JAET

Journal homepage: http://jae-tech.com

Journal of Applied Engineering & Technology

ISSN : 2523-6032 ISSN-L : 2523-2924

Recent Segmentation Trends of MRI-Based Brain Neoplasm: A Review

Noman Ahmed Siddiqui*[1], Tahir Qadri[1], Muhammad Tayyab[1], Umaira Shahid[1], Sadaf Raza[1]

[1]Electronic Engineering Department, Sir Syed University of Engineering & Technology, Karachi 75300, Pakistan.

*Corresponding Author

DOI: https://doi.org/10.55447/jaet.07.01.111

Abstract: A significant increase in medical-related cases of brain neoplasm has been noticed in the past few years affecting not only adults but children as well. Brain neoplasm segmentation isolated the different abnormal brain tissues from normal brain tissues which are complicated tasks in medical image examination. But simultaneously it plays a crucial role in time diagnosis which not only improved the treatment possibilities but also increased the rate of survival of the patients because a brain neoplasm is a treatable kind of cancer if diagnosed well on time. Magnetic resonance imaging (MRI) based segmentation are a more focused, attractive, and attentive study area in recent few years because MRI is noninvasive imaging, safe, and cost-effective. Detection of brain neoplasm using the manual procedure of segmentation is an extremely difficult, time-consuming, expensive, and individual task because large data of MRI images are produced in clinical practice which may delay the diagnosis. This increases the practical significance of the automatic segmentation techniques but due to brain neoplasm being extremely unpredictable concerning position, appearance, type, and size improving the methods for state-of-the-art segmentation process remain a complex task. To segment the brain neoplasm accurately, automatic segmentation is a solution with better performance. The goal of this paper is to provide an organized literature survey for recent MRI-based automatic brain neoplasm segmentation techniques with the modern participation of several researchers which helps new researchers in exploring future directions. There are several current surveys focused on traditional methods, but this paper focuses on recent trends including machine learning techniques accompanied by transfer learning, deep learning, neural network, and hybridization. Moreover, this survey also presents the findings and limitations of each article which show the effectiveness of the proposed work. Finally, this survey, found that after over two decades of research, the novel methods for segmenting brain neoplasms using computer-aided techniques are becoming more and more refined and becoming closer to being used often in clinical settings but in terms of computing complexity and memory consumption, these approaches lag.

Keywords: MRI, Brain Neoplasm (tumor) Segmentation, Neoplasm, performance measures, MRI modalities, Glioma, generic segmentation methods

1. Introduction

The uncontrollable, abnormal division and development of bodily cells are raised as cancer. A brain neoplasm is a mass that develops when these aberrant cell divisions and development occur in the

*Corresponding author: nomasida@ssuet.edu.pk

brain tissue. Although knowledge about brain tumors is uncommon among people as compared to lung and breast cancer, brain tumors are one of the most dangerous malignancies. Brain Tumors also called neoplasia have two classes i.e., Primary and Secondary brain tumors based on the initial source. And obviously, these different types of tumors have different treatments according to their characteristics. Primary brain tumors have their roots in the brain itself and their surroundings, identified by the cell types that gave rise to them and not spread to other body parts. Secondary (metastatic) brain tumors, on the other hand, already become cancerous or malignant by which spreading cancer cells from a further part of the body of the patient to the brain due to the bloodstream like breast cancer, lung cancer, melanoma, kidney cancer, etc. [1,2,3].

Motivation of the work: As we know, when the process is interrupted in which the healthy human body produces new cells, while the older cells die leading to the tumor because the older cells continue to exist in the body instead of dying during the generation of new cells due to this new cell proliferate in an unwanted manner. According to the above-defined statistics, a tumor is a fatal illness with a low likelihood of survival, and the cause of brain tumors has not yet been identified or proven. However, the WHO has observed that the rising radio frequency EMF field associated with modern devices like cellular phones may be cancer-causing. This provided a solid ground of motivation for this paper to compile various approaches used in various studies in one place. This will allow researchers to compare all of the techniques' limitations and choose the optimal one for their specific objectives.

The primary motivation of the study to compile the various brain tumor segmentation (BTS) models proposed by scholars around the world. The aim of the current effort is to give an abstract concept, specifically through a review of the techniques that are currently used for segmenting tumors in MRI images. The tumor was segmented from brain MRI images using several techniques and these techniques have been published with encouraging results. But modern techniques for BTS are covered in-depth and critically in our study as a platform. We hope that this survey will provide academics and industry with useful guidelines and cogent technological insights. Comparative study and the application of cutting-edge approaches are still required, even though previous studies examined a variety of segmentation methods as well as their advantages and disadvantages.

Background and Related Study: Brain tumors are categorized into two groups i.e.; primary Brain tumors are Benign (noncancerous) and secondary is Malignant (cancerous). The benign brain tumor is homogeneous in structure and devoid of living (cancer) cells whereas malignant brain tumors have active cells and an inconsistent structure. Slow-growing benign tumors do not metastasize or spread to neighboring tissues. However, they could strain the brain and impair its performance. On the other hand, malignant tumors progress quickly and invade nearby tissues [3,4]. A microscopic categorization of the brain tumor was provided by the AANS (American Association of Neurological Surgeons) for the educational purpose which showed that classes and sub-classes of the primary brain tumor [2,5,6]. Glioma, Pituitary, and Meningioma have usually recognized types of primary brain tumors, but the most vital and unsafe type is Glioma in brain tumor, it is the most well-known type of adult brain tumor that’s why most current research on brain tumor segmentation focuses on it [1,5,7]. Glioma stems from the most affected part of brain cells which is the glial cells [7].

Thus, the primary brain tumor can also be categorized as a glial tumor based on glial cells or a non-glial tumor formed in the brain structure through glands, blood vessels, nerves, etc. [5]. Fig.3 reveals classes of Glioma which are provided by AANS under the grades defined by WHO in which Low-grade gliomas include oligodendrogliomas and astrocytoma’s, while high-grade gliomas include glioblastoma multiform [1,2,6,7,12,13]. AANS showed the most broadly used marking scheme developed by WHO (World Health Organization) to classify the histological characteristics of brain tumors (especially for Glioma) under the magnifying lens into categories (Grade 1 to Grade 4) depending on their malignancy or benignity, shows in Fig.2 [2,5,8,9]. Those tumors that exist under

the category of Grade I and Grade II are benign low-grade brain tumors, less threatening, less belligerent, and have a long-life expectancy. While those tumors that exist under the category of Grade III and IV are High-Grade brain tumors that are malignant, more threatening, more belligerent, and have a short life expectancy of fewer than two years [8,10,11].
Dr. Rozenfeld published an article "Understanding Your Brain Tumor MRI & Brain Tumor Diagnosis" in which he described WHO's grading system [14]. Clinically, it is challenging to comprehend the presence of a brain neoplasm because of the variety in size, localization, the pace of growth, and pathology. The unregulated growth of irregular tissues in the brain encroaches on the skull, obstructs normal brain function, and damages normal brain tissue by increased pressure within the brain, movement of the brain or pressing on the skull, as well as invasion of nerves and healthy brain tissues [3]. Consequently, a brain tumor poses a major risk to the patient's health and life, so it is necessary for early treatment to be instigated by using effective brain imaging techniques. Chemotherapy, surgery, and radiation therapy are the clinical medication options for brain tumors [8,15].

Key Contributions
The following is a summary of the survey's contribution:

1. *It provides a detailed overview of the most recent methods for BTS using brain MRI data.*
2. *We provide the reader with a summary of the development of segmentation approaches for brain tumors and also provide some background information regarding MRI and the classification of brain tumors for better understanding.*
3. *The survey is different from traditional quantitative analysis-based surveys, providing limitations and key findings of segmentation techniques of the brain tumor along with the information of methods compared with the proposed technique in respective publications.*
4. *It assists medical professionals in choosing the appropriate diagnosis and subsequent course of therapy.*
5. *The analysis provided through limitations and key findings demonstrates the effectiveness and suitability of modern approaches.*
6. *It incorporates readers with brand-new areas of investigation into the segmentation of tumors in the brain.*

Paper Organization
The rest of this manuscript's structure is as follows: Section 2 discussed the problem statement and its proposed solutions. Section 3 explains the challenges in brain tumor segmentation and section 4 provides information about medical imaging and MRI mechanism. Section 5 explains brain tumor segmentation techniques. Then Sections 6 & 7 provide statistics and provide information about the commonly used database. Detail knowledge provides about generic methods of segmentation in Section 8 and provided some basics about deep learning. Section 9 provided a detailed survey of recent trends in BTS techniques and commonly used performance measures in the surveys provided in Section 10. Finally, Section 11 presents the discussion and concludes this manuscript along with future work in section 12 and 13.

2. Problem Statement and Proposed Solution

To comprehend the research gap in this field, the database and research effort in the specific domain of BTS need to be compiled in a advanced technique. The primary challenge in this field of study is effectively segmenting the brain tumor region. Here I have discussed the problems associated with BTS which are unsolved are as follows:

i. Anatomical brain segmentation, also known as brain tissue segmentation, tries to assign each unit a specific brain tissue class. They have to presume that there aren't any tumors or other abnormalities in the brain imaging.
ii. Segmenting a white matter lesion has the purpose of separating it from healthy tissue. Unlike tumor cores, which can be segmented using binary classification algorithms, the white matter lesion in their task doesn’t include such sub-regions.
iii. The goal of tumor detection is to find aberrant tumors or lesions and to indicate the tissue's expected class. Typically, this job yields a bounding box the same as a label for the classification result and the detection result.
iv. It is important to note that certain research approaches for BTS only provide the tumor core's center mask or the single-label segmentation without providing sub-region segmentation.

The above identified problems must have proposed solution in order to reduce the limitation in the domain. However, using MRI data, the issue of developing autonomous BTS models is still challenging. The challenges are brought on by some limitations, such as the impact of various noises encoded in the MRI images of the brain, movement, and metal objects during image capture, a lack of interpretability, low-resolution MRI images, and transparency in DL models. The noisy nature of an MRI image is one of the most challenging issues with BTS using ML Therefore, a critical pre-processing task for increasing the precision in BTS model is noise estimation and denoising MRI images. The durability of ML-based BTS is the same difficulties caused by motion, metal, and other artifacts. DL-based solutions may be minimizing these artifacts. Another significant issue is that deep models are difficult to analyze and are viewed as "black boxes." Finding any proof of the process they use is therefore challenging. However, the comprehensive integration of DL algorithms into medical diagnostics depends on their transparency and interpretability. Compared to other imaging methods, MRI produces a high-fidelity brain scan image. To enhance the efficiency of autonomous segmentation models of brain tumors, post-acquisition image processing methods, have been applied to enhance the quality of MR images using deep learning (DL) based approaches [3].

Glioma segmentation automatically is an extremely difficult problem. MRI data of the brain is 3D data that contains tumors that might vary substantially from patient to patient in terms of form, size, and location. Additionally, tumor borders are frequently ambiguous, irregular, and characterized by discontinuities, which presents a significant challenge, particularly for edge-based techniques. Additionally, the underlying complexity of brain tumor MRI data from clinical scans is high. For every single slice of the dataset's images, there may be intensity biases and other changes imposed by the MRI scanners and acquisition techniques that vary significantly from scan to scan. This intricacy is further increased by the requirement for many modalities to properly segregate tumor sub-regions [1].

3. Recent Challenges in Brain Tumor Neoplasm

Even though the Brain Tumor Neoplasm has seen great advancement, there are still a number of issues that modern DL techniques must resolve. The following categories might be used to group the challenges with BTS [9]: The segmentation of tumors, which is the most complex in MR modalities, is one of the challenges illustrated in this section from [15]. The challenges are often connected to the kind of brain tissue architecture and the data collection process. The following is a summary of these challenges:

Shape Variations Among Brain Tumors: Brain tumors can develop somewhere in the brain tissue and take on any form. This makes it challenging to use a statistical model, one can accurately identify brain tumors, or a model based on the shape short of any prior knowledge. Moreover, the organization of the surrounding normal tissues is also impacted by the tumor mass, which enhances the intensity due to the interaction between tumor regions and healthy tissues' edema.

Data imbalance: One of the biggest challenges with supervised-based segmentation, especially in the context of BTS or even in lesions of the white matter, is unbalanced MR image training datasets. This results from the larger region size of the healthy brain region compared to the aberrant region. The segmentation generated in this case is often inaccurate and biased towards the dominant class in the bigger region as a result of the unequal training datasets employed in this scenario. For instance, the area of normal brain tissues in multimodal MR imaging, which includes the intra-tumor regions of the brain, is greater than the region of abnormal brain tissues. Only tumor sub-regions make up around 1.54% of the total pixels in a picture, whereas ambient and functional brain tissue portions typically occupy 98.46% of the total pixels. The data resampling approach has been studied by several researchers as a potential remedy for the problem of data imbalance.

Data security: The fundamental flaw in supervised segmentation techniques for medical images that leads to fitting is data scarcity. This suggests that the model works well during data training but inadequately during data application. Since brain medical image analysis typically requires radiologists to manually categorize MR images in the field, training labels are frequently not available, which is labor-intensive, subjective, and frequently prone to error.

Bias field: The bias field, which is brought on by flaws in the acquisition procedures or radio frequency coil faults, is yet another difficulty encountered during the MR image processing step known as brain segmentation. The several biases related to MR images include partial volume effects, noise, shading, and artifacts.

Low Contrast: Images with high resolution and contrast are anticipated to carry a variety of image information. MRI images may have inadequate quality and contrast as a result of the image projection and tomography procedure this boundary between biological tissues is unclear and difficult to detect and precise segmentation is difficult to achieve because cells close to the boundary are difficult to classify.

Annotation Bias: Manual annotation is mainly dependent on human expertise, which might induce a bias when labeling data. While few annotations may accurately name each voxel, others prefer to link all the little areas together. During the learning phase, the segmentation algorithm is significantly impacted by the annotation biases.

Disproportion Issue: Different tumor areas have an unbalanced number of voxels. For instance, compared to the other two regions, the Necrotic Tumor Core (NCR/ECT) is a considerably smaller region. The unbalanced problem has an impact on the data-driven learning method because big tumor areas may have a significant impact on the extracted features.

There are many other challenges in the research area like the ability of segmentation algorithms to generalize. The majority of segmentation algorithms now in use are for a specific lesion, making it difficult to generalize them to brain tumors with multiple lesions or other issues. It is challenging to locate in the segmentation process because the ratio of the tumor target zone properly and efficiently to the background of the brain tumor in the MR image is too high. (Particularly the sub-region of brain tumor) is too low. Brain tumor Multimodal data includes MR images. The information between the images may become jumbled if the multimodal data is still not handled effectively for some reason, which could result in no gain or possibly a loss in segmentation accuracy. [16].

4. Overview of Medical Image Analysis

Medical imaging analysis has frequently been used in clinical care and fundamental medical research, such as in image-based applications, computer-aided diagnosis, and the administration of medical record data. Medical personnel can enhance the quality of patient care by using analysis of the medical image to better realize illnesses and look into clinical issues. Segmentation of brain tumors is one of several areas in medical image analysis that has drawn a lot of interest from researchers and has been the subject of ongoing study [9]. Medical imaging is the method of taking images of the human body's internal organs and analyzing them for diagnostic and therapeutic reasons. The study of human tissues and organs is a further application of this approach [12]. Usually, Biopsy is used for diagnosis purposes, but it is intrusive which may cause bleeding and injury [3]. Exceptional innovation in Medical Imaging techniques and the significance of imaging techniques in the diagnosis of patients with brain tumors is an important and significant effect on patients' health [17]. To obtain brain images and provide data about the parameters such as size, location, shape, and metabolism of brain neoplasms, imaging sensory procedures like X-Ray, Ultrasonography, MRI, PET (Positron Emission Tomography), MEG (Magneto Encephalography), CT (Computed Tomography), EEG (Electro Encephalography), SPECT (Single-Photon Emission Computed Tomography), MRS (Magnetic Resonance Spectroscopy), and FMRI (Functional MRI). can be used to make the doctor's plan more reactive and feasible treatment for patients [1,8]. For the detection and treatment of brain tumors, clinical specialists are essential. A radiologic evaluation is important to determine the precise location, size, and relationship of the tumor to the surrounding structures when clinical suspicion of a brain tumor has been established. The choice between various types of treatments depends heavily on this information. As a result, one of the major problems facing radiology departments today is the assessment of brain tumors using imaging techniques [8]. However, due to their broad obtainability and capacity to create high-resolution images of regular anatomical structures and diseases, CT and MR imaging are the most extensively employed procedures.

4.1 Magnetic Resonance Imaging (MRI)

Both MRI and CT scans are used for the segmentation of brain tumors but MRI-based segmentation is getting more and more attention because MRI is non-intrusive imaging, better soft tissue contrast, generated brain images without tissue damage, and provided detailed data without exposing the patient to harmless radiation [8]. In modern neuroimaging, MRI is the backbone for BTS because it used a non-dangerous magnetic field and radio waves to stimulate target tissues, with no damage, and no skull artifact in the human body and enables the clinical doctor to characterize the different properties of a brain tumor [3,16,17]. The simple MRI system is shown in Fig.1 Noise, inappropriate boundaries, and poor contrast are serious factors that affect BTS, but these issues can be minimized by using MR images [18]. MR imaging technique not only distinguishes between healthy and non-healthy tissues but also provides a complete analysis [4,15]. Excitation and repetition periods are changed during image capture to produce images of various MRI sequences. This can provide images of various forms of contrast tissue, which yield invaluable structural data and allow for the recognition of malignancies and the segmentation of their subregions [1]. These sequence images are the MRI modalities or called different modes of MRI images which required to view of different sections of the brain to avoid overlapping of the intensity value of normal and abnormal brain tissues [10,11].

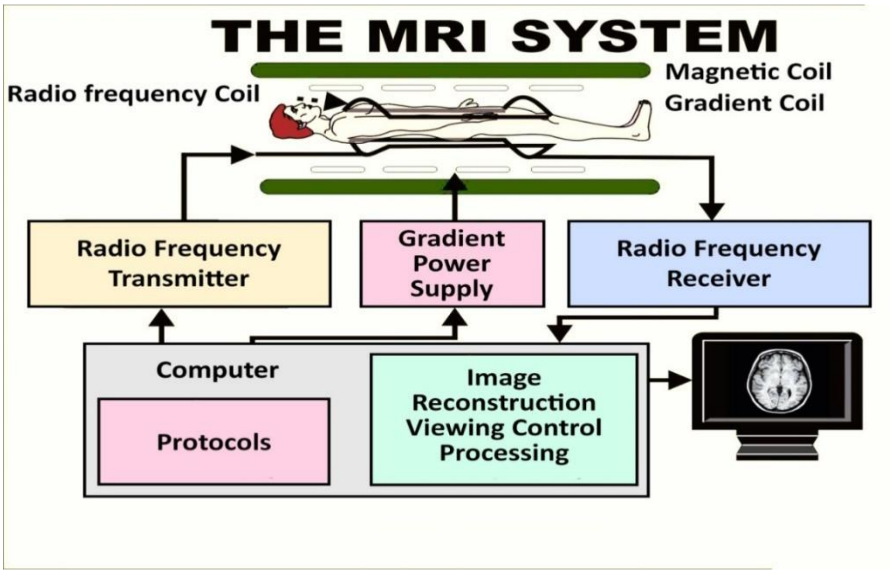

Fig. 1 Block Diagram of MRI System **[13].**

4.2 MRI Modalities

There are four different MRI modes or modalities used for brain tumor diagnosis like T1W (T1-weighted MRI), T1WC (T1-weighted MRI with contrast enhancement), T2W (T2-weighted MRI), Fluid-Attenuated Inversion Recovery (FLAIR) [1,8,10,11,16,18]. Fig. 2 shows four different MRI modalities. T1-W scans are frequently used to identify healthy tissues. Additionally, the tumor border clear signal of the gathered contrast agent (gadolinium ions) inside the active cell region of the tumor tissues is visible in T1-WC images. Despite the contrast agent's inability to engage with necrotic cells, the hypointense area of the tumor core can be employed to distinguish necrotic cells from active cell regions on the same sequence. In contrast, T2-W images are applied to demarcate the edema area, which produces a bright signal on the image. The signal from water molecules is muted in FLAIR images, which aids in differentiating the edema area from the cerebrospinal fluid (CSF) [16].

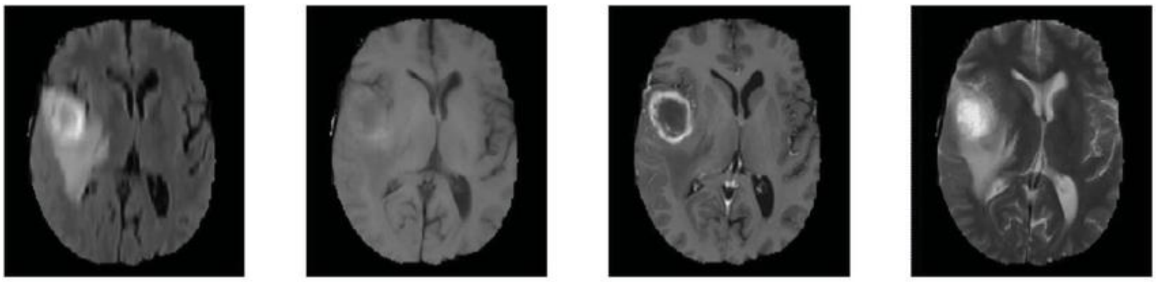

Fig. 2 Four different MRI modalities: From left; Flair, T1-W, T1-WC, T2-W **[1,19]**

4.3 Brain Neoplasm Diagnosis Process

Fig.3 shows the whole process of the Brain Tumor Diagnosis process which the first step is brain tumor detection. Several existing effective approaches can be employed for the tumor detection process. After detection, tumor segmentation is needed to section the tumor for the following stage which is the categorization of the tumor. Several existing and forthcoming approaches can apply for the classification of the tumor to adopt the exact treatment of the brain tumor. However, segmentation of the tumor plays a critical function in identifying the Region of Interest (ROI) for tumor classification prior to classification.

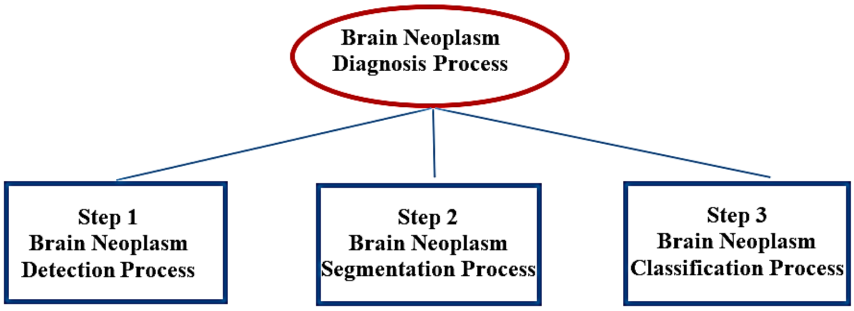

Fig. 3. Stages of Brain Neoplasm Analysis

5. Brain Neoplasm Segmentation Technique

Segmentation is a method to isolate a portion of an image for diagnosis and treatment tracking. Before any therapy or treatment segmentation is necessary to save healthy tissues because during therapy there is a maximum chance of damaging healthy tissues while damaging and destroying malignant cells [1]. Accurate segmentation of Brain MRI influences all the analysis of results and assisted in surgical planning, visualization, pre & post-operative observations, measurement of brain structures, delimiting lesions, evaluation of disease advancement, quantitative analysis, and improving the survival rate [9,12]. Tasks involved in segmentation are shown in Fig.4.

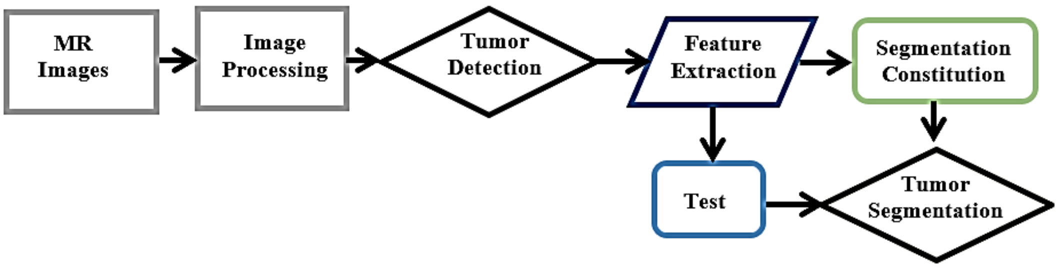

Fig. 4 Generic Process of Tumor Segmentation **[16]**

There are several regions in the human brain but primarily considered three regions for any healthy brain in conventional MRI scans are Cerebrospinal Fluid (CSF), White Matter (WM), and Gray Matter (GM) [3]. According to Fig. 5, these are the normal brain tissues in which a myelinated axon known as WM, which is 70 percent of water, links the cerebral cortex along with new regions of the brain. Furthermore, it links both left as well as right hemispheres of the brain and transports information between neurons. The basal nuclei, which are embedded deeply inside the WM, are found in the GM, which is 80 percent and comprises neuronal then glial cells that regulate brain motion. While the cerebrospinal fluid, which fills the crevices between the ventricular system in the brain, the brain attached to the skull, and the infoldings of the brain., is virtually entirely water (100% water) [3].

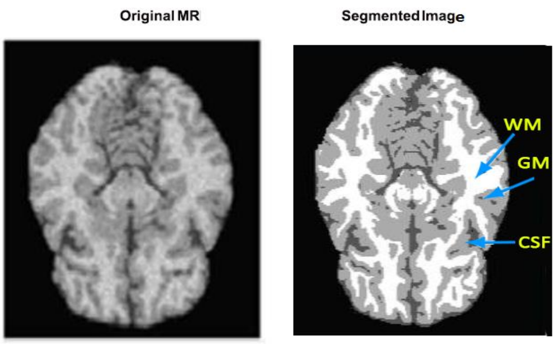

Fig. 5 Original MR image and Segmented Image with Marker: WM, GM CSF **[12]**

BTS is to split the abnormal brain tissues, for instance, solid or active cells (core tumor), necrotic core (necrosis), and together with WM, GM, and CSF edema from the normal brain tissues. [20] as shown in Fig.6. Edema is found close to active tumor boundaries, whereas a dead cell surrounded by a tumor core is present in necrosis. Edema is a swelling that develops as a result of fluid being confined around a tumor [3].

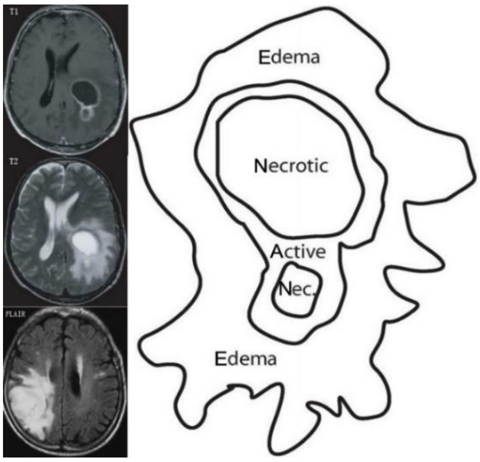

Fig. 6 Left image shows T1 with contrast, T2 and FLAIR of brain tumor MRI images, and the right image shows three main components after the BTS **[8]**

Additionally, these abnormal tissues frequently show similar intensity characteristics in structural MRI chronological sequence including FLAIR, T1-W, and T2-W. For example, it might be challenging to tell the primary tumor from the surrounding inflammation. Additionally, it is challenging to distinguish malignancies based just on signal intensities [3]. Fig. 7 shows four different MRI modalities with corresponding segmentation output.

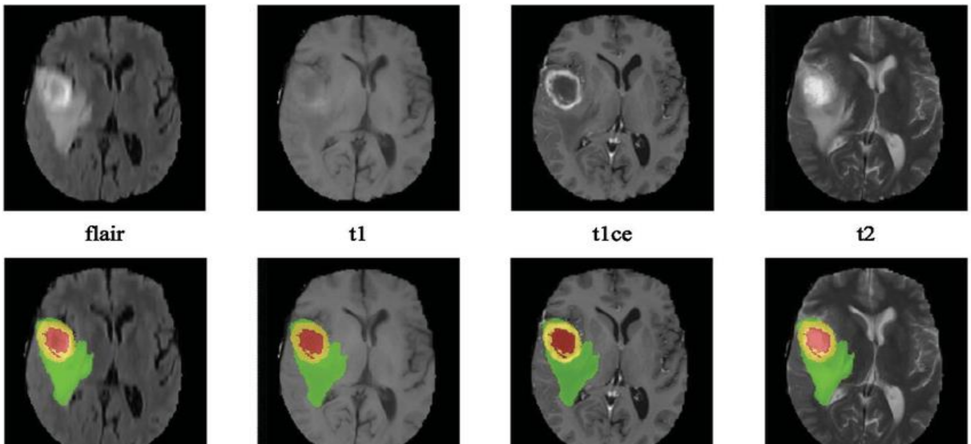

Fig.7 Corresponding Segmentation output of Four MRI Modalities **[19]**

BTS is very much needed in many neurological applications to provide quantitative analysis. Based on different levels of human intervention BTS is categorized into manual, semiautomatic, and fully automatic segmentation. It is unfeasible for medical doctors to segment the images manually in a reasonable time because of an excessive amount of data and images produced in recent years, so segmentation through semi-automatic or fully automatic is the solution [8,10]. For manual segmentation, a radiologist or expert is required with knowledge of brain tumors along with other professional knowledge, and then the expert analyses the examined images of the patient and segments the impacted regions [11,18]. But this is time-consuming, so manual segmentation is good enough for qualitative assessments. At the same time, quantitative assessments through semi or fully automatic segmentation provided significant information about tumor progress, shape, size, location, and effects on other parts of the brain [11]. But such systems always demand an expert opinion as a second thought because the effectiveness of automatic approaches exclusively depends on the knowledge bases even in the absence of specialists [18]. Fig.8 shows the relationship between actual segmentation as well as ground truth in which T0 and T1 represent the background region and ground truth tumor region whereas P0 and P1 represent the background area and tumor area of actual segmentation results [16].

Thus, scientists and researchers have been working to develop different MRI-based segmentation techniques for a brain tumor and over recent years have been successful in this field and proposed several methods with the improvement of such knowledge bases. The popular and most adoptable segmentation method by an expert is semiautomatic but for a few years, automatic segmentation gained interest in research areas that are more robust, efficient, reliable, and objective segmentation [1,11]. Segmentation of medical images is a demanding job due to weak spatial resolution, minimal contrast, ill-defined borders, non-uniformity, restricted volume impact, noise, and diversity of object shapes [4]. Solve these issues by more focus on using computer algorithms like traditional Machine learning (ML) and DL methodologies for the automatic tumors segmentation [1,11]. Recently, using DL methods achieved good performance in segmentation [1]. The development of neural networks, which do not need a domain expert and learn high-level characteristics from the images, is the primary driver of DL's remarkable success over traditional ML models [2].

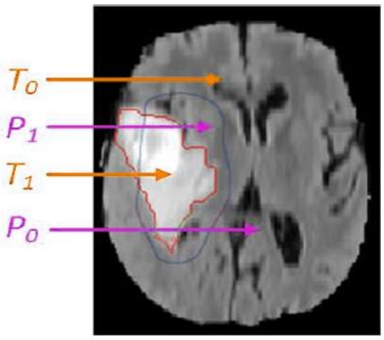

Fig.8 Actual segmentation and Ground truth Comparison **[16]**

6. BTS Statistical Analysis

One of the top 10 tumor types is a brain tumor, although people know very little about them, especially in Pakistan observed by World Brain Tumor Day conducted at Shaukat Khanum Memorial Cancer Hospital and Research Centre, Pakistan [21]. According to the study at Agha Khan University at the inaugural Symposium of the Pakistan Society of Neuro-oncology, PASNO, brain tumors have the lowest survival rates in Pakistan as compared to other cancers and according to preliminary study results, Pakistan has fewer high-grade tumors than other developed economies. However, compared to the West, brain cancer sufferers are often younger [22]. Brain Tumor has 11th Ranked in Pakistan as per the fact sheet of Global Cancer Observatory 2020 which uses the data provided by the International Agency for Research on Cancer associated with WHO. According to this fact sheet, the total number of cases is 4770 which is 2.7%, and deaths are 3934 which is 3.4% as compared to other cancers in Pakistan and 5 years prevalence of all ages is 4.58% per 100,000 cases annually [23]. Brain tumors account for 2% of all cancer deaths globally and have an annual incidence of 4-5/100,000. They are the most important cause of cancer-related mortality and morbidity.

In Pakistan, 150 000 new cases of cancer are diagnosed each year, and 60 to 80 percent of these cases result in death [24]. According to the American Cancer Society and National Cancer Institute, in the United States in 2022, the estimated number of new cases of malignant tumors in both males

and female are 25050 (4,170 in males and 10,880 in females) and deaths are 18280 (10,710 males and 7,570 females) and these stats much higher if benign tumors also included and the 5-year (from 2012-2018) relative survival rate is 32.5% [25,26,27]. The relative survival rate is used to compare the community as a whole with patients with the same type of tumor. When the 5-year relative survival rate for a specific type of brain tumor is 70%, for instance, it means that, on average, 70% more persons with that tumor will live for at least 5 years following diagnosis than those who do not [28]. The Central Brain Tumor Registry of the United States (CBTRUS) provided the data in table 1 based on patients who had therapy between 2001 and 2015. However, the survival rates for various types of brain and spinal cord cancer might vary based on age, as can be shown below. Younger people often have better prognoses than older ones. Generally, older people (65+) have poorer survival rates than younger people (age categories below) [28]. The incidence rate in the US was 24.23 cases per 100,000 people for all primary malignant and non-malignant brain and other CNS cancers, according to the CBTRUS, Statistical Report 2021 that used data from NPCR and SEER based on data from 2013 to 2017 that were analyzed in 2020, for a total of 431,773 incident tumors, with a malignant tumor rate of 7.06 per 100,000 cases (125,524) and a non-malignant tumor rate of 17.18 per 100,000 cases (306,249). Females experienced a higher rate (26.95 per 100,000) than males (21.35 per 100,000). In the US, 88,970 new instances of primary malignant and non-malignant brain tumors and other CNS malignancies are estimated in 2022. About 63,040 primary benign and 25,930 primary malignant brain as well as other CNS cancers are included in this total.
Primary incidence rates of CNS tumors, including brain tumors, were 3.5 per 100,000. in the world in 2020, age-adjusted to the global average population. Males experienced an incidence rate of 3.9 per 100,000 while females experienced a rate of 3.0 per 100,000. In 2020, it is expected that 308,102 persons, 168,346 men, and 139,756 women, will get a diagnosis with a primary malignant brain tumor. High-income nations had greater incidence rates (7.4 per 100,000) than low-middle-income (2.2 per 100,000) or low-income (1.8 per 100,000) countries [29].

Table 1: Survival rates for more frequent adult brain and spinal cord tumors in the US **[28]**

Tumor Types	**5-Year Relative Survival Rate**		
	Age		
	55-64	**45-54**	**20-44**
Low-grade (diffuse) astrocytoma	26%	46%	73%
Oligodendroglioma	69%	82%	90%
Glioblastoma	6%	9%	22%
Meningioma	74%	79%	84%
Anaplastic oligodendroglioma	45%	67%	76%
Anaplastic astrocytoma	15%	29%	58%
Ependymoma/anaplastic ependymoma	87%	90%	92%

7. Databases Selection

The BraTs (Brain Tumor Segmentation) database is the most widely used database for the segmentation of brain tumors, and only a few studies use clinical databases. The datasets BraTs2013, BraTs2015, BraTs2017, BraTs2018, BraTs2019, and BraTs2020 are the ones that are most often used [16].

7.1 BraTs Database Selection

The BraTs database is made available by the MICCAI (Medical Image Computing and Computer Assisted Intervention) conference. It serves as the official repository for the conference's brain tumour MR image segmentation challenge, and it is also heavily used by scientists that study this subject. Since the 2012 challenge, the BraTs database has already been periodically updated [16]. The BraTs database's URL is as follows [16].

BraTs 2013 (from https://www.smir.ch/BRATS/Start2013)
BraTs 2015 (from https://www.smir.ch/BRATS/Start2015)
BraTs 2017 (from https://www.med.upenn.edu/sbia/brats2017/data.html)
BraTs 2018 (from https://www.med.upenn.edu/sbia/brats2018/data.html)
BraTs 2019 (from https://www.med.upenn.edu/cbica/brats2019/data.html)
BraTs 2020 (from https://www.med.upenn.edu/cbica/brats2020/data.html)

7.2 Clinical Database Selection

With the patient's consent, the hospital gathers clinical information from MR brain tumor images while they are receiving therapy. Doctors utilize the gathered MR brain images to assess patient health and provide appropriate and efficient treatment programs. Researchers are prohibited from using such data for study without the consent of the patients and hospitals due to patient privacy concerns and ethical considerations. Since each hospital collects clinical data from different patients at different times and uses different technology to do so, the performance of segmenting data from different hospitals cannot be evaluated practically. [16].

8. Generic Methods for Brain Neoplasm Segmentation

Currently, segmentation approaches can divide into different classifications based on different principles, but segmentation is a process of breaking an image into many slices to detect tumor areas so based on how much clinical expert or doctor intervention involve in this process, In general, there are three types of segmentation including Manual, Semi-Automatic, and Fully Automatic Segmentation. Fig.9 shows obsolete, old and recent segmentation techniques.

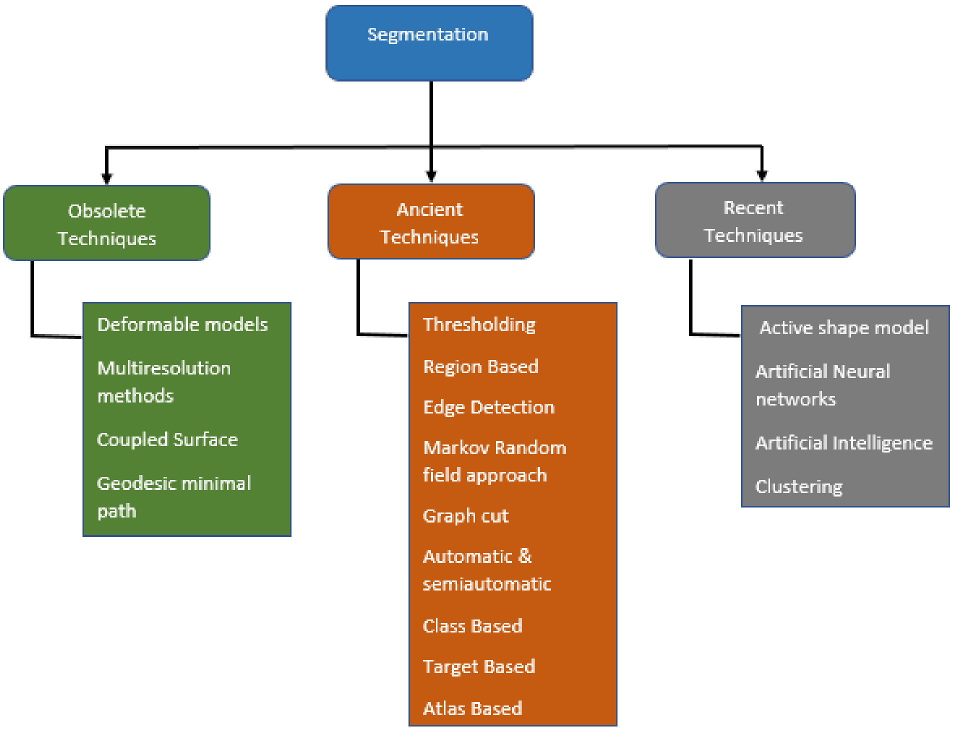

Fig. 9 Various Segmentation Techniques **[30]**

8.1 Manual Segmentation Approach

A radiologist or clinical doctor is required for manual segmentation. Brain tumors are manually segmented by either manually drawing the area of anatomical structures with distinct labels or manually marking the boundary of the tumor along with structures of interest. Clinical doctors (radiologists, anatomists, and trained technologists) apply extra knowledge, such as brain anatomy, and physiological knowledge on which the accuracy of segmentation depends got through training and experience in addition to the multi-modality information provided in the MR images while doing manual segmentation [1,12,20]. To make drawing regions of interest and image presentation easier during manual demarcation, software solutions with advanced graphical user interfaces are needed. In actuality, locating the location of a tumor or the region of interest is a laborious, error-prone, costly, and time-consuming process. Multiple two-dimensional cross-sections (slices) are produced in slices using MRI scanners and a radiologist must examine the multiple slices of the images dataset to choose the most illustrative ones (diagnose tumor) from which the pertinent areas are gently demarcated [12,20].

A single image is often used for manual segmentation of brain tumors, with an injected contrast agent providing intensity augmentation. However, it will probably produce subpar segmentation results if the ROI is not drawn by a radiotherapist, anatomist, or skilled technician who is familiar only together with that brain architecture. Slice by slice tumor location identification can occasionally limit human raters' judgment and result in pixelated images. The segmented images as a result exhibit a "stripping" effect and are less than best. Naturally, manual ROI delineation depends on the radiologist and the segmentation results are based on large intra- and inter-rater variability [19]. Fig. 10 gives an example in [19] in which four different radiologists perform segmentation on the same slice and patient but each has a noticeable disparity which clearly shows the case of inter-rater inconsistency. Both semi-automatic and fully automatic segmentation systems frequently use manual segmentation as a realistic validation, with the results being evaluated both qualitatively and numerically using the manual process, despite the potential for intra- and inter-rater variability. Semi-automatic or, preferably, fully automated segmentation methodologies will outperform manual demarcation. However, clinical research continues to frequently use manual segmentation, particularly when it takes a lot of human skill and knowledge to differentiate between tissues [1,19].

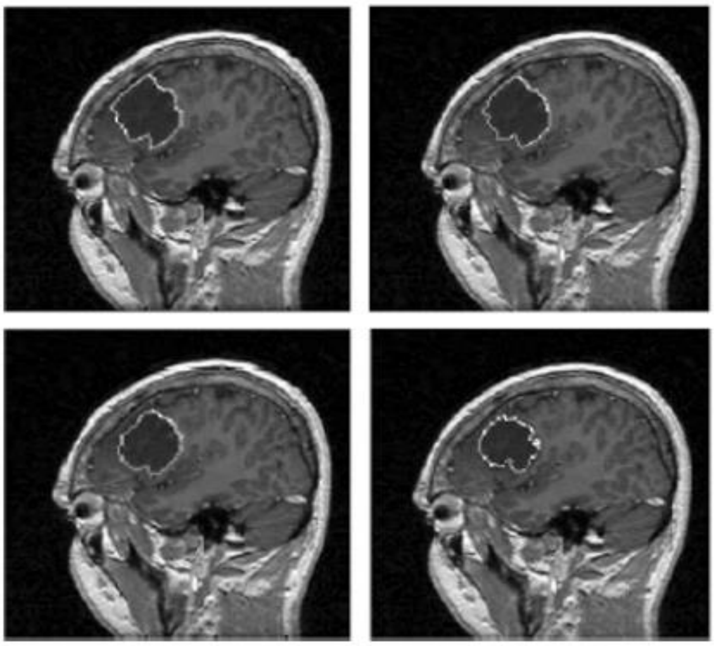

Fig. 10. Manual Segmentation by Four different clinical experts **[19]**

8.2 Semi-Automatic Segmentation Approach

Semi-automated segmentation uses both expert skills and computer aided system [11]. Clinical expert assistance is frequently required in semiautomatic segmentation to start the algorithm, verify the correctness of the output, or even adjust the segmentation outcome manually. To minimize human participation, the majority of existing research focuses on semiautomatic segmentation. The computational, interactive, and user interface components make up the core of a collaborative BTS approach. The computational component consists of one or more software modules that, given a set of parameters, can provide tumor delineation. The interactive component is in charge of serving as a communication bridge between the user and the computational component. It converts the computational segment's output into a graphical response for the user to put the parameters for the program. The user interface-controlled output and input devices serve as the primary means of communication between the computer and the user. The user examines the visual information displayed on the screen and responds as a result, giving the computer feedback. [8,19].
Initialization, intervention or feedback response, and evaluation are the three main purposes for which semiautomatic segmentation requires user interaction [1].

- ***Initialization****:* It involves entering claims or criteria (using a keyboard, mouse, or other input devices), preprocessing the image to improve the quality (such as sharpening or noise reduction), and evaluating the image data's complexity while inputting arguments or parameters to enhance decision-making. A three-dimensional representation or a preliminary slice of the data set, the user can choose the element to be digested. [19]. It implies that initialization is often carried out by designating a ROI that covers the approximate tumor region [1] for the automated algorithm to proceed.
- ***Intervention/Feedback reaction:*** responding in response to procedure-generated feedback data, either constantly or sporadically guiding the process towards the desired outcome; when negative findings are obtained, halting the operation in the midst to make changes, then restarting the process [19].
- ***Evaluation****:* Assessing if the process's result is accurate or sufficient by assessing it. If the results are unsatisfactory, the method is repeated, the justifications or variables are adjusted appropriately, and the results are modified—or, in very few cases, the results are flatly rejected [19].

The results of these approaches depend equally on strategy and computation since semiautomatic methods employ different strategies to integrate the knowledge of computers and experts. These techniques might include starting the segmentation process with the user at the center, being in control of the process at all times, or introducing creative behavior to raise the abstraction of participation. Although these strategies may indeed be used to acquire effective semiautomatic segmentation approaches for brain tumors and better results than manual segmentation, semiautomatic segmentation, like manual segmentation, is subjected to dissimilarities in findings from various experts or the similar expert at various times [8,19]. Even though semi-automatic techniques are faster than a manual technique for segmenting brain tumors and are capable of producing effective outcomes, they are nevertheless subject to intra-rater and inter-rater/user variability, and segmentation results still depend on clinical experts. Consequently, most recent research on BTS uses automatic techniques [1].

8.3 Fully Automatic Segmentation Approach

Except for any human or expert involvement, the computer segments the tumor in fully automatic methods. Fully automatic methods are typically developed using soft-computing combined with model-based techniques, and typically incorporate human intelligence or artificial intelligence and background knowledge into the algorithms to overcome the segmentation issue [1,19]. Fig.11 shows a detailed view of segmentation techniques.

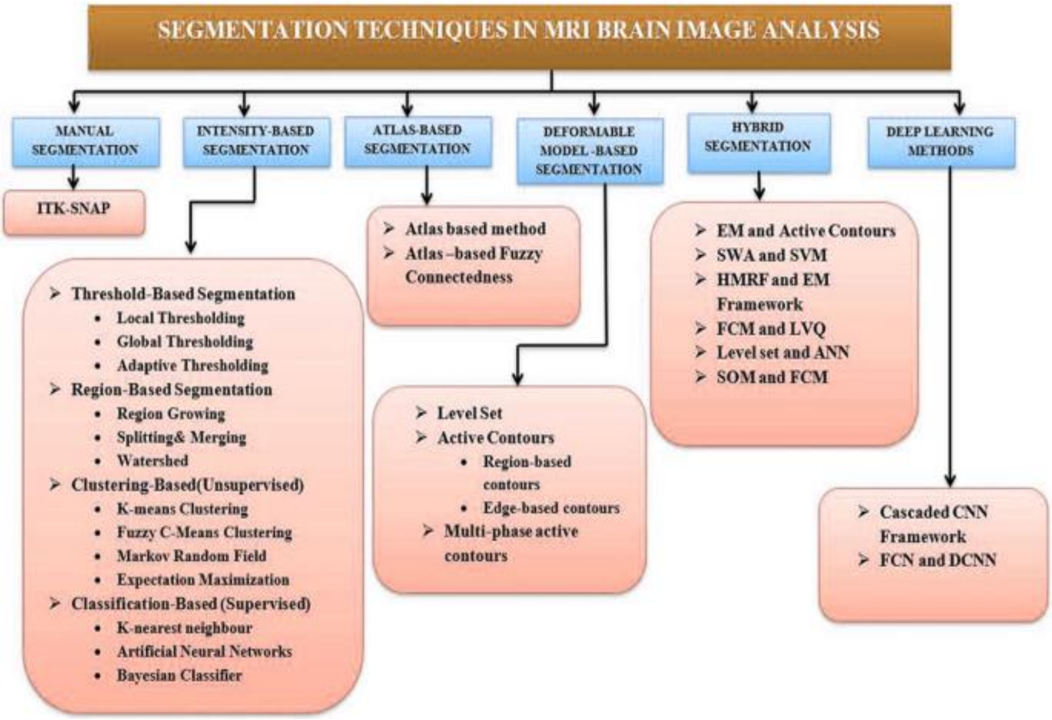

Fig. 11 Segmentation Techniques **[31]**

Automatic BTS is a fascinating topic for research in pattern recognition techniques because it is a challenge that humans can successfully solve due to the advancement of ML procedures that can successfully simulate human intelligence [8]. The challenge still lies in creating highly accurate automated methods. This is certainly justified by the existence of humans should use sophisticated graphical processing and specific field knowledge to complete this task, which makes it extremely challenging to develop fully automatic methods [12,19]. This is valid for many issues related to vision and pattern recognition but there are a few characteristics of BTS that minimize the benefit of having humans instead of computers. For example, it is evident from the anatomical features of the brain that the head appears in MR pictures primarily reliably, that the physiological processes of the brain are well-understood, and that the behavior of various tissue types in various MR modalities is well-characterized. Due to the lack of temporal components and the brain being stationary, Visual object tracking over time is not a helpful skill. Since the viewpoint is known and people see the data as a sequence of two-dimensional slices, their edge over machines is reduced. As a result, humans' capacity for using three-dimensional knowledge in segmentation is diminished in this job due to the lack of three-dimensional modeling of structures using a range of perspectives. Segmentation should be impacted by implicit or explicit anatomical information, such as size, shape, location, predicted tumor appearance, and bilateral symmetry, for reliable automated systems. The segmentation model may take into account this information as initial conditions, restrictions on the model shape parameters, data limits, or during the model fitting process. It is essential to create an automated segmentation model that not only accounts for the tumor's size, location, growth, and shape, but also allows for projected changes in these characteristics [19]. Fully automatic segmentation techniques usually depend on supervised learning, in which large datasets are used to understand associations between the input image and human-annotated data. Fig.12 shows the supervised and unsupervised segmentation methods.

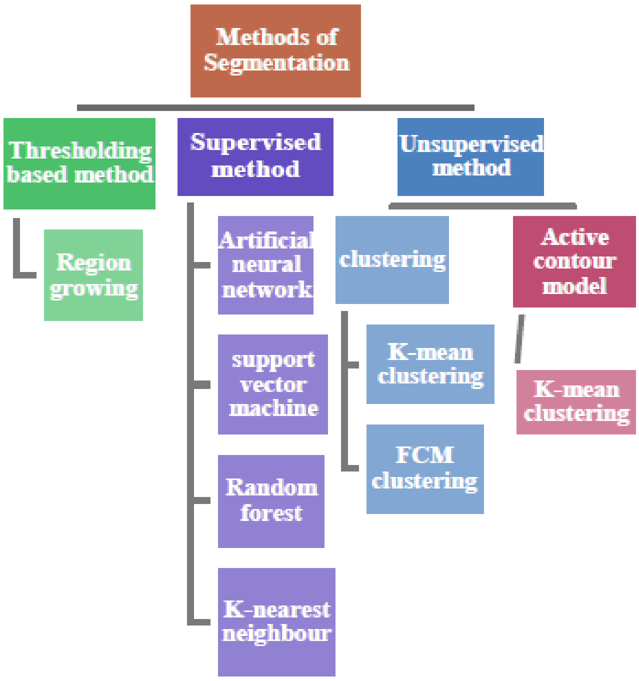

Fig. 12 Approaches of Segmentation **[7]**

Over the years, this group has made extensive use of traditional ML algorithms, which depend on manually created features. Due to the intricacy of medical images, these methods might not be able to fully use the training data. DL techniques have grown in prominence more recently due to their exceptional implementation is the ability of computer vision to directly extract information from data [11]. Fig.13 shows the classification of segmentation methods among conventional ML and DL techniques. Currently, only the research environment has access to completely automated segmentation algorithms, which are useful when processing large batches of images. It should be mentioned that practitioners do not generally support using these strategies in routine clinical practice. (Neurologists, radiologists, and to a much lesser extent pathologists). It has mostly been brought on by the segmentation process's lack of interpretability and transparency [19].

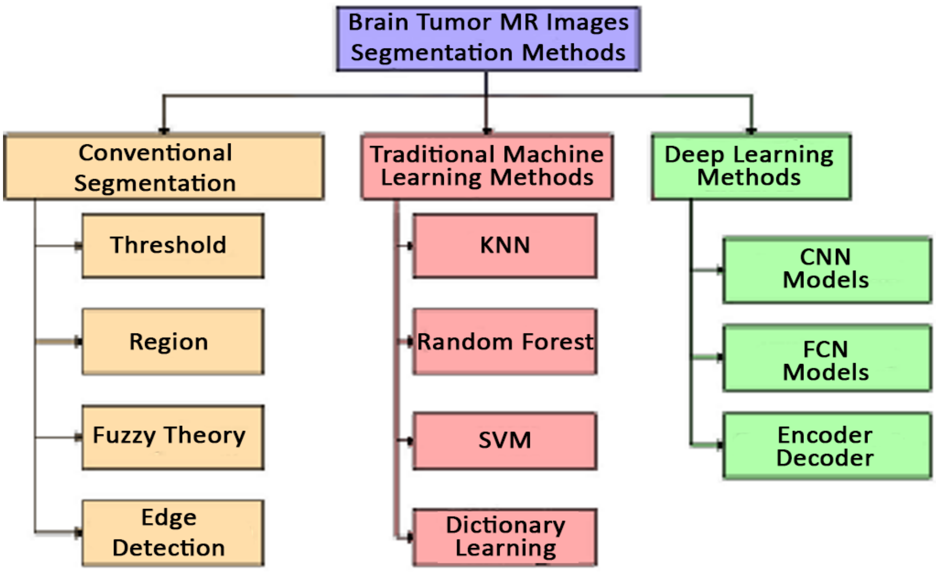

Fig. 13. Segmentation Methods **[16]**

Deep Learning Approach: It is another growing area of ML which is a subset of artificial intelligence. Because of its multiple-layer design, which represents data with several layers of abstraction, it can address several issues that arise in conventional ML techniques [18]. Due to its enhanced efficiency and ability to compile adaptive features automatically, which outperform manually created features, the DL-based technique has recently attracted a lot of academic attention. These features were additionally learned in a trend of rising feature complexity, which produces more reliable feature learning [15]. Before executing input picture segmentation based on the deep features, an image is often passed through a network of DL building blocks in the DL-based BTS strategy [3]. More research has been developed over the past few years employing a hybrid of the DL-based approach and the recent segmentation technique of brain tumors. Convolutional Neural Networks (CNN) were commonly used in research because they are effective in detecting patterns in images, especially MR images, and they have shown promising outcomes. To date, 2D, 2.5D, or 3D MR images have been used for DL-based segmentation [15]. Furthermore, its simplification and self-learning capabilities enable improved quantitative imaging feature analysis and, as a result, improved neurological problem diagnosis. DL-based segmentation and classification approaches are therefore becoming more popular in the area of medical imaging [18]. According to various network contexts, segmentation of the brain MR image based on Deep Neural Networks (DNN), CNNs, Deep Convolutional Neural Networks (DCNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Deep Auto-Encoders (AEs), Stacked Auto-encoders and Generative adversarial networks (GANs). Fig.14 shows a detailed view of DL techniques developed for efficient BTS. To obtain the highest performance, research is moving quickly to uncover more and more DL techniques. It has been observed that combining DL with other methods increases accuracy.

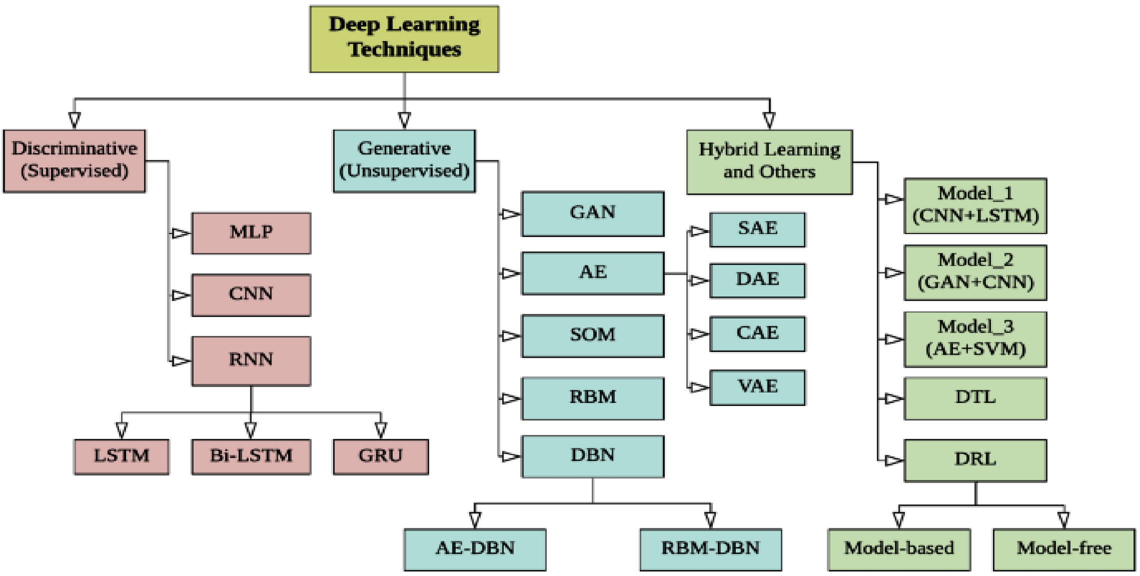

Fig. 14. Deep Learning Methods **[32]**

9. Recent Approaches of Brain Neoplasm Segmentation Techniques

BTS on images of MR involves complex algorithms and techniques in the field of AI and ML which help us doctors to diagnose brain tumors. Nowadays, this has been a popular area of research that helps in the crucial procedures for the treatment of brain tumors. Based on various concepts, there are different categories in which BTS techniques may be classified. There are a lot of techniques for segmentation that have been applied for the complex treatment of brain-tumor based on CNN, ML, neural networks, DL, etc. As a result, various survey works have been carried out to promote the research area and examine the techniques used in the segmentation of tumors in MR images. The manuscript focuses on reviewing this BTS technique or method on MR images after brain tumor detection. Table 2 presents a year-wise detailed overview of different BTS techniques.

S. No	Ref	Author	Methodology	Image Type	Validation	Key Findings and contributions	Limitation
1.	[33]	Jaspin and Suganthi	Fuzzy C-Means Optimization and Greedy Snake Model	MR Images	• k-means • GMM • FCM • New Threshold • Interactive	• Improve Dice-score, specificity, and sensitivity. • It provides a lesser values and small changes in segmented output	• Very small changes in segmented output • Less test images used
2.	[34]	Kaldera *et al*	Faster Region Based CNN	MR Images	• N/A	• Accuracy 99.81% • Sensitivity87.72% • Dice Score 91.14%	• Low accuracy level • Average dice score
3.	[35]	Abdelmajid Bousselham *et al*	Temperature distribution approach	MRI Images	• Level set method	• Significant improvement in segmentation accuracy • A new indication to enhance tumor segmentation.	• Inaccuracy in the temperature calculation • Due to isotropic modelling, do not represent the patient's realistic characteristics.
4.	[36]	Salma Alqazzaz *et al*	SegNet Max DT	MR images	• Kamnitsas • Casamitjana • Bharath	• Segment core and enhanced tumors are superior to cutting-edge techniques. • SegNet Max DT outperforms than standalone SegNet models.	• FCN and CNN must be used to increase proposed system performance. • Low detection accuracy for edema
5.	[37]	Javeria Amin *et al*	Score Level Fusion Using Transfer Learning	MRI Images	• Input Cascade CNN, FCNN +3D CRF, DNNs, Ensemble + CRF, 3D U-Net	• Light weight with accurate segmentation • Feature fusion outperforms separate features in terms of performance	• Future training for tumor identification might include coronial and sagittal views.
6.	[38]	Yalda Amirmoezzi *et al*	3D FLAIR images	MR Images	• Context-sensitive • Tumor-cut	• Real-time data indicated positive outcomes for the precise removal of the brain tumors.	• In clinical environments, one imaging modality may be utilized.
7.	[39]	Daniel E. Cahall *et al*	Inception Modules and U-Net.	MR Images	• DSC cross-validation model	• Inception modules beat models made to segment the glioma sub-regions.	• Findings demonstrate a only on the whole tumor (WT).

8.	[40]	Tamjid Imtiaz *et al*	Multi-Planar Super Pixel Level Features	MR Images	• Multimodal symmetric optimal template	• Better performance of measures like Dice score, Specificity, sensitivity, Jaccard and PPV.	• High levels of precision in the segmentation of the tumor region may further improve the desired performance metric values.
9.	[41]	Kai Hu *et al*	Conditional Random Field and Multi-Cascaded CNN	MR Images	• Efficient multi-scale 3DCNN • Optimal symmetric multimodal Template	• The method not only provides consistent segmentation values, but also has a very low level of computing cost, according to the given results.	• The performance decreases significantly when data are differed and not following 3D information
10.	[42]	Guotai Wang *et al*	Convolutional neural networks that are cascaded and include uncertainty estimation	MR Images	• Different scalable multimodal convolutional networks for the BTS.	• The proposed approaches determine that the cascaded framework with 2.5D CNNs used in testing with the BraTS 2017 dataset is the model that performs the best.	• The proposed approach may find some limitations such as false positives of edema so it me be addressed
11.	[43]	Wu Deng *et al*	HCNN AND CRFRRNN	MRI Images	• CRF-Recurrent Regression based Neural Network with Train CRF.	• The proposed method resulting high energy optimization, precision ratio and better sensitivity is achieved.	• CRFs could be applied to the deep network of post-processing in HCNN.
12.	[44]	Ping Liu *et al*	3D Squeeze and Excitation with EDNN	MRI Images	• Modified V-Net with 3D U-Net.	• Results comparing the 3D U-Net model and modified V-Net model show that the former performs efficiently.	• The receptive field problem is a flaw in this model.
13.	[45]	Jianxin Zhang *et al*	Attention Gate ResU-Net	MRI images	• AGU-Net • AGResU-Net • U-Net • ResU-Net.	• Results showing the crucial feature information while separating out noise and irrelevant feature responses	• The difficulty of using MRI brain imaging is a study limitation.
14.	[46]	Guohua Cheng *et al*	Revised multitask learning	MRI images	• IN & ReLU techniques	• The dice coefficient has improved for various types of brain tumor region by a margin of 0.4–1.0.	• Inaccurate results may be addressed by segmentation technique.
15.	[47]	Mobeen Ur Rehman *et al*	Modified U-Net Architecture	MRI images	• Baseline U-Net	• Better performance in terms of contextual features of the MRI scans	• During the 3D U-Net analysis the data may be lost
16.	[48]	Rui Hua *et al*	Multimodal in Cascaded V-Nets.	MRI Images	• Conventional CNN.	• Average dice scores for the proposed model were 0.9048, 0.8364, and 0.7768.	• 2D testing may also be used for better results comparison

17.	[49]	Florian Kofler *et al*	BraTS model	MRI Scans	• Analysis of BraTS segmentation model	• Proposed algorithm indicates better tumor growth identification using different BraTS segmentation model	• Errors in data acquisition and incomplete protocol is a limitation factor in the proposed model
18.	[50]	Soukaina and Hamid	Deep Learning and Hidden Markov method	MRI Images	• K-means clustering and LBP method	• In comparison to the U-net design, the provided results demonstrate the Markov approach's average accuracy.	• There may be more convolutional layers per block if a large dataset is used with the U-net model.
19.	[51]	Xiaoliang Lei *et al*	A sparse constrained level set algorithm	MRI Images	• Two-stage segmentation for brain tumors in MRI images.	• With an average accuracy of 96.20% for the MR images from the dataset Brats2017, the suggested results perform better than the competition.	• Future studies may increase the proposed model's data utilization rate.
20.	[52]	Mostefa Ben naceur *et al*	Multi-class weighted cross-entropy	MR Images	• CNNs architectures with and without post-processing	• Automatic segmentation model for the entire tumor region • This model can segment the entire brain in an average of 16 seconds.	• Trained using a number of heterogeneous datasets, such as the BRATS dataset, the proposed model is restricted in CNN performance degradation.
21.	[53]	Yi Ding *et al*	Multi-path Adaptive Fusion Network	MR Images	• Analysis of FC-Dense Net	• The proposed study performs better while using fewer parameters and segmenting data more quickly.	• Results could lead to improved multimodal BTS performance.
22.	[54]	Dingwen Zhang *et al*	Deep convolutional neural networks.	MR Images	• Baseline models (SA, SB, SA+SB)	• Without any human annotation, the results demonstrated the actual feature representations	• Proposed study may require the combination of network architectures
23.	[55]	Hikmat Khan *et al*	CNN and Cascading handcrafted features.	MR Images	• CNN • Generative model • Deep CNN.	• Comparing the proposed system to the intra-tumor regions, it produces better results for segmenting whole tumor region.	• Segmentation accuracy may be increased by using separate priority on each tumor type
24.	[56]	Khaled Bousabarah *et al*	Deep CNN	MR Images	• DCNN image data by manual segmentation	• The findings show that DCNNs perform clinically relevantly for the most of lesions.	• In future studies patients eligible for SRS may be considered •
25.	[57]	Qingyun Li *et al*	Tumor GAN	MR Images	• GAN with Pix2pix on four different modalities.	• Given approach can produce images that resemble the actual data distribution and can create picture pairings of excellent quality from a little quantity of paired data.	• Proposed method restricts the diversity of semantic labels which may be address in future work

26.	[58]	Dingwen Zhang *et al*	Cross-Modality Feature Transition and Fusion	MR Images	• 13 cutting edge techniques	• According to experimental results, segmenting the targeted regions of brain tumors may be done more precisely while using significantly reduced computing cost.	• The proposed approach might not investigate task structures for additional tasks in the field of in the more traditional image and video domains, such as medical image analysis.
27.	[59]	Chandan Ganesh Bangalore Yogananda *et al*	Fully Automated DL Network	MR Images	• Multi-label CNNs • Triple network architecture of 3D Dense U-Net CNN	• In terms of segmenting WT and ET • The proposed algorithm exceeded the top performers and offers quantitative analysis.	• Results are restricted for participants used to train the network in larger numbers.
28.	[60	Amjad Rehman Khan *et al*	k-means clustering and finetuned. CNN model	MR Images	• Suggested method Prior to and following synthetic data augmentation	• Overall accuracy of the proposed technique was 94.06% after synthetic data augmentation and 90.03% before.	• Proposed CNN based method may be compared with different data sets in future studies
29.	[61]	Fengming Lin *et al*	Path aggregation U-Net	MR Images	• Fully CNN • VGG • DUNet	• Proposed system results show that the path aggregation encoder and the enhanced decoder significantly boost segmentation performance.	• Enhance framework. • for merging multiple relevant components may be used in future to address lack of supervision
30.	[62]	R. Pitchai *et al*	DL and Fuzzy K-Means Clustering	MR Images	• 2D CN ConvNet technique, • Fully CNN • KNN methodology.	• With a maximum level of 94% accuracy, the suggested segmentation approach yields exceptional segmentation results.	• The performance of an ANN classifier is not improved when there are considerably fewer Hidden Neurons (HN). • As the number of HN rises, the ANN classifier provides reduce values of sensitivity, specificity, and accuracy.
31.	[63]	Prabhjot Kaur Chahal *et al.*	Weighted fuzzy k-means	MR Images	• FSVM KIFCM • EM + adaptive threshold + FFT + MRMR + SVM	• Proposed system on the DICOM Dataset, the outcomes of WFKM are compared with k-means, FCM, and canny edge detection techniques.	• Increase the system's accuracy by incorporating datasets of various sizes, which will help to validate the suggested WFKM.
32.	[64]	Antonio Di Ieva *et al*	Heuristic approach	MR Images	• Myronenko	• The proposed model achieves superior performance by using T1 + T1C + FLAIR segmentation	• Future research on the suggested technique may incorporate post-treatment images
33.	[65]	Francisco Javier Díaz-Pernas *et al*	Multiscale CNN	MR Images	• SVM, Fisher kernel CNN • CNN • KELM	• Results indicates better tumor classification accuracy performance	• FCN architecture may be used for the classification of the MRI images

34.	[66]	Asieh Khosravanian *et al*	Region-based image segmentation and intensity inhomogeneity of the image.	MR Images	• Multiplicative Intrinsic Component Optimization • Chan-Vese • Local Intensity Clustering,	• The mean values of the Dice, sensitivity, Jaccard and specificity metrics are, respectively, 0.86 0.03, 0.94 0.04, 0.77 0.05 and 0.99 0.003 in the proposed segmentation model of brain tumor.	• This strategy is typically expanded to include 3D/4D image segmentation.
35.	[67]	Ramin Ranjbarzadeh *et al*	Cascade CNN and Distance-Wise Attention mechanism.	MR Images	• Multi-Cascaded • Cascaded random forests	• The suggested model forecasts rapid clinical image preprocessing that eliminates a considerable portion of irrelevant pixels from the image.	• The proposed approach has limits when dealing with tumors that surround a third of the whole brain.
36.	[68]	Yan Zhang *et al*	A multi-scale mesh aggregation model	MR Images	• DLANet • U-Net++ • DLANet + • MSAFEB •	• To improve the final recognition, in addition to deep supervision, the proposed adaptive hybrid model also contains an aggregation block decoder.	• 3D model may be used to improves the dimensions of the images
37.	[69]	Xinyu Zhou *et al*	3D residual neural network	MR Images	• ResNet50 + Res decoder • ShuffleNetV1 + Res decoder • ShuffleNetV2 + Decoder	• Proposed model shows better segmentation process and lowest computational complexity.	• High number of decoder parameters may be used to achieve desired improvements. Did not achieved desired
38.	[70]	Farzaneh Dehghani *et al*	Deep convolutional neural network	MR Images	• 13 different ResNet models. • single and multichannel DL models.	• Evaluate the effectiveness of the single, dual, and multi-channel DL models. • Joint tumor segmentation performs better than single-channel segmentation.	• Even if the outcomes of many MR sequences have improved, the extended imaging time remains a significant obstacle.
39.	[71]	Ejaz Ul *Haq et al*	CNN, faster RCNN and Machine Learning classifier	MR Images	• Combination of CNN and ML	• Accuracy was 98.3% and DSC was 97.8% for the proposed SVM-RBF classifier and deep CNN	• The proposed model can be expanded in future by using larger data sets and other tumor types
40.	[72]	Szidónia Lefkovits *et al*	CNN of Amazon Sagemaker	MRI images	• Analysis of BraTs 2017 to 2020 data sets	• Provide a dice score for the entire tumor of approximately 90%, the tumor core of 84%, and the augmented tumor of 78%.	• Better results may be achieved by using binary classification steps. • Quality and resolution of images can be standardized

41.	[73]	Dongwei Liu *et al*	SGEResU-Net	MR Images	• Analysis of 3D U-Net models	• Results from the proposed model for brain tumors indicated that MRI BTS was a successful endeavor.	• The suggested model might be based primarily on other medical image segmentation applications.
42.	[74]	Salma Alqazzaz *et al*	ROI image generation, SegNet model and DT to classification	MR Images	• Analysis of BraTs Data set on proposed ROI approach	• In comparison to approaches, the proposed model SegNet GLCM DT method greatly enhanced segmentation for whole tumor.	• The accuracy of enhanced tumor (ET) and tumor core (TC) segmentation may be improved in future research.
43.	[75]	Ahmet Ilhan *et al*	U-net-based nonparametric localization and enhancement techniques	MR Images	• UNet	• The proposed model's get better results of 0.94, 0.85, 0.87, and 0.88 were obtained employing data from BRATS 2012, 2019 and 2020.	• Suggested model may be segmented in different medical fields
44.	[76]	Xi Guan *et al*	V-Net, Squeeze and Excite" (SE) and Attention Guide Filter (AG)	MR Images	• Performance analysis with classic methods of segmentation.	• Experimental results indicate the Dice score of, tumor core is 0.85, whole tumor is 0.68 and enhanced tumor is 0.70.	• The further segmentation of region of interest may be suggested to improve the accuracy of the model
45.	[77]	Shidong Li *et al*	Region of interest aided localization and UNet	MR Images	• 2D UNet • 3D UNet.	• The suggested method is best suited for early detection, diagnosis of Brain Tumor.	• R-CNN model may be used for the object detection in future studies
46.	[78]	Kh Tohidul Islam *et al*	Deep Learning Framework	MR Images	• Computed tomography (CT) • Magnetic resonance imaging (MRI).	• Experimental results indicating the improvement by adding synthetic CT modality and optimizing network configurations	• The proposed methodology may be expanded to include more modalities.
47.	[79]	Mohammad Ashraf Ottom *et al*	ZNet method	MR Images	• UNet	• The average DSC for the experimental results during model training was 0.96, and for independent testing was 0.92.	• Proposed Znet model may be extended to 3D MRI volumes for further improvements.
48.	[80]	T. Ruba *et al*	3D UNet and LSIS operator	MR Images	• 3D MRI data containing Higher Grade Glioma.	• Proposed novel model shows improvements in feature extraction, accuracy and sensitivity	• The proposed algorithm not applied on LGG images.

This prominent study also helps scholars to understand the modern segmentation techniques applied to MR images of the brain.

In 2019, Jaspin and Suganthi [33] Greedy Snake Model and the optimization of Fuzzy C-Means that has been used which is an efficient automatic BTS that first determines ROI by eliminating the region of non-tumor using two-level morphological reconstruction method dilation and erosion also included. To increase the precision of Greedy Snake algorithm's segmentation a mask is created by thresholding the reconstructed image and is eroded. The snake model calculates the boundaries of a new tumor by using the boundary of a mask as a snake's initial contour. These new boundaries are considered to be accurate if they have sharp edges, but less accurate if ramp edges. To get accurate segmentation output, the fuzzy C-means is used to further optimize inaccurate boundaries.

Finally, the area with the largest perimeter is selected to remove the inaccurate segmented regions. Kaldera *et al* [34] proposed Glioma segmentation in MR images using DL algorithms that segment the Glioma cells using fast Region based (R-CNN) and techniques of edge detection. For BTS classify the ROI called Glioma cells with a high level of confidence and localizes the tumor images in MR with a tumor mask. Abdelmajid *et al* [35] present a technique for the Segmentation of tumors which is based on Thermal information of Tumors. In this study consider, Tumor cells act as a heat source their temperature is higher than that of normal cells of the brain and the size of the brain tumor affects the temperature distribution due to this to minimize false positive (FP) and false negative (FN) results of segmentation done on images, the information of temperature changes on pathologic area can be used. To tackle this in Salma *et al* [36], SegNet, a fully CNN, for four MRI modalities there are 3D datasets that were applied which perform the automated segmentation of tumor and sub-tumor parts, including (necrosis, tumor enhancing, and edema). The purpose of the algorithm accurately segments the brain tumor into four sub-tumor parts by locating the entire tumor volume.

To improve the segmentation of tumors even further. [37] proposed an approach that segments and classifies the tumor cases. This method, which has been based on score level fusion uses transfer learning which fuses scores of Google deep structured learning using MRI modality. Yalda *et al* [38] proposed knowledge-based segmentation using 3D FLAIR images in which developed a semi-automatic algorithm based on a single imaging modality to recognize tumors in MR images that is comparatively accurate, and quick, which is primarily used for clinical. SUSAN algorithm is used to correct the noise for a given image and then histogram normalization and intensity scaling are used to the correction of intensity non-uniformity in ROI. This multiple-classifier-based system was categorized as tumor/non-tumor for each voxel in ROI and inspected T1-, T2-weighted images and fluid-attenuated (FLAIR). The issue of computer-assisted segmentation is extremely difficult due to variations of structural and spatial, as well as intensity inhomogeneity across images due to this most of the time physicians waste on manually defining the various brain structures.

To tackle this issue Daniel E. Cahall *et al* [39] The segmentation architecture of U-Net image and inception modules are two cutting-edge architectures of ML in AI that we use to propose a new framework of image segmentation for the delineation of tumors. In this framework, there are two learning regimes i.e., segmentation of intra-tumoral structures learning and segmentation of glioma sub-regions learning are combined into Dice coefficient (DSC) based on newly proposed loss-function, Tamjid Imtiaz *et al* [40] introduced a new method of tumor segmentation in which the superpixel level, features extracted based on the three planar from (3-D MRI) data. In this technique, each image belonging to a specific plane is subdivided into irregular arrays based on spatial similarity and intensity to avoid pixel randomizations and get the exact boundaries of a heterogeneous brain tumor, then at the edges of the tumor, to get better labeling on the superpixels, different textural and statistical features are extracted from superpixel based on three planar. A feature selection based on histogram which is based on local descriptor pattern analysis and consistency analysis which reduced substantial feature dimensions and Extremely Randomized Trees used for supervised classification to categorize super-pixels into tumor/non-tumor. According to the decisions obtained on each plane, Pixel level decisions are made.

To get accurate BTS, which is a crucial factor for the diagnosis of cancer and its treatment Kai Hu *et al* [41] propose a novel technique for BTS which is based or dependent on (MCCNN) and fully connected conditional random files (CRFs). In this work, to obtain the cancer contour, designed the MCNN architecture by modeling the dependencies of labels that performed coarse segmentation by extracting more differentiable multi-scales features. Then apply CRFs to further refine the segmentation results by filtering out some erroneous outputs and considering spatial contextual information. To get the final segmentation results, train the three segmentation models by using the image patches from several views (coronal, sagittal views, axial) respectively. Guotai Wang *et al* [42] proposed a BTS with hierarchical sub-regions from multimodal MR images named cascaded CNN. This technique introduced a 2.5D network to address the issue of large memory consumption with the 3D network. This technique not only trades off between receptive fields, model complexity, and memory consumption but also give us uncertain information associated with segmentation result. In 2020, Wu Deng *et al* [43] proposed DL based on BTS through CRF and (HCNN) in a unified system that is not only recognized but also orders the tumor type. Ping Liu *et al* [44] proposed a BTS by using EDNN. In this technique added the Batch-Normalization and bottom RB in the original V-Net to modify it. Combined modified SE with V-Net module in every stage of encoder and decoder. To increase the network's convergence incorporated 3D deep supervision into the network. In a manuscript of Jianxin Zhang *et al* [45] demonstrate the efficiency of the attention mechanism in the BTS technique based on U-Net architecture and also demonstrate the effectiveness of the attention gate (attention module) for BTS task. It also presented a novel model i.e., Attention Gate Residual U-Net model (AGRes U-Net) which combined attention gates and residual modules with the basic and the architecture of a single U-Net for the BTS task. In Guohua Cheng *et al* [46] suggest a modified multitask learning method that segments various tumor regions using a thin network with only two scales, and also designed a hybrid hard sampling technique that takes sample effectiveness and a small number of scattered samples into account. Mobeen Ur Rehman *et al* [47] proposed a unique model BU-Net to accurately segment and categorize the brain tumor/cancer regions after modification in existing U-Net architecture. Modifications were performed in the encoder-decoder architecture of U-Net by adding two new blocks i.e., RES and WC. Rui Hua *et al* [48] represented a novel technique for BTS in Multimodal MR images named Cascaded V-Nets. This cascaded framework enhanced V-Net performance and distributed the difficult task of segmentation which has been changed into two easier sub-tasks i.e., the overall tumor segmenting from background and segmentation of tumor substructure from whole cancer. Florian Kofler *et al* [49] addressed the challenge of translation of computational technique into a clinical routine and scientific practice by presenting BraTS Toolkit. This toolkit is the next step in the modernization of automatic BTS. Users can successfully distribute dockerized BTS methods obtained through the BraTS challenge by minimizing resource and expertise barriers.

Soukaina and Hamid [50] presented a DL approach through U-Net architecture for segmentation with Markov method to calculate the class correlation to further improved the founded classes. Xiaoliang Lei *et al* [51] addressed the issues of classic segmentation methods and proposed sparse constraint level set algorithm for BTS. In this technique, a sparse representation model is constructed by combining a variational level set model with sparse shape constraints using the characteristics of the brain tumor's shape. By cogitating this model, constructed an energy function which is based on the level set method. Mostefa Ben naceur *et al* [52] presented a DCNN-based fully automatic BTS that segmented the high- and low-grade Glioblastoma brain tumors. To form the DNN architecture used the DL-based selective attention method called the Occipito-temporal pathway which is useful to extract the appropriate features from MR images. This method also addressed the class imbalance issue uses of multi-class weighted cross entropy and the issues of spatial relationship among image Patches using overlapping patches. For Multimodal BTS Yi Ding *et al* [53] proposed a framework

called Multipath AFN to make use of entire hierarchy features by applying the idea of skip connection to successfully promulgated the low-level features and adaptively fused the low-level and high-level features by applying the adaptive fusion.
To segment, the brain tumors from multi-modality MRI data Dingwen Zhang *et al* [54] proposed a novel framework called Novel Cross Modality Deep Feature Learning. The main idea is to extract rich patterns through multimodal data to compensate for the inadequate data scale. This method applied the two processes of learning, the CMFT process, and the CMFF process. The fundamental goals of the CMFT and CMFF processes are to execute the cross-modality feature transition process and, separately, to fuse knowledge from various modalities of data. Hikmat Khan *et al* [55] used the modern way Internet of Things (IoT) to generate medical images for BTS and proposed a Cascaded approach for automatic BTS. In this approach combined two existing methods for BTS i.e., Handcrafted features-based techniques and CNN. In this method, three handcrafted features were computed. For the automated segmentation of Brain Metastases which is trained on the clinical data, DL based technique DCNN was proposed by Khaled Bousabarah *et al* [56]. In this method data obtained during clinical practice is used to develop neural networks, networks which are capable of automated image segmentation.
The collection of image pairs obstructs the implementation of DL techniques for BTS. Qingyun Li *et al* [57] addressed the issue of collecting paired medical imaging data especially multi-modal image pairs by proposing a technique TumorGAN which is a novel image to image framework for brain tumor image augmentation which generates the image segmentation pairs that is based on unpaired adversarial training. Dingwen Zhang *et al* [58] proposed a BTS technique by taking rules in clinical practice. In this work represented the novel TSBTS network based on the task-task structured. For MMBTS both task structure and modality are significant and explored by a deep neural network. For task structural learning need to predict the multiple types of brain tumor areas in different modules of a network because different modalities have different significance for tumor area segmentation. Chandan Ganesh Bangalore Yogananda *et al* [59] developed a procedure for BTS which is automated and depends on DL. In this method developed 3 separate 3D Dense UNets for the segmentation of MRI-based gliomas. Individual binary-segmentation issues for each subcomponent were created, simplifying the complex multiclass segmentation problem.
In 2021, Amjad Rehman Khan *et al* [60] presented a K-means clustering approach for BTS which emphasizes the ROI for accurate feature extraction and DL approach using the concept of synthetic data augmentation for tumor classification. Fengming Lin *et al* [61] proposed a Path aggregation U-Net model which is a novel model of a neural network for BTS. This model works with three aspects: First, Path aggregation encoder reduces the network's distance between deep layers and the output layer, facilitating the transmission of deep information. Second, to keep more accurate information, provide the enhanced decoder (ED). Third, the segmentation results are generated using an effective feature pyramid (EFP) that connects multi-level features and makes optimum use of memory resources. In R. Pitchai *et al* [62] performed BTS using DL-based Fuzzy K- Means clustering. This technique is a combination of ANN and Fuzzy K-means Algorithm which have four phases to segment the tumor. First filter the noise by using a wiener filter, secondly, extract the significant features by using Crow Search Optimization Algorithm (CSOA), then classify between normal and abnormal images using DL-based classification. To find more significant clusters, Prabhjot Kaur Chahal and Shreelekha Pandey in [63] presented a novel hybrid weighted fuzzy k-means (WFKM) algorithm for BTS. This approach, which is based on the fuzzification of weights, gives quantization weights to pixel values to improve pixel clustering. This fuzzification of weights operates on the spatial context, together with the illumination penalize membership method, which aids in resolving problems with multiple memberships in pixels as well as exponential growth in the number of iterations. Antonio Di Ieva *et al* [64], demonstrated the reliability of applying DL, an AI technology, to the problem of segmenting brain tumors. This work validated the state-of-the-art CNN application to autonomously extract glioma edges from MRI images, and for the first time demonstrated that

many models may be trained to achieve optimal tumor segmentation without the need for complete MRI sequences. Francisco Javier Díaz-Pernas *et al* [65], presented a Multi-scale approach based DCNN for BTS and classification. In this approach processed the input MR images in 3D using three different processing pathways which segmented and classified the three types of Brain Tumors: glioma, meningioma, and pituitary tumor without the need to remove the skull and vertebral column parts. In order to segment the images with intensity inhomogeneity in MRI scans for brain tumors, a unique region-based level set approach is developed in Asieh Khosravanian *et al* [66]. In order to do this, the inhomogeneous zones are first represented as Gaussian distributions with different means and variances, and then moved into a new domain, where each region's Gaussian intensity distribution is kept but with improved separation. Additionally, this approach is capable of bias field correction. In order to do this, a linear combination of smooth base functions is used to describe the bias field, which improves intensity inhomogeneity modeling. As a result, the suggested technique modifies the bias field and level set fundamental formulation.

Ramin Ranjbarzadeh *et al* [67] To create a flexible and successful BTS system, it was initially suggested a preprocessing method focus just on a small portion of the image rather than the complete image. This method eliminates the over-fitting problems in a Cascade DL model while cutting down on computation time. A simple and efficient Cascade Convolutional Neural Network (C-ConvNet/C-CNN) is described since this method simply uses a smaller amount of each slice of the brain. In this approach, a novel Distance-Wise Attention (DWA) mechanism is also developed which takes into account the impact of the brain and the tumor's central placement inside the model to increase the segmentation accuracy of brain tumors. Yan Zhang *et al* [68] presented a creative method for BTS named multi-scale mesh aggregation network (MSMANet) in which to integrate and extract useful information from several receptive fields, typical convolution in the encoder has been replaced by an enhanced inception module. In this approach, enhance the shallow features and improve the semantic gap by mesh aggregation strategy aggregating the features of different levels. Xinyu Zhou *et al* [69] addressed an issue of computational complexity in DL methods for BTS and presented a computationally efficient and less GPU memory consumption method named 3D residual neural network (ERV-Net). In this method, ShuffleNetV2 is used as an encoder to minimize memory consumption and enhance the performance of ERV-Net, and further avoid degradation using a decoder with residual blocks (Res-decoder).

In 2022, Farzaneh Dehghani *et al* [70] focused on the study to automatically demarcate brain tumors from FLAIR, T1-weighted, T2-weighted, and T1-weighted contrast-enhanced MR sequences by using DL, with a particular emphasis on identifying which MR sequence, alone or in combination, would achieve the highest level of accuracy in this regard and proposed DCNN based joint BTS from multi-MR sequences. The goal of this research is to create a DL model that will automatically BTS from various MR sequences. This goal will be achieved by creating enough DL models to perform brain tumor delineation on each MR sequence (single-channel input) and any combination of those sequences (multi-channel input), allowing us to independently identify the most effective MR sequences for this use. In [71], Ejaz Ul Haq *et al* proposed a hybrid approach for the BTS and classification using MRI which is based on DCNN and ML Classifiers. This study proposes an integrated and hybrid approach based on DCNN and ML classifiers for the precise segmentation and categorization of brain MRI tumors into glioma, meningioma, and pituitary without user interaction. In the initial step, CNN is suggested to learn the feature map from brain MRI image space into the tumor marker region. For the localization of the tumor region in the second stage, a quicker region-based CNN is created, followed by a region proposal network (RPN). To further hone the segmentation and classification process and provide more precise results and findings, create a structure by sequentially incorporating DCNN and ML classifiers in the final stage.

To investigate an automated BTS approach based on CNN network building tools in AWS Sagemaker and hyper-parameter optimization methods Szidónia Lefkovits *et al* [72] presented BTS of HGG (high-grade glioma) and LGG (low-grade glioma) in multi-modal MRI using tool Amazon

Sagemaker by applying built-in pre-trained CNN. In this paper, proposed, using a several number of DL methods made available by the AWS SageMaker Framework. The purpose of this article is to test the tool Amazon Sage-maker and its built-in architectures, including FCN (Fully Convolutional Network), PSPNet (Pyramid Scene Parsing Network), and DeepLab, as well as to demonstrate automatic model search utilizing grid search for hyper-parameter optimization in provided ranges. In [73], Dongwei Liu *et al* develop the SGEResU-Net model, a novel 3D U-Net model, in this study to segment brain tumors. SGEResU-Net integrates spatial group-wise enhance (SGE) attention modules and residual modules into a single 3D U-Net architecture. SGE attention modules are used to improve the feature learning of semantic regions and minimize potential noise and interference with essentially no additional parameters. In order to obtain satisfactory segmentation accuracy, additionally include the self-ensemble module into the network, which was prompted by its efficacy. To adapt to the complicated feature distribution of images of brain tumors, SGEResU-Net swaps out the horizontally connected portion of the baseline network with an enhanced 3D SGE module.

In addition to being a lightweight module that can easily adjust BTS models, the 3D SGE module can learn sub-features and reduce noise in a targeted manner for each group. DL is unable to give the necessary local features related to changes in tissue texture brought on by tumor growth; to address this issue Salma Alqazzaz *et al* [74] proposed an approach in which features are combined in region of interest (ROI) for BTS. In this approach creates a hybrid technique that combines hand-crafted and ML features. The hand-crafted features are created using texture features based on the grey-level co-occurrence matrix (GLCM), while the ML features are created using a semantic segmentation network (SegNet). Additionally, the suggested method suppresses the intensity of other irrelevant areas and only uses the ROI, which reflects the extent of the entire tumor structure, as input. To categorize, the pixels of ROI MRI images into the various tumor sections, including edema, necrosis, and enhanced tumor, a decision tree (DT) is utilized. The segmentation task is challenging because some tumors are undetectable or low-contrast, and because they resemble normal brain tissues, to address this challenge Ahmet Ilhan *et al* [75] proposed a non-parametric localization and enhancement methods with Unet-based BTS in MR images. Based on tumor localization and enhancement techniques and a DL architecture known as U-net, this study provides an effective method for the segmentation of entire brain tumors from MRI pictures. The suggested tumor enhancement approach is utilized to modify the localized regions to augment the visual appearance of unclear or low-contrast tumors after the histogram-based nonparametric tumor localization method has been used to locate the tumorous regions. The original U-net design receives the output images and segments the whole brain tumors. The segmentation algorithm research mostly focuses on the 2D plane, which somewhat compromises the accuracy of 3D image feature extraction. It is challenging to split the contours effectively in MRI images because of the grayscale offset fields.

To meet these challenges Xi Guan *et al* [76] proposed a framework for automatic MRI based BTS called 3D AGSE-VNet which is improved based on VNet. In this model the Squeeze and Excite (SE) module is added to each encoder (five encoders), and the Attention Guide Filter (AG) module is added to each decoder (four decoders). These modules make use of the channel relationship to automatically enhance the channel's useful information while suppressing its useless information. They also make use of the attention mechanism to direct the edge information and eliminate the influence of irrelevant information, such as noise. In [77] Shidong Li *et al* proposed a ROI aided and segmentation U-Net based BTS technique. The goal of this research is to create a new ROI aided DL method for automatically BTS in MRI images. Two main steps make up the approach. The first step is to locate the tumor ROI using a 2D network with U-Net design in order to minimize the impact of disrupted normal tissue. Then, in step 2, a 3D U-Net is used to segment the tumor inside the designated ROI.

Kh Tohidul Islam *et al* [78] proposed a method for BTS based on DL framework using MRI and synthetically generated CT images. Multi-modal images give information that is not available from a single image modality alone, and it is difficult to integrate this information for segmentation purposes. Here, proposed a solution to this problem of BTS. In order to do this, first provide a technique for boosting an already-existing MRI dataset by creating synthetic CT images. Discuss the systematic optimization of a CNN architecture using this improved dataset after that. In this technique CT images are generated from MRI images by using a modified U-Net architecture. Mohammad Ashraf Ottom *et al* [79] proposed a BTS method for 2D MRI using DL called Znet. DNN and data augmentation techniques are used in this study, and a novel approach for identifying 2D brain tumors in MR images is proposed. The recommended approach (Znet) propagates the inherent affinities of a relatively small number of precisely defined tumours by utilising the ideas of skip-connection, encoder-decoder topologies, and data amplification, for example, hundreds of patients with low-grade glioma (LGG), too many thousands of synthetic cases. T. Ruba *et al* [80] designed an automatic BTS system based on novel LSIS operators and DL. This research proposes a novel approach for segmenting higher-grade Glioma (HGG) from tumors in 3D MRI data. With this method, the tumor is not only localized but the intra-tumor regions are also segmented (necrosis, edema, non-enhancing tumor, and enhancing tumor). In actuality, the proposed cascaded CNN consists of two sub-networks, including the Tumor Localization Network (TLN) and LSIS (Local Symmetry Inter Sign)-based Intra tumor Segmentation Network (ITSN) or (LITSN = LSIS based ITSN). 3DUNet architecture was utilized in TLN to locate or segment the complete tumor region.

10.Discussion

Since there have been a lot more cases of brain tumors in recent years, researchers and scientists working in associated fields are challenged with the exciting task of creating effective methods for diagnosing brain tumors. An overview of various techniques for BTS from MR images is given in Table 2. Here the comparison is built on their limitations and key findings. It is observed that most of the research publications used in this study employed segmentation techniques based on DL and its methodologies. The most often utilized dataset for technique analysis by academics is BRATS 2017 and BRATS 2018. It is observed that several researchers have theoretically demonstrated that their approaches are more than 90% efficient on test datasets. It remains to be seen, though, how they may be put into practice in a real-world setting. To ensure that the processes are accurate, this field mainly requires cooperation between medical professionals and computer scientists. DL looks to offer a potential solution for these issues. DL-based approaches have recently emerged, methods for segmenting brain tumors using conventional ML are useless. The DL based technique achieves a complete tumor segmentation using an MRI image. These models frequently eliminate the requirement for manually built features by automatically extracting tumor descriptive information. However, their use in the medical professions is constrained by the necessity of a large dataset to train the models on, as well as the difficulty in understanding the models. However, computation time is another crucial factor, in addition to the assessment of the reliability and validity of the results of the BTS. The average calculation time is only a few minutes. Although achieving segmentation in real-time will be challenging, calculation times longer than a few minutes are inappropriate for practical clinical use. Robustness is another important factor for BTS techniques. Clinicians will lose faith in an automatic segmentation method if it fails in a few situations and stop using it. As a result, resilience is a crucial criterion for any new approach employed in clinical practice. The recent techniques for segmenting brain tumors deliver reliable findings in a manageable amount of time. Brain tumor automated segmentation technology has the ability to improve treatment choices. Automatic BTS is also challenging but the availability of open-access datasets gave researchers a shared platform to create and impartially assess their approaches using the available techniques. DL and ML are two broad categories for brain image segmentation, and both have collective aim to segment out the abnormal tissues and identify the ROI. This study concludes that each type of technique may address specific segmentation issues by contrasting the segmentation performance of various approaches. Generalization has several drawbacks, though. For instance, segmenting brain tumors using standard techniques is often straightforward and quick to perform, but processing complicated pictures is challenging, and accuracy of segmentation is typically low. Conceptually simple segmentation algorithms based on conventional ML techniques might be difficult to analyze large amounts of data. DL based segmentation algorithms can be used to extract the information from an MR image, but their interpretability is lacking.

11.Conclusion

This study provides a thorough and comprehensive analysis of the several segmentations of brain tumor methods currently in use. The goal of this study is to increase interest in this challenging subject among new researchers and familiarize them with current challenges, advancements, and improvement zones in it. This review not only aids selecting an appropriate technique for BTS but also provides support to readers and physicians with new directions for expanding the field of study. The diagnosis, therapy, and patient follow-up may all be greatly improved by automating the BTS. Unquestionable advancements have been made in automating BTS through the use of numerous methodologies, including traditional DL and ML methods. The development of a fully autonomous system that can be deployed on clinical floors is currently challenging. Automating brain tumors segmentation using DL techniques has several advantages over ML algorithms because DL techniques have the ability of potent feature learning. According to the review of several techniques, it was revealed that DL algorithms outperformed the conventional ML algorithms and occupied a dominant position in this field but too much relied on ground truth. Medical image analysis must deal with practical problems that have not been the purview of computer vision. These problems are mostly caused by the fact that doctors utilize the end systems the most. The human element is crucial since every effective solution must be approved by a doctor and included in the workflow of medical procedures. The varieties of relevant approaches are severely limited as a result.

12.Future Work

Similar critical assessments of other body parts, such as the stomach, kidney, and liver, are suggested in the future. This will facilitate the process for researchers to develop a computer-aided diagnostic system for the early detection of cancer. Despite the fact that the majority of BTS algorithms produce generally positive outcomes in the area of analyzing medical images, there remains a significant gap in medical applications. Physicians still frequently use manual segmentation to diagnose brain tumors since researchers and clinicians don't frequently collaborate. Numerous tools are available; however, they are almost never helpful to physicians because they are designed for use in pure research. As a result, it will be necessary in the future to integrate the developed tools into settings that are easier for users to use. Furthermore, MRI based segmentation already produced good results and definitely will be improve further in future but other advanced MRI methods such as Perfusion Imaging (PI), Magnetic Resonance Spectroscopy (MRS) and Diffusion Tensor Imaging (DTI), may be employed in the future for the segmentation of brain tumors.

References

[1] Ali Isin, Cem, Cem Direkoglu, Melike Sah, “Review of MRI-based brain tumor image segmentation using deep learning methods”, 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29-30 August 2016, Vienna, Austria.

[2] Arti Tiwari, Shilpa Srivastava, Millie Pant, “Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019”, Pattern Recognition Letters, Volume 131, 2020, Pages 244-260, ISSN 0167-8655,

[3] Biratu Erena Siyoum, Friedhelm Schwenker, Yehualashet Megersa Ayano, and Taye Girma Debelee. "A survey of brain tumor segmentation and classification algorithms." Journal of Imaging 7, no. 9 (2021): 179.

[4] Wadhwa, Anjali, Anuj Bhardwaj, and Vivek Singh Verma. "A review on brain tumor segmentation of MRI images." Magnetic resonance imaging 61 (2019): 247-259.

[5]https://www.aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments/Brain-Tumors#:~:text=Types%20of%20Brain%20Tumors&text=Primary%20tumors%20are%20categorized%20as,glands)%20and%20benign%20or%20malignant.

[6] https://www.aans.org/Media/Classifications-of-Brain-Tumors

[7] Sharma, Preeti, and Anand Prakash Shukla. "A review on brain tumor segmentation and classification for MRI images." 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, 2021.

[8] Liu Jin, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, and Yi Pan. "A survey of MRI-based brain tumor segmentation methods." Tsinghua science and technology 19, no. 6 (2014): 578-595.

[9] Liu, Zhihua, Lei Tong, Long Chen, Zheheng Jiang, Feixiang Zhou, Qianni Zhang, Xiangrong Zhang, Yaochu Jin, and Huiyu Zhou. "Deep learning based brain tumor segmentation: a survey." Complex & Intelligent Systems (2022): 1-26.

[10] Ghaffari Mina, Arcot Sowmya, and Ruth Oliver. "Automated brain tumor segmentation using multimodal brain scans: a survey based on models submitted to the BraTS 2012–2018 challenges." IEEE reviews in biomedical engineering 13 (2019): 156-168.

[11] Magadza Tirivangani, and Serestina Viriri. "Deep learning for brain tumor segmentation: a survey of state-of-the-art." Journal of Imaging 7, no. 2 (2021): 19.

[12] Otman Basir, Kalifa Shantta, "Automatic MRI Brain Tumor Segmentation Techniques: A Survey". IRA-International Journal of Applied Sciences, ISSN 2455-4499; Vol.16, Issue 02 (Q.2 2021), Pg. no. 25-38.

[13] Sravan, V., K. Swaraja, K. Meenakshi, Padmavathi Kora, and Mamatha Samson. "Magnetic resonance images based brain tumor segmentation-a critical survey." In 2020 4th international conference on trends in electronics and informatics (ICOEI)(48184), pp. 1063-1068. IEEE, 2020.

[14] https://www.docpanel.com/blog/post/understanding-your-brain-tumor-mri-brain-tumor-diagnosis [15] Fawzi, Ali, Anusha Achuthan, and Bahari Belaton. "Brain image segmentation in recent years: A narrative review." Brain Sciences 11, no. 8 (2021): 1055.

[16] Zhang, Wenyin, Yong Wu, Bo Yang, Shunbo Hu, Liang Wu, and Sahraoui Dhelim. "Overview of multi-modal brain tumor mr image segmentation." In Healthcare, vol. 9, no. 8, p. 1051. MDPI, 2021.

[17] Tjahyaningtijas, Hapsari Peni Agustin. "Brain tumor image segmentation in MRI image." In IOP Conference series: materials science and engineering, vol. 336, no. 1, p. 012012. IOP Publishing, 2018.

[18] Chahal, Prabhjot Kaur, Shreelekha Pandey, and Shivani Goel. "A survey on brain tumor detection techniques for MR images." Multimedia Tools and Applications 79, no. 29 (2020): 21771-21814.

[19] Xiong, Siyu, Guoqing Wu, Xitian Fan, Xuan Feng, Zhongcheng Huang, Wei Cao, Xuegong Zhou et al. "MRI-based brain tumor segmentation using FPGA-accelerated neural network." BMC bioinformatics 22, no. 1 (2021): 1-15.

[20] Gordillo, Nelly, Eduard Montseny, and Pilar Sobrevilla. "State of the art survey on MRI brain tumor segmentation." Magnetic resonance imaging 31, no. 8 (2013): 1426-1438.

[21] https://shaukatkhanum.org.pk/about-us/blog/world-brain-tumor-day/

[22]https://www.aku.edu/news/Pages/News_Details.aspx?nid=NEWS002324#:~:text=Brain%20tumors%20have%20one%20of,of%20Neuro-oncology%2C%20PASNO%2C

[23] https://gco.iarc.fr/

[24] Nida Zahid, Wardah Khalid, Khabir Ahmad, Shireen Shehzad Bhamani, Iqbal Azam, Nargis Asad, Adnan Abdul Jabbar, Mumtaz Khan, and Ather Enam. “Resilience and quality of life (QoL) of head and neck cancer and brain tumour survivors in Pakistan: an analytical cross-sectional study protocol.” BMJ open vol. 9,9 e029084. 20 Sep. 2019, doi:10.1136/bmjopen-2019-029084

[25] https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/about/key-statistics.html

[26]https://cancerstatisticscenter.cancer.org/?_ga=2.209864081.540755022.1659804987-2079072212.1659804980#!/

[27] https://seer.cancer.gov/statfacts/html/brain.html

[28]https://www.cancer.org/cancer/brain-spinal-cord-tumors-adults/detection-diagnosis-staging/survival-rates.html

[29] https://cbtrus.org/cbtrus-fact-sheet-2021/ [30] Chowdhary, Chiranji Lal, and D. Prasanna Acharjya. "Segmentation and feature extraction in medical imaging: a systematic review." Procedia Computer Science 167 (2020): 26-36.

[31] Saman, Sangeetha, and Swathi Jamjala Narayanan. "Survey on brain tumor segmentation and feature extraction of MR images." International Journal of Multimedia Information Retrieval 8, no. 2 (2019): 79-99.

[32] Sarker, Iqbal H. "Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions." SN Computer Science 2, no. 6 (2021): 1-20.

[33] Sheela C. Jaspin Jeba, and G. Suganthi. "Automatic brain tumor segmentation from MRI using greedy snake model and fuzzy C-means optimization." Journal of King Saud University-Computer and Information Sciences (2019).

[34] Kaldera H. N. T. K., S. R. Gunasekara, and Maheshi B. Dissanayake. "MRI based Glioma segmentation using Deep Learning algorithms." In 2019 International research conference on smart computing and systems engineering (SCSE), pp. 51-56. IEEE, 2019.

[35] Bousselham Abdelmajid, Omar Bouattane, Mohamed Youssfi, and Abdelhadi Raihani. "Towards reinforced brain tumor segmentation on MRI images based on temperature changes on pathologic area." International journal of biomedical imaging 2019 (2019).

[36] Alqazzaz Salma, Xianfang Sun, Xin Yang, and Len Nokes. "Automated brain tumor segmentation on multi-modal MR image using SegNet." Computational Visual Media 5, no. 2 (2019): 209-219.

[37] Amin Javeria, Muhammad Sharif, Mussarat Yasmin, Tanzila Saba, Muhammad Almas Anjum, and Steven Lawrence Fernandes. "A new approach for brain tumor segmentation and classification based on score level fusion using transfer learning." Journal of medical systems 43, no. 11 (2019): 1-16.

[38] Amirmoezzi Yalda, Sina Salehi, Hossein Parsaei, Kamran Kazemi, and Amin Torabi Jahromi. "A knowledge-based system for brain tumor segmentation using only 3D FLAIR images." Australasian Physical & Engineering Sciences in Medicine 42, no. 2 (2019): 529-540.

[39] Cahall Daniel E., Ghulam Rasool, Nidhal C. Bouaynaya, and Hassan M. Fathallah-Shaykh. "Inception modules enhance brain tumor segmentation." Frontiers in computational neuroscience 13 (2019): 44.

[40] Imtiaz Tamjid, Shahriar Rifat, Shaikh Anowarul Fattah, and Khan A. Wahid. "Automated brain tumor segmentation based on multi-planar superpixel level features extracted from 3D MR images." IEEE Access 8 (2019): 25335-25349.

[41] Hu Kai, Qinghai Gan, Yuan Zhang, Shuhua Deng, Fen Xiao, Wei Huang, Chunhong Cao, and Xieping Gao. "Brain tumor segmentation using multi-cascaded convolutional neural networks and conditional random field." IEEE Access 7 (2019): 92615-92629.

[42] Wang Guotai, Wenqi Li, Sébastien Ourselin, and Tom Vercauteren. "Automatic brain tumor segmentation based on cascaded convolutional neural networks with uncertainty estimation." Frontiers in computational neuroscience 13 (2019): 56.

[43] Deng Wu, Qinke Shi, Miye Wang, Bing Zheng, and Ning Ning. "Deep learning-based HCNN and CRF-RRNN model for brain tumor segmentation." IEEE Access 8 (2020): 26665-26675.

[44] Liu Ping, Qi Dou, Qiong Wang, and Pheng-Ann Heng. "An encoder-decoder neural network with 3D squeeze-and-excitation and deep supervision for brain tumor segmentation." IEEE Access 8 (2020): 34029-34037.

[45] Zhang, Jianxin, Zongkang Jiang, Jing Dong, Yaqing Hou, and Bin Liu. "Attention gate resU-Net for automatic MRI brain tumor segmentation." IEEE Access 8 (2020): 58533-58545.

[46] Cheng, Guohua, Jingliang Cheng, Mengyan Luo, Linyang He, Yan Tian, and Ruili Wang. "Effective and efficient multitask learning for brain tumor segmentation." Journal of Real-Time Image Processing 17, no. 6 (2020): 1951-1960.

[47] Rehman Mobeen Ur, SeungBin Cho, Jee Hong Kim, and Kil To Chong. "Bu-net: Brain tumor segmentation using modified u-net architecture." Electronics 9, no. 12 (2020): 2203.

[48] Hua Rui, Quan Huo, Yaozong Gao, He Sui, Bing Zhang, Yu Sun, Zhanhao Mo, and Feng Shi. "Segmenting brain tumor using cascaded V-nets in multimodal MR images." Frontiers in computational neuroscience 14 (2020): 9.

[49] Kofler Florian, Christoph Berger, Diana Waldmannstetter, Jana Lipkova, Ivan Ezhov, Giles Tetteh, Jan Kirschke, Claus Zimmer, Benedikt Wiestler, and Bjoern H. Menze. "BraTS toolkit: translating BraTS brain tumor segmentation algorithms into clinical and scientific practice." Frontiers in neuroscience (2020): 125.

[50] Tairi Hamid. "Segmentation of medical images for the extraction of brain tumors: A comparative study between the Hidden Markov and Deep Learning approaches." In 2020 International Conference on Intelligent Systems and Computer Vision (ISCV),pp.1-5.IEEE, 2020.

[51] Lei Xiaoliang, Xiaosheng Yu, Jianning Chi, Ying Wang, Jingsi Zhang, and Chengdong Wu. "Brain tumor segmentation in MR images using a sparse constrained level set algorithm." Expert Systems With Applications 168 (2021): 114262.

[52] Akil Mohamed, Rachida Saouli, and Rostom Kachouri. "Fully automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-class weighted cross-entropy." Medical image analysis 63 (2020): 101692.

[53] Ding Yi, Linpeng Gong, Mingfeng Zhang, Chang Li, and Zhiguang Qin. "A multi-path adaptive fusion network for multimodal brain tumor segmentation." Neurocomputing 412 (2020): 19-30.

[54] Zhang Dingwen, Guohai Huang, Qiang Zhang, Jungong Han, Junwei Han, and Yizhou Yu. "Cross-modality deep feature learning for brain tumor segmentation." Pattern Recognition 110 (2021): 107562.

[55] Khan, Hikmat, Pir Masoom Shah, Munam Ali Shah, Saif ul Islam, and Joel JPC Rodrigues. "Cascading handcrafted features and Convolutional Neural Network for IoT-enabled brain tumor segmentation." Computer Communications 153 (2020): 196-207.

[56] Bousabarah Khaled, Maximilian Ruge, Julia-Sarita Brand, Mauritius Hoevels, Daniel Rueß, Jan Borggrefe, Nils Große Hokamp et al. "Deep convolutional neural networks for automated segmentation of brain metastases trained on clinical data."Radiation Oncology15,no.1(2020):1-9.

[57] Li Qingyun, Zhibin Yu, Yubo Wang, and Haiyong Zheng. "TumorGAN: A multi-modal data augmentation framework for brain tumor segmentation." Sensors 20, no. 15 (2020): 4203.

[58] Zhang Dingwen, Guohai Huang, Qiang Zhang, Jungong Han, Junwei Han, Yizhou Wang, and Yizhou Yu. "Exploring task structure for brain tumor segmentation from multi-modality MR images." IEEE Transactions on Image Processing 29 (2020): 9032-9043.

[59] Yogananda Chandan Ganesh Bangalore, Bhavya R. Shah, Maryam Vejdani-Jahromi, Sahil S. Nalawade, Gowtham K. Murugesan, Frank F. Yu, Marco C. Pinho et al. "A fully automated deep learning network for brain tumor segmentation." Tomography 6, no. 2 (2020): 186-193.

[60] Khan Amjad Rehman, Siraj Khan, Majid Harouni, Rashid Abbasi, Sajid Iqbal, and Zahid Mehmood. "Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification." Microscopy Research and Technique 84, no. 7 (2021): 1389-1399.

[61] Lin Fengming, Qiang Wu, Ju Liu, Dawei Wang, and Xiangmao Kong. "Path aggregation U-Net model for brain tumor segmentation." Multimedia Tools and Applications 80, no. 15 (2021): 22951-22964.

[62] Pitchai R., P. Supraja, A. Helen Victoria, and M. Madhavi. "Brain tumor segmentation using deep learning and fuzzy k-means clustering for magnetic resonance images." Neural Processing Letters 53, no. 4 (2021): 2519-2532.

[63] Chahal Prabhjot Kaur, and Shreelekha Pandey. "A hybrid weighted fuzzy approach for brain tumor segmentation using MR images." Neural Computing and Applications (2021): 1-15.

[64] Di Ieva Antonio, Carlo Russo, Sidong Liu, Anne Jian, Michael Y. Bai, Yi Qian, and John S. Magnussen. "Application of deep learning for automatic segmentation of brain tumors on magnetic resonance imaging: a heuristic approach in the clinical scenario." Neuroradiology 63, no. 8 (2021): 1253-1262.

[65] Díaz-Pernas Francisco Javier, Mario Martínez-Zarzuela, Míriam Antón-Rodríguez, and David González-Ortega. "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network." In Healthcare, vol. 9, no. 2, p. 153. MDPI, 2021.

[66] Khosravanian Asieh, Mohammad Rahmanimanesh, Parviz Keshavarzi, and Saeed Mozaffari. "A level set method based on domain transformation and bias correction for MRI brain tumor segmentation." Journal of Neuroscience Methods 352 (2021): 109091.

[67] Ranjbarzadeh Ramin, Abbas Bagherian Kasgari, Saeid Jafarzadeh Ghoushchi, Shokofeh Anari, Maryam Naseri, and Malika Bendechache. "Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images." Scientific Reports 11, no. 1 (2021): 1-17.

[68] Zhang Yan, Yao Lu, Wankun Chen, Yankang Chang, Haiming Gu, and Bin Yu. "MSMANet: A multi-scale mesh aggregation network for brain tumor segmentation." Applied Soft Computing 110 (2021): 107733.

[69] Zhou Xinyu, Xuanya Li, Kai Hu, Yuan Zhang, Zhineng Chen, and Xieping Gao. "ERV-Net: An efficient 3D residual neural network for brain tumor segmentation." Expert Systems with Applications 170 (2021): 114566.

[70] Dehghani Farzaneh, Alireza Karimian, and Hossein Arabi. "Joint brain tumor segmentation from multi MR sequences through a deep convolutional neural network." arXiv preprint arXiv:2203.03338 (2022).

[71] Haq Ejaz Ul, Huang Jianjun, Xu Huarong, Kang Li, and Lifen Weng. "A Hybrid Approach Based on Deep CNN and Machine Learning Classifiers for the Tumor Segmentation and Classification in Brain MRI." Computational and Mathematical Methods in Medicine 2022 (2022).

[72] Lefkovits Szidónia, László Lefkovits, and László Szilágyi. "HGG and LGG Brain Tumor Segmentation in Multi-Modal MRI Using Pretrained Convolutional Neural Networks of Amazon Sagemaker." Applied Sciences 12, no. 7 (2022): 3620.

[73] Liu Dongwei, Ning Sheng, Tao He, Wei Wang, Jianxia Zhang, and Jianxin Zhang. "SGEResU-Net for brain tumor segmentation." Mathematical Biosciences and Engineering 19, no. 6 (2022): 5576-5590.

[74] Alqazzaz Salma, Xianfang Sun, Len DM Nokes, Hong Yang, Yingxia Yang, Ronghua Xu, Yanqiang Zhang, and Xin Yang. "Combined features in region of interest for brain tumor segmentation." Journal of Digital Imaging (2022): 1-9.

[75] Ilhan Ahmet, Boran Sekeroglu, and Rahib Abiyev. "Brain tumor segmentation in MRI images using nonparametric localization and enhancement methods with U-net." International Journal of Computer Assisted Radiology and Surgery 17, no. 3 (2022): 589-600.

[76] Guan Xi, Guang Yang, Jianming Ye, Weiji Yang, Xiaomei Xu, Weiwei Jiang, and Xiaobo Lai. "3D AGSE-VNet: an automatic brain tumor MRI data segmentation framework." BMC medical imaging 22, no. 1 (2022): 1-18.

[77] Li Shidong, Jianwei Liu, and Zhanjie Song. "Brain tumor segmentation based on region of interest-aided localization and segmentation U-Net." International Journal of Machine Learning and Cybernetics (2022): 1-11.

[78] Islam Kh Tohidul, Sudanthi Wijewickrema, and Stephen O'Leary. "A Deep Learning Framework for Segmenting Brain Tumors Using MRI and Synthetically Generated CT Images." Sensors 22, no. 2 (2022): 523.

[79] Ottom Mohammad Ashraf, Hanif Abdul Rahman, and Ivo D. Dinov. "Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation." IEEE Journal of Translational Engineering in Health and Medicine (2022).

[80] Ruba T., R. Tamilselvi, and M. Parisa Beham. "Brain tumor segmentation in multimodal MRI images using novel LSIS operator and deep learning." Journal of Ambient Intelligence and Humanized Computing (2022): 1-15.