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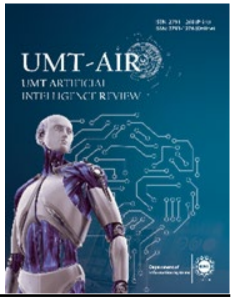

Title:	**A Comprehensive Review of Automatic Semantic Segmentation of Brain MRI: Techniques, Discussion, Challenges**
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A Comprehensive Review of Automatic Semantic Segmentation of Brain MRI: Techniques, Discussion, and Challenges

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ABSTRACT Automated segmentation is also essential in planning treatment and enhancing patient outcomes because early and correct brain tumor detection is crucial for multi-modal 3D MRI, which is still difficult. Image variability, inhomogeneity of tumor morphology, inhomogeneous intensity, motion, compromise, and noisiness, along with non-homogeneous borders of the tumor, compromise generalization and consistency. Manual delineation, although still common in clinical settings, is labor-intensive and operator-dependent. Semi-automatic processes are less labor-intensive yet still require user intervention and close tuning of parameters. Fully automatic methods are promising, particularly with recent deep learning models, which are high-quality, but they require high-quality data, a large volume of computation, and careful handling of domain shift issues. This literature review summarizes traditional and modern MRI-based segmentation algorithms, such as classical clustering and atlas-based algorithms, convolutional networks, and new CNN–Transformer hybrid models, along with their strengths, weaknesses, and common failure modes. We outline practical considerations for clinical translation (robustness, uncertainty, efficiency, and interpretability) and identify opportunities for future work in data-efficient learning, multi-site validation, and workflow integration. Advancing along these directions can yield more accurate, scalable, and clinically useful brain tumor segmentation systems.

INDEX TERMS automated detection, brain tumor, diagnostic accuracy, medical imaging, MRI segmentation

I. INTRODUCTION

The brain examination images are normally acquired by Magnetic Resonance Imaging (MRI). Noise or attenuation problems, including changes in intensity during acquisition, may affect them. MRI is an appropriate tool to use in brain tumors with non-invasive characteristics. In addition, the images of the brain also depict other brain structures, including grey matter, cerebral fluid, skull tissues, and white matter [1]. These steps, namely, preprocessing, segmentation, extraction of relevant tumor features, and classification, set the workflow of the system [1]. Preprocessing includes the denoising of the image frames, the coarsening of the frames, and skull tissue removal. In the preprocessing stage, common filters used are skull stripping, histogram equalization, and the median filter. Segmentation accuracy can be improved, and computation time can be reduced by

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partitioning the preprocessed images. Processing involves the multiplexing of input and output images, calculating a global threshold, reconstruction opening, and morphological closing. Thereafter, valuable features are collected and trimmed down. Statistical features are derived, and the Grey Level Co-occurrence Matrix (GLCM) is calculated. Then, principal components are determined and features are extracted using GLCM, among others.

The images fall into the benign and malignant categories. In this step, a Support Vector Machine (SVM) classifier is trained, its parameters are adjusted, and test images are predicted. Classification accuracy serves as the basis for evaluation, and metrics such as the confusion matrix are utilized to compute sensitivity and specificity. These processes are frequently implemented with the use of well-known programs, such as Python and MATLAB. This is demonstrated by a segmentation method described in [1], [2]. This method used a dataset consisting of 19 brain images impacted by four tumor types, namely meningioma and sarcoma, glioma, metastatic, and adenocarcinoma. Dataset details are critical for the current study. There are tumors of three sizes: small, medium, and large. More recent work highlights that advanced deep learning models, including transformer-based architectures and foundation models, are increasingly integrated into MRI analysis for tumor detection and segmentation, improving generalization across datasets and clinical settings [3], [4].

A. IMAGE SEGMENTATION

Image segmentation divides the images into homogenous and contiguous parts based on predefined classes. It plays an important role in the diagnosis of brain tumors employing MRI technology [2]. Various techniques are employed. These include (a) A threshold-based method was introduced that uses global thresholds and morphological operations for brain tumor segmentation [2], [5], (b) Edge detection techniques employing Sobel operators with automatic thresholding are used to identify intensity changes in tumors [6], [7], (c) Wavelet Transformation, utilized for noise reduction and data compression in MRI, decomposes signals into different scales [7], (d) Morphological operations, including dilation and erosion have been used to extract tumors from low-intensity MRI [8], (e) The Region Growing method was proposed for brain tumor segmentation, segments tumor regions based on pixel similarity using spatial and texture-related information [9], [10], (f) The Watershed algorithm was improved for brain tumor segmentation, segments images without markers but is prone to over-segmentation [2], [11], (g) A Genetic Algorithm integrated with K-means clustering was proposed for brain tumor segmentation, optimizes tumor segmentation inspired by natural evolution [12], (h) Fuzzy clustering techniques were used for accurate tumor boundary delineation, classifies pixels based on membership values [13], [14], (i) K-means clustering has been used to effectively cluster data within MRI regions [15], (j) Deformational models have been applied using Support Vector Machines (SVM) with Vector Field Convolution (VFC), define curves or surfaces using both local and global properties for brain region segmentation [16], (k) Atlas-based methods have been utilized for brain tumor segmentation, combine intensity templates and segmented labels for accurate registration using mesh-free techniques [17]–[19], (l) Markov Random Field (MRF) models have been integrated, enhance segmentation by incorporating spatial features [20], [21], (m) Artificial Neural Networks (ANNs) have been employed, process input features to improve accuracy and handle complex data in brain tumor segmentation [22]–[25], (n) Hybrid methods combining Stationary Wavelet Transform (SWT) and Pulse-Coupled Neural Networks (PCNN), and active contour models for a robust and accurate MRI-based brain tumor segmentation [26]–[28], (o) and Future Challenges of MRI, as outlined by the current research [5], include artifacts, intensity, inhomogeneity, and tumor variability, necessitating high-resolution imaging and advanced filtering techniques to maintain segmentation accuracy in clinical applications.

Recent advances, however, show that semi-supervised learning and transfer learning approaches (e.g., VGG-19 integrated U-Net) address these challenges, achieving dice scores above 0.96 on BraTS and clinical datasets [29]. Similarly, models such as ResSAXU-Net and optimized nnU-Net pipelines improve segmentation robustness by up to 15% over traditional CNNs, particularly for small and enhancing tumor regions [30].

B. BRAIN TUMOR IMAGE SEGMENTATION

Brain tumor image segmentation entails the dissection of normal brain tissues, including Gray matter (GM), White matter (WM), Cerebralspinal fluid (CSF), and Skull, versus tumor brain tissues in brain MRI images. The segmentation of the image into various sections is adopted by the application of the clustering method called Fuzzy C-means due to its superior performance in past studies. The BraTS dataset is used to measure different automatic brain tumor segmentation methods, and the results are mainly measured by metrics such as dice score, specificity, and sensitivity of the different tumor regions, such as whole tumor, core tumor (no edema), and active tumor (active only cells) [2]. Recent studies chose deep learning neural networks as the state-of-the-art in glioma localization, based on multimodal MRI data, such as Magnetic Resonance Spectroscopy (MRS). To improve accuracy, Positron Emission Tomography (PET) and Diffusion Tensor Imaging (DTI) have to be used [7], [8], [13]. Challenges with the classical segmentation strategies involve the mapping of the prior knowledge to probabilistic maps and the choice of strong features for classifiers [31], [32]. Deep learning automatic semantic segmentation systems, e.g., that use the Convolutional Neural Networks (CNNs) and OpenCV, in an attempt to classify and segment medical pictures, including those of brain tumors, with a high level of accuracy [12]. Discriminative techniques accentuate managed learning approaches that involve phases of feature extraction and classification, and generative methods employ probabilistic models on the basis of available atlases of healthy tissues to determine the tumor compartments [13], [33].

The processing pipelines usually involve noise elimination [34], feature extraction techniques including Discrete Wavelet Transforms (DWT) [7] and first-order statistical feature techniques [35], and classification using a variety of algorithms, which can include Support Vector Machines (SVM) [36], AdaBoost [37], Neural Networks (NNs) [38], K-Nearest Neighbor (KNN) [28], Random Forests (RFs) [39], and Self-Organizing Maps (SOMs) [23]. Advanced techniques such as Conditional Random Fields (CRF) [36], [39] and Connected Components (CC)

[40], [41] are being explored to refine segmentation results. The current trends aim to further automate and enhance brain tumor segmentation techniques for improved diagnostic capabilities [2], [42]. In particular, studies from 2023–2025 demonstrate that transformer-based architectures such as Swin-HAFNet and new datasets such as BRISC (2025, 6,000 MRI scans) set new benchmarks, while lightweight two-sequence models (T1C + FLAIR) have been shown to achieve comparable Dice scores (≈ 0.87–0.93) to full four-sequence pipelines [43].

II. Literature Review

Convolutional Neural Networks (CNNs) are frequently employed in brain tumor diagnosis, as they yield reliable results by classifying brain tumors as either benign or malignant. Tools such as MATLAB and WEKA are used for DNN training and evaluation, respectively, to obtain better accuracy [44]. The segmentation work was transformed into a voxel classification objective, which can be performed on the same brain scan [42], [45].

In this study, it is claimed that semantic segmentation CNNs effectively deal with large image sizes, address data imbalance, and can be trained end-to-end on voxel-wise objectives. The segmentation process is modeled as voxel categorization. It selects a subset of voxels for each MRI scan that may indicate various tissue categories. Voxels are categorized into numerous categories based on their respective levels of intensity, thereby making accurate brain tumor segmentation possible [46].

A Deep Neural Network (DNN) was proposed to detect tumors based on convolutional features obtained using GoogleNet. The model was tested on two datasets: BraTS 2018 and BraTS 2019 [43]. The study found that the model is more accurate and less time is needed to train the neural network. In the study, DNN proved to be more accurate in tumor detection than traditional techniques. A Convolutional Neural Network (CNN) model was developed to detect brain tumors by categorizing MRI scans into glioma, meningioma, and pituitary tumors [30]. Their CNN model is more accurate than a number of existing machine learning methods. A deep learning architecture was proposed to classify brain tumors using a Convolutional Neural Network (CNN). The model was trained on 3,064 MRI scans [34]. The findings showed that the proposed CNN model is more accurate at classification than conventional machine learning approaches [47].

Another study introduced a brain tumor segmentation approach that relies on Convolutional Neural Networks (CNNs) using small 3D patches of MRI scans [48]. The suggested scheme relies on intensity normalization and data augmentation to address problems related to scarce data and intensity variation. The research observes that the algorithm demonstrates competitive behavior in tumor segmentation issues. Based on their findings, the proposed CNN model is more precise in segmentation, and it can be trained on small datasets [49].

A CNN-based brain tumor segmentation architecture was designed for use on a large-scale dataset [25]. Their model is much easier to compute and has lower memory requirements than the conventional ones. As noted in the paper, the proposed CNN architecture demonstrates the latest brain tumor segmentation performance, and it can be implemented on a grand scale. Similarly, an ensemble of 11 Convolutional Neural Networks (CNNs) combined with a 3D Conditional Random Field (CRF) was proposed to segment brain tumors [50]. The suggested model performs better than a number of other available approaches in both its accuracy and segmentation, and shows greater efficiency in computation [51], [52].

A CNN-based brain tumor segmentation method that combines local and global contextual features to detect brain tumors was proposed [29], [30]. They combined multi-scale characteristics to improve the accuracy of segmentation. As per their observations, the proposed CNN model is significantly better at segmentation than the traditional ones. Another 3D Convolutional Neural Network (CNN) model was proposed for brain tumor segmentation [53]. Variational autoencoder regularization is added to the model to enhance its generalization. The paper describes how the proposed 3D CNN model performed best in the BraTS 2018 competition, proving that it is an effective mode of brain tumor segmentation [54], [55].

Medical image analysis is an important procedure in brain tumor detection. Proper brain tumor identification helps to determine the location and size of tumors, which is important in diagnosing and planning tumor treatment. Different studies have used CNN-based models to detect brain tumors. An example is the Capsule Network (CapsNet) proposed by Afshar et al. [56] to classify brain tumors with the help of MRI scans. The study indicates that the CapsNet model is more accurate and stronger than the conventional CNN models. Furthermore, a multi-grade brain tumor classification framework was trained using a deep Convolutional Neural Network (CNN). A deep Convolutional Neural Network (CNN) model was introduced to classify brain tumors [57]. They trained their model on 3,064 T1-weighted contrast-enhanced MRI scans. Based on their study, the proposed CNN model shows state-of-the-art performance in brain tumor classification. Another study proposed a hybrid algorithm that combines Convolutional Neural Networks (CNNs) and genetic algorithms to classify brain tumors [44]. The researchers stated that the hybrid model outperforms the traditional CNN models in terms of classification accuracy and robustness.

The CNN-based models have shown considerable promise in detecting brain tumors, as well as in classifying and segmenting them. These models are more effective than the classical machine learning models since they prove to be more accurate, efficient, and robust. The literature review shows that CNN-based approaches are successful in analyzing brain tumors and may be used in clinical practice. More recent work (2020-2025) extends these advances: lightweight deep learning pipelines have achieved a classification accuracy of above 98% and dice segmentation scores exceeding 0.95 on benchmark datasets [4], [29]. Empirical comparisons of various deep architectures indicate that the model and the training configuration significantly affect the semantic segmentation of medical images [58]. These results validate the idea that the world is evolving towards scalable, highly automated, and clinically relevant brain tumor analysis systems [45], [47], [54], [59].

III. DISCUSSION

The level of user interaction determines the division of the brain tumor segmentation methods into either manual, semi-automatic, or fully automatic methods. The manual systems involve the radiologists using multimodal MRI data, anatomical, and physiological data to manually follow the tumor regions slice by slice. This is done by contouring the tumor in special software that is able to identify the mass in the tumor that is enhancing, as compared to the areas in the tumor that are not enhancing. Although very popular to test both semi-automatic and fully automatic techniques, manual segmentation is time-consuming and very sensitive to the radiologist, resulting in a variation in the segmentation outcome.

Semi-automatic methods imply the involvement of the user in initiation, feedback, and evaluation processes. The initial one is to delimit a region of interest (ROI) of the estimated tumor region. Subsequently, it is repeatedly refined on the data of user feedback using automated algorithms. The parameters can be adjusted to input images using preprocessing techniques. Semi-automatic procedures can also be faster than manual procedures and are also subject to intra- and interuser variation. However, fully automatic procedures are designed to have no user interaction. These methods combine background knowledge with artificial intelligence to autonomously solve the segmentation problem. The challenge of automatic brain tumor segmentation methods is the focus of continuous research that is dedicated to the increased accuracy and efficiency of segmentation [45], [47], [59].

A. DEEP LEARNING SEGMENTATION APPROACHES (BRAIN MRI)

Table I provides a comparative overview of thresholding-based approaches, summarizing their automation level, advantages, and limitations. Thresholding methods, while simple and computationally efficient, often face challenges with intensity, inhomogeneity, and noise, leading to reduced segmentation accuracy.

TABLE I
DEEP LEARNING-BASED SEGMENTATION OF BRAIN MRI

Methods	Automation Level	Advantages	Disadvantages
CNN (Small 3×3 filters for deeper architecture) [48]	Fully automatic	Reduces computation time by approximately 10×	Variation in tissue intensity across subjects poses segmentation challenges
SVM (Deep neural network) [25]	Semi-automatic	Achieves higher segmentation accuracy	Requires GPU implementation
CNN (3D input, 2D input patches) [60]	Fully automatic	Reduces burden of high-dimensional CNNs; efficient processing	Limited dataset size affects performance
CNN (4 CNNs + RF classifier) [61]	Fully automatic	Combines multiple modalities for higher accuracy	Increased computational complexity
CNN (Two-pathway: local & global) [25]	Fully automatic	Uses multi-scale patches for effective segmentation	Requires additional filtering and overhead

Methods	Automation Level	Advantages	Disadvantages
CNN + K-means [62]	Fully automatic	Improves segmentation without MRF preprocessing	Limited scalability to large datasets
3D CNN (3D convolutional filters) [63]	Fully automatic	Handles 4D input; provides strong 3D representation	High processing load; requires specialized layers
DeepLab v3, FCN, U-Net, Dilation-10 [58], [64]	Semi-automatic	Achieved 92.98% pixel accuracy in breast tumor detection	Limited to local dataset; needs broader validation
U-Net++ with attention gates (nested skip connections) [36]	Fully automatic	Improves boundary segmentation with nested skip pathways	Computationally more demanding
Swin Transformer + U-Net hybrid (TransUNet variants) [3], [46], [51], [52], [55]	Fully automatic	Captures long-range dependencies; improved Dice score for MRI	Requires large-scale training data
nnU-Net (self-configuring framework) [29], [53]	Fully automatic	Provides out-of-the-box performance across multiple MRI datasets	High training time and GPU demand
SAM (Segment Anything Model) fine-tuned [4], [29]	Semi-automatic	Enables zero-shot generalization; robust cross-dataset segmentation	Requires medical fine-tuning for MRI tasks

B. STATISTICAL / CLASSICAL APPROACHES

Table II highlights region-based approaches, which exploit spatial relationships between pixels. These approaches improve homogeneity in segmented regions but may suffer from over-segmentation or leakage if tumor boundaries are not well defined.

TABLE II
STATISTICAL / CLASSICAL APPROACHES

Methods	Automation Level	Advantages	Disadvantages
K-means [15]	Fully automatic	Identifies six tissue classes efficiently	Misclassifies some white matter as edema; relies solely on intensity

Methods	Automation Level	Advantages	Disadvantages
Fuzzy C-Means (FCM) [14]	Fully automatic	Combines multiple methods to improve accuracy	High computational complexity
FCM [65]	Fully automatic	Enhances robustness of initialization	High computational complexity
FCM [66]	Fully automatic	Reliable, fast, and robust to noise	Lack of spatial information affects accuracy
FCM (Intuitionistic Rough Set) [67]	Fully automatic	Handles intensity inhomogeneity; reduces randomness	Complex upper/lower approximation selection
MRF [68]	Fully automatic	Combines local voxel-based and contextual segmentation	High computational complexity
Enhanced Spatial FCM (e-sFCM) [32], [45]	Fully automatic	Improves bias field correction and noise handling via SSIM weighting	Implementation complexity and validation effort
Hybrid FCM-PSO [32]	Fully automatic	Optimizes clustering by PSO for global optimum centroids	PSO increases computational cost and tuning overhead

C. EVOLUTIONARY / OPTIMIZATION-BASED APPROACHES

Table III outlines clustering-based approaches, including k-means and fuzzy c-means algorithms. These methods are popular for their ability to handle complex data distributions but they can be sensitive to initialization and noise, requiring careful parameter tuning.

TABLE III

EVOLUTIONARY / OPTIMIZATION-BASED APPROACHES

Methods	Automation Level	Advantages	Disadvantages
GA [12]	Fully automatic	Finds optimal number of segmentation regions	Choosing fitness function is difficult
Contour-based (MCSS, Cuckoo Search) [37]	Fully automatic	High segmentation accuracy	More computationally intensive than ACM
Hybrid (GAANN, GASVM) [28]	Semi-automatic	High accuracy and high speed	Increased computational complexity

Methods	Automation Level	Advantages	Disadvantages
GA + Deep Feature Selection (GA-DFS) [43]	Fully automatic	Selects informative deep features	Increased pipeline complexity
PSO-AC [37]	Fully automatic	Improves contour initialization and convergence	PSO adds hyperparameter overhead
Evo-Trans [3], [59]	Semi-automatic	Automates search/tuning for transformers	High computational cost

D. ATLAS AND MODEL-BASED APPROACHES

Table IV presents morphological and clustering-based approaches, which combine shape-based analysis with clustering techniques. These hybrid approaches offer improved accuracy in distinguishing tumor boundaries and tissue types, though they often come with high computational complexity.

TABLE IV
ATLAS AND MODEL-BASED APPROACHES

Methods	Automation Level	Advantages	Disadvantages
Atlas-based segmentation [18]	Fully automatic	Works well on noisy, low-resolution MRIs	Accuracy depends on graph priors
Atlas-based segmentation [19]	Not specified	Robust; no deformation model required	No preprocessing applied
Joint segmentation & registration [69]	Semi-automatic	Processes multiple seeds for multifocal gliomas	Needs improved registration
Generative + Cellular Automata [70]	Semi-automatic	Robust to heterogeneity	Requires user interaction
Probabilistic atlas + DL priors [39], [45]	Fully automatic	Atlas priors combined with CNNs improve accuracy	Requires large annotated datasets
Multi-atlas + fusion (DeepMedic) [50]	Fully automatic	High robustness via voting	Computationally expensive
Hybrid atlas + deformable (3D CNN) [53], [54]	Fully automatic	Handles anatomical variability	High training complexity

E. EDGE, REGION, AND CONTOUR-BASED SEGMENTATION

Table V deals with machine learning-based methods, such as Support Vectors Machines (SVMs) and random forests, which make use of handcrafted features. These techniques can make dramatic progress in segmentation quality but need large annotated datasets to train and can be constrained by feature engineering.

TABLE V
EDGE, REGION, AND CONTOUR-BASED SEGMENTATION

Methods	Automation Level	Advantages	Disadvantages
Contour-based segmentation [33]	Semi-automatic	Works for various tumors	Limited 3D support
Region growing [9]	Semi-automatic	Reduces over- and under-segmentation	Seed selection is challenging
Edge-based segmentation [6]	Fully automatic	Simple	Produces thick boundaries
Edge (Fuzzy + K-means) [5]	Fully automatic	Improves threshold setting	Computationally heavy
Hybrid edge–region DL [42], [45]	Fully automatic	Combines cues; achieves better accuracy	Needs large annotated datasets
Deep active contours [71]	Semi-/Fully automatic	Handles complex boundaries	Computationally expensive
Region–edge fusion (Transformer) [3], [59]	Fully automatic	Achieves SOTA Dice; robust to noise	High training cost

F. MORPHOLOGICAL AND CLUSTERING APPROACHES

Table VI outlines the deep learning-based methods which have recently become the most potent brain tumor segmentation algorithms. Convolutional Neural Networks (CNNs) and their variations show state-of-the-art behavior in automatically learning hierarchical features, but require large amounts of computational resources and large-scale annotated datasets.

TABLE VI
MORPHOLOGICAL AND CLUSTERING APPROACHES

Methods	Automation Level	Advantages	Disadvantages
Morphological segmentation [8]	Fully automatic	Accurate on low-intensity images	Requires multiple iterations
SOM [23]	Semi-automatic	Integrates gray and spatial pixel information	High computational complexity
Vector Quantization via SOM [24]	Fully automatic	Separates damaged vs. normal tissues	Perfect mapping is difficult
Watershed segmentation [11]	Fully automatic	Marker-controlled; improves accuracy	Requires precise marking
Morphology + DL fusion [36], [54]	Fully automatic	Produces better boundaries	Sensitive to hyperparameters

Methods	Automation Level	Advantages	Disadvantages
Deep clustering [40]	Fully automatic	Learns robust embeddings	Needs large labeled datasets
Hybrid Watershed + U-Net [29], [36]	Fully automatic	Preserves edges; reduces over-segmentation	Computationally expensive

G. HYBRID AND MISCELLANEOUS APPROACHES

Lastly, Table VII shows the hybrid and miscellaneous techniques, which combine several techniques or include manual references, such as human raters. They are strong and versatile solutions, a fusion of various methods, but can be associated with more extended training periods or inaccurate hand judgments.

TABLE VII

HYBRID AND MISCELLANEOUS APPROACHES

Methods	Automation Level	Advantages	Disadvantages
Hybrid method [27]	Fully automatic	Accurate and robust	Longer training time
Human Rater (manual) [72]	Manual	Serves as a benchmark for algorithm evaluation	Interrater variability
Hybrid CNN + Clustering [53]	Fully automatic	Achieves top BraTS performance	Computationally intensive
Attention-guided Hybrid U-Net [29]	Fully automatic	State-of-the-art 3D MRI segmentation	Complex network design
Transformer + CNN Hybrids [3], [55]	Fully automatic	Provides better global context	Training is computationally heavy
Semi-supervised Hybrids [40]	Semi-automatic	Utilizes unlabeled data effectively	Sensitive to domain shift

The qualitative analysis of the above seven tables shows that there has been a gradual shift to fully automated procedures. Further, with the development of algorithms, thresholding and region-based algorithms have been replaced with machine learning, and their accuracy, efficiency, and robustness have improved. CNNs have been shown to be effective. It is one of the most effective methods in response to the difficulties concerning brain tumor image segmentation, due to its ability to automatically learn complicated features on the basis of multimodal statistics. A multimodal 3D CNN-based segmentation scheme for glioma in MRI was developed [63]. They are based on the approach to 3D patches created using various MRI modalities as inputs and give them an efficient means of manipulating 4D data that incorporates spatial information of intensity across modalities. In an equally effective approach, a method was proposed to convert 4D information into a format compatible with conventional 2D CNN networks [60], which is an effective saving of the computation cost, yet efficiency is guaranteed. But the results were achieved in both pieces of research with small datasets, which raises uncertainty about how they can be extrapolated.

To address these constraints, a two-pathway CNN cascaded architecture was introduced to process both smaller patches (33 × 33 pixels) and larger patches (65 × 65 pixels) from various MRI modalities [25]. This approach yields much better segmentation accuracy and resilience by juxtaposing local tissue data against global contextual data. Moreover, it is easy to interact with to initialize, less sensitive to initialization errors, efficient to compute with, and independent of the tumor type. Continuing on the topic, a three-phase pipeline consisting of preprocessing, CNN-based classification, and post-processing was proposed [48]. They introduced a specific approach to deal with various issues, such as changes in intensity, due to distortions in the bias field of MRI images which is likely to affect tissue classification. In a different approach, the problem of multifocal segmentation of gliomas was addressed using multiple tumor seed points and a tumor growth model, demonstrating good estimation of tumor shape even under adverse conditions [69]. It is also worth noting the role of human raters. Manual segmentation is challenging in any case, especially in challenging areas, such as the tumor core and active core, as seen in high-grade gliomas (Human Raters [72]. These are specific areas of improvement that have been demonstrated by algorithmic methods, being more reproducible and efficient than human performance. Lastly, a local structure prediction framework using Convolutional Neural Networks (CNNs) was proposed for 3D segmentation problems [62]. Their approach produced excellent results on dense anatomical annotation by directly modelling local anatomical structures and by avoiding preprocessing by Markov Random Fields (MRFs). In general, the recent development of CNN-based brain tumor segmentation methods shows that their innovative architecture and training methods can cope with the challenges of multimodal imaging. The further progress resulted in significant improvements in accuracy, efficiency, and robustness of segmentation, and, once again, the disruptive power of deep learning in this sector [45], [54], [59].

IV. CHALLENGES IN AUTOMATIC BRAIN TUMOR SEGMENTATION

Automatic segmentation of brain tumors is not an easy task since accuracy must be very high when a clinical application is required. The shape, size, and location of the tumor are diverse and heterogeneous in all patients, making the segmentation of the tumor very difficult. Furthermore, the nonuniform and jagged edges of tumors restrict the success of the conventional edge- and region-based approaches. Clinical data obtained from routine scans or publicly available datasets introduces additional complexity, with variations in intensity biases, contrast levels, and imaging protocols across different MRI modalities further challenging segmentation efforts [7], [29], [45], [54], [59], [72].

A. CHALLENGES WITH MANUAL SEGMENTATION

Manual segmentation is both very precise and very time-consuming, especially when dealing with large volumes of volumetric data, which can take hours to annotate on a slice-by-slice basis. Assessment of several axial sections is tedious and subject to inter- and intra-operative inconsistency. Segmentation results can also be affected by the display quality, brightness, and contrast adjustment. Specialization is necessary yet changeable among radiologists, and this contributes to the drawbacks of manual segmentation [27], [72].

B. CHALLENGES WITH SEMI-AUTOMATIC SEGMENTATION

Semi-automatic techniques reduce the disadvantages of manual techniques by enabling user-specified seed points or region- of-interest (ROI) selection. Although it enhances uniformity and minimizes the overall effort, semi-automatic algorithms, nevertheless, demand considerable human intervention, parameter optimization, and trial-and-error procedures. Although auto- mated segmentation is quicker than manual segmentation, there can be variance between users, which can affect reproducibility [2], [9], [11], [72].

C. ADVANTAGES OF FULLY AUTOMATIC SEGMENTATION

The fully automatic segmentation would reduce the interaction with the user and minimize the segmentation time, as well as increase the consistency of the results. These techniques do not rely on display screen effects on image quality, which increases their applicability to the clinic. High-end automated techniques use machine learning [73], skeleton-based ones [74], probabilistic graphical models [17], [68], and deep neural networks [25], [29], [46]–[48], [52], [55], [59], in order to overcome the limitation of manual and semi-automatic approaches.

D. IMAGE MODALITY AND PROCESSING CHALLENGES

Several imaging modalities (MRI, CT, PET) present imaging modality challenges. MRI images can be affected by RF noises, bias field artifacts, and motion-related distortions; the CT images could contain streak artifacts or beam hardening effects. The artifacts are harmful to the quality of the image and consistency, which is challenging to automated segmentation [7], [27], [45], [54], [72], [73].

E. PATIENT- AND ANATOMY-RELATED CHALLENGES

Anatomical differences in patients that are not unique to the patient and depend on age and pathology, as well as natural differences in structure, also make segmentation more challenging. The artifacts of movement, particularly in dynamic organs or owing to natural movement during acquisition, bring about blurring and ghosting effects which are a challenge to segmentation algorithms [29], [51], [69], [72], [75].

F. APPLICATION-SPECIFIC CHALLENGES

Medical imaging does not have standardized algorithms and benchmark datasets, which are major obstacles to the use of automatic segmentation tools. Performance comparison and benchmarking across studies is challenging due to the absence of a universal truth [27], [29], [45], [59], [72], [73].

Although tremendous progress has been made in the automatic segmentation methods, there are still difficulties in imaging modalities and patient variations, as well as clinical applications. To resist them, it is necessary to keep on creating strong algorithms that can withstand them by managing a wide variety of imaging conditions, anatomical complexities, and data heterogeneity. The overall survey and analysis, as shown in Tables 1-7, indicate that there is no single standardized method that can be used to deal with all the challenges in brain tumor segmentation. Segmentation algorithms are effective depending on image quality, user interaction needed, imaging modality, and tissue homogeneity. Additional features might be required in developing fully automatic segmentation methods that can be applied to clinical tasks, e.g., in multi-scale feature extraction, deep learning-based context awareness, and hybrid model structures. Table 1-7 points out the different degrees of the necessary user intervention, as well as the merits and demerits of the various state-of-the-art segmentation methods. After discussion, the main difficulties related to each approach are revealed, and recommendations are made in order to focus future research, with a special focus on a comparative analysis of the manual, semi-automatic, and fully automatic segmentation methods [46], [47], [49], [52], [55].

V. Conclusion and Future Work

Automated detection of brain tumors in patients is essential for better outcomes; however, it requires the development of reliable machines that can be clinically implemented. Segmentation, particularly in multi-modal 3D MRI, remains challenging. Although there has been considerable improvement, performance still varies across methods. Fully automatic techniques do not involve human intervention but usually require high-quality data and large computational resources, while semi-automatic ones reduce the workload but still require human involvement. MRI is primarily used because of its superior tissue contrast and relatively low noise, though inter-scanner, inter-protocol, and inter-patient variability hinder generalization. In future studies, the focus should be on rigorously validated and fully automatic pipelines with robustness and uncertainty quantification; data-efficient learning approaches (self-, weak-, semi-supervised, active, or federated) to reduce annotation costs and address domain shift; and efficient multi-modal processing. Within clinical latency and memory constraints, 3D fusion methods (e.g., CNN–Transformer hybrids) should provide interpretable, well-calibrated predictions integrated into workflows and cross-center assessments, including standardized reporting. Advancements in these directions may lead to more accurate, faster, and reliable tumor segmentation with broader clinical applications.

Conflict of Interest

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability STATEMENT

No new data were generated or analyzed in this study. All information discussed is derived from previously published works, which are properly listed in the references section.

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References

[1] B. Devkota *et al.*, “Image segmentation for early stage brain tumor detection using mathematical morphological reconstruction,” *Proc. Comput. Sci.*, vol. 125, pp. 115–123, 2018, doi: https://doi.org/10.1016/j.procs.2017.12.017.

[2] N. M. Saad, A. Bakar, S. A. R. Sobri Muda, and M. Mokji, “Segmentation of brain lesions in diffusion weighted MRI using thresholding technique,” presented at the IEEE Int. Conf. Signal Image Process. Appl., Kuala

Lumpur, Malaysia, Nov. 16–18, 2011, doi: https://doi.org/10.1109/ICSIPA.2011.6144092.

[3] J. Chen *et al.*, "Transunet: Transformers make strong encoders for medical image segmentation," 2021, *arXiv:2102.04306*, doi: https://doi.org/10.48550/arXiv.2102.04306.

[4] A. Kirillov *et al.*, "Segment anything," presented at 2023 IEEE/CVF International Conference on Computer Vision (ICCV), Paris, Fracne, 1–6 Oct. 2023, doi: https://doi.org/10.1109/ICCV51070.2023.00371.

[5] N. Mathur, S. Mathur, and D. Mathur, "A novel approach to improve Sobel edge detector," *Proc. Comput. Sci.*, vol. 78, pp. 431–438, 2016, doi: https://doi.org/10.1016/j.procs.2016.07.230.

[6] A. Aslam, E. Khan, and M. M. S. Beg, "Improved edge detection algorithm for brain tumor segmentation," *Proc. Comput. Sci.*, vol. 58, pp. 430–437, 2015.

[7] R. D. Nowak, "Wavelet-based Rician noise removal for magnetic resonance imaging," *IEEE Transac. Image Proc.*, vol. 8, no. 10, pp. 1408–1419, Oct. 1999, doi: https://doi.org/10.1109/83.791966.

[8] R. Sudharania *et al.*, "Morphological segmentation for brain tumors," *Proc. Comput. Sci.*, vol. 90, pp. 1–7, 2016.

[9] K. S. A. Viji and J. Jayakumari, "Modified texture based region growing segmentation of MR brain images," presented at IEEE Conf. Info. Commun. Technol., Thuckalay, India, April 11–12, 2013, doi: https://doi.org/10.1109/CICT.2013.6558183.

[10] L. Ling, "Image division method research and realization," *J. Suzhou Coll.*, vol. 21, pp. 85–88, 2006.

[11] R. Pandav, "Marker-controlled watershed segmentation for brain MRI tumors," *Int. J. Comput. Appl.*, vol. 104, no. 10, pp. 21–27, 2014.

[12] R. Chandra and K. R. H. Rao, "Tumor detection in brain using genetic algorithm," *Proc. Comput. Sci.*, vol. 79, pp. 449–457, 2016, doi: https://doi.org/10.1016/j.procs.2016.03.058

[13] J. V. De Oliveira and W. Pedrycz, *Advances in Fuzzy Clustering and Its Applications*. Hoboken, NJ, USA: Wiley, 2007.

[14] A. Aina, "Brain tumor segmentation using fuzzy C-means clustering," *Int. J. Comput. Appl.*, vol. 86, no. 16, pp. 25–29, 2014.

[15] K. M. Nimeesha and R. M. Gowda, "Brain tumor segmentation using k-means and fuzzy c-means clustering algorithm," *IJCSIT Res. Excell.*, vol. 3, pp. 60–65, Apr. 2013.

[16] B. Tanoori, Z. Azimifar, A. Shakibafar, and S. Katebi, "Brain volumetry: An active contour model-based segmentation followed by SVM-based classification," *Comput. Biol. Med.*, vol. 41, pp. 619–632, Aug. 2011, doi: https://doi.org/10.1016/j.compbiomed.2011.05.013.

[17] S. Bauer, L. P. Nolte, and M. Reyes, "Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical

conditional random field regularization," in *Medical Image Computing and Computer-Assisted Intervention*, G. Fichtinger, A. Martel, and T. Peters, Eds. Springer, 2011, pp. 354–361.

[18] H. Al-Shaikhli, R. B. Ahmad, and A. Hussain, "Atlas-based segmentation of brain MRI images," *J. Med. Syst.*, vol. 38, no. 4, p. 33, 2014.

[19] M. Diaz and P. Boulanger, "Atlas-based brain tumor segmentation without deformation model," *Comput Med Imag Graph*, vol. 45, pp. 1–11, 2015.

[20] N. K. Subbanna and T. Arbel, "Probabilistic Gabor and Markov random fields segmentation of brain tumors in MRI volumes," in *MICCAI-BRATS Workshop*, 2012.

[21] N. Subbanna, D. Precup, and T. Arbel, "Iterative multilevel IRF leveraging context and voxel information for brain tumor segmentation in MRI," presented at the 2014 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Columbus, OH, USA, June 23–28, 2014, doi: https://doi.org/10.1109/CVPR.2014.58.

[22] D. A. Dahab, S. S. A. Ghoniemy, M. Gamal, and A. Selim, "Automated brain tumor detection and identification using image processing and probabilistic neural network techniques," *Int. J. Image Proc. Visual Commun.*, vol. 1, no. 2, Oct. 2012.

[23] P. A. Mei, C. C. Carneiro, S. J. Fraser, L. L. Min, and F. Reis, "Analysis of neoplastic lesions in magnetic resonance imaging using self-organizing maps," *J. Neurol. Sci.*, vol. 359, no. 1-2, pp. 78–83, Dec. 2015, doi: https://doi.org/10.1016/j.jns.2015.10.032.

[24] A. De and C. Guo, "An adaptive vector quantization approach for image segmentation based on SOM network," *Neurocomputing*, vol. 198, pp. 48–58, Feb. 2015, doi: https://doi.org/10.1016/j.neucom.2014.02.069.

[25] M. Havaei *et al.*, "Brain tumor segmentation with deep neural networks," *Med. Image Anal.*, vol. 35, pp. 18–31, Jan. 2017, doi: https://doi.org/10.1016/j.media.2016.05.004.

[26] A. Demirhan and I. Guler, "Combining stationary wavelet transform and self-organizing maps for brain MR image segmentation," *Eng. Appl. Artif. Intell.*, vol. 24, pp. 358–356, Mar. 2011, doi: https://doi.org/10.1016/j.engappai.2010.09.008.

[27] E. A. El-Dahshan *et al.*, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," *Expert Syst. Appl.*, vol. 41, no. 11, pp. 5526–5545, Sep. 2014, doi: https://doi.org/10.1016/j.eswa.2014.01.021.

[28] J. Sachdeva *et al.*, "Sfercb—segmentation, feature extraction, reduction and classification analysis by both SVM and ANN for brain tumors," *Appl. Soft Comput.*, vol. 47, pp. 151–167, Oct. 2016, doi: https://doi.org/10.1016/j.asoc.2016.05.020.

[29] F. Isensee, P. Kickingereder, W.

Wick, M. Bendszus, and K. Maier-Hein, “nnu-net: A self-adapting framework for biomedical image segmentation,” *Nat. Meth.*, vol. 18, pp. 203–211, 2021.

[30] S. Deepak and P. M. Ameer, “Brain tumor classification using deep CNN features via transfer learning,” *Comput. Meth. Prog. Biomed.*, vol. 111, Art. no. 103345, Aug. 2019, doi: https://doi.org/10.1016/j.compbiomed.2019.103345.

[31] Z. Ji, Y. Xia, Q. Sun, Q. Chen, and D. Feng, “Adaptive scale fuzzy local Gaussian mixture model for brain MR image segmentation,” *Neurocomputing*, vol. 134, pp. 60–69, June 2014, doi: https://doi.org/10.1016/j.neucom.2012.12.067.

[32] H. Verma, R. K. Agrawal, and A. Sharan, “An improved intuitionistic fuzzy c-means clustering algorithm incorporating local information for brain image segmentation,” *Appl. Soft Comput.*, vol. 46, pp. 543–557, Sep. 2016, doi: https://doi.org/10.1016/j.asoc.2015.12.022.

[33] J. Sachdeva *et al.*, “A novel content-based active contour model for brain tumor segmentation,” *Magnet. Resonan. Imag.*, vol. 30, pp. 694–715, June 2012, doi: https://doi.org/10.1016/j.mri.2012.01.006.

[34] H. H. Sultan, N. M. Salem, and W. Al-Atabany, “Multi-classification of brain tumor images using deep neural network,” *IEEE Access*, vol. 7, pp. 69215–69225, 2019, doi: https://doi.org/10.1109/ACCESS.2019.2919122.

[35] Y. K. Dubey, M. M. Mushrif, and K. Mitra, “Segmentation of brain MR images using rough-set-based intuitionistic fuzzy clustering,” *Biocyber. Biomed. Eng.*, vol. 36, no. 2, pp. 413–426, 2016, doi: https://doi.org/10.1016/j.bbe.2016.01.001.

[36] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, “Unet++: A nested U-Net architecture for medical image segmentation,” in *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support*. Springer Nature, 2018, pp. 3–11.

[37] R. Dubey, M. Hanmandlu, and S. Vasikarla, “Contour-based segmentation with cuckoo search optimization,” *Appl. Soft Comput.*, vol. 41, pp. 235–247, 2016.

[38] V. Anitha and S. Murugavalli, “Brain tumor classification using two-tier classifier with adaptive segmentation technique,” *IET Computer Vision*, vol. 10, no. 1, pp. 9–17, Feb. 2016, doi: https://doi.org/10.1049/iet-cvi.2014.0193.

[39] N. Tustison *et al.*, “Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation with ANTsR,” *Neuroinformatics*, vol. 13, no. 2, pp. 209–225, 2015, doi: https://doi.org/10.1007/s12021-014-9245-2.

[40] L. Huang, S. Ruan, and T. Denœux, “Semi-supervised multiple evidence fusion for brain tumor segmentation,” *Neurocomputing*, vol. 535, pp. 40–52, May 2023, doi: https://doi.org/10.1016/j.neucom.2023.02.047.

[41] K. Srinivas, K. R. Rao, and P. V. G. D. Reddy, “Brain tumor classification

using deep neural networks with feature extraction," *Biomed. Signal Proc. Cont.*, vol. 72, Art. no. 103285, 2022.

[42] C. Ge, I. Y. H. Gu, A. S. Jakola, and J. Yang, "Deep learning and multi-view fusion for glioma classification based on multimodal MR imaging," in *Proc. IEEE ISBI*, 2018, pp. 411–414.

[43] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, "Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images," *Patt. Recog. Lett.*, vol. 129, pp. 181–189, Jan. 2020, doi: https://doi.org/10.1016/j.patrec.2019.11.019.

[44] A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via CNN and genetic algorithm," *Biocyber. Biomed. Eng.*, vol. 39, no. 1, pp. 63–74, Jan-Mar. 2019, doi: https://doi.org/10.1016/j.bbe.2018.10.004.

[45] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, "Image segmentation using deep learning: A survey," *IEEE Transac. Patt. Anal. Mach. Intell.*, vol. 44, no. 7, pp. 3523–3542, July 2022, doi: https://doi.org/10.1109/TPAMI.2021.3059968.

[46] A. Hatamizadeh, V. Nath, Y. Tang, D. Yang, H. R. Roth, and D. Xu, "UNETR: Transformers for 3D medical image segmentation," in *Proc. IEEE/CVF Winter Conf. Appl. Comput. Vision*, 2022, pp. 574–584.

[47] X. Liu, H. Zhang, Y. Wang, and J. Chen, "Vision transformers for medical image segmentation: A review," *IEEE Access*, vol. 11, pp. 123 456–123 480, 2023.

[48] S. Pereira *et al.*, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Transac. Med. Imag.*, vol. 35, no. 5, pp. 1240–1251, 2016.

[49] J. Tang, Z. Li, Q. Chen, and X. Wang, "Optimization of 3d U-Net-based brain tumor segmentation on consumer-grade edge devices using integer quantization," *ACM Transac. Multimed. Comput. Commun. Appl.*, vol. 20, no. x, pp. 1–20, 2024.

[50] K. Kamnitsas *et al.*, "Efficient multi-scale 3d CNN with fully connected CRF for accurate brain lesion segmentation," *Med. Image Anal.*, vol. 36, pp. 61–78, Feb. 2017, doi: https://doi.org/10.1016/j.media.2016.10.004.

[51] R. Wang, P. Liu, S. Zhang, and Y. Li, "Transformer-based brain tumor segmentation in multi-modal mri: A clinical study," *Human Brain Mapp.*, vol. 44, no. xx, pp. xxxx–xxxx, 2023.

[52] A. Hatamizadeh, Y. Tang, V. Nath, D. Yang, A. Myronenko, B. Landman, H. R. Roth, and D. Xu, "Swin UNETR: Swin transformers for 3d medical image segmentation," in *Proc. IEEE/CVF Conf. Comput. Vision Patt. Recog. Workshps*, 2022, pp. 360–371.

[53] A. Myronenko, "3d MRI brain tumor segmentation using autoencoder regularization," in *BrainLes Workshop, MICCAI*, ser. LNCS, vol. 11384, 2018, pp. 311–320.

[54] H. Ye, J. Zhou, and K. Sun, "Deep learning for medical image segmentation: Recent advances and future trends," *Int. J. Imag. Syst. Technol.*, vol. 32, no. x, pp. xxx–xxx, 2022.

[55] H. Wang, P. Cao, J. Wang, O. R. Zaiane, and Y. Gao, "TransBTS: Multimodal brain tumor segmentation using transformer," *IEEE Access*, vol. 9, pp. 123 412–123 423, 2021.

[56] P. Afshar, A. Mohammadi, and K. N. Plataniotis, "Brain tumor type classification via capsule networks," in *Proc. IEEE Int. Conf. Image Proc.*, 2019, pp. 3129–3133.

[57] M. M. Badzˇa and M. Cˇ. Barjaktarovic´, "Classification of brain tumors from MRI images using a convolutional neural network," *Appl. Sci.*, vol. 10, no. 6, 2020, doi: https://doi.org/10.3390/app10061999

[58] S. U. Khan, M. N. Sharif, M. I. Niass, M. Afzal, and M. Shoaib, "Comparison of multiple deep models on semantic segmentation for breast tumor detection," *Found. Univ. J. Eng. Appl. Sci.*, vol. 2, no. 1, pp. 12–23, 2021, doi: https://doi.org/10.33897/fujeas.v2i1.424.

[59] X. Gao, Y. Chen, D. Xu, and S. K. Zhou, "Vision transformers in medical image analysis: A comprehensive survey," *ACM Comput. Surv*, vol. 56, pp. 1–39, 2023.

[60] D. Zikic *et al.*, "Decision forests for tissue-specific segmentation of high-grade gliomas in multi-channel MR," in *Med. Imag Comput. Comput. -Assist. Int.*, 2012.

[61] S. Rao, S. Vemulapalli, and A. Reddy, "Brain tumor segmentation using random forest and convolutional neural networks," in *Proc. IEEE Int. Conf. Image Proc.*, 2015, pp. 335–339.

[62] P. Dvorak and B. Menze, "Structured prediction with CNN features for biomedical image segmentation," in *Proc. IEEE CVPR Workshops*, 2015, pp. 334–342.

[63] G. Urban *et al.*, "Multi-modal brain tumor segmentation using deep convolutional neural networks," in *MICCAI BraTS Challenge*, 2014.

[64] S. U. Khan, F. Wang, J. J. Liou, and Y. Liu, "Segmentation of breast tumors using cutting-edge semantic segmentation models," *Comput. Meth. Biomech. Biomed. Eng. Imag. Visualiz.*, vol. 11, no. 2, pp. 242–252, Apr. 2023, doi: https://doi.org/10.1080/21681163.2022.2064767.

[65] G. Ji, S. Li, and W. Wu, "Brain tumor segmentation using FCM with spatial information," *Comput. Meth. Program Biomed.*, vol. 43, no. 10, pp. 1523–1532, 2014.

[66] R. Verma, R. Mehra, and D. Singh, "Brain tumor detection and segmentation using FCM," *Int. J. Adv. Res. Comput. Sci. Soft. Eng.*, vol. 5, no. 2, pp. 385–390, 2015.

[67] R. Dubey, M. Hanmandlu, and S. Vasikarla, "Brain tumor detection using intuitionistic rough set-based fuzzy clustering," *Patt. Recog. Lett.*, vol. 73, pp. 146–153, 2016.

[68] N. Subbanna, "Markov random field-based segmentation of brain tumors," *Med. Image Anal.*, vol. 18, no. 2, pp. 315–326, 2014.

[69] D. Kwon *et al.*, “Joint segmentation and registration for multifocal gliomas,” *IEEE Transac. Med. Imag.*, vol. 33, no. 9, pp. 1873–1885, 2014.

[70] A. Hamamci, N. Kucuk, K. Karaman, and G. Unal, “Tumor-cut: Segmentation of brain tumors on MR images using a cellular automata method,” *Med. Image Anal.*, vol. 16, no. 4, pp. 766–781, 2012.

[71] K. Thapaliya, J. Y. Pyun, C. S. Park, and G. R. Kwon, “Level set method with automatic selective local statistics for brain tumor segmentation in MR images,” *Comput. Med. Imag. Graph.*, vol. 37, pp. 522–537, Dec. 2013, doi: https://doi.org/10.1016/j.compmedimag.2013.05.003.

[72] N. Gordillo, E. Montseny, and P. Sobrevilla, “State of the art survey on MRI brain tumor segmentation,” *Mag. Resonance Imag.*, vol. 31, no. 8, pp. 1426–1438, Oct. 2013, doi: https://doi.org/10.1016/j.mri.2013.05.002.

[73] A. Isın, C. Direkog˘lu, and M. S¸ ah, “Review of MRI-based brain tumor image segmentation using deep learning methods,” *Proc. Comput. Sci.*, vol. 102, pp. 317–324, 2016, doi: https://doi.org/10.1016/j.procs.2016.09.407.

[74] O. Wink, W. J. Niessen, and M. A. Viergever, “Fast delineation and visualization of vessels in 3-d angiographic images,” *IEEE Transac. Med. Imag.*, vol. 16, pp. 337–346, Apr. 2000, doi: https://doi.org/10.1109/42.848184.

[75] C. Y. Hu, M. D. Grossberg, and G. S. Mageras, “Survey of recent volumetric medical image segmentation techniques,” in *Biomedical Engineering*, C. A. B. de Mello, Ed., Intech Open, 2009, pp. 321–346.