diverse datasets [63].

Additionally, achieving real-time diagnosis is essential for integrating segmentation algorithms into clinical workflows. This can be facilitated by designing lightweight models or employing optimization techniques such as pruning and quantization to reduce computational demands while maintaining accuracy. Finally, embedding segmentation algorithms into clinical decision support systems can provide actionable insights for treatment planning. Future research must prioritize interpretability and explainability to build clinician trust and ensure these models deliver meaningful and reliable guidance for effective patient management.

The recent advances and future trends in brain tumor image segmentation, as illustrated in Figure 2, highlight the progression of technologies and methodologies shaping this field.

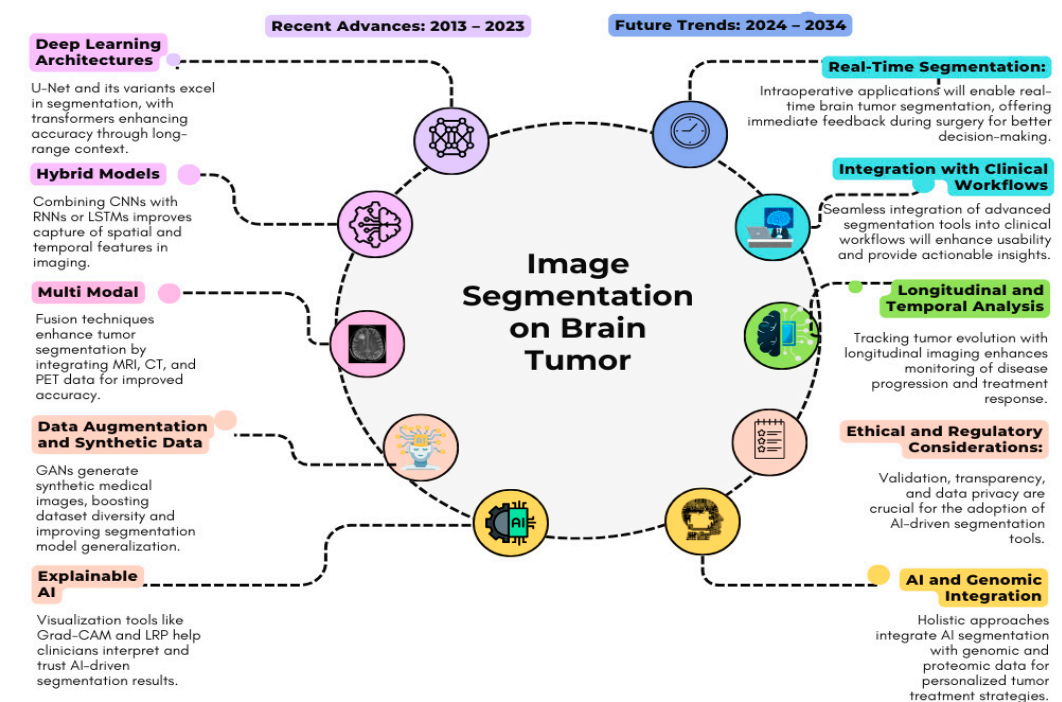


Figure 2. Recent advances and future trend of image segmentation for brain tumor classification.

4. Conclusions

In conclusion, advancements in brain tumor segmentation have significantly improved accuracy and efficiency, particularly through CNN-based methodologies such as U-Net and V-Net. These models leverage robust architectures and innovative techniques like transfer learning, attention mechanisms, and multi-modal fusion to address complex tumor detection challenges. However, limitations such as data imbalance, generalization issues, and computational demands remain critical obstacles. Future research must focus on overcoming these challenges by developing balanced datasets, enhancing model adaptability, and optimizing real-time performance while integrating interpretability into clinical decision support systems for widespread practical applications.

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as a reviewer, providing critical feedback on the paper's structure and organization. She suggested improvements to enhance the clarity, flow, and overall coherence of the manuscript. Together, both authors worked closely to ensure the accuracy and relevance of the review to the field of CNN-based image segmentation techniques for brain tumor classification. All authors have read and agreed to the published version of the manuscript.

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