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Comparative Review of Brain Tumor Segmentation Techniques: Classical Methods, CNN/U-Net Models, and Hybrid Frameworks

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Abstract- Brain tumor segmentation is a critical task in medical imaging, supporting accurate diagnosis, treatment planning, and continuous monitoring of tumor progression. Over the years, a variety of segmentation strategies have been proposed, each offering distinct advantages and limitations. Early traditional approaches—including thresholding, edge-based detection, and region-growing methods—are computationally efficient and simple to implement, but they often perform poorly in the presence of noise, intensity inhomogeneity, and complex or ambiguous tumor boundaries. Statistical and model-driven techniques, such as clustering methods and deformable models, improve adaptability to anatomical variability but typically require careful parameter selection and may involve higher computational cost. In recent years, machine learning and deep learning methods have transformed brain tumor segmentation, particularly through the use of Convolutional Neural Networks (CNNs) and U-Net-based architectures, which have demonstrated strong accuracy and robustness across large and diverse MRI datasets. More recently, hybrid methods that combine classical image processing with deep learning have gained attention for improving efficiency, interpretability, and generalization. This review summarizes the evolution of brain tumor segmentation methods, compares major categories of approaches, and discusses current challenges and promising future research directions.

Keywords – Brain Tumor Segmentation, MRI, Medical Imaging, Deep Learning, CNN, U-Net, Hybrid Segmentation Methods.

I. INTRODUCTION

Brain tumors remain one of the most complex challenges in modern medicine due to the delicate structure of the brain and the wide variability in tumor appearance, location, and growth behavior. Accurate detection, segmentation, and treatment planning are critical not only for clinical decision-making but also for improving patient outcomes and supporting ongoing medical research. Magnetic Resonance Imaging (MRI) is widely used as the primary imaging modality for brain tumor assessment because it provides high-resolution visualization of brain anatomy and abnormalities. However, despite significant improvements in MRI technology, achieving fast and precise tumor detection and segmentation continues to be a major challenge, particularly because brain tumors often present with heterogeneous and unpredictable characteristics.

Machine Learning (ML), as a key area of artificial intelligence, has significantly advanced brain tumor analysis by enabling data-driven interpretation of MRI scans. Unlike conventional rule-based techniques, ML algorithms learn patterns from large datasets and can identify subtle imaging features, support automated segmentation, and assist in outcome prediction. This transition from heuristic methods to learning-based approaches has reshaped brain tumor diagnostics, improving both accuracy and consistency and establishing more reliable standards for clinical practice. Figure 1 presents an example of a brain tumor along with its corresponding segmentation.

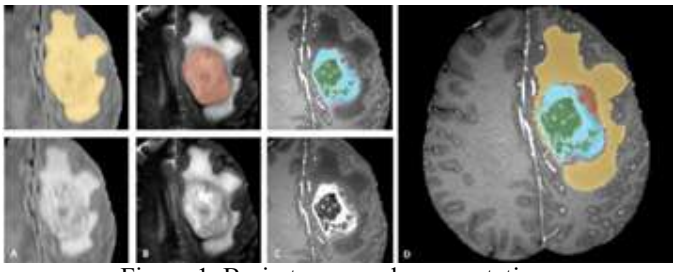

Figure 1. Brain tumor and segmentation.

As with any significant technological shift, combining MRI-based brain imaging with machine learning introduces both strong potential and important limitations. Key concerns, including data quality and availability, algorithmic transparency and interpretability, rigorous validation, and real-world clinical usability strongly influence whether these methods can be safely and effectively adopted in practice.

This review explores the convergence of machine learning and MRI for brain tumor detection and segmentation. It outlines the

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historical progression of automated MRI analysis, examines the major machine learning approaches developed in this field, and critically discusses their strengths, weaknesses, and practical challenges. By synthesizing evidence from a broad range of studies, the paper aims to present a structured overview of the current research landscape and identify promising future directions for machine learning-assisted brain tumor analysis.

Early attempts to automate MRI tumor analysis during the 2000s primarily relied on rule-based and handcrafted feature-driven algorithms. Although these approaches were pioneering, they often lacked robustness and generalization, particularly when faced with the wide variability in tumor size, shape, location, and intensity patterns across patients. A major shift occurred in the late 2010s with the rapid advancement of machine learning especially deep learning models based on neural networks. Inspired by the way biological neurons process information, neural networks introduced improved adaptability and the ability to learn complex representations directly from data. Within this space, Convolutional Neural Networks (CNNs) became foundational for medical image recognition and segmentation, demonstrating strong performance on MRI-based tumor analysis tasks. Figure 2 illustrates an example of brain tumor detection and segmentation in MR images.

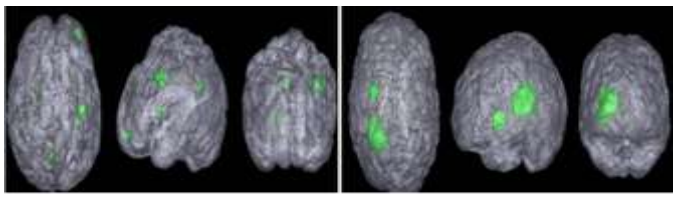

Figure 2. Brain tumor detection and segmentation in MR images.

Diving Deeper into Brain Imaging: The human brain is widely regarded as one of the most complex organs in the body, and its sensitivity makes neurological disorders especially brain tumors particularly challenging to diagnose and manage. Malignant tumors can progress rapidly and may lead to serious neurological deficits, cognitive impairment, and, in severe cases, death if they are not detected and treated at an early stage.

MRI: A Milestone in Neuroimaging: Magnetic Resonance Imaging (MRI) has become a foundational tool in neuroimaging due to its ability to generate high-resolution images of brain anatomy without ionizing radiation. Unlike X-ray or CT imaging, MRI uses strong magnetic fields and radiofrequency signals to produce detailed multi-slice scans with different contrast settings. These imaging capabilities enable clinicians to clearly differentiate between healthy and abnormal tissues, making MRI especially valuable for soft-tissue evaluation and for detecting subtle structural abnormalities that might be difficult to observe using other modalities.

The Machine Learning Era: The growth of computational power and the increasing availability of imaging data have accelerated the adoption of machine learning (ML) in medical image analysis. MRI produces large volumes of complex data, and manual interpretation can be time-intensive and subject to inter-observer variability. ML methods can learn patterns from labeled datasets to automate tasks such as tumor detection and segmentation, thereby improving efficiency and supporting more consistent diagnosis. Techniques range from classical ML approaches such as Support Vector Machines (SVMs) to deep learning architectures—particularly Convolutional Neural Networks (CNNs)—which have demonstrated strong performance in image recognition and segmentation tasks.

Integrating MRI with Machine Learning: The combination of MRI and ML represents a major advancement in modern medical imaging. When trained on high-quality MRI datasets, ML algorithms can detect subtle anomalies and imaging patterns that may be difficult to identify through visual inspection alone. This integration can streamline diagnostic workflows, support quantitative tumor assessment, and contribute to more personalized treatment strategies by providing patient-specific information that strengthens clinical decision-making.

Challenges and the Road Ahead: Despite significant progress, several barriers remain before ML-based systems can be fully integrated into routine clinical practice. Key challenges include ensuring reliable performance across datasets from different institutions, managing data privacy and security concerns, and incorporating AI tools into real clinical workflows. Interpretability is also a critical issue: in medical contexts, clinicians often need to understand why a model produced a particular output in order to trust and act on its recommendations.

Current Research Landscape: Machine learning-based brain tumor detection and segmentation is a rapidly evolving research area. Recent improvements in model architecture and hardware are continuously increasing accuracy and computational efficiency. Transfer learning—where models pre-trained on large datasets are adapted to medical imaging tasks—has become particularly useful for addressing limited labeled data, which is often restricted due to privacy regulations. However, concerns such as biased datasets, inconsistent image quality, and limited transparency in model decisions continue to affect reliability and clinical adoption.

The Path Ahead: This review examines the major machine learning and deep learning models used for MRI-based brain tumor detection and segmentation. It evaluates their key strengths and limitations, identifies emerging innovations, and highlights future research directions. Progress in this field depends not only on algorithmic development but also on close collaboration among radiologists, clinicians, engineers, and

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data scientists to ensure that machine learning tools are accurate, interpretable, and clinically meaningful—ultimately improving patient care and outcomes.

II. LITERATURE REVIEW

Monitoring Metastatic Brain Diseases
Monitoring metastatic brain diseases is particularly challenging, especially when multiple metastases are present. The RANO-BM guideline remains widely used for therapy response assessment, but accurate volumetric evaluation of lesions and peri-lesional edema is equally crucial. Brain metastases are often smaller than 10 mm, which makes segmentation difficult. Unlike gliomas, which usually present as larger masses, metastases vary widely in size and morphology. To address these complexities, the BraTSMETS dataset was introduced to facilitate advancements in automated detection and segmentation of brain metastases [1].

Advances in Brain Tumor Segmentation
Brain tumor segmentation continues to play a pivotal role in medical imaging. Despite its complexity, deep learning approaches have shown remarkable success in this domain. A comprehensive survey of more than 150 papers on deep learning–based segmentation highlights innovations in network design, methods for handling imbalanced data, and multi-modality integration. The survey also points to promising directions for future research [2].

Deep Learning Models for MRI-Based Detection
MRI remains the gold standard for early-stage brain tumor detection. However, tumor variability makes detection challenging. To overcome this, researchers proposed an Improved Invasive Bat (IIB)-based Deep Residual Network model, demonstrating strong results with high accuracy, sensitivity, and specificity [3].

When different segmentation techniques were applied to the BRATS-2018 dataset, methods such as Otsu's thresholding, watershed, level set, K-means clustering, discrete wavelet transform (DWT), and convolutional neural networks (CNNs) were compared. Among them, CNN-based approaches achieved the highest accuracy and fastest response times, reaffirming their dominance in tumor imaging tasks [4].

Hybrid and Optimized Approaches
More advanced models have pushed performance boundaries even further. A hybrid Deep Convolutional Neural Network (DCNN) classifier, enhanced with a LuNet algorithm and Laplacian of Gaussian (LOG) filter for feature extraction, achieved 99.7% accuracy, significantly improving over traditional classifiers [5].

Similarly, an optimized eXtreme Gradient Boosting (XGBoost) model has been proposed for brain tumor identification, yielding high accuracy and precision. This approach highlights the potential of ensemble learning methods in medical imaging [6].

Another study focused on segmentation across multiple brain diseases using data from Harvard Medical School, where a deep learning–based method delivered strong accuracy and sensitivity, further supporting its clinical utility [7].

CNN Architectures in Practice
The VGG16 model, trained on MRI images from Kaggle, classified cases as either "normal" or "tumor" with an accuracy of 97.33%. While effective, VGG16 is often criticized as a "black box" model. To improve transparency, Layer-wise Relevance Propagation (LRP) was employed, allowing insight into the decision-making process [8].

Another approach tackled the challenge of distinguishing tumors from normal tissues—an inherently difficult task due to their similar appearances. Preprocessing with a HOFilter, followed by segmentation using edge detection and morphological operations, achieved 96.46% accuracy and 96.19% precision [9].

Diagnostic Methods with Deep Learning
Accurate early-stage diagnosis remains critical for effective treatment. Studies using MRI have demonstrated reliable classification of gliomas, meningiomas, pituitary tumors, and healthy brains. Among the tested algorithms, 2D CNNs achieved 96.47% accuracy, while auto-encoder networks reached 95.63%. Traditional machine learning techniques were also compared, with K-Nearest Neighbors (KNN) delivering the highest accuracy among them [10].

Toward More Precise Brain Tumor Diagnosis
Early detection of brain tumors—whether malignant or benign—is critical because of their disruptive effects on surrounding cells. To enhance diagnostic accuracy, researchers proposed a CNN model fine-tuned with ResNet50 and U-Net, achieving strong segmentation metrics (IoU = 0.91, DSC = 0.95) [11].

Advances in Object Detection Architectures
Recent innovations in detection frameworks have also shown promise. An enhanced YOLOv7 model demonstrated reliable identification of pituitary gland, meningioma, and glioma tumors. This architecture integrated data augmentation, a CBAM attention mechanism, and a Bi-directional Feature Pyramid Network (BiFPN), yielding superior feature extraction and rapid feature fusion, making it both accurate and clinically relevant [12].

Hybrid and Novel Deep Learning Models
Efforts to refine segmentation further led to the design of a convolution-based hybrid model, which achieved Dice scores

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of up to 93.10% across multiple datasets, thanks to its unique preprocessing structure [13]. Complementary reviews emphasize the central role of CNNs in MRI-based segmentation, highlighting how deep learning has driven many of the recent breakthroughs [14].

Multi-Modal and Feature-Based Enhancements
The integration of U-Net with 3D CNNs, enhanced by Gray Level Co-occurrence Matrix (GLCM) features, demonstrated accuracies of up to 99.4% in aggressive glioma segmentation [15]. However, a key barrier remains: preprocessing steps such as skull-stripping. Studies show that the choice of brain extraction method can affect performance by up to 15.7%. Interestingly, training directly on raw images without skull-stripping reduced processing time without compromising accuracy, pointing toward more streamlined pipelines [16].

Classical Machine Learning with Deep Learning Synergy
Deep learning continues to dominate, but classical ML techniques retain value when used strategically. For example, ANN and MLP architectures were used with preprocessed MRI features to achieve reliable tumor detection [17]. Meanwhile, WBM-DLNets, which tested 16 pretrained networks and 8 optimization algorithms, revealed that combinations like DenseNet-201 with GWOA and EfficientNet-b0 with ASOA achieved the highest classification accuracy [18].

Emerging Segmentation Techniques
Hybrid frameworks are also gaining traction. A novel method combining AMSOM and FKM improved segmentation efficiency, outperforming existing models on the BraTS-18 dataset with a 10% performance gain [19]. Broader reviews underscore the diversity of approaches—ranging from computational intelligence to advanced CNNs—and their utility in dissecting the morphological complexity of brain tumors [20].

Next-Generation Architectures
Improved Residual Networks (ResNet variants) have been shown to outperform traditional models, delivering around a 10% boost in performance metrics [21]. CNNs remain central to diagnostic AI, with studies benchmarking them against architectures like ResNet-50 and VGG16. Results consistently show CNN superiority in tumor detection tasks [22]. Similarly, SGC-ARANet, designed with four specialized modules, achieved superior boundary segmentation when tested on BraTS 2019 and 2020 datasets [23].

Handling Missing Modalities and Resource Efficiency
Medical imaging often suffers from incomplete modality data. Addressing this, a meta-learning strategy improved performance in partial-modality scenarios, outperforming competing methods [24]. Another study proposed a harmony search algorithm–based MRI segmentation method, which matched CNN and DLA in accuracy but excelled in speed and computational efficiency—critical for resource-constrained environments [25].

Beyond Medical Imaging: Cross-Domain AI Applications
Several parallel advances in AI showcase transferable methods relevant to brain tumor detection. Examples include:

- AIIoT devices for real-time object detection for visually impaired users [26].
- Efficient Arithmetic Logic Unit (ALU) designs using QCA technology [27].
- Hierarchical clustering for social recommendations.
- Deep learning applications in mask detection [28], cancer prediction [29], and object detection with Mask-RCNN [31].

Patch-Based and Ensemble Learning Methods
In MRI-focused research, a Patch-Based Convolutional Neural Network (PBCNN) was introduced for early segmentation [32]. U-Net architectures, trained on the MICCAI BRATS 2018 dataset, also achieved strong performance in automated segmentation tasks [33]. To address small-tumor detection, techniques employing dilated convolution and level-based learning improved detection across scales [34]. Additionally, an ensemble Bagging KNN (BKNN) approach boosted classification accuracy to 97.7%, further validating hybrid strategies [35].

III. RESEARCH GAP

Use of X-rays for Brain Imaging: Traditional approaches to brain tumor detection and segmentation have relied heavily on imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. These methods provide high-resolution structural details and have become the gold standard for neuroimaging. In contrast, X-rays, though widely used in other areas of medical imaging, are rarely considered for brain tumor diagnosis due to their limited capacity to capture the brain's intricate soft tissue structures. This creates a clear research gap, as relatively few studies have explored the potential of X-rays for tumor detection, segmentation, or even as a supplementary imaging modality. Investigating this underexplored area could open new avenues for cost-effective and accessible diagnostic tools.

Integration with Machine Learning: Machine learning (ML) has demonstrated significant promise in medical imaging, particularly in the analysis of MRI and CT scans for tumor detection and segmentation. However, its application to X-ray imaging in the context of brain tumors remains underexplored. The majority of research efforts have concentrated on modalities offering richer detail, such as MRI, leaving X-rays largely unaddressed. This represents an important gap, as leveraging ML to enhance the interpretive power of X-rays could potentially compensate for their inherent limitations in

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resolution and contrast, while also broadening the scope of diagnostic possibilities.

Quality of X-ray Images: One of the primary challenges associated with X-ray imaging for brain tumor detection lies in the quality of the images themselves. Unlike MRI and CT scans, X-rays provide lower-resolution images with limited soft tissue contrast, making it difficult to differentiate tumor tissue from healthy brain matter. While advanced image processing techniques exist, the specific challenges of handling low-quality X-ray brain images have not been fully addressed in the literature. This gap highlights the need for specialized preprocessing pipelines and enhancement methods that can make X-rays more clinically useful in this domain.

Diverse Algorithms for X-rays: Machine learning algorithms that have proven effective for MRI or CT imaging may not necessarily perform well on X-ray images. The inherent differences in image quality, texture, and contrast demand algorithms tailored specifically to the characteristics of X-rays. However, most existing studies employ general-purpose architectures without sufficient customization for this modality. This gap underscores the need for research focused on developing or adapting algorithms that can reliably extract meaningful features from X-ray data for brain tumor detection and classification.

Real-time Detection: X-rays are generally faster and less resource-intensive to acquire and process compared to MRI or CT scans. This positions them as a potentially valuable tool for real-time tumor detection, particularly in emergency or resource-limited settings. However, there is little research exploring the feasibility of combining X-ray imaging with machine learning for immediate diagnostic feedback. Addressing this gap could result in practical solutions that enable faster clinical decision-making while still maintaining reasonable accuracy.

Dataset Availability: A critical bottleneck for advancing X-ray-based tumor detection using machine learning lies in the scarcity of publicly available datasets. While MRI and CT datasets are relatively well-established and widely used in competitions such as BraTS, comparable datasets for brain X-rays with labeled tumor regions are nearly nonexistent. Without sufficient annotated data, it is difficult to train and validate robust machine learning models. Developing large-scale, high-quality X-ray datasets thus represents a major research opportunity in this field.

Clinical Validation: Even if machine learning models tailored for X-ray brain tumor detection are developed, their clinical utility remains uncertain without extensive validation. To date, most research efforts on brain imaging with ML have concentrated on experimental setups rather than large-scale clinical trials. This lack of validation represents a major gap in understanding the real-world applicability of such models, and addressing it would be crucial for gaining acceptance among healthcare professionals.

Interdisciplinary Collaboration: Brain tumor detection through X-ray imaging with machine learning would require strong interdisciplinary collaboration between radiologists, data scientists, and ML engineers. Radiologists bring domain expertise on X-ray interpretation, while data scientists provide the computational and algorithmic knowledge needed to process complex data. Current research, however, shows limited collaboration across these disciplines, which hampers the development of clinically meaningful solutions. Bridging this gap could ensure that proposed models are both technically sound and clinically relevant.

Patient Safety: The safety implications of repeated X-ray exposure also remain underexplored in the context of brain tumor detection. Unlike MRI, which uses non-ionizing radiation, X-rays involve ionizing radiation, raising concerns about cumulative exposure, especially for vulnerable populations. Few studies have comprehensively compared the safety trade-offs of using X-rays versus MRI or CT for repeated diagnostic imaging. Investigating this gap could help establish clearer guidelines for when and how X-ray-based methods might be used in a safe and ethical manner.

Comparative Studies: Finally, there is a lack of comparative studies evaluating the relative strengths and weaknesses of X-ray-based machine learning models against those trained on MRI and CT data. Such studies would be invaluable in determining whether X-rays can serve as a viable complementary or alternative modality for brain tumor detection. Comparative analyses could also help identify contexts where X-ray imaging is particularly advantageous, such as in low-resource settings or for preliminary screening. Addressing this gap would provide a more holistic understanding of the potential role of X-rays in neuro-oncology diagnostics.

IV. EXISTING METHODOLOGY

Thresholding and Region-Based Methods: One of the earliest and simplest strategies for brain tumor segmentation is thresholding, which relies on the intensity values of pixels in MRI scans. Since tumorous cells typically display intensity values that differ from surrounding healthy tissue, applying a threshold allows pixels beyond this value to be classified as potential tumor regions. While this method is computationally efficient and easy to implement, its effectiveness is compromised in cases where images exhibit non-uniform illumination, intensity inhomogeneity, or noise, often leading to false positives or missed regions. To address these shortcomings, region-based methods were introduced. These approaches focus on identifying areas of the image that share

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common properties such as intensity or texture, and then grouping them into candidate tumor regions. Popular techniques include region growing, where segmentation starts from a seed point and expands based on similarity criteria, and region merging, where small regions are combined to form larger, coherent tumor areas. Although more robust than simple thresholding, these methods depend heavily on the accurate selection of seed points or merging criteria, making them sensitive to initial conditions.

Edge Detection Methods: Another fundamental category of segmentation techniques relies on edge detection, which identifies boundaries or transitions between regions of differing intensity. Tumors often manifest as regions with sharp contrast relative to surrounding tissues, making edges an intuitive feature for localization. Algorithms such as the Sobel, Canny, and Prewitt operators are commonly employed to highlight these boundaries. When applied to tumors with well-defined margins, edge detection methods can yield precise outlines, assisting in clear delineation. However, tumors often present with irregular, diffused, or poorly defined boundaries, where these methods struggle to perform effectively. In such cases, the reliance on gradient-based detection can lead to incomplete or fragmented contours, limiting their reliability as a standalone approach.

Statistical Methods: Statistical approaches offer a more data-driven perspective by exploiting the inherent differences in distribution between tumor and non-tumor regions. These methods often employ clustering algorithms, which group pixels or voxels based on shared features such as intensity, texture, or spatial proximity. The K-means clustering algorithm is particularly popular, segmenting the image into clusters that can then be mapped to tumor and non-tumor tissues. Statistical techniques bring sophistication beyond basic thresholding, as they can adapt to varying intensity levels and identify subtle differences. However, their success is strongly dependent on the selection of initial parameters, such as the number of clusters or centroid initialization, which can significantly affect outcomes. Poor parameter choices may result in over-segmentation, under-segmentation, or misclassification.

Model-Based Approaches: Model-based approaches attempt to represent the tumor explicitly by constructing a mathematical or geometric model of its shape and behavior. Among the most widely used are deformable models, such as active contours (snakes), which iteratively adjust their shape to fit the tumor boundary. These models are guided by internal forces (encouraging smoothness) and external forces (attracted to image features like edges or intensity changes). This makes them highly flexible and capable of capturing irregular tumor shapes. However, they come with significant limitations: they are computationally intensive, requiring iterative refinement, and are prone to getting trapped in local minima, which can lead to suboptimal boundaries. Despite these challenges, deformable models remain influential due to their ability to incorporate prior knowledge about tumor geometry into the segmentation process.

Machine Learning and Deep Learning Techniques: The rapid rise of machine learning has transformed brain tumor segmentation. Early applications employed traditional classifiers such as Support Vector Machines (SVMs) and Random Forests, which could leverage hand-crafted features to distinguish between healthy and tumor tissue. However, the true breakthrough arrived with the advent of deep learning, particularly Convolutional Neural Networks (CNNs). CNNs have the ability to learn hierarchical features directly from raw image data, eliminating the need for manual feature engineering and dramatically improving accuracy. Architectures such as U-Net and its numerous variants have become the state-of-the-art in brain tumor segmentation, excelling in their ability to combine global context with local detail through encoder-decoder designs and skip connections. These methods not only outperform traditional techniques in terms of accuracy but also demonstrate robustness across diverse datasets and modalities, marking a paradigm shift in medical image analysis.

Hybrid Methods: Recognizing that no single method is universally optimal, researchers have increasingly turned to hybrid approaches that combine complementary techniques. For instance, thresholding may be used as a preprocessing step to narrow down candidate regions, which are then refined using clustering or model-based methods. Similarly, edge detection results can be incorporated into deformable models to guide boundary evolution more accurately. In the deep learning era, hybrid methods often involve combining CNNs with classical approaches or integrating multiple architectures into an ensemble framework. The goal is to mitigate the weaknesses of one method by leveraging the strengths of another, thereby achieving higher accuracy, robustness, and generalizability. Such approaches reflect the evolving trend toward multi-strategy solutions, tailored to the complexities of real-world medical imaging.

V. CONCLUSION

Brain tumor segmentation has advanced significantly, progressing from classical image processing techniques to modern deep learning and hybrid frameworks. Early methods such as thresholding, edge detection, and region-based segmentation established the foundation for automated analysis, but their performance was often constrained by imaging noise, low contrast, and wide variation in tumor size, shape, and appearance. Statistical and model-based techniques improved flexibility and could better handle complex structures, yet they typically required careful parameter tuning and involved higher computational cost. The emergence of deep learning—particularly CNN-based architectures such as

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U-Net—marked a major breakthrough by enabling highly accurate, robust, and automated segmentation across diverse datasets. More recently, hybrid approaches have further improved outcomes by combining complementary strengths from traditional and deep learning methods, often enhancing generalization and stability. Future progress will depend on addressing practical clinical requirements, including the adoption of explainable AI for trustworthy decision-making, real-time or near-real-time processing for workflow integration, and large-scale multi-center clinical validation to ensure reliability across populations and imaging settings.

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