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Brain tumor segmentation and classification: A one-decade review

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Abstract

Image segmentation is a common technique in digital image processing and analysis that partitions an image into several regions or zones, frequently based on the pixels' attributes. Brain tumor segmentation is a crucial task in medical image processing. Early identification of brain tumors enhances treatment options and increases the patient's chance of survival. Brain segmentation from a significant number of MR images obtained in medical treatment is a challenging and time-consuming assignment for cancer diagnosis and other brain diseases. That is why it is crucial to establish an efficient automatic image segmentation system for the diagnosis of brain tumors and other prevalent nervous diseases. The goal of this research is to undertake a systematic review of MRI-based brain tumor segmentation approaches. Deep learning techniques have proven useful for automatic segmentation in recent years and gained prominence, as these methods produce superior results and are thus better suited to this task than other methods. Deep learning algorithms may also be used to process enormous volumes of MRI-based image data quickly and objectively. Many review papers on traditional MRI-based brain tumor image segmentation algorithms are available.

Keywords: brain tumor, denoising, Magnetic Resonance Imaging (MRI), Convolutional Neural Networks (CNN), Deep Learning (DL), segmentation, classification
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1 Introduction

Over the last few years, advances in the image processing and computer vision fields have aided humanity in the computer - aided diagnosis of a variety of diseases [21, 47, 65]. Image enhancement, image segmentation, object identification, and image classification technologies have garnered considerable attention recently, and they're mostly used in disease diagnosis and early treatment planning [26]. Any abnormality in the brain has the potential to endanger human health. Brain tumors are the most serious of these disorders. Brain tumors are unregulated and unnatural cell proliferation in the brain that fall into two categories: primary tumors and secondary tumors [36, 37, 41].

The examination of the cerebrum MR images manually is a demanding job due to the large quantity of information contained in each image. To address this issue, automatic approaches for examining brain MRI images have been

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developed [10]. Computer vision-based biomedical imaging technology has attracted more and more interest because it provides radiologists with recognition information for more effective treatment. Recently, many medical imaging techniques and procedures that have a substantial influence on patient diagnosis and treatment include X-ray, magnetic resonance imaging, computed tomography (CT), and ultrasound. These have undergone many developments to make them more accurate and use them more widely to diagnose diseases and predict their occurrence [55].

MRI is considered a non- surgical imaging technique that offers high-resolution structural information about human organs' soft tissues. MRI is a good and safe way to image the human brain, and it can help detect a variety of diseases such as spinal cord injuries, strokes, infections, tumors, cysts, edema, and more [35, 40, 62, 72]. Before undertaking any treatment, brain tumor segmentation entails identifying, defining, and separating tumor tissues. It's critical to segment the tumor so that healthy tissues are protected while malignant cells are destroyed during treatment. Manual annotation and segmentation of a huge number of multimodal MRI images in medical care are now part of this initiative. Because manual segmentation is considered a conservative technique taking long processing time, adopting an automated and error-free tumor detection method to assist clinicians in detecting brain tumors is critical [8, 31, 34, 37, 59].

The detection, segmentation, and categorization of brain tumors are critical in minimizing the likelihood of surgery (biopsy). When radiologists are confused about the type of a tumor or want to perform a complete visual study of it, they can use this technique [27, 45, 59].

A tumor is identified by its size, position, and location, which aid in determining its stage, which ranges from grade I to IV [42]. The tumor's grade determines whether the tumor is benign or malignant. Tumors classified as grade IV are the most dangerous, whereas tumors classified as grade I (early diagnosis) are easily treatable [20].

When segmented manually, tumors can vary greatly in shape, size, location, and characteristics. Furthermore, the tumor's levels of intensity are comparable to those of normal brain tissue. When a tumor develops, It regularly deforms healthy tissues in the surroundings, resulting in an aberrant size and shape. For efficient tumor segmentation, an automatic tumor segmentation approach has been proposed to overcome these constraints [9, 56, 73].

Tumors are classified as either cancerous (malignant tumors) or noncancerous (benign tumors). Even though they develop fast and spread to other areas of the brain and spine, malignant brain tumors are more life-threatening than benign tumors. Because of their placement in the human body's neurological system, benign tumors can incapacitate the brain and cause permanent harm [5]. A broad study that explores and discusses all relevant methods of brain tumor segmentation and classification is important. This review research aims to provide a fresh look at the brain tumor segmentation and classification literature.

2 Magnetic Resonance Imaging (MRI)

Despite significant advances in advanced imaging methods over the last several decades, structural magnetic resonance imaging (MRI) is still regarded the gold standard in neuro-oncology [69].

Magnetic resonance imaging (MRI) is the ideal technique for studying structural and functional brain, spinal cord, and vascular anatomy because it provides images with excellent contrast for soft tissues and great spatial resolution.

It also poses no known health hazards. Quantitative analysis of brain MRI has been used to characterize brain disorders such as Alzheimer's disease, benign tumors, malignancies, epilepsy, infectious and degenerative diseases.

The segmentation of MR images taken at multiple time points is required for quantifying changes in brain structures. Furthermore, the discovery and accurate placement of the aberrant tissue and surrounding healthy tissues are crucial for diagnosis, surgical planning, postoperative analysis, and radiation therapy planning [2].

Automated and efficient brain tumor segmentation MRI images are technically complex due to a variety of issues. Image intensity profiles, which frequently overlay with nearby healthy tissue, are used to define tumor areas. Tumors can grow in any region of the brain and can be of various shapes and sizes. Finally, studies utilizing multimodal MRI volumes such as T1, T1c, T2, and FLAIR, shown in Figure 1, are required in order to collect rich biological information and better segmentation by applying a unique label to each kind of tissue [2, 69]. Table 1 provides an overview of several MRI methods and their clinical utility.

3 Search strategy, data abstraction and analysis

A comprehensive search for a variety of relevant topics was conducted from the beginning of October 2021, and it was updated in December 2021. Subject headings, keywords, standardized index terms, abstracts, and results were

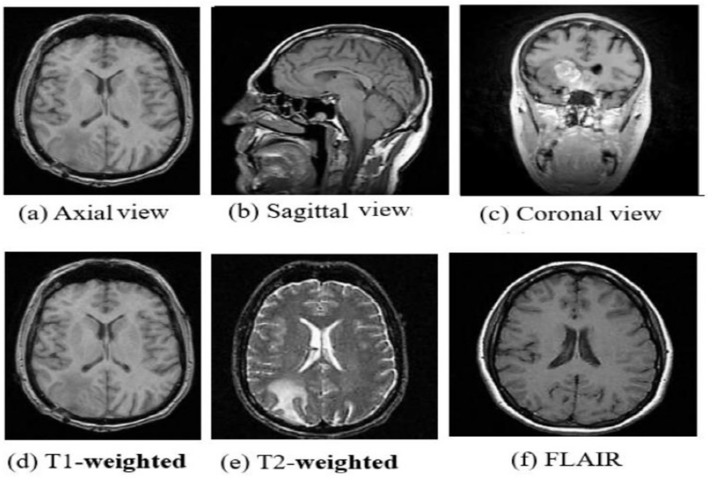

Figure 1: (a) Axial view, (b) Sagittal view, (c) Coronal view and T1-weighted, (e) T2-weighted, and (f) FLAIR Images of MRI. (Image Courtesy: AtheroPoint^{TM}).

Table 1: MRI Techniques in Brain Tumor Imaging and Their Applications [69]

MRI technique	Clinical utility
T1	Evaluates tissue architecture
	· Precontrast high intensity seen in blood products, mineralization, fat, melanin
	· Postcontrast enhancement reflects nonspecific breakdown of the blood–brain barrier
T2/FLAIR	Evaluates tissue architecture
	· High intensity seen in peritumoral edema (vasogenic and infiltrative), nonenhancing tumor, white matter injury, gliosis
T2* (SWI)	Sensitive to magnetic susceptibility
	· Low intensity seen in blood products, tumoral vascularity, calcification, radiation-induced microhemorrhage
DWI	Probes random motion/diffusion of water, can be presented as ADC map
	· Reduced (high signal intensity) in highly cellular tumor or regions of tumor with increased cellularity and in cytotoxic edema or postoperative injury
MRS	Assesses tumor biochemical/metabolic profile
	· Tumor spectra include elevated Cho, decreased NAA; higher grade glioma show higher Cho/NAA and Cho/Cr ratios than lower grade gliomas
	· Lipid and lactate peaks are not normal and represent necrosis and hypoxia, respectively
Perfusion	DSC—main metric is cerebral blood volume
	· Perfusion curves in gliomas should return close to baseline, perfusion curves in tumors with leaky capillaries (metastases, choroid plexus tumors, extra-axial tumors) generally do not return to baseline
	· Higher blood volume suggests higher grade or progressive/recurrent tumor
	DCE—main metric is the volume transfer constant, a measure of permeability
	· High permeability suggests higher grade and within a tumor may identify regions of higher grade as well or progressive/recurrent tumor
	ASL—main metric is cerebral blood flow
	· Noncontrast technique
	· Higher blood flow can be used for tumor grading or to identify progressive/recurrent tumor
DTI	Analyzes direction of diffusivity and orientation of white matter tracts
	· Tractography demonstrates displacement or infiltration of white matter fiber tracts for surgical planning
fMRI	Assesses brain activation by detecting alterations in blood oxygenation level
	· Task-based fMRI is used for preoperative functional localization
	· Resting-state-fMRI is primarily a research technique

ADC, apparent diffusion coefficient; ASL, arterial spin labeling; Cho, choline; Cr, creatine; DCE, dynamic contrast enhanced; DSC, dynamic susceptibility contrast; DTI, diffusion tensor imaging; DWI, diffusion-weighted imaging; FLAIR, fluid-attenuated inversion recovery; fMRI, functional magnetic resonance imaging; MRS, magnetic resonance spectroscopy; NAA, I, susceptibility-weighted imaging

used to develop the search methods. The researchers looked into studies that developed or validated brain tumor segmentation for the diagnosis of brain tumors using either one or a combination of different methodologies. Only studies that employed MRI-based medical imaging were considered for inclusion. All citations have been downloaded into Mendeley reference manager [78], IEEE Xplore, Springer, Science Direct, MDPI, PubMed, Frontiers, Scopus, and

Google Scholar were among the databases comprehensively investigated for this study.

Data were abstracted from all review papers that met eligibility criteria, including evaluation data, testing results, prior studies, and current and previous related works; discrepancies were resolved through further discussion. Studies were excluded if they did not report brain tumor segmentation or classification events by using magnetic resonance images. We considered that if two or more studies produced different results for the same or different algorithms, they were assumed to be independent of one another. The study's purpose was to offer an analytical summary of multiple investigations rather than precise point estimations, so this assumption was accepted. Table 2 provides a list of review articles included in this study.

Table 2: Previous review studies

No:-	Reference	Database\Dataset	Publication year	Aim
1.	[41]	BrainWeb BRATS 2012 IBSR	2014	overview for MRI-based brain tumor segmentation methods.
2.	[51]	BRATS 2012 BRATS 2013 BRATS 2013 BRATS 2014 BRATS 2015 DICOM Harvard Hospital Dataset IBSR NCI-MICCAI 2013 PGIMER PIMS Web resource	2018	Survey for brain tumor grade classification.
3.	[71]	BRATS 2013 BRATS 2015 BRATS 2017	2019	Review for brain tumor segmentation.
4.	[44]	ADNI BRATS 2015 BRATS 2018 CAMELYON17 HVSMR 2016 ISIC 2018 ISLES 2018 OpenNeuro TCIA UK Biobank	2019	overview of deep learning methodologies in medical imaging with focusing on MRI.
5.	[55]	BRATS 2012 BRATS 2013 BRATS 2013 BRATS 2014 BRATS 2015 BRATS 2016 BRATS 2017 BRATS 2018 BRAINIX Figshare Cheng 2017 Hospital Dataset IBSR TCIA TCGA Web resource	2020	Review and Analysis of Brain Tumor Empowered with Deep Learning.

6.	[67]	ABIDE Brain Web BRAINIX BRATS 2015 BRATS 2016 BRATS 2017 BRATS 2018 DICOM Harvard IBSR ISLES 2015 PGIMER Rider SPL TCIA	2020	Review for brain tumor segmentation and classification.
7.	[24]	ADNI BRATS 2018 IXI Dataset REMBRANDT TCGA-GBM TCGA-LGG Web resource	2020	review of brain disease detection based on deep learning techniques.
8.	[13]	ADNI BrainWeb BRATS 2013 BRATS 2014 BRATS 2015 BRATS 2017 BRATS 2018 BRATS 2019 Figshare Local dataset MICCAI 2015 Rembrandt TCIA	2021	Review of brain tumor segmentation and classification models, with an emphasis on region growth, machine learning, and deep learning.
9.	[46]	BRATS 2012 BRATS 2013 BRATS 2014 BRATS 2015 BRATS 2016 BRATS 2017 BRATS 2018 BRATS 2019 Decathlon	2021	A review at the most up-to-date deep learning approaches for segmenting brain tumors.

4 Convolutional Neural Networks Architecture

Convolutional Neural Networks (CNNs) are multi-layer, fully trainable models capable of capturing exceedingly nonlinear input-output mappings. These models are well-suited to image-related applications as they were inspired by computer vision issues [25, 64].

Convolutional networks are frequently employed for image classification tasks, with a single class label serving as the output. However, the intended output in many visual tasks, especially in medical image processing, should also include localization, which implies that each pixel should be assigned a class name [61].

CNNs have been shown to be effective at processing medical and natural images [64], such as image segmentation, object recognition, and object localization in medical image analysis [19, 23]. CNN architectures have demonstrated significant generalizability for image classification. As a result, CNN designs may be adaptable enough to be used for a wide range of applications with only minor modifications [38]. For MRI segmenting, CNNs have the benefit of being able to dynamically Integrate and combine multi-modality brain images in real time. To build segmentation maps, CNNs employed complementary and multi-modality information from T1, T2, and FA photos as inputs and outputs [25].

In general, In CNN training, the forward and back-propagation phases are the two fundamental processes. The image is fed into the network in the first phase, and the inputs and weights are multiplied; the convolution operation is applied to each layer to form the network output in the second phase. After that, the output result is used to estimate network error, which is then used to modify network settings. The result is compared to the ground truth using an error function to identify the network error. The back-propagation stage then begins, where the gradient of each parameter is computed and all parameters are adjusted to find an optimal rate, depending on the error rate. This process is continued until the halting requirements are satisfied [33].

CNN architecture contains subsequent layers of convolution, pooling, activation, and classification. By convolving a kernel over the input image, the convolutional layer generates feature maps. The maximum or average of the defined neighborhood is utilized as the value supplied to the next layer by the pooling layer to down sample the output of preceding convolutional layers [2, 12, 58].

The output scores of the final CNN layer are coupled to a loss function to accomplish an input data prediction (e.g., cross-entropy loss that normalizes scores into multinomial distribution over labels) [74].

On a collection of manually segmented data in the networks, millions of trainable parameters were changed. Patches centered on a pixel were utilized as inputs, and the tissue class of the central pixel was outputted. This allowed all pixels in the vicinity to decide a pixel's segmentation results [50, 61].

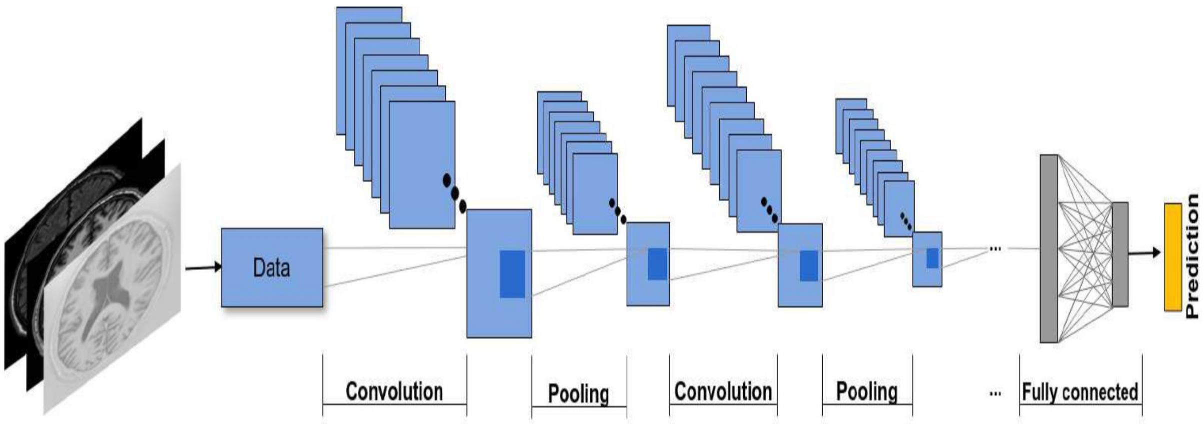

Figure 2: Generic architecture of convolutional neural networks [12]

5 Preprocessing

In the medical field, preprocessing seems to be the most vital phase. Typically, image noise reduction or enhancement occurs during preprocessing. Medical noises would definitely increase the uncertainties in measuring processes and severely decrease the image quality, rendering them diagnostically useless. The preprocessing phase must be efficient enough to remove as much noise as possible while preserving crucial image elements, this will aid in the segmentation of medical imaging that is influenced by pathology [52].

Image enhancement and noise reduction were investigated in a number of studies in order to enhance an image's quality for better visualization. Several noise reduction and image enhancing techniques are employed. Developing a successful image enhancement system requires, in most circumstances, a detailed grasp of the underlying image modalities. For MR image denoising and enhancement, D. Ray et al. suggested an adaptive multiscale data condensation (MDC) technique. The technique is focused on choosing representative neighborhoods based on the information content of the complete filter mask. Information's content is calculated based on its characteristics and relative location inside a search window. When dealing with Rican noise, it outperforms both the Wiener Filter and the Wavelet Transform [60].

Many strategies have been developed to improve filters by efficiently decreasing noise while preserving data edges. To preserve edges, Da Silva et al. presented a denoising approach based on wavelet transformations. The image is divided into blocks, and the data is then translated into the wavelet domain. To efficiently eliminate noise while maintaining key characteristics of the original image, an adaptive thresholding approach based on edge strength is used [17].

Amiri Golilarz et al. present a wavelet-based de-noising approach for MRI brain images. To improve the performance of typical soft and hard threshold functions for image de-noising in the wavelet domain, adaptive soft and hard threshold functions are presented initially. After that, an adaptive generalized Gaussian distributed oriented threshold function is used on the MRI images to improve the outcomes of the adaptive soft and hard threshold functions [4].

Image denoising can benefit from the deployment of a deep convolutional neural network. K. Zhang et al. presented an image denoising technique using a deep convolutional neural network with residual learning to separate noise from noisy observations. Batch normalization and residual learning are combined to speed up the training process and increase denoising performance. Several strategies were utilized in network construction and training to provide rapid and effective discriminative denoising, such as using a noise level map as input and denoising in down-sampled sub-image space [75, 76].

Chang, Y., et al. presented a two-stage convolutional neural network for represent both of the image and the noise at the same time, with both components handled equally. The proposed cascading CNN model is designed to adapt to diverse noise categories and levels [15].

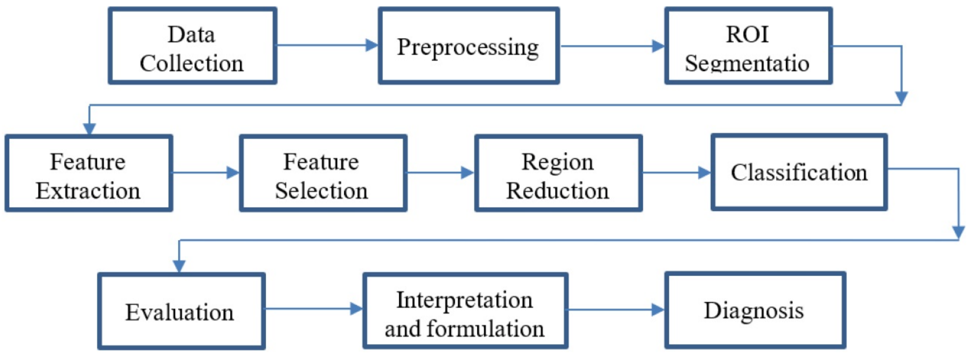

Figure 3: Block Diagram of Brain tumor identification

6 Segmentation

Image segmentation has been a major challenge for computer vision researchers since the field's beginnings. Image segmentation can be thought of as the challenge of providing semantic labels to pixels, separating specific objects, or both. Because semantic segmentation involves pixel-level labeling using a set of item categories for all image pixels, it is more complex than whole-image classification. Convolutional networks have also changed semantic segmentation problems. Because CNNs are more intuitive when it comes to object classification, they are a better choice. Instance segmentation broadens the scope of semantic segmentation by recognizing and defining each object of interest in a picture [3, 6, 32, 49].

The segmentation of brain tumors using neuroimaging modalities is a crucial step in enhancing disease diagnosis, monitoring, treatment strategy, and clinical trials. Accurate segmentation is essential to determine the position and extent of a brain tumor. Manual segmentation of magnetic resonance (MR) images, on the other hand, is a time-consuming and costly operation. Moreover, there is inter- and intra-observer heterogeneity in manual labeling. The limitations of manual techniques make labeling large groups of participants, which is commonly necessary for neuroimaging investigations, difficult. As a result, a precise automatic technique for parceling the brain into various structures is required. Because brain tumors have features that make segmentation difficult, automated and accurate brain tumor segmentation is technically demanding. Tumors can appear in a variety of locations and can be practically any shape or size. Furthermore, they are frequently poorly contrasted, and a tumor's intensity value may overlap with that of healthy brain tissue. As a result, distinguishing healthy tissue from malignant tissue is difficult [18, 22, 39, 48, 77].

Based on the degree of required human interaction, brain tumor segmentation approaches are mainly grouped into three categories: manual, semi-automatic and fully automatic segmentation. Manual segmenting brain tumors in MR images is a time-consuming procedure that is also vulnerable to rater variability. As a result, over the last two decades, there has been a lot of interest in reliable automatic and semi-automatic segmentation of brain tumors, resulting in hundreds of distinct algorithms [37].

P. Rupa Arasi and M. Suganthi devised a model for segmenting brain tumor regions that employs a Genetic Optimized Median Filter followed by a Hierarchical Fuzzy Clustering Algorithm. Then GLCM is utilized as a feature extraction approach. The Lion Optimized Boosting Support Vector Machine model is used to classify tumors [7].

By separating the MRI images of the brain into two halves, Pratima P.G. and Vinayak K.B. devised a feature extraction algorithm. To improve computing efficiency, statistical features are taken from the selected slice. A Support Vector Machine is used to extract the tumor area using statistical characteristics [28].

Pre-processing, features extraction, features reduction, and classification are the four steps that were proposed by Muhammad Assam et al. The noise and undesirable components such as the scalp and skull are removed using the median filter. To extract different features from the MR images, the discrete wavelet transform (DWT) approach was utilized. Furthermore, Color Moments (CMs) are used to achieve an optimal set of characteristics by reducing the number of features. Classification methods include Feed Forward-ANN (FF-ANN), Random Forest, and Random Subspace with Bayesian Network [10]. For feature extraction, Neelum Noreen et al., proposed a model that relies on fine-tuned Inception-v3 and fine-tuned Xception. Many algorithms, such as softmax, Random Forest, Support Vector Machine, and K-Nearest Neighbors approaches, have been used to classify brain tumors [57].

An anisotropic filter was suggested by E. Brumancia et al. to remove noise from the surroundings of the brain image. To separate tumor-affected regions from non-affected areas, researchers employed a hybrid genetic algorithm in conjunction with a support vector machine [14]. Lu Si-Yuan et al. suggested a brain tumor diagnosis system that uses three RNNs for classification and uses the pre-trained ResNet-18 as the backbone model for feature extraction. The presented system is built using MATLAB 2021a and the deep learning toolbox [43]. For brain tumor knowledge characterization, Madona B. Sahaai et al. suggested a method for brain MR image segmentation for tumor site detection using DNN with stacked auto encoders [62]. Shanaka R. Gunasekara et al. presented a model that localizes tumor regions of interest using a deep convolutional neural network. The Chan–Vese segmentation algorithm has been used to contour the tumor boundaries for the segmentation process [29].

Hasan Ucuzal and colleagues created a deep learning-based web-based software that will be used to identify and detect brain tumors (glioma, meningioma, and pituitary). The Keras package is used in the development of deep learning algorithms [68]. Other reviewed articles are summarized in table below.

Table 3: Summary of Techniques for Brain Tumor Segmentation and Classification

No: -	**Reference**	**Dataset**	**Approach**	**Level of user interaction**	**Purpose**
1.	[59]	BRATS 2013 BRATS 2015	CNN with (3×3) filters for deeper architecture	Automatic	Brain tumor area extraction
2.	[5]	IXI REMBRANDT TCGA-GBM TCGA-LGG	Convolutional neural networks Convolutional neural networks (CNNs) and genetic algorithm (GA)	Automatic	Glioma brain tumor classification technique. Glioma is classified into different grades, as well as two additional common tumor forms.
3.	[30]	BRATS 2012 BRATS 2013	Cascaded Two-pathway CNNs for simultaneous local and global processing	Automatic	brain tumor segmentation method based on Deep Neural Networks
4.	[66]	BRATS 2015	Convolutional neural networks (CNNs) with loss function optimization by BAT algorithm	Automatic	Brain tumor segmentation based on Deep Neural Networks
5.	[70]	Not mentioned	Convolutional neural networks (CNNs) in addition with Support Vector Machine (SVM)	Semi-Automatic	Brain tumor segmentation and classification model based on CNN. SVM was used to classify tumor
6.	[16]	CANDI 2011	Convolutional neural networks (CNNs), with patch-based strategy for automatic brain MRI segmentation	Automatic	automatic brain MRI segmentation

7.	[63]	Not mentioned	CNN model, fine-tuned for multi-grade brain tumor classification using a pre-trained VGG-19 CNN	Automatic	multi-grade brain tumor classification system based on deep learning
8.	[1]	BRATS 2017	Two parallel deep convolutional neural networks	Automatic	Brain tumor detection and low-grade gliomas (LGGs), or high-grade gliomas (HGGs) classification
9.	[54]	BRATS 2017	three end-to-end Incremental Deep Convolutional Neural Networks	Automatic	segmentation of Glioblastomas brain tumors
10.	[53]	Harvard Medical School website	combined Deep Neural Network (DNN) with discrete wavelet transforms (DWT)	Automatic	categorize the brain MRIs into Normal and three malignant brain tumors
11.	[11]	Not mentioned	CNN model with Softmax	Automatic	classify the brain MRIs into three tumor's types

7 Conclusion

Various medical MR image denoising, segmentation, and classification approaches used to detect tumors in MRI images are discussed in this review study. Despite extensive research, there is no universally approved approach for these methodologies since a variety of factors influence the outcome. As a result, no single procedure can be considered suitable and efficient for obtaining a precise outcome. The majority of the studies looked at automated approaches. Median filtering, skull stripping, image sharpening, registration, and anisotropic diffusion filtering were the most widely utilized preprocessing procedures. Because most algorithms, notably the traditional technique, are susceptible to MR image noise, The emphasis should be on decreasing the detrimental impacts of Rician noise, which is the most common type of MR image noise. Threshold Based Segmentation, Region Based Segmentation, Edge Detection, Clustering, Statistical Models and ANN are the six major categories revealed by this survey. As the preceding literature review demonstrates, there are numerous strategies for brain tumor segmentation. The goal of all methods is to produce an accurate and efficient system that makes it simple to discover tumors in the shortest amount of time with the highest level of accuracy.

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