A REVIEW OF MEDICAL IMAGE ANALYSIS FOR MULTIMODAL BRAIN TUMOR SEGMENTATION

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ABSTRACT

The requirement for quick and accurate evaluation of massive amounts of data has increased interest in MRI-based medical image processing of brain tumor studies.Early discovery of brain tumors is critical to a patient's treatment. Life expectancy is improved when brain tumors are discovered early. For expert brain tumor diagnosis, a time-consuming and difficult to perform manual segmentation is typically used.Medical images may be utilised for diagnosis, surgery planning, training, & research since they carry a wealth of information.The subject of tumor brain segmentation is currently being studied with the use of automatic segmentation. Traditional MRI brain tumor image segmentation approaches have been reviewed in a number of studies.Methods for segmenting brain tumors using MRI are reviewed in this research. Medical image analysis has just begun to make use of Deep Learning (DL) techniques, and this work examines DL as it pertains to the interpretation of MRI brain medical images.MRI-based image data may also be processed efficiently and objectively using deep learning approaches.For accurate brain diagnosis, multimodal brain tissue segmentation from medical imaging is crucial.Multimodal imaging technologies ("such as PET/CT and PET/MRI") that include data from numerous imaging techniques are more effective in the segmentation of brain tumors. An overview of brain tumorsusing deep learning techniques is also discussed prior to discussion on. An evaluation of the existing status and potential advances to standardise MRI-based brain tumor segmentation technologies into everyday clinical routine is addressed at the end of this paper. In conclusion, the enormous amounts of Magnetic resonance visual information can also be processed efficiently and systematically evaluated using deep learning algorithms.

Keywords: Brain tumor, deep learning, medical images, image segmentation. MRI images

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I. INTRODUCTION

Brain tumors& surrounding tissues, including edema, non-enhancing tumors and necrotic areas need to be accurately segmented for analysis of illness progressions, therapeutic response and treatment planning [1].When it comes to diagnosing and following the course of cancer, magnetic resonance imaging is frequently used. Tumor analysis is made easier with the use of MRI, which enables a visual depiction, as well as a comparison, of a tumor's spread to other methods like CT & PET (PET). On the other hand, multi-modal MRI methods are frequently employed to examine brain tumor tissue because they can distinguish between different tissue types utilizing a specific sequence based on tissue features [2].World Health Organizations (WHO) standards for defining brain tumors are currently based on histological criteria, which restricts their practical use [3].As a result of this constraint, medical imaging is increasingly being used to diagnose and treat patients, including more automated treatments. Neurosurgeons & medical scientists are finding it more difficult to keep up with the ever-increasing volume of brain MR imaging data, which has opened up new possibilities while also creating new challenges [4].

Methods for segmenting brain tumors can be categorised according to several criteria [5]Generative and discriminative approaches are the two broad groups into which these techniques may be sorted. In most cases, generative approaches rely on pre-existing knowledge about the emergence of healthy tissues as well as cancerous ones. Many of the models that have been developed consider segmentation to be an a posteriori estimate issue of a distribution. When it comes to discriminative techniques, the annotated training photographs are used to learn a distribution from a huge number of low image attributes without any prior information [6].Computational techniques such as classification are mostly used in medical image-based tumor diagnostics to categorise images into benign & malignant categories. Image classification tasks are also being used to classify tumors in medical imaging [7].The location and size of brain tumors can be determined using imaging techniques such as MRI. MRI is superior to other imaging modalities, such as CT, in terms of its ability to distinguish between distinct brain tissues [8].

Segmentation of the braintumor in MRI images is a fundamental process that has several uses in neurology, including quantitative analysis, planning and operations, and functional imaging [9].Poor spatial resolutions and low contrast, as well as inhomogeneity & other acquisition artefacts such as noise and partial volume impact make medical image segmentation a difficult task. In addition, anatomical models that capture all possible deformation in each retrieved structure make it even more difficult [10, 11].When clinical images are segmented and then assessed for quantitative lesions, useful information about brain disorders may be gleaned. This information is crucial for treatment planning, illness monitoring, and tracking the development of individual patients' outcomes. Furthermore, particular deficiencies based on impaired brain structure are linked to specific injury regions[12].

The radiology department is most concerned with early identification and diagnosis of low-grade brain tumors since they are more likely to evolve into high-grade brain tumors if left untreated [13].Color, contrast, brightness, and grey level are just a few of the attributes that may be used to segment a picture [14].Medical images such as MR images and other present imaging modalities used to segment tumor tissues separate edema and necrosis (dead cells) from normal brain tissue, such as WM and CSF[15, 16].There are several ways to detect tumor tissue from imaging modalities, such as segmentation and advanced medical image modalities, which are used to evaluate patients with brain tumors and offer them with specialised patient care [17].An effort is made to divide a brain tumor into many sections by the use of brain tumor segmentation. Necrosis, edema, non-enhancing tumor, and enhancing tumor are the four main types of brain tumors. The presence of damage to the blood-brain barrier is reflected in an enlarging tumor. The degree of tissue degradation is reflected in the degree of necrosis. It is therefore critical to appropriately identify and categorise the brain tumors in four MRI scans. However, the sheer volume of data generated by MRI makes it impossible to do manual segmentation with precision in a reasonable amount of time [18].

A brain tumor is formed when abnormal groupings of cells are formed in or around the brain. A patient's health is negatively impacted by the aberrant cells that interrupt the brain's natural functioning [19].Researchers, radiologists, and clinical professionals are primarily focused on brain image analysis, diagnosis, and therapy using accepted medical imaging techniques [20].Brain tumors are a leading cause of death in developed countries, making it imperative to thoroughly examine any available imaging of the brain. The National Brain Tumor Foundation (NBTF) estimates that 29,000 people in the United States are diagnosed as brain cancer each year, & that 13,000 of these individuals die each year [21].Brain tumors may be studied using MRI using a variety of sophisticated imaging methods, including Diffusion Tensors Imaging ("DTI"), MR Spectroscopy ("MRS"), and Perfusion MR [22, 23].Brain tumors may be divided into two basic categories: malignant tumors, which are cancerous, and benign tumors. The World Health Organizations (WHO) further classifies malignant tumors into classes I through IV [24].

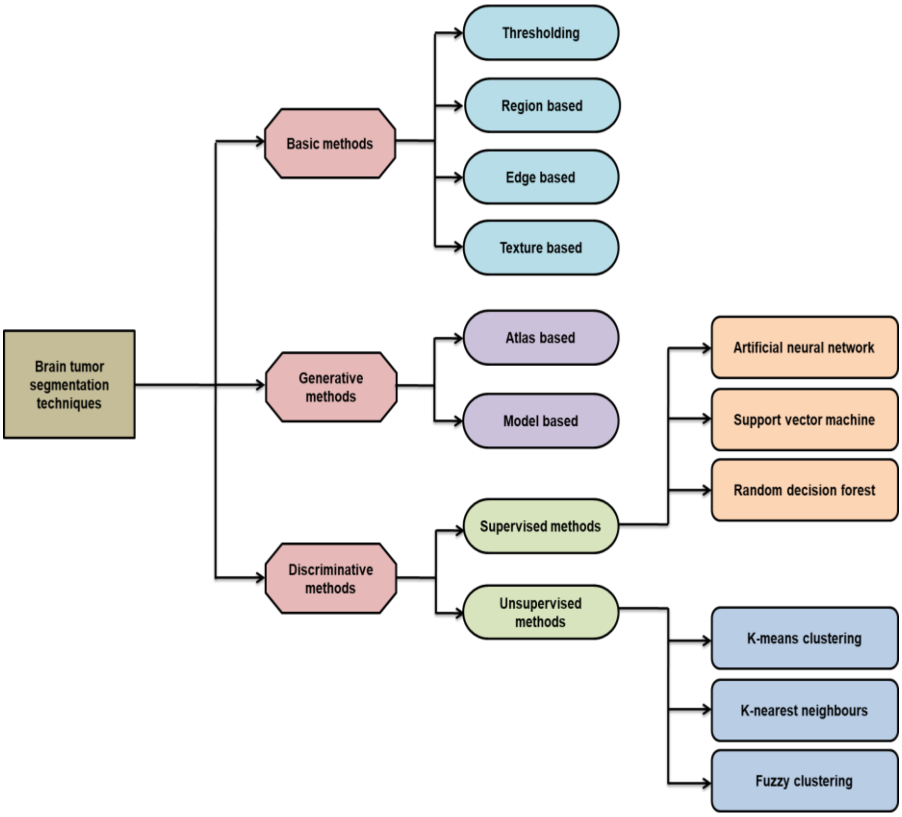

Figure 1. Brain tumor segmentation techniques

Image textures [25], local histograms [26], and structural tensor eigenvalues [27] are all aspects of MRIs that are used in brain tumor segmentation investigations.Pattern classification is a common application of machine learning algorithms likes as Support Vector Machines ("SVMs") [28,29] and Random Forests ("RFs") [30].Since they perform better in image analysis domains including object recognition [31], image classifications [32], and semantic segmentations [33], deep learning-based techniques and methodologies were gaining interest in brain tumor segmentations research.

II. COMPARISON WITH PREVIOUS SURVEYS

Table1 shows a number of studies on brain tumor segmentation.

S.NO	Surveys	Reference	Years	Advantage	Disadvantage
1.	An examination of MRI-based medical imaging analysis of research of brain tumors	Bauer and Wiest [34]	2013	Brain tumors and their imaging are briefly discussed in this survey to provide a comprehensive perspective.	CT scans are less expensive than MRI scans. Discomfort of the procedure among the patient
2.	Brain tumor segmentation using deep learning: a survey	Liu and Tong [35]	2007	Deep learning-based brain tumor segmentation algorithms will be thoroughly examined in this survey.	The downstream network's segmentation effect is strongly dependent on the upstream network's performance.
3.	A survey of the state of art for medical image fusion	James and Dasarathy [36]	2014	Medical image fusion has a long range of scientific obstacles, which this survey aims to address head-on.	The primary drawback of MRI scans is their relative sensitivity to movements, which makes them a challenging approach for evaluating organs that entail movement, like oral cancers.
4.	A survey on the segmentation & feature extraction of brain tumors using MR images	Saman and Jamjala [37]	2019	The most prominent brain MRI features and MR brain image segmentations are reviewed and presented with an emphasis on its properties, benefits,	There are two significant limitations to using the hybrid segmentation approach: lower processing time and a bigger number of parameters that must be modified for a specific

				and drawbacks.	application.
5.	MRI-based medical image analysis: grade classification of brain tumors	Mohan and Subashini [38]	2018	Tumor-infected human brains have been segmented and classified. This study's primary focus is on MR imaging with a focus of gliomas (astrocytomas).	The acquisition time of MRI scans is substantially longer than that of CT scans, and patient comfort may be compromised as a result.
6.	A review of MRI-based techniques for brain tumor segmentation	Liu and Li [39]	2014	In this survey, MRI-based brain tumor segmentation algorithms are examined in detail for the first time.	The region expanding method's primary flaw is the partial volume impact, which affects segmentation accuracy in MR brain images.
7.	State of a art survey on MRI brain tumor segmentations	Gordillo and Montseny [40]	2013	This survey focuses on the segmentation of MRI brain tumors. There is a focus on both semiautomatic and fully automated procedures.	Tumors can be separated into numerous regions, the number of regions needs to be predetermined, and the borders of the regions' intensities or textural features are not always distinct.
8.	A study of MR imaging methods for detecting brain tumors	Chahal and Pandey [41]	2020	Several segmentation and classification procedures for a wide variety of brain illnesses are found in this survey, which is intended to help researchers discover a basic characteristic of different types of brain tumors.	If proper ear protections is not worn, the loud pounding noises produced by the magnetic fields as they fluctuate over time could damage hearing.
9.	A study on U-shaped networks in the segmentation of medical images	Liu and Cheng [42]	2020	U-shaped network applied to medical picture segmentation tasks are reviewed comprehensively in this survey, which	Over segmentation and high noise sensitivity are the fundamental problems with traditional picture segmentation systems.

				focuses on the topologies, expanded mechanisms and application domains in these studies.	
10.	Survey on brain tumor segmentation m ethods	Yang and Zhao [43]	2013	This survey provides an in-depth look into MRI-based strategies and technologies for treating brain tumors.	It's important to choose a threshold because the wrong decisions could lead to over- or under-segmentation.
11.	A survey of convolutional neural networks in medical image understan ding	Sarvamanga la and Kulkarni [44]	2021	An in-depth look at the use of CNNs in medical images interpretation is presented in this article.	Large amounts of practise data are required, yet the object's location and orientation are not encoded.
12.	A survey of brai n MRI image segmentation m ethods and the issues involved	Hiralal and Menon [45]	2016	Segmentation strategies for MRI images are examined in this survey.	If an MRI scan uses radiofrequency energy, it may cause the body to overheat.
13.	A study of medical picture using deep learning	Litjens and Kooi [46]	2017	There is a wide range of applications of deep learning in picture categorization and object detection.	In order to performs better than other strategies, it requires a big volume of data. The complexity of the data models makes training exceedingly expensive.
14.	A survey of deep learning's applications with MRI images	Liu and Pan [47]	2018	The results of the survey provide a thorough overview of MRI image processing & analysis based on deep learning.	An MRI image collection is typically limited in size due to the complexity and cost of the acquisition technique.
15.	A comprehensive survey of brain tumor detection & classification	Amin Sharif [48]	2021	It is the goal of this survey to provide researchers with a complete literature review of brain	There must be a lot of data to train on, and it must be inclusive/unbiased and of good quality.

	utilizing machine learning			tumor detection using magnetic resonance imaging.	

Brain tumor segmentation techniques based on deep learning have produced satisfactory results. Early brain tumor segmentation algorithms are written under strict conditions and based on unrealistic assumptions. Although semi-automatic approaches for segmenting brain tumors take less time than manual techniques and produce effective results, they are nevertheless subject to intra and inter-rater/user variability. Instead of using image processing to extract features, brain tumor segmentation primarily relies on network architecture design.

III. BRAIN TUMOR SEGMENTATION

A) Image segmentation

Two-dimensional functions like f(y,x) can be used to define a intensity or grey level for a digital image in terms of spatial coordinate and a value of f at every points (y,x).A pixel, a picture element, is represented by each dot in an image. There are I rows and J columns in the matrix, A, which can be thought of as the function f.

$$B = f(y,x) = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots \\ \vdots & \ddots & \\ a_{I,1} & & a_{I,J} \end{bmatrix} \tag{1}$$

Segmenting a digital images into numerous distinct parts, each with its own unique characteristics, is a common practise in computer vision. The most common use of this technique is to identify the boundaries of objects in photographs. An image A can be labelled according to the colour, texture, or intensity of each of its pixels (y,x) [49].

Table 2. Various image segmentation techniques

Various techniques	Advantages	Disadvantages
Active contour method	• models with dynamic contours • efficiently preserves global line forms	• The contour should be driven by strong image gradients. • a lack of precision due to a lack of image boundaries and noise
Watershed method	• based on morphological mathematics • aids in increasing the capture range	segmentation in excess
Threshold method	Check for pixels on the edges.	the detected edges are consisted

B) Segmentation techniques in MRI brain tumor analyses

Slicing the pixels in medical images to identify and separate lesioned areas from surrounding healthy tissue is a technique known as segmentation. For brain tumors, it is a difficult task because of a tumor's unique MR imaging properties [50]. A focus on human brain tumor-containing MR brain images led us to this study. Tissue features have been used to build MRI segmentation algorithms over the years [51].Methods that use intensity, manual segmentation, atlas, surface, and hybrid segmentation are among the most popular. Figure 2 depicts the many ways of segmentation. Image segmentation is increasingly relying on hybrid algorithms (which combine many methods) & soft computing techniques.

When it comes to picture segmentation, hybrid techniques (the combination of two or more techniques), such as fuzzy logic and neural networks (as well as genetic algorithms), have found widespread use. When it comes to solving problems in a cost-effective, scalable, and robust manner, soft computing relies on its tolerance for imperfection and ambiguity in order to get the job done. It is also commonly used in picture segmentation, which mirrors the human brain in terms of speed and accuracy.

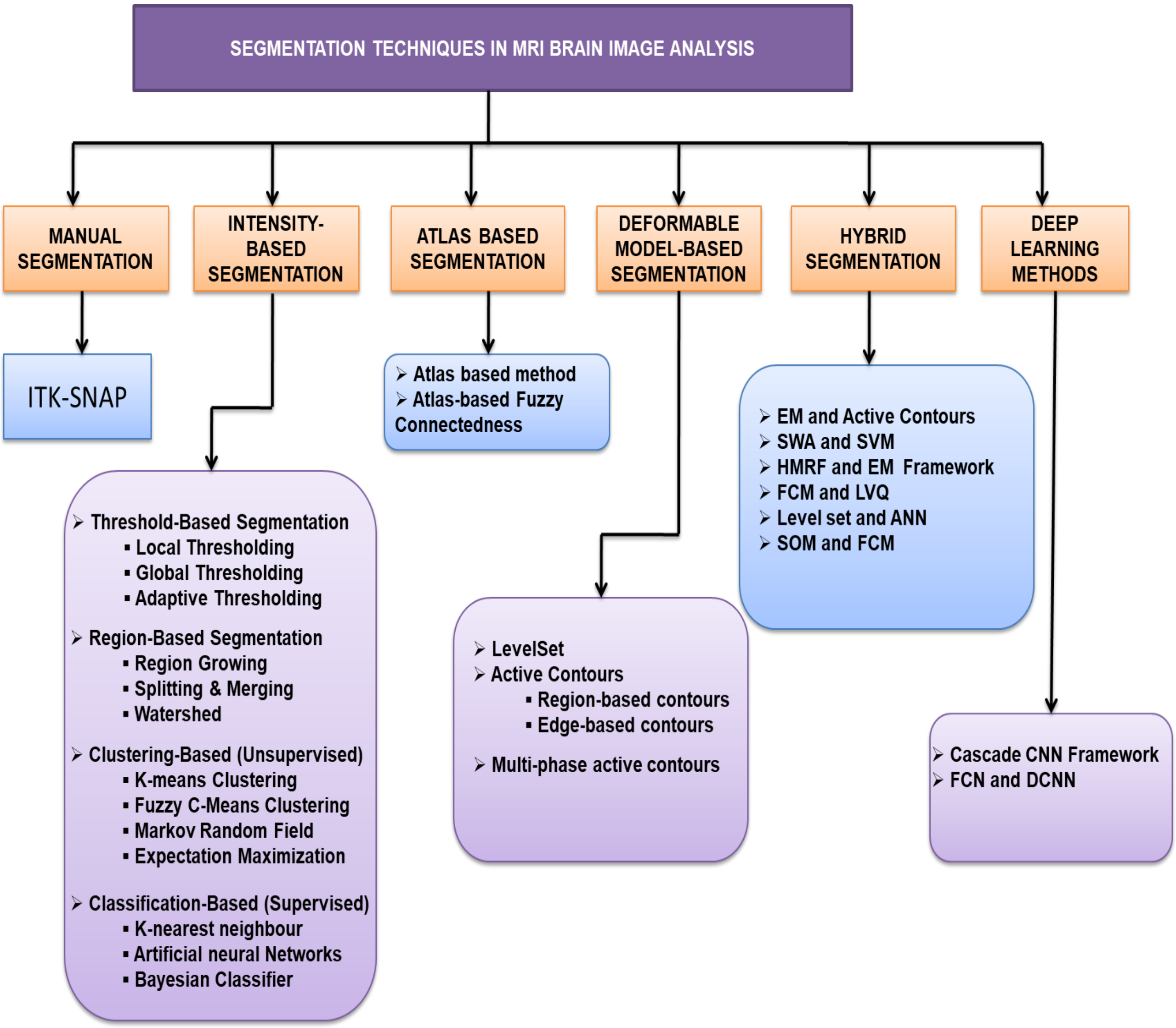

Figure 2. Various segmentation techniques in MRI brain image analyses

a)Manual segmentation

Since the only way to identify tumors on all continuous slices where the tumor is suspected to be present is through the laborious and expensive process of manual segmentation. Various witnesses may arrive to varied conclusions concerning the presence or absence of tumor due to human errors & variety. Even a single observer may come to a different conclusion on a different day. An automated tumor segmentation method must be employed without a shadow of a doubt[52].

b)Pixel-based or intensity-based segmentation techniques

Individual pixels and voxels can be classified using algorithms based on intensity or image segments. There are three forms of brain tissue that can be distinguished by MRI: white matter, grey matter, & cerebrospinal fluid. This includes dealing with issues like inhomogeneity (noise and partial volumes), partial volumes, and intensity overlap between non-brain tissues in MRI scans. Discussions on algorithms based on predetermined thresholds or regions are coming up next [53].

i) Threshold based methods

Simple and effective, threshold-based segmentation is achieved by comparing the intensity of each object to one or more thresholds. Currently, there are two types of threshold-based methods: global and local.The intensity histogram can be used to estimate a threshold value for each region, which can then be used to establish local thresholding. When estimating the threshold values for local thresholding, it is common to use local statistical features such as the T1w MRI mean intensity value, prior knowledge, and partial volume calculations of each region. Gaussian distribution was used to calculate normal MRI thresholds as well.

ii) Region based methods

It is possible to generate different regions in an image by combining adjacent pixels that share the same homogeneity properties. Region-growing & watershed segmentation is extensively used in the segmentation for brain tumors, respectively.

Region expansion is an excellent alternative for developing connected areas. As previously stated, the region-growing method of segmenting MR images of brain cancer has been found to be more effective & lower computationally intensive than earlier methods, particularly for homogeneous tissues & regions. When employing the region growth technique to segment MR brain images, accuracy suffers due to the partial volume effect. A voxel may represent more than one tissue at the boundary among two tissue types, reducing the distinction between different tissue classes. As a refinement stage, several segmentation algorithms incorporate the region-growing process. For the automatic segmentations of brain tumors with MRI, a fuzzy information fusing framework was suggested. As the first stage in developing this framework, we registered multispectral images and used a prior information, fuzzy features fusion, and a fuzzy region growth adjustment.

iii) Classification and clustering methods

Automated analysis and diagnosis of medical pictures can be achieved using machine learning. This could reduce the stress on radiologists by allowing them to make more informed decisions based on solid evidence rather than simply guessing at relationships. Classifying machine learning algorithms may be done in several ways. Unsupervised, semi-supervised, and supervised learning algorithms are all classifications of this technique, which is based on the usage of training sample labels.

In supervised learning, both the input and also the output observations or labels were included in each sample. To be able to use the results from training data on test data, supervised learning reduces functional correlations. Sustained learning techniques like the classification algorithm are examples of this approach.

Unsupervised learning relies on only a single set of observations for each sample. A common application of unsupervised learning is the discovery of hidden latent variables or correlations between data. The clustering algorithm is an example of unsupervised learning.

c)Atlas-based segmentation methods

When tumors or lesions occupy a considerable portion of brain space, it may be difficult to accurately partition brain structures and substructures. The atlas-based segmentation has a comparative benefit over the previous segmentation approaches because it is able to segment the image without explicitly relating regions and pixel intensities [54].When it comes to medical image analysis, the deformable model has been successfully used to studies in [56] [57], where it was shown to be an effective way for segmenting brain areas based on their morphometric differences.

[58] Recent years have witnessed an upsurge in the usage of atlas-based MRI segmentations of a newborn brain. Complex anatomical structure & low MRI quality make it more challenging for researchers to segment brain tissue in newborn infants than in adults. Utilizing a probabilistic atlas for a newborn brain, which takes into account the spatial variation in the structure of the tissue, these various types of tissue are then segmented. When it comes to neonatal brain development between 29 and 44 weeks, a dynamic, probabilistic atlas [59] was necessary.Fuzzy connectedness & parametric bias field corrections were developed by [60] to provide a foundation for fully automated brain MRI segmentation.

d)Methods of segmentation based on deformable models

Medical images are segmented using deformable structures, such as surfaces and curves. Because of their long life, they've been widely used in medical imaging analysis. Segmenting regions of interests or their backgrounds that lack a significant textural contrast can be accomplished by using surface-based techniques. There is a lot of literature out there about surface-based segmentations in volumetric MR brain images, so in a following three subsections, we'll go over some of it.

e) Hybrid segmentation methods

More than 10 years ago, there were more challenges with application-oriented brain MRI segmentation; as a result, new techniques were constantly being developed and presented [61].A mix of several strategies may be necessary to achieve a segmentation aim as a result of this. As a result, improved segmentation accuracy has been achieved using hybrid or combination segmentation algorithms in numerous brain MRI segmentation applications [62].Expectation maximisation, binary mathematics morphological, and active contours models were used to separate diverse brain tissue in adults using 2D MRI [63]. Employing morphological data from the surrounding environment to segment brain blood vessels based on model-based region growth [64].

i) FCM algorithms

Using FCM method of clustering, a single set of data can be separated into many groups. This is a common method used in pattern recognition. To put it mathematically, this technique works by assigning membership to data sets associated with every cluster centre based on distance. A cluster's membership is more likely the closer a piece of data is to the cluster centre.

An unsupervised FCM clustering technique was used to separate the brain tumor into tissue groups including active cells, necrotic core and edema. From raw MR scans, it is possible to construct segmentation pictures that reveal therapeutically relevant neuroanatomic and neuropathologic tissue contrast information. Researchers have since added extra information to feature vectors being clustered utilizing FCM.

ii) SVM algorithms

Supervised classification difficulties were addressed using SVM as a parametrically kernel-based technique. The high classification capacity of SVM has made it a popular choice for brain tumor segmentation.It has been proposed to use one-class SVM to segment brain tumors. With the help of SVM parameter training with an implicit learning kernel, this strategy was able to learn a nonlinear distribution of visual information without prior knowledge & achieve superior segmentation results of the extraction of brain tumors than the fuzzy cluster analysis. Feature vectors based on intensity were constructed by some researchers using a large variety of MRI modalities and then categorised using support vector machines (SVMs).

In addition to segmenting healthy tissues, this approach was able to distinguish between healthy and tumorous regions. SVM-based methods have been presented that are extremely comparable, although they only segment one tumor region and use fewer modalities. The feature selections with kernel class separability improved this strategy and yielded better results. Using a feature selection and fusion technique, a multi-kernel SVM was suggested to differentiate a brain tumor using multi-sequence MRI images. A multikernel SVM is used to categorise the tumor region, which is then improved using both distance and maximum likelihood measurements.

IV. EXPLORING DEEP FEATURES FOR BRAIN TUMOR

Brain tumors can be detected using MRI images by exploring and representing their deep features. Oncologists use MRI images to extract deep characteristics for use in diagnosis, treatment, and prognosis.

Image attributes are directly linked to biological factors and provide radiologists with familiar qualitative information [65]. When the network is pre-trained as a feature extractor, deep learning achieves cutting-edge performance for prediction and classification. Cancer patients' overall survival time can be better predicted using deep feature extraction methods and approaches [66]. A deep learning activation strategy is used to train classification and segmentation deep learning networks. A variety of strategies are used in the activation features method, including feature selection, feature pooling, & data augmentation algorithms [67].

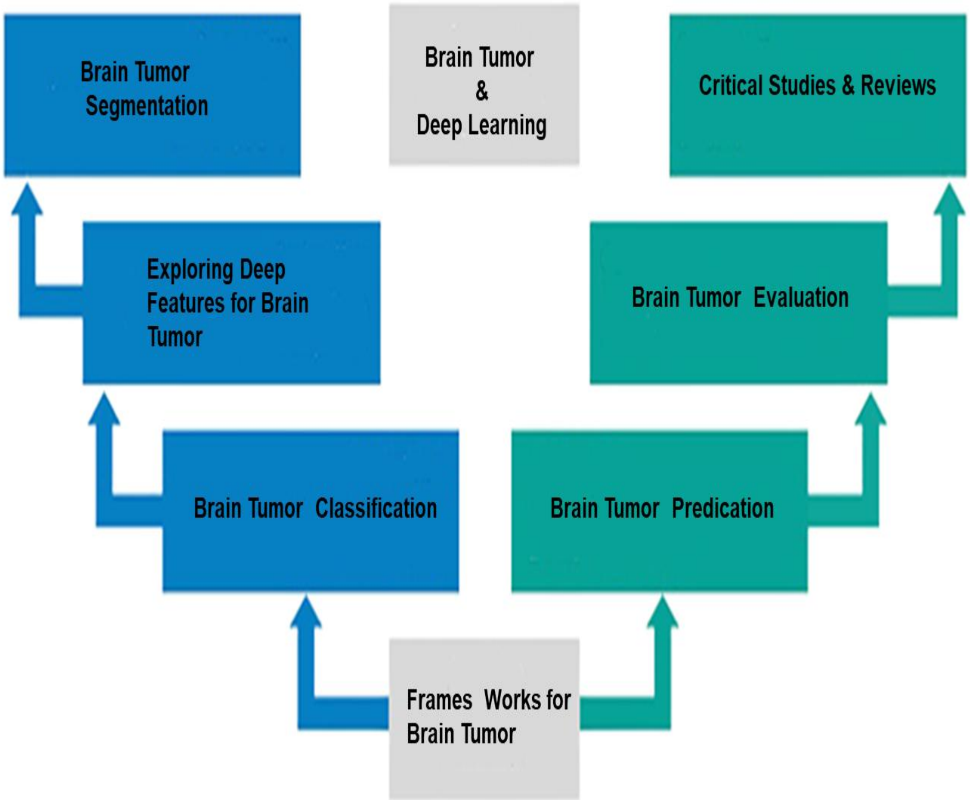

Figure 3. Literature of brain tumor using deep learning

Brain tumor image matching was missing from the most famous learning to link deep neural networks to deep learning (DL) structure designs, using electrons microscopy neuron imagery for the pixel-wise classification of covering and no-covering pixels [68].Since [69] & others, attention to applying DL architecture to brain tumor MRI images has skyrocketed in the present time.Many specific issues arise while dealing with brain tumor MRI picture interpretation and segmentation. It is important that uncomplaining data in health checks can be extremely variable, with the same pathology being treated by patients in completely different ways depending on their symptoms. Further complicating image segmentation is the fact that there is a limited amount of information available, as well as defective or non-conformant information live forms.Many specific issues arise while dealing with brain tumor MRI picture interpretation and segmentation. [70], where the same pathology can attend in exceptionally polar opposite methods across sufferers. Health check picture segmentation is further complicated by the relatively little information set available and defective or non-conformant data living forms.

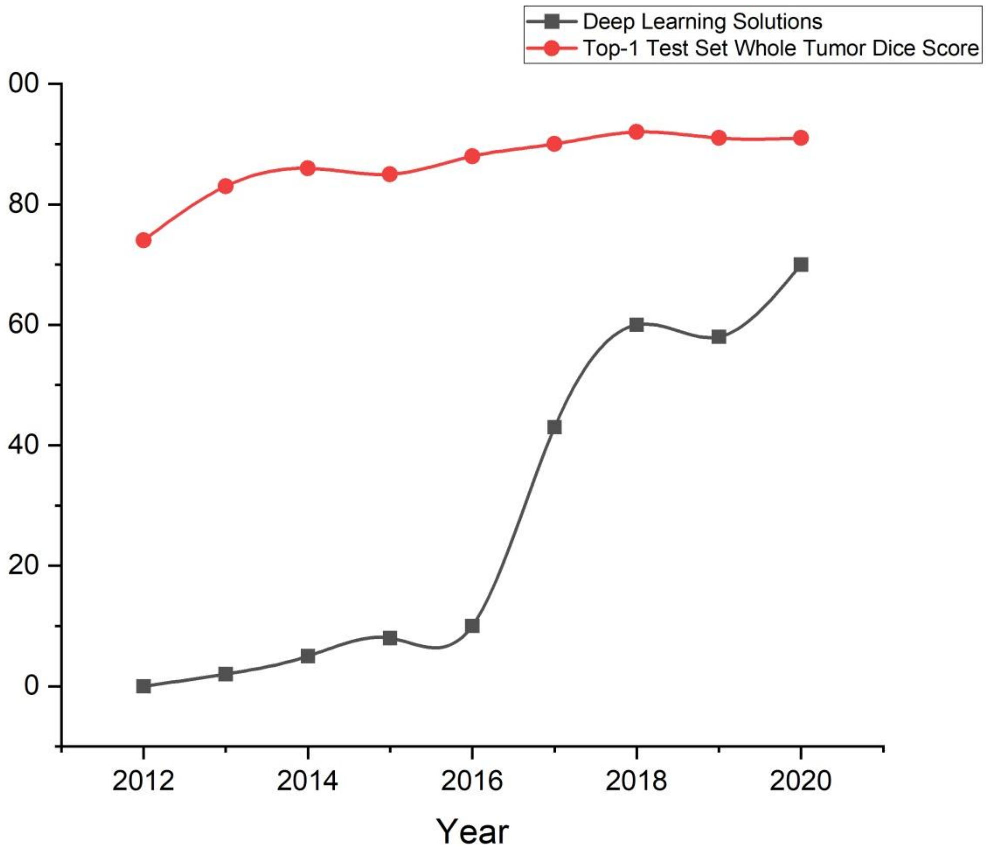

Figure 4.Growing of scientist's attention in brain tumor segmentation using deep learning

About a combination of challenges including ambiguous location, morphological uncertainty, poor contrast images, annotation bias, and data. uncertainty, accurate segmentation for brain tumors remains a serious challenge for academics. In order to automatically extract features representation and achieve accurate and steady performance while segmenting brain tumors, a variety of sophisticated deep learning algorithms have been used (see Figure 4).

Since the Multimodal Brain Tumors Segmentations Challenges (BraTS) was launched, the number of deep learning-based solutions has steadily grown. The year's top-1 tumors dice score of each test set is shown in the red line. Since 2012, researchers have focused on deep learning-based segmentation algorithms because of their great feature learning capacity & systematic performance.

V. CONTRIBUTIONS OF THE PAPER

The brain tumor segmentation technique contributes to various stages of the development of an MRI system for the diagnosis and treatment of brain illnesses. Pre-processing, extraction, image segmentation, and classification are the first steps in the process. The goal of the current work is to offer an abstract idea, specifically by analysing the previous paper on segmenting tumors in MRI images. There are several ways to separate the tumor from the brain MRI pictures. Even if the survey paper details many segmentation techniques along with their benefits and drawbacks, there is still space for comparative analysis and the addition of cutting-edge techniques. The following are the study's salient features:

- It gives a thorough analysis of current techniques for separating brain tumors from brain MRI images.
- It aids medical professionals in making an appropriate diagnosis and determining the subsequent treatment plan.
- Additionally, it offers readers fresh lines of inquiry into the segmentation of brain tumors.

VI. CONCLUSION

In this paper, we discussed about the medical image analysis for multimodal brain tumor segmentation.This work examines Deep Learning (DL) as it relates to the interpretation for MRI brain medical images, which is a relatively new use for DL in medical image analysis. In comparison with previous surveys, this paper reviewsa number of studies on brain tumor segmentation.There are a number of medical images analysis concerns that present substantial technical challenges, such as varying image intensities, noisy/ill-defined boundaries, & irregularly shaped with high variability. The low-grade brain tumor may necessitate surgery, if all of a tumor can be removed. If a visible tumor is found following surgery, radiation and chemotherapy may be used. We plan to investigate the effects of various image normalisation strategies on segmentation results in our next research.

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