Brain Tumor Segmentation of MRI Images: A Comprehensive Review on the Application of Artificial Intelligence Tools

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Abstract

Background

Brain cancer is a destructive and life-threatening disease that imposes immense negative effects on patients' lives. Therefore, detection of brain tumors at an early stage improves the impact of treatments and increases patients' survival rate. However, detecting brain tumors in their initial stages is a demanding task and an unmet need.

Methods

The present study presents a comprehensive review of the recent Artificial Intelligence (AI) methods of diagnosing brain tumors using MRI images. These AI techniques can be divided into Supervised, Unsupervised, and Deep learning (DL) methods.

Results

Diagnosing and segmenting brain tumors usually begin with Magnetic Resonance Imaging (MRI) on the brain since MRI is a noninvasive imaging technique. Another existing challenge is that the growth of technology is faster than the rate of increase in the number of medical staff who can employ these technologies. It has resulted in an increased risk of diagnostic misinterpretation. Therefore, developing robust automated brain tumor detection techniques has been studied widely over the past years.

Conclusion

The current review provides an analysis of the performance of modern methods in this area. Moreover, various image segmentation methods in addition to the recent efforts of researchers are summarized. Finally, the paper discusses open questions and suggests directions for future research.

Keywords: Brain Tumor, Artificial Intelligence, Tumor Segmentation, Tumor Classification, MRI Modalities.

1. Introduction

Brain is an important organ containing one hundred billion nerve cells or neurons. According to the reports, brain tumors are the 10th main cause of mortality among the adults and children for both genders in developed countries [1], [2]. It is anticipated that the incidence of primary brain tumors will cause 18280 deaths in adults in the USA in 2022 [3]. Brain tumors, known as intracranial tumors, include a diverse set of cancerous cells that start in the intracranial tissues of the brain and can range in malignancy from benign to advanced [4],[5]. Brain tumor begins in case of cell division rates increase and multiply uncontrollably. Any portion of the brain or skull can develop a brain tumor, including the brain's protective lining, skull base, brainstem sinuses, nasal cavity, and many other places [6]. There are more than 150 kinds of brain tumors. The two basic classifications of brain tumors are cancerous and noncancerous [7], [8].

The brain is made up of several cell types, each with its own special characteristics. It is impossible to generalize results from malignancies in other organs to those arising in the brain [9]. The unique biology and microenvironment of the brain is the main aspect of brain cancers. Each form of tumor has its own biology, course of therapy, prognosis outlook, and a different set of risk factors [10], [11], and this makes the brain tumor classification difficult to describe. Pressure in the head caused by a brain or spinal cord tumor is a common sign of brain cancer. People with brain tumors are more likely to have specific symptoms, such as exhaustion, nausea, or discomfort. The other side effects of living with brain tumors and brain cancer are fever, rash, and increased pulse. The experts can link signs and symptoms to describe the problem with more certainty. However, brain tumors do not always cause symptoms [12], [13].

Diagnosing a brain tumor involves three different tests and procedures, including imaging tests, neurological exams, and biopsy. The most common and well-established method to diagnose brain cancers is using Magnetic Resonance Imaging (MRI) [14]. During an MRI scan, a dye can be injected into a vein. Experts assess the tumor and make treatment plans based on the MRI scan elements, e.g., perfusion MRI, functional MRI, and magnetic resonance spectroscopy. In some circumstances, further imaging tests like Positron Emission Tomography (PET) and Computed Tomography (CT) are used in combination with MRI. Problems in any area can signify which part of the brain is affected by a tumor [15], [16]. In this case, neurological tests can help the expert for a better diagnosis. During the neurological examination, the expert checks the hearing, vision, coordination, balance, strength, and reflexes of the patient. For a more precise diagnosis, a biopsy is utilized. In this procedure, a sample of abnormal tissue collects and examined under the microscope [17], [18].

If the practitioners can diagnose the disease early, it can result in a timely treatment which increases the likelihood of survival. However, because tumor regions frequently have unclear morphological structures, the identification of malignancies can be challenging [19]. Physicians have recently used Computer-Aided Diagnostic (CAD) tools to aid in the diagnosis of cancer more accurately [20]–[23]. These innovative methods of brain imaging have increased the detection ratio

of brain tumors [24]. Due to the requirement for intelligence in CAD systems, significant changes have occurred recently, and Artificial Intelligence (AI) is integrated with CAD to reduce the recognition time and system memory requirements [25], [26]. Also, it aids in the development of a useful knowledge-based design system. Comparing the new AI assistance with the traditional CAD system, one can realize that the new AI assistance, when combined with CAD, proves to be more efficient. The accuracy and algorithms of AI systems have improved as a result of the growing application of Deep Learning (DL) in medical research and the growth of big data analytics. For example, a radiologist can apply the latest AI technology and advanced computer-assisted detection and diagnosis to collect more details about the normal and tumor tissues [27]. Furthermore, it is possible to assess the patient's status by employing CADs and analyzing imaging and/or non-imaging patient data. Over the last decades, this technology significantly influenced early cancer detection and its timely treatment [28].

This review has summarized more than 100 scientific research papers from 2015- 2022 (until 1st September 2022). To find out the number of investigations on brain tumor diagnosis through supervised learning, unsupervised learning, and DL models a statistical report is provided based on the "Scopus" database. The keywords searched in this database were "brain tumor" AND "name of the technique (e.g., Random Forest)" OR "brain cancer" AND "name of the technique".

This paper focuses on reviewing the studies that applied AI techniques for brain tumor segmentation. Abbreviations used in this paper are referenced in Table 1.

The rest of the paper is organized as follows: Detailed images of body organs in Magnetic Resonance Imaging (MRI) is described in section 2. Different types of tumors and their characteristics are implied in section 3. In section 4, more details about supervised and unsupervised techniques are represented. Next, some Deep learning models applied in the field of brain tumor segmentation are discussed in section 5. In the next step, some top databases for the brain tumor segmentation are represented in section 6. Then, performance measures are described in section 7. Finally, discussion and conclusion parts are provided in sections 8 and 9.

Table 1. List of abbreviations.

Description	Abbreviation	Description	Abbreviation
Magnetic Resonance Imaging	MRI	Cerebrospinal Fluid's	CSF
Artificial Intelligence	AI	Glioblastoma Multiforme	GBM
Positron Emission Tomography	PET	Low-Grade Glioma	LGG
Computed Tomography	CT	High-Grade Glioma	HGG
Computer-Aided Diagnostic	CAD	Radio Frequency	RF
Repetition Time	TR	Time To Echo	TE
Fluid Attenuated Inversion Recovery	FLAIR	Support Vector Machine	SVM
Artificial Neural Network	ANN	Random Forest	RF
K-Nearest Neighbors Algorithm	KNN	Linear Discriminant Analysis	LDA
Genetic Algorithm	GA	Maximum Marginal Hyperplane	MMH
Social Ski Driver	SSD	Kernel Support Vector Machine	KSVM
Random Decision Forest	RDF	Gaussian Mixture Model	GMM

Decision Tree	DT	Random Forest Classifier	RFC
Proton density	PD	Chemical shift imaging	CSI
Whale Optimization Algorithm	WOA	An Adaptive Artificial Neural Network	AANN
Fuzzy-C-Mean	FCM	Naive Bayes Classifier	NBC
Harmony-Crow Search	HCS	Particle Swarm Optimization	PSO
Learning Vector Quantization	LVQ	Self-Organizing Maps	SOM
Principal Component Analysis	PCA	Adaptive Kernel Fuzzy C-Means	AKFCM
Contrast Enhanced Fuzzy C-Means	CEFCM	Pixel-Based Voxel Mapping Technique	PBVMT
Multiscale Fuzzy C-Means	MsFCM	Gray-Level Co-Occurrence Matrix	GLCM
Edge Adaptive Total Variation Denoising Technique	EATVD	Imaging Mass Spectrometry	IMS
Hierarchical Cluster Analysis	HCA	Region Of Interest	ROI
Association Allotment Hierarchical Clustering	AAHC	Density-Based Spatial Clustering of Applications with Noise	DBSCAN
Gustafson-Kessel	(G-K)	Convolutional Neural Network	CNN
Enhancing Tumor	ET	Whole Tumor	WT
Tumor Core	TC	Recurrent Neural Network	RNN
Long Short-Term Memory	LSTM	Generative Adversarial Networks	GAN
Residual Cyclic Unpaired Encoder-Decoder Network	RescueNet	Sailfish Political Optimizer	SPO
Deep Belief Networks	DBN	Stacked Sparse Autoencoder	SSAE
Reinforcement Learning	RL	Gated Recurrent Unit	GRU
Density-Based Spatial Clustering	DBSCAN	Gaussian Mixture Models	GMM
Earthworm Optimization Algorithm	EWA	Monarch Butterfly Optimization	MBO
Harris Hawks Optimization	HHO	Moth Search Algorithm	MSA
Hunger Games Search	HGS	Runge Kutta Optimizer	RUN
Slime Mould Algorithm	SMA	Colony Predation Algorithm	CPA

2. Magnetic Resonance Imaging In Brain Tumor Detection

Clinicians can plan the most effective and practical treatment for patients involved with brain cancer by obtaining information from several restorative diagnostic imaging technologies, including MRI, PET, and CT [29]. However, better images of organs and soft tissues can be produced using MRI. Using radio waves and strong magnetic fields, MRI releases detailed images of body organs [30]. Compared to a CT scan or X-rays, MRI provides clearer images and it is a better option when doctors should see soft tissues. Brain tumor location and size are determined using imaging methods like MRI [8]. MRI images typify significant data about tissue characteristics, for example, Proton density (PD), spin-lattice (T1), and spin-spin (T2) relaxation durations, chemical shift imaging (CSI), and flow velocity. These facts allow for a more accurate representation of brain tissue [31], [32]. MRI scans can acquire images with various contrasts using various procedures or acquisition parameters. T1 weighted images with contrast material Gadolinium (T1c) aid in distinguishing tumor borders from surrounding normal tissues. T2 weighted (T2) images are typically employed to provide an underlying assessment, identify

different tumor types, and distinguish cancers from normal tissues. No enhanced tumors are seen using the T2 weighted scan in axial viewing with FLAIR. Given these unique characteristics, MRI provides a decision-making advantage in investigations of brain tumors [12]. Table 2 indicates the four types of MRI images.

Table 2. MRI image modalities [34].

Type	Feature
T1	T1-weighted MRI Calculate the tissue's T1 (longitudinal) relaxation time. Brighter tissue has shorter relaxation times.
T2	T2-weighted MRI Calculate the tissue's T2 (transverse) relaxation time. Longer relaxation times result in brighter tissue
T1c	T1 weighted images with contrast material Gadolinium. The signal for tumor increase
FLAIR	Fluid Attenuated Inversion Recovery MRI. Cerebrospinal fluid's (CSF) bright signal is suppressed. Can more accurately identify small hyper-intense lesions.

3. Brain Tumor Types

Brain tumor, sometimes referred to as an intracranial tumor, is an abnormal lump where cells are amassed to reproduce uncontrollably [35]. Currently, over 120 types of brain tumors are detected, two basic types of which are primary and metastatic. Primary brain tumors, also known as Meningioma, are tumors that develop from the brain's tissues or its immediate surroundings and account for more than 30% of all brain tumors [36]. Glial (consisting of glial cells) and non-glial (formed on or in the brain structures; i.e., nerves, glands, and blood vessels) primary tumors are classified as benign or malignant. Those tumors developed in other parts of the body, like the lungs or breast, and spread to the brain typically through the blood flow are referred to as metastatic brain tumors [37]. Malignant tumors with metastases are regarded as cancer. There are several types of brain tumors. Table 3 represents the most common brain tumors.

Table 3. Different types of brain tumors [38].

Brain Tumor Types		Subtype
1	Gliomas	Astrocytoma
2		Pilocytic Astrocytoma (grade I)
3		Diffuse Astrocytoma (grade II)
4		Anaplastic Astrocytoma (grade III)
5		Glioblastoma Multiforme (grade IV)
6		Oligodendroglioma (grade II)
7		Anaplastic Oligodendroglioma (grade III)
8		Ependymoma (grade II)

9		Anaplastic Ependymoma (grade III)
10	Craniopharyngioma	
11	Epidermoid	
12	Lymphoma	
13	Meningioma	
14	Schwannoma (neuroma)	
15	Pituitary adenoma	
16	Pinealoma (Pineocytoma, Pineoblastoma)	

One of the most common types of brain cancer is Gliomas and account for almost 33% of all brain cancers [37], [39]. As gliomas frequently mix with healthy brain tissue and develop within the substance of the brain, they are sometimes referred to as intra-axial brain tumors. Glioblastoma, also named Glioblastoma Multiforme (GBM) and is challenging for experts to diagnose and cure. Fig. 1 shows the Glioblastoma imaging.

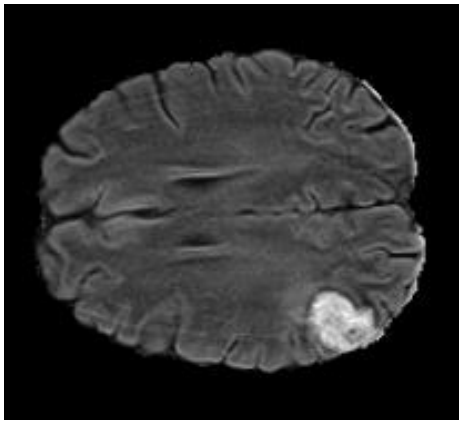

Fig. 1. MRI image of Glioblastoma.

Glioblastoma often has a blend of cell grades and changes synchronous to their growth. The features of tumors that appear under a microscope and the aggressiveness of the tumor make it possible for the experts to recognize tumor types. For example, if the grades are low, it means they are least aggressive, and if the grades are high, it indicates they are most aggressive. You can see the characteristics of Glioma scales in Table 4.

Table 4. Glioma grades and their characteristics [37].

Grade	Characteristic
I	Near to normal appearance Least malignant Slow growing cells Commonly indicates long-term survival
II	Cells growing fairly slowly Fairly abnormal appearance Able to attack nearby tissue In some cases recur as a higher grade

III	Actively creating abnormal cells Abnormal appearance Infiltrate normal tissue Tend to recur, often as a higher grade
IV	Rapidly reproducing abnormal cells Highly abnormal appearance Area of dead cells (necrosis) in center Form new blood vessels to continue growth

In glioma, grades I and II (Table 4) are categorized as Low-Grade Glioma (LGG), and grades III and IV are High-Grade Glioma or HGG [40]. Taking the best procedure for treatment depends on the early diagnosis of Glioma and its grade [8], [37], and MRI imaging is one of the bests screening methods for diagnosing Glioma. In this screening method, the protons which are randomly oriented inside the water nuclei of the tissue are brought into alignment using a strong, uniform, external magnetic field. The subsequent disruption of this alignment (or magnetization) is caused by the addition of an external Radio Frequency (RF) energy. Through a variety of relaxation mechanisms, the nuclei return to their resting alignment and release RF energy in the process. The emitted signals are evaluated after a certain amount of time has passed from the first RF. The signal from each place in the imaged plane is converted using the Fourier transform into the relevant intensity levels, which are then represented as shades of gray in a matrix of pixels [41]. Different forms of images can be produced by altering the order in which RF pulses are delivered and collected. The T1- and T2-weighted scans are very popular MRI sequences. Short Time to Echo (TE) and Repetition Time (TR) is utilized to create T1-weighted images. T1 characteristics of tissue are primarily responsible for determining the contrast and brightness of the image. On the other hand, longer TE and TR times are used to create T2-weighted images. The T2 characteristics of the tissue determine the contrast and brightness in these images. The Fluid Attenuated Inversion Recovery (Flair) sequence is a third frequently utilized sequence. The TE and TR timings of the Flair sequence are significantly longer than those of a T2-weighted image [42]. Fig. 2 indicates the MRI image T1, T2, FLAR modalities.

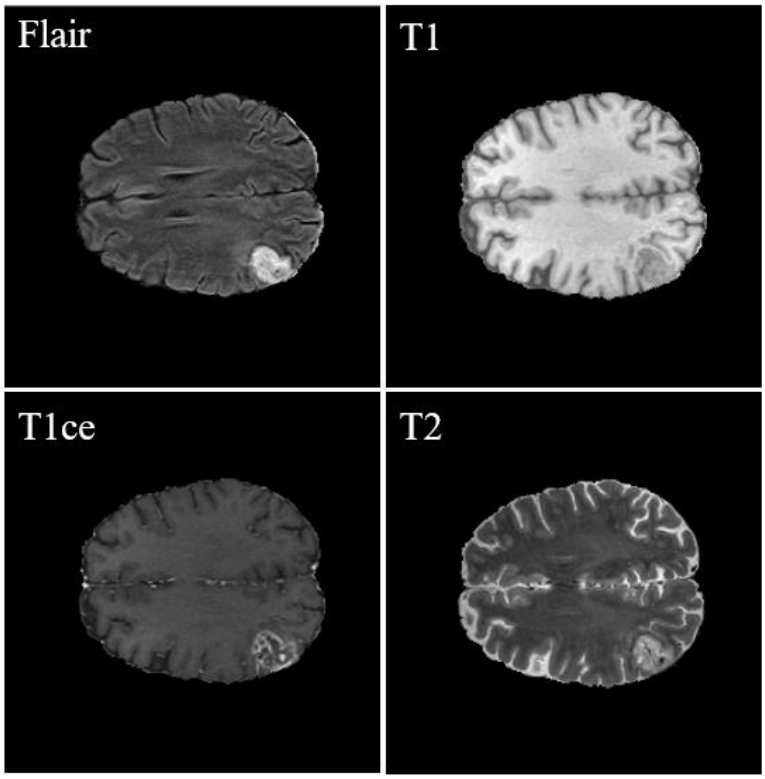

Fig. 2. Some examples of MRI images including T1, T1ce, T2, and Flair.

Table 5 shows the frequently-used MRI sequences, along with an estimate of their TR and TE times for different tissues.

Table 5. Most common sequences of the MRI images [43].

Tissue	T1	T2	FLAIR
White matter	Light	Dark gray	Dark gray
CSF	Dark	Bright	Dark
Fat	Bright	Light	Light
Cortex	Gray	Light gray	Light gray
Inflammation	Dark	Bright	Bright

4. Brain Tumor Segmentation

Segmentation means grouping regions or pixels of images into many coherent subregions and categorizing each subregion into one of the specified classes based on the extracted features, such as color or texture attributes [44]–[46]. Segmentation is a form of image compression and has extensive applications in the development of CAD that works based on radiological images such as MRI. Generally, image segmentation can be categorized into two main groups: supervised and unsupervised [47]–[49]. Unsupervised segmentation approaches include thresholding, edge detection, graph cutting, and deformation to define the boundaries of the target item in the image [50], [51]. In contrast, supervised segmentation techniques apply training samples to include prior

knowledge about the image processing problem. Fig. 3 shows the categories of supervised and unsupervised approaches.

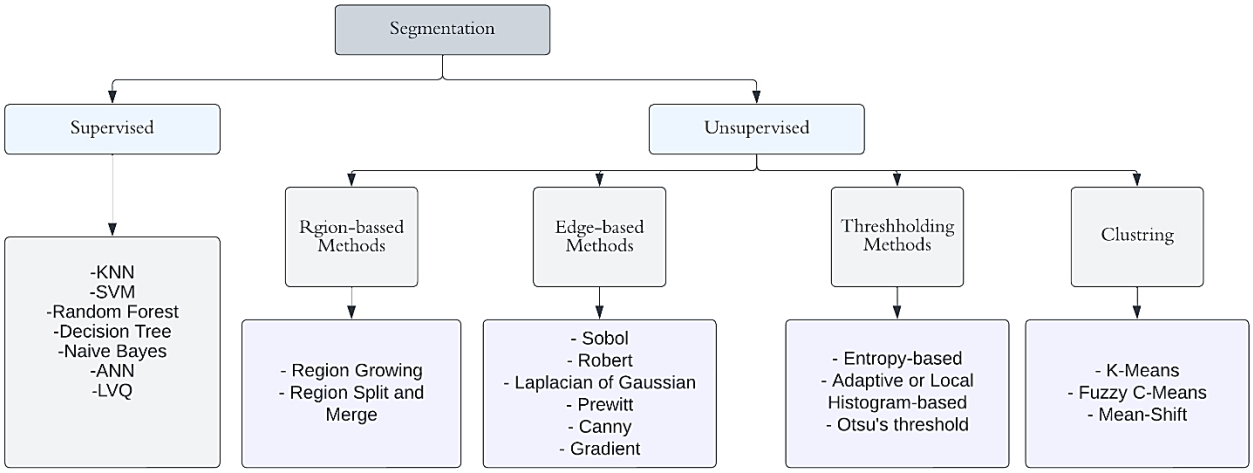

Fig. 3. Brain tumor segmentation approaches.

To find out the number of investigations on brain tumor diagnosis through supervised and unsupervised learning, a statistical report is provided based on the "Scopus" database. The keywords searched in this database were "name of the method (e.g., SVM)" AND "brain tumor" OR "name of method" AND "brain cancer." The date of publication was set from 2015- 2022 (until 1st September 2022). Fig. 4 shows the number of publications that used Machine Learning (ML) approaches to diagnose brain cancer. According to Fig. 4, "Support Vector Machine (SVM)," with 1136 papers published between 2015 to 2022, is the most used approach for brain tumor classification or segmentation. This approach is employed in two ways, directly applied to databases or used in a hybrid with other techniques. SVM, more than 90% of the time, indicated a high accuracy rate, and this is the main reason for the highest number of publications based on this approach. The second approach that is applied to diagnose brain tumors is "Artificial Neural Network (ANN)". The number of investigations conducted based on this approach is about 846 papers. Random forest is the third popular approach with 834 papers. In the following, the ML approaches are introduced briefly and the several papers that applied the approach are discussed.

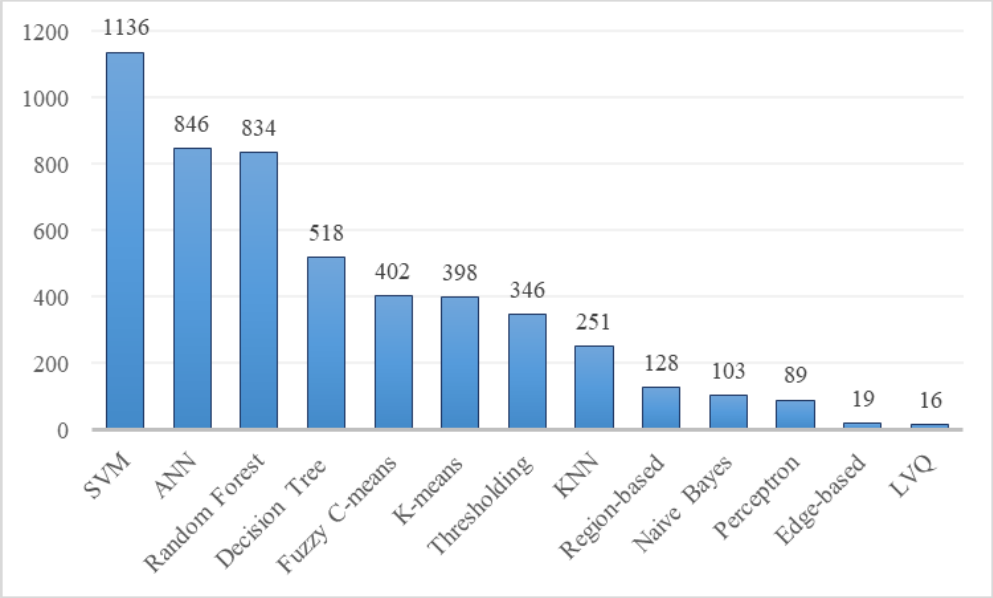

Fig. 4. Number of publications between 2015 to 2022 for brain tumor segmentation using supervised and unsupervised learning techniques.

4.1 Supervised Learning

Supervised learning is a popular branch of ML algorithms and commonly is referred to as supervised ML. In this approach, labeled datasets are utilized to train computers in order to properly categorize data or predict outcomes [52], [53]. The model modifies its weights until the model is properly fitted, which is a part of the cross-validation process. A training set is used in supervised learning to instruct patterns to produce optimal results. This training dataset has accurate input data and outputs (labels), enabling the model to develop through time. The algorithm evaluates precision using the loss function and modifies it to minimize the error. Supervised learning techniques assist in finding large-scale solutions to real-world issues, including in the medical field. Various methods of supervised learning have been applied to diagnose a brain tumor. In the following, a list of techniques is provided.

The most important benefit of these methods is that they allow to produce a data output or collect data from the prior experience. The main disadvantage of these models is inability to correctly classify an input data that was not belonged to any classes in the training data.

4.1.1 K-nearest Neighbors Algorithm

The K-Nearest Neighbors (KNN) algorithm is a supervised learning classifier that employs proximity for classifications or predictions about the grouping of a data point [54]. Although it can be applied to classification or regression issues, it is commonly employed as a classification method since it relies on the concept that similar points can be discovered near one another [55]. It is also known as a lazy learner algorithm. KNNs have been common in brain cancer segmentation, and the results of studies had different accuracy rates. For example, Havaei et al.

[56] created a structure for interactive brain tumor segmentation and applied it to MICCAI-BRATS 2013. This study suggested a semi-automatic method to enhance the effectiveness of various classification techniques, including SVM, KNN, and random forests. The improved KNN reported 85%, 91%, and 87% for accuracy, specificity, and sensitivity rates, respectively. But SVM outperformed and yielded better rates.

Çınarer et al. [57] investigated the statistical features of the input images in order to categorize the data. Then, a variety of methods were employed to examine the accuracy rate of various ML algorithms, including KNN, LDA (linear discriminant analysis), RF (random forest), and SVM. However, KNN's accuracy rate was lower than SVM's 90% accuracy rate. Kumar et al. [58] proposed a four-modular framework that employed an adaptive KNN classifier to categorize MRI images of brain tumors into normal or abnormal categories. Then, the optimal probabilistic Fuzzy C-Means (FCM) clustering approach is applied to separate the tumor areas. The application of the proposed work on BRATS MICCAI dataset indicated the evaluation's findings show that the suggested technique, which employs KNN-based brain tumor classification, achieved the highest accuracy of 96.5%. The maximum sensitivity was 100%, while the maximum specificity was 93%. Ajai et al. [59] performed analyses on various pre-processing algorithms that can be utilized to enhance images prior to applying the active contour without performing the technique called edge-based segmentation. Moreover, both the linear kernel SVM and KNN classifiers' accuracy were compared. According to the findings, KNN is superior to linear SVM for classifying brain tumors when active contouring without an edge-based method of segmentation is utilized.

In order to identify and categorize the different types of tumors, Ramdlon et al. [60] created a tumor classification system based on the KNN method that can identify tumors and edema in T1 and T2 imaging sequences. The tumor categorization reported 89.5% in terms of accuracy, which can give more precise and detailed information about tumor detection. For the classification of glioblastoma, Wibowo et al. [61] compared the use of KNN and SVM methods. Additionally, the Genetic Algorithm (GA) was applied to identify the chosen relevant features and categorize them using KNN and SVM techniques. With 92.35 percent accuracy, the findings demonstrated that the SVM-GA method outperformed the KNN-GA strategy.

Although the KNN technique is much faster than other strategies that require training (such as decision tree, random forest, and SVM), but It does not learn anything in the training period (Lazy Learner). Moreover, as the KNN technique doesn't need any training dataset before making estimation, new input training samples can be added without impacting the performance of the model.

4.1.2 Support Vector Machines

SVMs are effective and adaptable supervised ML algorithms used for both classification and regression. However, they are typically implemented for classification. An SVM model is just a hyperplane in a multidimensional space that represents two or more classes. SVM will construct the hyperplane in an iterative manner in order to reduce error [62]. An SVM technique aims to classify samples in order to identify a Maximum Marginal Hyperplane (MMH). As a result of its

flexibility in handling several continuous and categorical variables, SVM methods are widely-used ML techniques [63], especially for brain cancer segmentation and classification. For example, Amin et al. [64] developed an automated approach to identify brain tumors whether malignant or benign in MRI images. To compare the proposed framework's precision, an SVM classifier was applied with various cross-validations on the features set. The approach obtained average accuracy, sensitivity, and specificity of 97.1%, 91.9%, and 98.0%, respectively.

Padlia et al. [65] suggested a method for identifying and segmenting brain tumors using T1-weighted and FLAIR brain images. In order to enhance images and remove noise, a fractional Sobel filter is utilized. Bhattacharya coefficients and mutual information are employed for detecting asymmetry in brain image. After extracting features of the region of interest through the windows and patches, SVM is used to categorize the statistical features to separate the tumor area from the tumor hemisphere. Their method gained an average accuracy of 98.03%. In another study, Khairandish et al. [66] presented a hybrid model, which integrated CNN and SVM models for classification. Also, a threshold-based algorithm for detecting the brain tumor. The hybrid CNN-SVM got a 98.49% overall accuracy. Rao and Karunakara [67] focused on efficient classification and segmentation, using KSVM-SSD for more accurate classification. In this study, the malignant tumor is further graded as a low, medium, and high utilizing the SSD (Social Ski Driver) optimization method after being diagnosed as cancerous and non-cancerous using Kernel Support Vector Machine (KSVM). The proposed KSVM-SSD model is shown to be superior regarding classification accuracy assessed on the BRATS datasets, with accuracy values of 99.2%, 99.36%, and 99.15% for the corresponding years of 2018, 2019, and 2020 BRATS datasets.

Rashid et al. [68] aimed to shed some light on the area of the brain being damaged by the tumor. The major steps of the described technique include using abnormal MRI brain images as input, anisotropic filtering to remove noise, an SVM classifier for segmentation, and morphological procedures to distinguish the damaged area from the normal one. The results indicated that the segmentation accuracy of the SVM was 83%. For the categorization of medical images, Deepak & Ameer [69] applied CNN features with SVM to enhance the quality of classification. In comparison to the most recent technique, the proposed model outperformed with 95.82% accuracy.

Although SVM is able to work well with even semi structured and unstructured data using an appropriate kernel function, but finding a good kernel function is not an easy task.

4.1.3 Random Forest

Random Forest (RF) strategies are a collection of ML algorithms paired with several classifier trees. Each classifier tree casts a unit vote for the most popular class, and the final sort of result is obtained by combining these results [70]. High classification accuracy, good noise and outlier tolerance, and no overfitting are all features of RFs. In addition to building each tree from a separate bootstrap sample of the data, the RF technique modifies how classification or regression trees are built [71]. In an RF model, node splitting is based on a random subset of features for each tree. By comparing this counterintuitive approach to many other classifiers, it turns out to perform very well. Therefore, this technique has been widely employed for brain cancer tumors. For

example, Lefkovits et al. [72] developed and fine-tuned a discriminative RF model to segment brain tumors in multimodal MRI images. Finding the optimal parameter values and the discriminative model's most important constraints is the goal of tuning. The proposed method obtained 75-91% for the whole tumor and 71-82 % for the core section in terms of dice index. Ellwaa et al. [73] expanded a previously described Random Decision Forest (RDF) based brain tumor segmentation technique. The RDF is trained via an iterative process, where certain patients were introduced to the training data using heuristics approaches rather than a randomly selected training dataset. The obtained dice score of the model was reported to be over 80%.

Anitha & Raja. [74] introduced brain tumor identification and segmentation methods based on random forest classifiers to classify the brain modality into two groups of normal and abnormal. The proposed approach's sensitivity and specificity rates were 97% and 98%, respectively. Yang et al. [75] utilized Small Kernels of Two-Path Convolutional Neural Network (SK-TPCNN) and RF to provide an automated segmentation approach. The sensitivity scores for the whole tumor, core tumor, and enhancing tumor were 96%, 92.2%, and 83.2%, respectively. Rajagopal. (2019) suggested an approach based on a random forest classifier to detect the Glioma brain tumor. In this study, the characteristics of texture are extracted from MRI images of the brain and optimized using Ant Colony Optimization (ACO) algorithm. The resulting optimized sets of characteristics were categorized thanks to the random forest classification method. The result of this study indicated 97.7% of sensitivity, 96.5% of specificity, and 98.01% of accuracy [76].

Although RF helps to improve the accuracy by diminishes overfitting in decision trees and works well with both continuous and categorical data, but it requires much time for training.

4.1.4 Decision Tree

Decision tree models (DTs), i.e., non-parametric supervised learning techniques are used in regression and classification. The objective is to learn simple decision rules derived from the features of the data to build a model to predict a target variable's value. One can assume a tree as a piecewise constant approximation [77], [78]. The tree is utilized to let individuals or organizations evaluate probable actions against each other based on their benefits, costs, and probabilities. A single node is the starting point of a decision tree, which then forks into probable outcomes. Then, every single outcome results in additional nodes, which lead to other probabilities [79]. Previous studies have employed DT approaches for brain cancer diagnosis. For example, Naik and Patel [80] applied a Decision Tree algorithm to discern brain tumors in MRI images and compared the results with a Naive Bayes classification algorithm. The researchers reported that the Decision Tree classifier outperformed a Naive Bayes in the task with an accuracy of 96% and sensitivity of 93%. Chaddad et al. [81] implemented Gaussian Mixture Model (GMM) to take out attributes from brain tumors' MRI images and applied the Decision Tree classifier to GMM features to evaluate the performance of cancer detection. They defined the task to detect brain tumors based on the T1, T2, and FLAIR MRI images. For the T1 and T2 weighted images, the accuracy performance was 100 %. The accuracy decreased to 94.11 % in FLAIR mode. Hussain et al. [82] implemented multiple feature extraction strategies on MRI images of the brain and so

tested the performance of different classification algorithms for tumor detection. The researchers reported that the Decision Tree classifier was the second-best algorithm for the task with a total accuracy of 97.81%, after the Naïve Bayes classifier with total accuracy of 100%.

Thayumanavan and Ramasamy [83] developed a framework for the diagnosis and segmentation of tumors in the brain using MRI images and compared the performance of Decision Tree (DT), Random Forest Classifier (RFC), and SVM. The experimental results showed that RFC reached the best result with an accuracy of 98.37%. Moreover, RFC showed a specificity of 99.09%, followed by DT and SVM with 95.68% and 88.78% respectively. Rajendran and Madheswaran [84] developed a hybrid method based on Association Rule Mining and Decision Tree algorithms for brain tumor classification using CT scan images. They showed that the proposed method reached the accuracy and sensitivity of 95% and 97%, respectively.

Although DT doesn't need scaling and normalization of data, but it requires much time for training. Also, a small change in input data leads to large changing in the structure of the model.

4.1.5 Artificial Neural Network

An ANN is a paradigm for information processing that takes its ideas from how biological nervous systems can learn target patterns. Multiple layers of basic processing units known as neurons make up an ANN structure [85]–[87]. The neuron carries out two tasks: gathering inputs and producing an output. Nodes or artificial neurons are connected to other nodes together with their threshold and weight. When the output of a node is higher than a certain threshold value, that node is activated, and the data is sent to the next layer of the network. Otherwise, data won't be sent to the next layer [88]. ANN has been widely-used for brain cancer. An SVM and an ANN were utilized by Chithambaram and Perumal [89] to create two hybrid ML models (GA-SVM and GA-ANN), which were then evaluated on two different datasets. Virupakshappa & Amarapur [90] developed a technique for classifying data based on an Adaptive Artificial Neural Network (AANN) approach. Utilizing the Whale Optimization Algorithm (WOA), the values of neurons in the adaptive ANN are optimized. The result of classification accuracy was reported at 98%. Virupakshappa et al. [91] suggested an effective tumor segmentation model based on FCM clustering, multiple feature extraction using Gabor wavelets, and an ANN classifier. Based on the result of this study, it is proved that system accuracy levels up to 85%.

Although an ANN model is able to process unorganized data, an effective visual analysis, and ability to process in parallel, but it is economically and computationally expensive and needs a long training process.

4.1.6 Naïve Bayes

A collection of supervised learning algorithms, Naïve Bayes methods, are founded on implementing Bayes' theorem with the "naive" assumption that each pair of characteristics is conditionally independent given the value of the class variable [92], [93]. Bayes' Theorem is a straightforward mathematical procedure for conditional computing probabilities. Conditional probability is defined as the possibility of an event occurring due to the occurrence of another

event before it (via assumption, supposition, statement, or evidence). The Naive Bayes Classifier (NBC) is among the easiest and most efficient classification algorithms. It helps develop rapid ML models, which can make accurate predictions [94]. There are several researches that applied Naïve Bayes to diagnose brain cancer in medical images. For example, Kaur and Oberoi (2019) applied a Naïve Bayes classifier to discover brain tumors in MRI images. The proposed algorithm showed 86% accuracy for brain tumor segmentation [95].

Raju et al. [96] implemented a Bayesian fuzzy clustering algorithm for the segmentation and the Harmony-Crow Search (HCS) optimization algorithm-based multi-SVNN classifier for the classification of brain tumors. The researchers reported that the proposed method reached an accuracy of 93%. Ulku and Camurcu [97] utilized histogram equalization and morphological image processing techniques to develop a computer-aided brain tumor detection method based on MRI images. Six different classification algorithms were tested. Based on the final results, SVM-PSO and KNN algorithms reached 100% accuracy. The Decision Tree algorithm showed 98.11% accuracy in negative samples, while Naïve Bayes showed the weakest performance with 83.71% accuracy in negative samples.

Although Naïve Bayes methods are appropriate for solving multi-class prediction problems and require much less training data, but they face the 'zero-frequency problem' where they assign zero probability to a categorical sample whose class in the test samples wasn't available in the training samples.

4.1.7 Learning Vector Quantization

The Learning Vector Quantization (LVQ) is a prototype-based supervised classification algorithm. With the use of piecewise linear decision surfaces, this algorithm aims to approximate the theoretical Bayes decision boundaries in the input domain of the principal observation vectors [98]. The class codebook vectors are supposedly placed in signal space in an ideal manner. As the classification decision is based on the nearest-neighbor selection among the codebook vectors, its computation is very fast. LVQ algorithms have things in common with other competitive learning algorithms, including Self-Organizing Maps (SOMs) and c-means [99]. This method has been widely used for analyzing medical images and some researchers employed the LVQ approach for brain tumor detection. For example, Liu et al. [100] employed the LVQ neural network for the brain cancer prognosis. A normal diagnostic accuracy of 85.7% and a glioma diagnosis accuracy of 89.5% were achieved by using the suggested procedure. Sonavane et al. [101] proposed a proper and precise classification system for brain tumor detection. This technique uses the LVQ approach to group brain tumors into two groups of normal or abnormal. With respect to the DDSM mammography database and the clinical brain MRI database, the suggested system's accuracy was 68.85% and 79.35%, respectively. Sonavane & Sonavane [102] developed a four-stage system and classified brain tumors using the Adaboost technique and LNQ neural network. For clinical brain MRI images, the accuracy rate was 95%, while it was 79.3% for DDSM.

The LVQ is intuitive, simple, and easy to implement while still yielding decent performance. However, if the data have a lot of dimensions or are noisy, the Euclidean distance is not a good solution.

4.2 Unsupervised Learning

Unsupervised learning, as known as unsupervised ML, analyzes and groups unlabeled datasets using ML algorithms. These algorithms cluster data and discover hidden patterns without the intervention of a human [103]–[105]. In other words, unsupervised learning algorithms work based on finding similar attributes, naturally occurring patterns and trends, or relationships in a given dataset [106], [107]. In contrast to supervised learning, it is not possible to apply unsupervised learning methods directly to a regression or a classification problem because there is no knowledge about the values of the output [108]. Unsupervised learning algorithms enable to do more complex processing tasks than supervised learning does. Moreover, dimensionality can be easily reduced thanks to this approach. Unsupervised learning can help to understand raw data. This learning resembles human intelligence as it happens gradually and weighs the result afterwards. Clustering is an unsupervised method that clusters the data into a number of groups. There are many clustering approaches that have been widely used in the medical imaging area, especially clustering brain tumors into a benign and malignant one.

Unsupervised learning methods have less complexity in comparison with supervised learning and don't require to labeled data. However, the outcomes often have lesser accuracy and may be difficult to understand or unpredictable.

4.2.1 K-means

As a clustering method, K-means is a simple and well-liked algorithm of unsupervised ML [109]. K-means clustering algorithm is prototype-based and seeks to find K non-overlapping clusters. This approach aims to categorize a given collection of data into K distinct clusters, where k has a predetermined value [110]. Benefiting from linear time complexity, K-means algorithm is optimal for large datasets. K-means uses big unlabeled data to provide deep insights and be beneficial. K-means have been employed in many investigations for brain tumor diagnoses. For example, Khilkhal et al. [111] applied K-means clustering, thresholding, and morphological operations, for segmenting brain tumors in MRI images. The morphological procedure removed non-brain tissue to increase the final accuracy results. The experiments were implemented on BRATS datasets utilizing High-Grade Glioma (HGG) and LGG images. Islam et al. [112] proposed an improved outline to detect brain tumors that makes use of Template-based K-means (TK) with a superpixel technique and Principal Component Analysis (PCA) in order to detect brain tumors efficiently. Their method could obtain an acceptable segmentation result with a shorter processing time in MRI images. Kumar et al. [113] proposed a five stages methodology to segment brain tumors in MRI image segmentation. A rough K-means algorithm was used to achieve this aim. The results are indicative of the fact that the suggested methodology gained better scores in evaluation in comparison with previous works.

The K-means model is simple, easy to implement, and Guarantees convergence. However, it is highly dependent on initial values and clustering outliers.

4.2.2 Fuzzy C-Means

Another well-known technique to cluster data is FCM where datasets are classified into n clusters and is frequently used for pattern recognition [114]. Every segmented data point in the dataset belongs to over one group with distinctive values for membership. If the data is closer to the cluster center, its membership inclines more toward that particular cluster center [115]. Enabling memberships of data points through time may be the main benefit of FCMs clustering. These data points are known to have degrees in [0,1] and this technique makes it possible to show that data points do not necessarily belong to one cluster. Moreover, FCM can provide the best result for the overlapped data set [116]. Devi et al. [117] developed a clustering method called Adaptive Kernel Fuzzy C-Means (AKFCM) for diagnosing brain cancer based on MRI images. Then, they applied a Hybrid Convolution Neural Network- Long Short-Term Memory (CNN-LSTM) to enhance the accuracy of tumor categorization. The results indicated that the proposed method did better than the present methods.

Debnath et al. [118] applied the Contrast Enhanced Fuzzy C-Means (CEFCM) clustering method to accurately categorize the 2D tumor regions from MR images. Pixel-based Voxel Mapping Technique (PBVMT) mapped the decision values for each pixel location from the segmented image into 3D space and showed the overall accuracy, sensitivity, and specificity of 94.8%, 92.14%, and 96.97%, respectively. Sheela et al. [119] proposed a method to segment brain tumors in MRI images based on rotating triangular sections with FCM optimization. At first, the background should mostly be eliminated through morphological reconstruction processes in two levels, after which thresholding happens. To assess the proposed structure's performance, they employed T1-a weighted contrast-enhanced image dataset. The final assessment of the proposed method is indicated. Soleymanifard et al. [120] applied a classification method, which was a Multiscale Fuzzy C-Means (MsFCM) with 12 scales to discern enhancing tumors in the image cropped from the former stage. Then, thanks to using a neural network classifier, they managed to specify the input tumors' grade in the MR image. The DICE score results show that the model proposed is highly competitive in comparison with newer segmentation methods.

The Fuzzy C-Means model gains best results for overlapped sample points and comparatively better than k-means strategy. However, it is highly dependent on the predefined number of clusters.

4.2.3 Mean-Shift Clustering

Mean shift clustering algorithm is a powerful nonparametric technique based on centroid that is proven to be useful in various unsupervised learning use cases [121], [122]. This algorithm works by moving data points toward centroids to become the average of nearby points. Mode-seeking algorithm is another name for mean shift clustering. The algorithm's advantage is that it clusters the data without automatically determining how many clusters there should be based on defined bandwidth [123]. Researchers have implemented mean-shift clustering for the clustering

of brain tumors. Vallabhaneni and Rajesh [124] developed a method based on mean-shift clustering, and Gray-level Co-Occurrence Matrix (GLCM) features for automatically diagnosing brain tumors in noise-corrupted images. The researchers implemented Edge Adaptive Total Variation Denoising Technique (EATVD) for preserving the edges in the denoising process of images. The experimental results showed an increased precision in tumor detection in noisy images. Singh et al. [125] implemented modified mean-shift-based FCM segmentation for brain tumor detection in MRI images. The results indicated a high level of efficiency and accuracy for the suggested technique. Kim et al. [126] offered a strategy for reducing file sizes and brain tumor discovery in MRI images using modified K-means and mean-shift clustering techniques. The researchers reported that the proposed method reached a precision of 0.914052 and a recall of 0.995641.

The Mean-Shift clustering approach is able to define the number of clusters automatically and no problem generated from outliers. However, this method unable to work well in case of changing the number of clusters changes abruptly (high dimension).

4.2.4 Hierarchical clustering

Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm to categorize similar objects in groups called clusters [127]. Hierarchical clustering includes a multilevel hierarchy tree where clusters at one level are joined as clusters at the next level. The algorithm clusters together object with similar attributes [128]. Finally, the algorithm returns a set of clusters or groups, where clusters are different from each other and objects within clusters are similar to each other. These algorithms have been applied in the medical domain for brain tumor clustering. For instance, Hiratsuka et al. [129] examined samples of human brain tumors using imaging mass spectrometry (IMS). IMS analysis was integrated with the Region Of Interest Analysis (IMS-ROI) and a novel Hierarchical Cluster Analysis (IMS-HCA). IMS-HCA and IMS-ROI appear to be promising methods for finding biomarkers in brain cancer samples, according to the study's findings. Tamilmani & Sivakumari [130] proposed a novel Association Allotment Hierarchical Clustering (AAHC) approach for early brain cancer detection. The final results revealed that the suggested approach reached an accuracy of 100%, outperforming the state-of-the-art method. Moreover, the method was proven to be more computationally efficient compared to other models.

The Hierarchical clustering approach is able to define the number of clusters. However, this method unable to work well with huge datasets or vast amounts of data.

4.2.5 DBSCAN

DBSCAN or Density-Based Spatial Clustering of Applications with Noise is a state-of-the-art algorithm based on density [131]. The prominent feature of this algorithm is detecting clusters in all sizes and shapes in different databases, even those with noise and outliers [132]. This approach was employed to diagnose brain tumors. For instance, Muthaiyan et al. [133] proposed systems to discover brain tumors using images taken using MRI and PET by different classification methods, such as Gustafson-Kessel (G-K) algorithm, k-means clustering algorithm, DBSCAN, and FCM. The effectiveness of various algorithms is compared, and DBSCAN is not among the most

effective methods for detecting brain cancer. Moreover, Bandyopadhyay [134] used DBSCAN and K-means clustering for the problem of segmenting and grouping brain tumors from MRI images of the human brain, and the result of the study indicated the effectiveness of the DBSCAN approach in comparison with the K-means technique.

The DBSCAN clustering approach not only is able to define the number of clusters but also is able to find arbitrarily shaped and size of clusters. However, this method fails in case of varying density clusters.

4.2.6 Gaussian Mixture Models

As a probabilistic model, GMM presumes that a combination of a limited number of Gaussian distributions, which have unknown parameters, generate all the data points [135]. To investigate the effectiveness of GMM in brain cancer segmentation, Chaddad [136] introduced a unique technique for extracting Glioblastoma (GBM) features from MRI data using GMM. The accuracy performance for the T1-WI and T2-WI was 97.05% and 97.05%, respectively. The accuracy dropped to 94.11 % in FLAIR mode. These experimental findings show promise for improving heterogeneity features and, consequently, early GBM treatment. Pravitasari et al. [137] segmented the MRI-based brain tumor utilizing the GMM and the Reversible Jump Markov Chain Monte Carlo algorithm. The study's findings showed that the suggested technique executed the algorithm quickly and efficiently.

The GMM approach is less sensitive to the number of parameters. However, this method has a slow convergence rate and is sensitive to initialization values.

4.3 Overview of Supervised and Unsupervised Methods Application

Table 6 displays the 12 papers that applied either supervised or unsupervised approaches. It should be mentioned that all these papers are selected randomly. According to this table, as most of the researchers applied the BRaTS dataset, MRI image modalities are T1, T1c, T2, and FLAIR. The advantages of each approach are mentioned in the last column.

Table 6. Overview of recent segmentation methods.

Author	Method of Segmentation	MRI Modalities	Dataset	Advantage
Bonte et al.[138]	Random Forest	T1ce and FLAIR MRI	BRaTS 2013 database	1. Requires fresh training sets. 2. Very much sensitive to noise
Bahadure et al. [139]	watershed	-	15 images with 9 slices using 3 Tesla Siemens Magnetom Spectra MR machine	1. Sensitivity to intensity variants. 2. Ignore the blurry boundaries. 3. High system complexity.
	FCM			
	DCT			
	BWT			

Author	Method of Segmentation	MRI Modalities	Dataset	Advantage
Reddy & Reddy. [140]	Region growing algorithm	T1, T1c, T2, and FLAIR	BRATS 2015	1. Over segmentation. 2. Need seed point selection.
Xie & Xiaozhen. [141]	KNN	T1 and T2	-	1. Poor run-time performance. 2. Only using T1 and T2 modalities.
Raja & Rani. [142]	Bayesian fuzzy clustering	T1, T1c, T2, and FLAIR	BRATS 2015	1. High system complexity. 2. Time-consuming.
Ilhan & Ilhan. [143]	Novel Threshold-based method	Flair, T2 and T1C	TCIA: 100 MRI images	1. Poor run-time performance. 2. High system complexity
Aslamet al. [144]	Sobol Edge-detection	-	-	1. Not acceptable result at fuzzy borders. 2. Not clear the process of the model.
Kermi et al. [145]	region-based + boundary-based	T1, T1ce, T2, and Flair	BRaTS'2017	1. Poor run-time performance
Sheela & Suganthi. [146]	Region of Interest + Region Growing + Morphological Operation	-	medical MR Images of 120 patient	1. High system complexity. 2. Class imbalances not considered.
Khan et al. [147]	k-means+ VGG19	T1, T1c, T2, and FLAIR	BRaTS 2015	1. Many features are required. 2. Easy to lose information
ŞİŞİK & SERT. [148]	BTS-ELM-FRFCM	T1	3200 pieces MRI image	1. Only using T1 modality. 2. Class imbalances not considered.
Khosravanian et al. [149]	superpixel fuzzy clustering +lattice Boltzmann	T1, T1ce, T2, and Flair	BRaTS 2017	1. Ignore the blurry boundaries. 2. High system complexity

5. Deep Learning Application in Brain Tumor Segmentation

DL is a form of ML and AI that mimics how humans gain specific subjects. In data science, which also encompasses statistics and predictive modeling, DL plays a significant role. Multiple visual analysis tasks, including classification, object detection, and tracking, have provided notable performance gains due to DL techniques [150]–[154]. Additionally, DL techniques have had a significant impact on the automation of medical image processing tasks while showing state-of-the-art accuracy. Over the last decades, many DL techniques have been developed and applied in different areas, including brain tumor diagnosis [155]. In the following, the popular DL approaches that are utilized for brain cancer diagnosis are introduced. Fig. 5 illustrates the number of papers

that applied different approaches of DL to investigate their performance in brain cancer segmentation and classification. According to the Fig. 5, the number of studies that applied CNN-based approaches is considerably higher than other DL approaches with 1793 publications between 2015 to 2022. LSTM is the second DL approach that has been employed in brain tumor diagnosis with 282 papers.

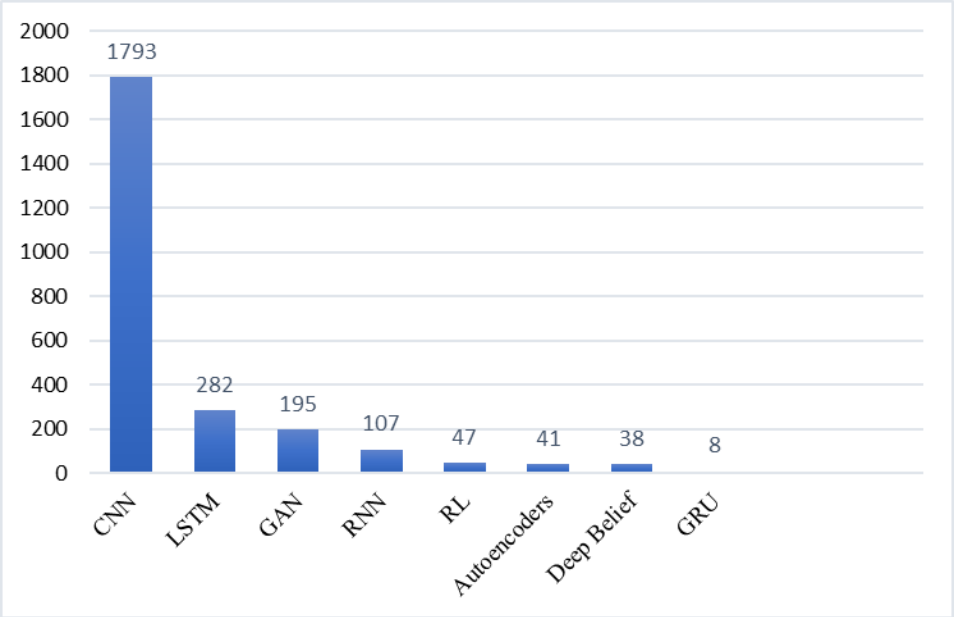

Fig. 5. Number of publications between 2015 to 2022 for brain tumor segmentation using DL models.

5.1 Convolutional Neural Network

A Convolutional Neural Network (CNN), or ConvNet, sets the basis for DL [156], [157]. In this method, learning is received straight from the data, so there is no need to extract features manually [51]. The most significant usage of CNNs is in discovering patterns in images [158]. A CNN network can be trained using a large dataset from scratch by fine-tuning an existing model or utilizing "off-the-shelf CNN features" [152]. Fine-tuning involves transferring weights of the first n layers learned from an earlier-based network to the new network [159]. The dataset obtained for the new network is trained to perform specific tasks. By effectively learning general image features through transfer learning, CNNs are able to tackle the majority of computer vision problems by combining these features with straightforward classifiers [50]. This is the main reason why the CNN approach has been applied considerably for brain tumor diagnosis. For example, Abd El Kader et al. [160] used deep differential CNN to categorize brain tumors in MRI images. This method achieved maximum accuracy of 99.25%.

Bacanin et al. [161] deployed the firefly algorithm to optimize CNN for glioma brain tumor grade classification. The researchers reported that the introduced method reached the maximum multi-class accuracy of 97.9% and the maximum accuracy of 96.5% in the images containing brain tumors. Wang et al. [162] offered a ground-breaking structure based on CNN with a dilated

convolutional feature pyramid called DFP-ResUNet to categorize multimodal brain tumors. The results of testing the suggested model on the BRaTS 2018 dataset showed the mean Dice value of different subregions to be Enhancing Tumor (ET) 0.8431, Whole Tumor (WT) 0.897, and Tumor Core (TC) 0.9068. Gurunathan and Krishnan [163] applied CNN for brain tumor detection and diagnosis using MRI images. The method reached the maximum classification accuracy of 98.3%, the sensitivity of 97.2%, and the specificity of 98.9%.

The CNN models are able to explore hidden patterns inside the input data automatically and share weights between layers. However, these models fail to encode the orientation and position of objects.

5.2 Recurrent Neural Network

As an ANN, a Recurrent Neural Network (RNN) employs time series data or sequential data [164]. RNNs have the concept of "memory," which enables the method to retain the qualities or details of the former inputs in order to produce the following output in the sequence. RNNs are characterized by their capacity to transmit data over time steps [165]. RNNs feature an extra parameter matrix in their structure for connections between time steps, which encourages training in the temporal domain and makes use of the input's sequential nature. In the RNN technique, the predictions made at each time step are trained to be based on both the most recent input and data from earlier time steps [166]. RNNs hold the second place of the most favored approaches to diagnose brain cancer and have been implemented in many studies. For example, SivaSai et al. [167] used fuzzy RNN to categorize brain tumors in MRI images automatically. The results showed an accuracy of 87.8% and it was proven that the proposed framework is much more computationally efficient. Zhou et al. [168] deployed DenseNet and RNN for a holistic screening and categorization of brain tumors via MRI images. By testing the proposed structure on public datasets, the researchers reported that the DenseNet-RNN approach reached the maximum accuracy of 84.61%. However, DenseNet-LSTM achieved an accuracy of 92.13% and performed better than RNN based approach. Begum and Lakshmi [169] combined optimal wavelet statistical texture and RNN to discover and classify brain tumors in MRI images. The proposed method achieved a maximum accuracy of 96% and a maximum sensitivity of 100% in the classification. Moreover, the introduced approach reached the maximum accuracy and sensitivity of 95% and 97%, respectively for the segmentation.

The RNN models are capable of processing inputs of any length and each sample can be assumed to be dependent on former samples. However, these models face issues like Vanishing Gradient or Exploding Gradient.

5.3 Long Short-Term Memory

There are recurring neural networks able to learn order dependency in issues related to predicting sequences; these networks are called Long Short-Term Memory (LSTM) networks [170]. LSTM is one of the most widely-used RNN designs to date. It is the best option for modeling

sequential data and is thus utilized to learn the complex dynamics of human behavior. The word "cell state" refers to long-term memory. Previous data is stored in the cells because of their recursive nature. LSTM was specifically created and developed in order to address the disappearing gradient and exploding gradient issues in long-term training [171]. Fig. 6 shows an example of LSTM structure and the way this technique works.

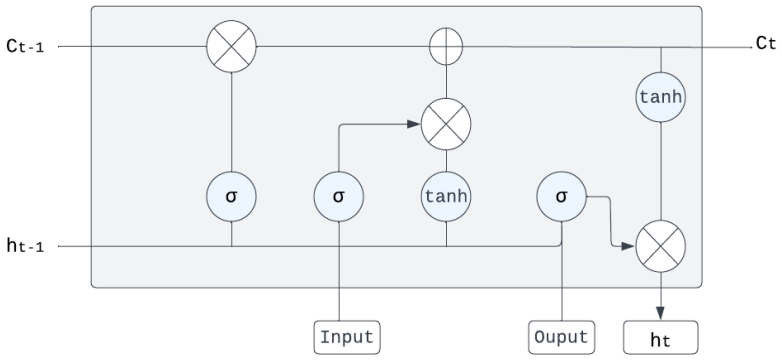

Fig. 6. An example of LSTM structure.

This approach has been utilized in previous studies to diagnose a brain tumor. For example, Dandıl and Karaca [172] used stacked LSTM for pseudo brain tumor detection based on MRI spectroscopy signals. The experimental results indicated an accuracy of 93.44% for the categorization of pseudo brain tumor with glioblastoma, 85.56% accuracy for a pseudo brain tumor with diffuse, 88.33% for a pseudo brain tumor with astrocytoma, and 99.23% for a pseudo brain tumor with metastatic brain tumors. Xu et al. [173] proposed an LSTM Multi-modal UNet to categorize tumors using multi-modal MRI. The experimental results by testing the model's performance on the BRATS-2015 dataset showed that the proposed LSTM multi-modal UNet outperformed the standard U-Net with fewer model parameters. Shahzadi et al. [174] developed an approach according to a cascade of CNN with an LSTM network for 3D brain tumor MR image classification. The researchers reported an accuracy of 84% for the proposed method.

The LSTM models are capable of learning long-term dependencies. However, these models prone to overfitting and need a lot of resources, high memory-bandwidth, and time to get trained.

5.4 Generative Adversarial Network

Generative Adversarial Network (GAN) is one of the categories of generative models [175]. These models have the capacity to create or develop new data with the statistics similar to the training set given. For instance, a GAN trained on images can produce new images with numerous realistic features that appear to be created by humans, at least on the surface [176]. Fig. 7 indicates the simple structure of the GAN approach.

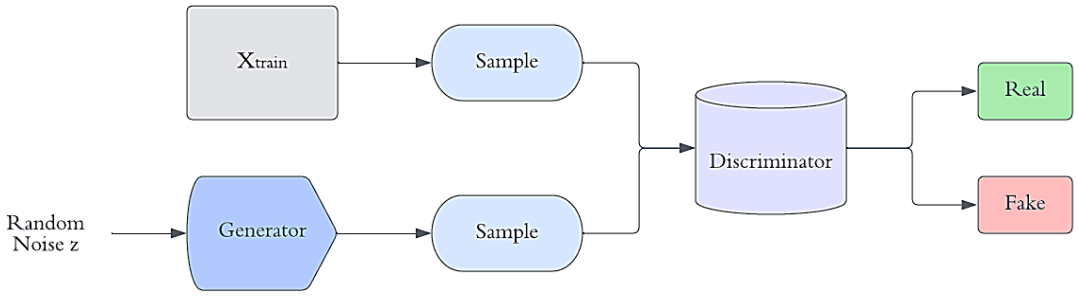

Fig. 7. An example of the GAN method structure.

In order to evaluate the efficiency of the GAN method in segmenting brain tumors, several studies have been conducted. For example, Nema et al. [177] developed a novel architecture called residual cyclic unpaired encoder-decoder network (RescueNet) to segment brain tumors which is trained based on an unpaired GAN. The results showed a Dice value of 0.9401% and 0.9463% for the BRaTS 2015 and BRaTS 2017 datasets, respectively. Neelima et al. [178] provided an approach founded on the Optimal DeepMRSeg strategy trained by a devised Sailfish Political Optimizer (SPO) algorithm to segment the tumors and then applied GAN to classify brain tumors using MRI images. The elevated accuracy, segmentation accuracy, sensitivity, and specificity resulted from this method were 91.7%, 90%, 92.8%, and 92.5%, respectively. Rezaei et al. [179] proposed a new method according to the adversarial network called voxel-GAN for mitigating imbalanced data problems in segmenting the tumors using 3D brain MR or CT images. Once the suggested method was evaluated on the ISLES dataset, the results showed a Dice value of 0.83, a Hausdorff score of 9.3, a precision of 0.81, and a recall of 0.78.

The LSTM models are capable of improving data instances, lowering costs, and increasing data production. However, these models require strong technical knowledge and advanced datasets.

5.5 Deep Belief Network

Deep Belief Networks (DBNs) are a type of graphical representation that is fundamentally generative, producing all possible values for the given case. It combines ML and neural networks with probability and statistics [180]. DBNs are made up of many layers with values, but there is no relationship between the values and the layers. The major objective is to assist the system in categorizing the data into distinct categories. Fig. 8 represents a simple structure of the DBN approach.

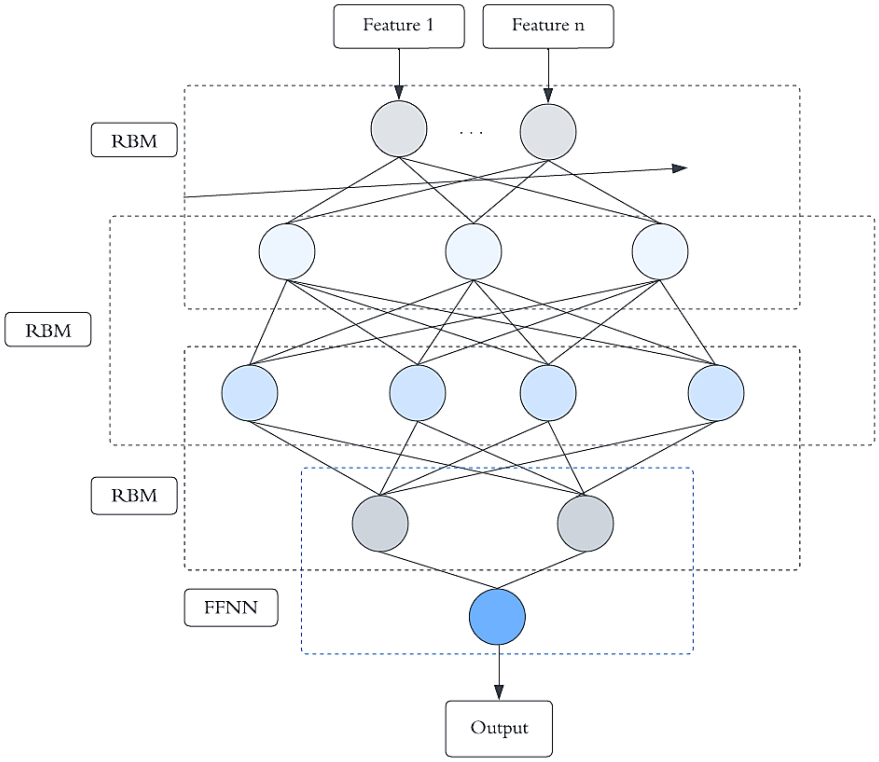

Fig. 8. An example of DBN method structure.

In other cancer studies, it is indicated that DBN is among the best approaches to segment tumors. There are several research works that used DBN for brain tumor segmentation. For example, Kharrat and Néji [181] implemented personalized DBNs for brain tumor classification using MRI images. The researchers trained the proposed model on the BRaTS dataset and showed the model reached an accuracy of 91.6%. Raju et al. [182] offered a strategy according to a DBN and hybrid active contour model to split and classify the tumors of the brain via MRI images. The outcomes indicated the accuracy of 0.945, sensitivity of 0.9695, and specificity of 0.99348 for the proposed model.

The DBN models are capable of providing the best performance results even if the amount of data is huge. However, these models require strong technical knowledge and huge data to perform better.

5.6 Autoencoders

Autoencoders are an unsupervised learning method that uses neural networks for the presentation learning task [183]. Specifically, it is a neural network architecture with an imposed bottleneck that represents a compact knowledge of the specified input [184]. Amin et al. [185] deployed Stacked Sparse AutoEncoders (SSAE) to detect brain tumors. They tested the suggested model on the BRaTS datasets and reached the average accuracies of 100%, 90%, 95%, 100%, 97%, and 95% on the 2012 dataset, 2012 synthetic dataset, 2013 dataset, Leaderboard 2013 dataset,

2014 and 2015 datasets, respectively. Badža and Barjaktarović [186] implemented a convolutional autoencoder to segment brain tumors based on MRI images. The researchers reported that the proposed method achieved 99.23% average accuracy for pixel classification and an average accuracy of 99.28% for 5-fold cross-validation and one test.

The Autoencoders can reduce the dimensionality of the data, provide an appropriate way to diminish the noise of input data greatly, and make the creation of DL frameworks much more efficient. However, learning and reproducing input features in training autoencoders is unique to the data they are trained on and don't work for new data.

5.7 Reinforcement Learning

Reinforcement Learning (RL) is the training of ML models to make a sequence of decisions. The agent gains the ability to do a task in a possibly complex and uncertain environment. An AI encounters a scenario similar to a game during RL. In order to solve the problem, the computer uses trial and error. AI is rewarded or punished for the steps it takes to make the machine do what the programmer desires. The goal of the RL algorithm is to maximize the total reward Stember and Shalu [187] automatically extracted labels from clinical reports and then utilized deep RL classifier to classify3D MRI brain volumes. The results revealed that the presented method provides 100% accuracy.

The RL models are desired to gain long-term outcomes, which are challenging to obtain. Moreover, a perfect model can be created to solve a particular problem. However, RL models need plenty of data and computation and are not preferable to utilize for solving simple problems.

5.8 Gate Recurrent Unit

Gated Recurrent Unit (GRU) is the upgraded version of the standard RNN, i.e. RNN, which was offered by Kyunghyun Cho et al. [188] GRUs are very similar to Long Short Term Memory (LSTM). Resembling the LSTM, GRU employs gates to supervise the flow of information, which are newer than LSTM. Therefore, they improve LSTM and focus on simplifying the architecture. Fig. 9 displays the structure of the GRU model.

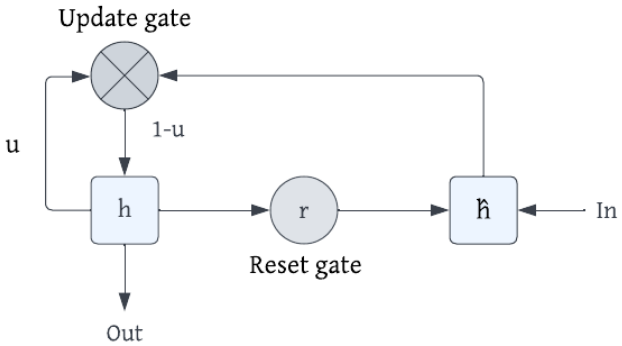

Fig. 9. An example of GRU method structure.

One of the main usages of the GRU is increasing the memory capacity of a RNN and facilitating the training of a model. On top of that, we can employ the hidden unit and solve the problem of vanishing gradients in RNNs. There are investigations that applied the GRU technique for brain cancer diagnosis. For example, Gab Allah et al. [189] employed a combination of a VGG-16 network and a GRU model to increase the brain tumor segmentation in the presence of even fuzzy borders. Table 7 indicates the 16 papers that used DL approaches to classify and segment brain tumors.

Unlike LSTM, GRU models do not have a separate cell state (Ct) and only have a hidden state (Ht). These models are much faster due to the simpler architecture.

Table 7. Overview of segmentation through DL approaches.

Author	Method of Segmentation	MRI Modalities	Dataset	Limitations
Chang et al. [190]	CNN+FCRE	T1, T2, T1c, FLAIR	BRaTS2013	1. Requires fresh training sets. 2. Only using HGG patient subjects.
Kaldera et al. [191]	Faster R-CNN	T1	MRI dataset of Nanfang Hospital and General Hospital in China	1. Requires fresh training sets. 2. Only using T1 modality.
Sajjad et al [192]	CNN + Data augmentation	T1	Radiopaedia dataset	1. Need a post-processing step. 2. Only using T1 modality.
Murthy et al [193]	Optimized CNN	-	kaggle	1. Requires fresh training sets. 2. Need a post-processing step.
Rehman et al [194]	3D CNN	T1, T2, T1c, FLAIR	BRaTS 2015, 2017, and 2018	1. Fail to detect the unobvious and small brain tumors. 2. High system complexity
Amin et al [195]	LSTM	T1, T2, T1c, FLAIR	BRaTS +SISS database	1. High system complexity. 2. Requires fine-tuning of the network parameters.
Liu et al [196]	DRL + DTCWT	T1, T2, T1c, FLAIR	BRaTS2018 + CQ500 + hospital databases	1. High system complexity 2. Lack of spatial consistency.
Kumar et al [197]	DBN + GS-MVO	T1	Kaggle dataset	1. The feature selection is not clear. 2. Only using T1 modality.

Author	Method of Segmentation	MRI Modalities	Dataset	Limitations
Harish & Baskar [198]	R-CNN + Alex Net model	-	-	1. Many layers, which increases system complexity. 2. Requires fresh training sets.
Ahmad et al. [199]	Variational Autoencoders + GAN	T1	Figshare	1. Requires fine-tuning of the network parameters 2. Only using T1 modality.
Mukherkjee et al. [200]	Optimized GAN method	T1, T2, T1c, FLAIR	BRaTS 2020 dataset	1. High computational cost. 2. High system complexity.
Takrouni & Douik [201]	DPGM+DDM	T1, T2, T2c & FLAIR	BRaTS 2013 + 2015 +2017	1. Need a lot of training data. 2. High system complexity.
Chattopadhyay & Maitra [202]	CNN	T1, T2, T2c & FLAIR	BRaTS 2020	1. Weak interpretability. 2. Requires fresh training sets.
Kesav & Jibukumar [203]	RCNN	T1	Figshare + Kaggle	1. Requires fine tuning of the network parameters 2. Only using T1 modality.
Vankdothu et al [204]	CNN + LSTM	T1	Kaggle	1. High system complexity. 2. Only using T1 modality.
Ranjbarzadeh et al. [18]	CNN + Attention	T1, T2, T2c & FLAIR	BRaTS 2018	1. High system complexity. 2. Requires fresh training sets.

6. Brain Tumor Imaging Database

There are many advanced databases of medical images taken from patients suffering from brain tumors to facilitate the development and validation of new images. Table 8 outlines the list of top brain databases used in recent investigations. The number of data and their modalities mentioned.

Table 8. Top database for the brain tumors.

Dataset	From	Number of images	Available Modalities
BRATS 2012	MICCAI 2012 Challenge	45 3D	T1, T2, T1c, FLAIR
BRATS 2013	MICCAI 2013 Challenge	65 3D	T1, T2, T1c, FLAIR
BRATS 2014	MICCAI 2014 Challenge	50 3D	T1, T2, T1c, FLAIR
BRATS 2015	MICCAI 2015 Challenge	300 3D	T1, T2, T1c, FLAIR
BRATS 2016	MICCAI 2016 Challenge	300 3D	T1, T2, T1c, FLAIR
BRATS 2017	MICCAI 2017 Challenge	285 3D	T1, T2, T1c, FLAIR
BRATS 2018	MICCAI 2018 Challenge	285 3D	T1, T2, T1c, FLAIR
BRATS 2019	MICCAI 2019 Challenge	335 3D	T1, T2, T1c, FLAIR
BRATS 2020	MICCAI 2020 Challenge	-	T1, T2, T1c, FLAIR

Dataset	From	Number of images	Available Modalities
BRATS 2021	MICCAI 2021 Challenge	-	T1, T2, T1c, FLAIR
ADNI1	Alzheimer's disease neuroimaging initiative	400	T2, FLAIR, DTI
BrainnWeb	McConnell Brain Imaging Centre	21	T1, T2, PD- weighted
RIDER	TCIA	365 3D	T1, T2- weighted
AANLIB	Harvard Medical School	-	T1, T2- weighted MRI
The IBSR	The CMA	39	T1- weighted
Allen brain atlas	Allen Institute Publications for Brain Science	20	T1, T2, DTI
Figshare	Jun Change	3064	T1
Kaggle	-	3264	-
SISS	-	-	FLAIR, DWI, T2, T1

6.1 BRaTS Database

According to Table 8, BRaTS are the most used data set for brain cancer diagnosis. BRaTS database employs special MRI scans that are multi-institutional and pre-operative to concentrate on parting incongruous brain tumors, i.e., gliomas, which are different in appearance, shape, and histology. Table 9 indicates the dice and Hausdorff parameter for the papers that applied the different methods to diagnose brain tumors based on BRaTS database.

Table 9. Dice and Hausdorff index of investigations based on BRaTS 2020-2017.

BRaTS 2020						
Method	**Dice**			**Hausdorff 95%**		
	Comp	Core	Enh	Comp	Core	Enh
3D U-Net [205]	89%	84%	81%	6.4	19.4	15.8
nnU-Net [206]	89%	85%	82%	8.50	17.33	17.80
Multiple U-net [207]	89%	84%	78%	6.7	19.55	20.4
Scale Attention Network [208]	88%	84%	82%	5.2	17.97	13.43
Variational-autoencoder + regularized 3D U-Net [209]	89%	79%	70%	4.62	10.07	34.30
Deep Layer Aggregation [210]	88%	83%	79%	5.32	22.32	20.44
Lightweight U-Nets [211]	87%	80%	75%	6.2	19.6	21.46
HI-Net [212]	88%	84%	79%	-	-	-
Modified UNet [213]	89%	85%	79%	-	-	-
DR-Unet104 [214]	87%	80%	75%	10.41	21.84	24.68
BRaTS 2019						
Method	**Dice**			**Precision**		

	Comp	Core	Enh	Comp	Core	Enh
Two-stage Cascade UNet [215]	89%	84%	83%	4.62	4.13	2.65
Encoder-decoder + Combined loss function [216]	88%	84%	83%	4.7	3.97	2.20
CNN [217]	87%	78%	78%	7.3	6.8	3.7
3D UNet [218]	85%	80%	78%	6.5	6.3	3.5
RMU-Net [219]	92%	91%	83%	-	-	-
Deep Layer Aggregation [220]	87%	83%	79%	5.32	22.32	20.44
DNN [221]	88%	86%	81%	4.8	5.6	2.4
Multi-Resolution 3D CNN [222]	82%	72%	70%	8.42	9.14	5.59
3D Residual U-Net [223]	83%	77%	70%	14.64	26.69	25.56
3D FCN [224]	89%	78%	76%	-	-	-
BRaTS 2018						
Method	**Dice**			**Precision**		
	Comp	Core	Enh	Comp	Core	Enh
3D UNet [225]	86%	82%	76%	7.01	5.63	5.6
Deep CNN [226]	88%	79%	78%	5.5	6.9	2.93
3D UNet [227]	87%	77%	71%	6.5	8.31	4.14
Contour-aware 3D CNN [228]	89%	79%	72%	8.05	7.5	5.2
S3D-UNet [229]	84%	78%	69%	9.2	7.7	4.5
HTTU-Net [230]	88%	89%	82%	7.53	8.81	4.43
Auto-encoder Regularization [231]	88%	81%	77%	5.9	4.8	3.8
Cascaded UNet [232]	88%	78%	72%	-	-	-
CNN [233]	87%	77%	78%	6.55	27.05	15.90
CNN + Test-time Augmentation [234]	88%	80%	75%	5.97	6.71	4.16
BRaTS 2017						
Method	**Dice**			**Precision**		
	Comp	Core	Enh	Comp	Core	Enh
UNet [235]	81%	76%	65%	-	-	-
Random Forest +CNN [236]	85%	69%	67%	6.12	28.72	23.55
FCN [237]	70%	55%	40%	-	-	-
Anisotropic CNN [238]	87%	77%	78%	6.5	27	15.90
EMMA [239]	89%	80%	73%	5.01	23.1	36.0
CNN [240]	83%	65%	65%	-	-	-
UNet [241]	88%	76%	64%	-	-	-
Pixel Net [242]	87%	76%	68%	9.8	12.30	12.93
Multi-path CNN [243]	84%	69%	60%	-	-	-

Ensemble-of-Forest [244]	42%	41%	42%	21.17	40.06	69.12

7. Performance measures

The performance assessment of the classification or segmentation strategies can be accomplished using different methods. Researchers employ various strategies for validating the obtained outcomes. The most popular and widely used performance measures including Sensitivity (Recall or True Positive Rate), Specificity, Accuracy, and Precision, Confusion matrix, Jaccard Index, and Dice Similarity. These criteria can be defined as follows:

Confusion matrix (CM) is used to provide crucial information about actual and estimated outcomes created by the classification or segmentation techniques. One example of a two-class classification task is demonstrated as in Table 10.

Table 10. The details of classification criteria for two classes.

Category	Estimated Brain tumor	Ordinary tissue
Brain tumor	True Positive (TP)	False Negative (FN)
Ordinary tissue	False positive (FP)	True Negative (TN)

Where TP,FP, FN, and TN are described as:

TP: Correctly classified or segmented brain tumor.

TN: Correct classified or segmented of Ordinary tissue as Ordinary tissue.

FN: Wrong classified or segmented of actual tumor tissue as Ordinary tissue.

FP: Wrong classified or segmented of an ordinary tissue.

$$Accuracy = \left(\frac{TN + TP}{TN + TP + FP + FN}\right) \quad (1)$$

$$DICE = \left(\frac{2 \times TP}{(2 \times TP) + FP + FN}\right) \quad (2)$$

$$Precision = \left(\frac{TP}{TP + FP}\right) \quad (3)$$

$$\text{Specificity} = \left(\frac{TN}{TN + FN}\right) \quad (4)$$

$$\text{Sensitivity or Recall} = \left(\frac{TP}{TP + FN}\right) \quad (5)$$

$$\text{Jaccard Index (A, B)} = \frac{|A \cap B|}{|A \cup B|} \quad (6)$$

8. Discussion

The brain tumor is one of the fatal diseases that occurs when the growth of cells in the brain is out of control. The mortality rate of this cancer made researchers investigate approaches for early brain cancer diagnosis. MRI images are one of the best tools to diagnose cancer by providing a picture of soft tissue in the brain. Over the last decades, many ML-based and DL-based approaches have been developed. However, due to the large number of articles that implemented these approaches, it is important to summarize the current studies and methods. In this work, we provide a holistic approach and summarize ML-based segmentation approaches, DL-based segmentation methods, a review of top DL and ML papers, the top database of brain cancer, and a comparison of accuracy rate in applying different methods on publicly available datasets. The application of CAD systems that work based on DL and ML approaches in brain tumor diagnosis increases accuracy, decreases failure in diagnosis, early detection, and provides better treatment approaches. Also, in underdeveloped countries with a scarcity of experts, CAD-based systems can provide early diagnosis, which results in a decrease in mortality rate.

The analyses of the previous studies indicated that MRI is the best imaging technique for brain tumor diagnosis (Tables 6 and 7). The main reason for the widespread usage of MRI is that this imaging technique provides more details compared to other approaches like CT scans. Moreover, over the last years, the application of DL approaches was significantly more than ML techniques. According to Figs. 4 and 5, the number of total papers that applied DL approaches has increased significantly. However, the number of papers that implemented ML techniques or hybrid methods is still more than DL-based approaches. SVM and CNN are the most used ML and DL approaches for brain tumor segmentation. Moreover, in most papers, BRaTS datasets are employed. According to Table 9, the dice and Hausdorff rate indicate that the BRaTS dataset can also be used in future studies as they are reliable.

9. Conclusion

Brain tumor segmentation has widely benefitted from advancements in AI. Researchers have been applying AI algorithms and techniques for detecting brain tumors, computing tissue volumes, abnormality detection, pathology, planning of treatments, and computer-aided surgery. These techniques work well in tasks related to segmenting brain tumors as their features enable distinguishing abnormal tissues from normal ones. This paper offers a general survey of methods applied to brain tumor segmentation. A long array of automatic and semi-automatic brain tumor segmentation, classification, and feature extraction methods is covered in this study. The current paper quantitatively measures the up-to-date approaches based on multiple evaluation metrics to help readers and medical experts both to develop future research directions and, more importantly, identify the most effective and precise strategies to segment tumors of the brain. This paper proposes that the upcoming research aiming to enhance the performance of the current systems for brain segmentation can be followed in several directions: (*i*) Gathering larger databases with

images from various qualities, (ii) Focusing on improving the classification accuracy of current methods by developing novel methods for feature extraction, and (iii) Developing hybrid systems consisting of multiple approaches regarding ML and DL.

Except the techniques employed in this study, some of the most representative computational intelligence techniques can be utilized to solve the problems, like Harris hawks optimization (HHO), Monarch Butterfly Optimization (MBO), Earthworm Optimization Algorithm (EWA), Moth Search Algorithm (MSA), Colony Predation Algorithm (CPA), Slime Mould Algorithm (SMA), Hunger Games Search (HGS), and Runge Kutta Optimizer (RUN).

However, it is still questionable whether the abundance of computational resources, deep learning technology, and training data needed to run DL at full performance is meaningful, considering other learning techniques that may yield fast, higher interpretability, and close performance with less parameterization, tuning, and fewer resources.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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