Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools

5 authors, including:

Ramin Ranjbarzadeh
Dublin City University
31 PUBLICATIONS   **988** CITATIONS

SEE PROFILE

Annalina Caputo
Dublin City University
91 PUBLICATIONS   **609** CITATIONS

SEE PROFILE

Erfan Babaee Tirkolaee
Istinye Universitesi
152 PUBLICATIONS   **4,018** CITATIONS

SEE PROFILE

Saeid Jafarzadeh Ghoushchi
Urmia University of Technology
87 PUBLICATIONS   **2,291** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

COVID-19 Projects View project

Special Issue in Environmental Science and Pollution Research (Q2, IF: 4.223) "Circular Economy Application in Designing Sustainable Medical Waste Management Systems"
View project

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

Ramin Ranjbarzadeh[1], Annalina Caputo[2], Saeid Jafarzadeh Ghoushchi[3], Erfan Babaee Tirkolaee[4,*], Malika Bendechache[5]

[1] School of Computing, Faculty of Engineering and Computing, Dublin City University, Ireland.

ramin.ranjbarzadehkondrood2@mail.dcu.ie (corresponding author)

[2] School of Computing, Faculty of Engineering and Computing, Dublin City University, Ireland.

annalina.caputo@dcu.ie

[3] Faculty of Industrial Engineering, Urmia University of Technology, Urmia, Iran.

s.jafarzadeh@uut.ac.ir

[4] Department of Industrial Engineering, Istinye University, Istanbul, Turkey.

erfan.babaee@istinye.edu.tr (corresponding author)

[5] Lero & ADAPT Research Centres, School of Computer Science, University of Galway, Ireland.

malika.bendechache@universityofgalway.ie

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].

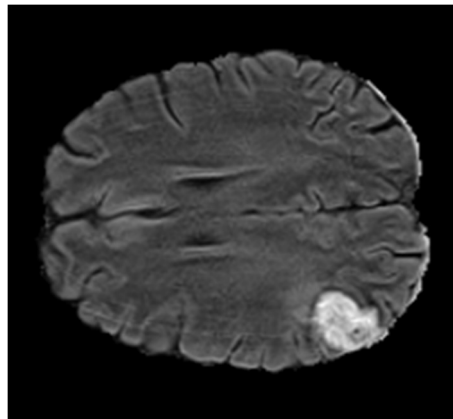| Type	Feature
T1	T1-weighted MRI Calculate the tissue's T1 (longitudinal) relaxation time. Brighter tissue has shorter relaxation times.
T2	T2-weighted MRI Calculate the tissue's T2 (transverse) relaxation time. Longer relaxation times result in brighter tissue
T1c	T1 weighted images with contrast material 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		Astrocytoma
2		Pilocytic Astrocytoma (grade I)
3		Diffuse Astrocytoma (grade II)
4		Anaplastic Astrocytoma (grade III)
5	Gliomas	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	

155

156   In glioma, grades I and II (Table 4) are categorized as Low-Grade Glioma (LGG), and grades
157   III and IV are High-Grade Glioma or HGG [40]. Taking the best procedure for treatment depends
158   on the early diagnosis of Glioma and its grade [8], [37], and MRI imaging is one of the bests
159   screening methods for diagnosing Glioma. In this screening method, the protons which are
160   randomly oriented inside the water nuclei of the tissue are brought into alignment using a strong,
161   uniform, external magnetic field. The subsequent disruption of this alignment (or magnetization)
162   is caused by the addition of an external Radio Frequency (RF) energy. Through a variety of
163   relaxation mechanisms, the nuclei return to their resting alignment and release RF energy in the
164   process. The emitted signals are evaluated after a certain amount of time has passed from the first
165   RF. The signal from each place in the imaged plane is converted using the Fourier transform into
166   the relevant intensity levels, which are then represented as shades of gray in a matrix of pixels
167   [41]. Different forms of images can be produced by altering the order in which RF pulses are
168   delivered and collected. The T1- and T2-weighted scans are very popular MRI sequences. Short
169   Time to Echo (TE) and Repetition Time (TR) is utilized to create T1-weighted images. T1
170   characteristics of tissue are primarily responsible for determining the contrast and brightness of
171   the image. On the other hand, longer TE and TR times are used to create T2-weighted images. The
172   T2 characteristics of the tissue determine the contrast and brightness in these images. The Fluid
173   Attenuated Inversion Recovery (Flair) sequence is a third frequently utilized sequence. The TE
174   and TR timings of the Flair sequence are significantly longer than those of a T2-weighted image
175   [42]. Fig. 2 indicates the MRI image T1, T2, FLAR modalities.

176
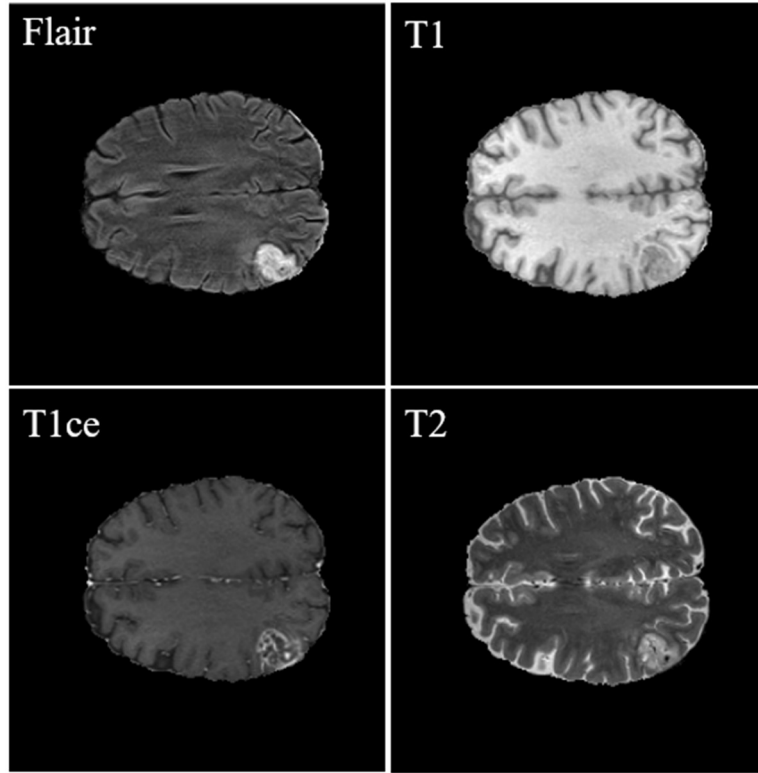
Fig. 2. Some examples of MRI images including T1, T1ce, T2, and Flair.

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

192 knowledge about the image processing problem. Fig. 3 shows the categories of supervised and
193 unsupervised approaches.
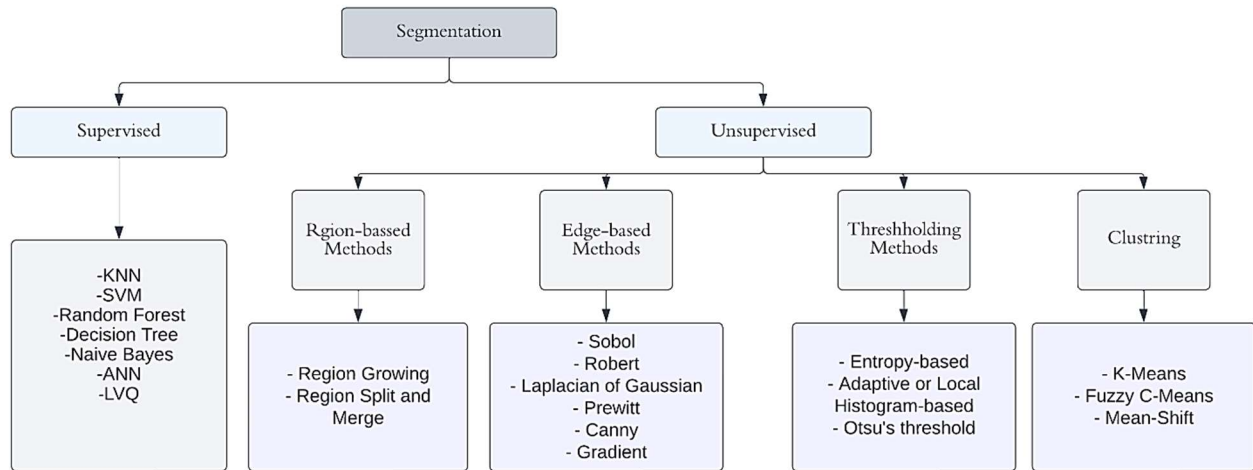
194
195 **Fig. 3.** Brain tumor segmentation approaches.

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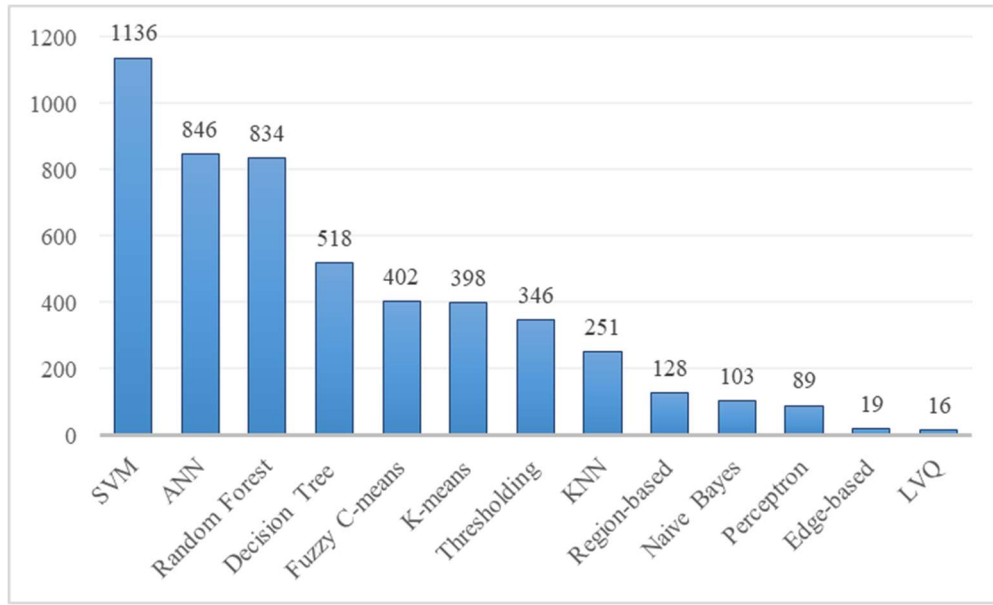
Fig. 4. Number of publications between 2015 to 2022 for brain tumor segmentation using supervised and unsupervised learning techniques.

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

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

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

550 *4.2.6 Gaussian Mixture Models*

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

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

563 **4.3 Overview of Supervised and Unsupervised Methods Application**

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

568

569 **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.
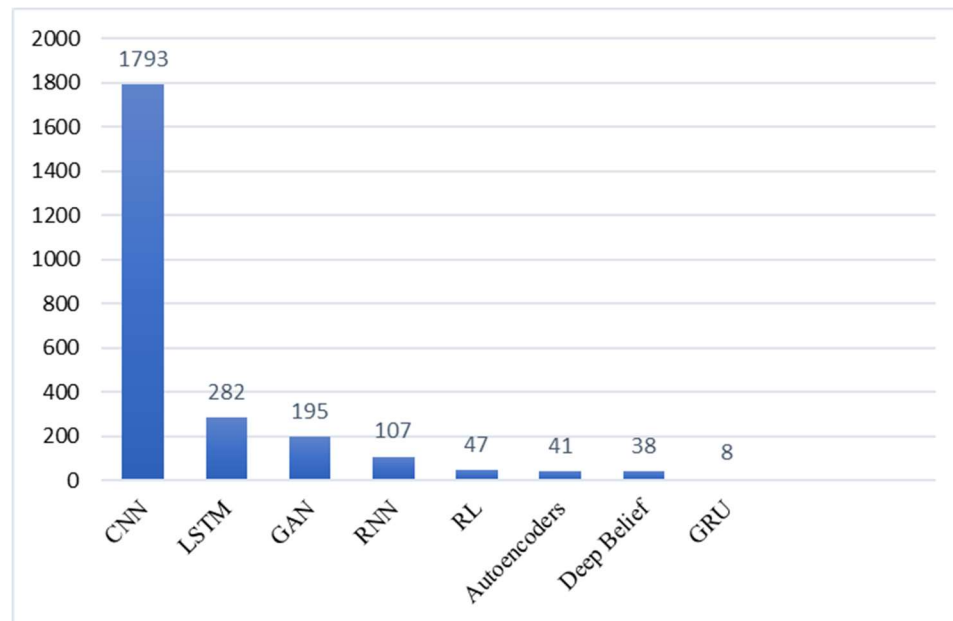
Fig. 5. Number of publications between 2015 to 2022 for brain tumor segmentation using DL models.

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.
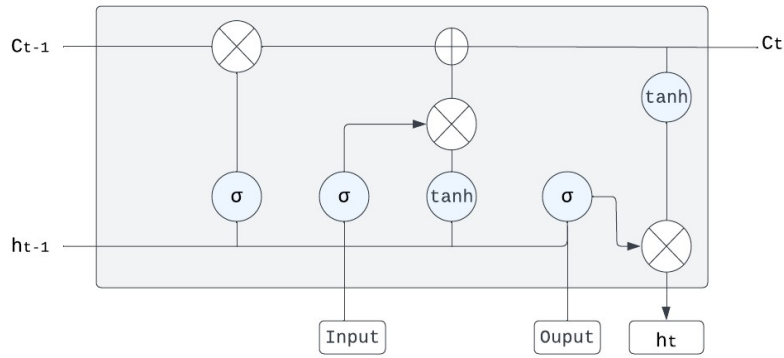

Fig. 6. An example of LSTM structure.

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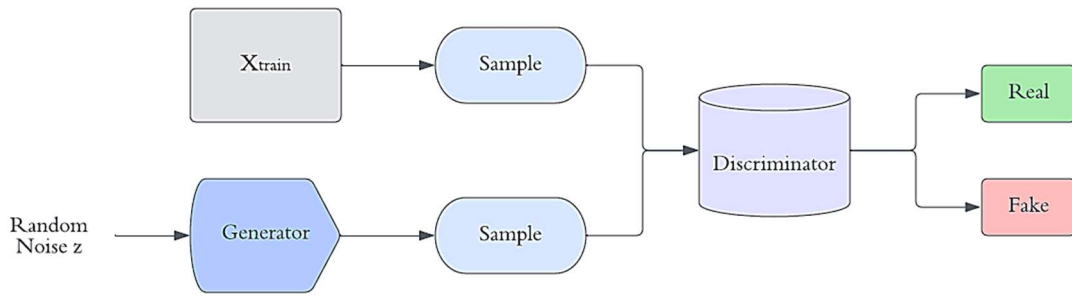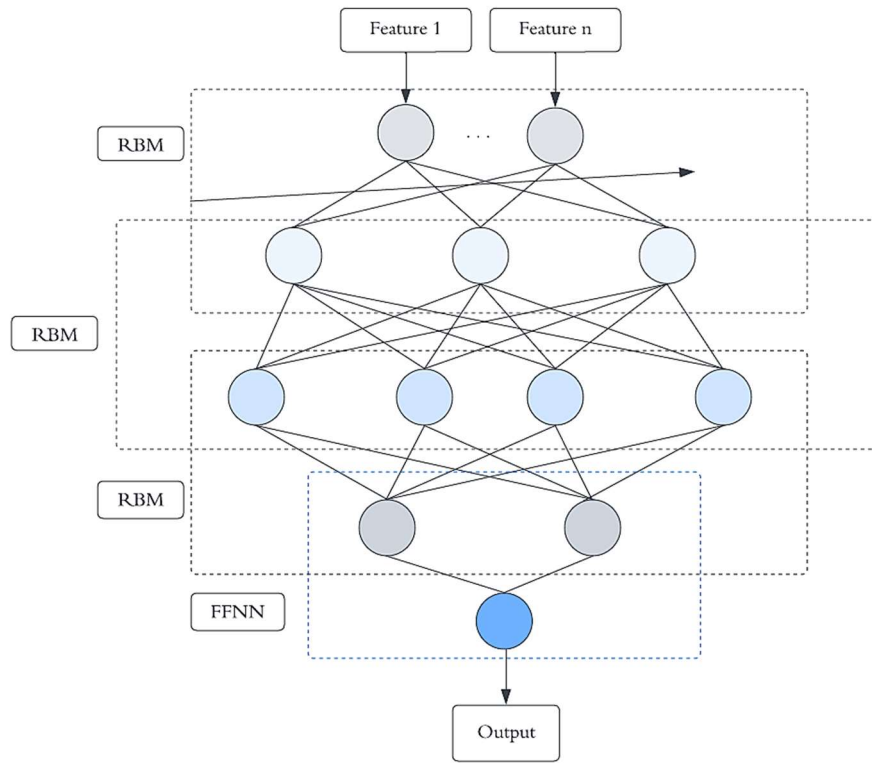
Fig. 7. An example of the GAN method structure.

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.
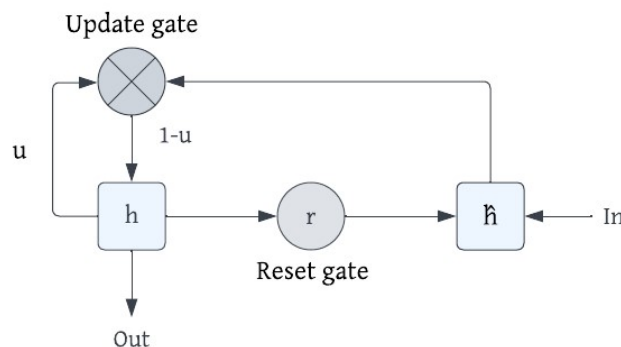
Fig. 9. An example of GRU method structure.

753

754   One of the main usages of the GRU is increasing the memory capacity of a RNN and facilitating
755 the training of a model. On top of that, we can employ the hidden unit and solve the problem of
756 vanishing gradients in RNNs. There are investigations that applied the GRU technique for brain
757 cancer diagnosis. For example, Gab Allah et al. [189] employed a combination of a VGG-16
758 network and a GRU model to increase the brain tumor segmentation in the presence of even fuzzy
759 borders. Table 7 indicates the 16 papers that used DL approaches to classify and segment brain
760 tumors.
761   Unlike LSTM, GRU models do not have a separate cell state (Ct) and only have a hidden state
762 (Ht). These models are much faster due to the simpler architecture.
763

764   **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

772

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**		

Method	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.

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

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

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

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

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

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

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.

Acknowledgement

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.

References

[1]   A. Petruzzi, C. Y. Finocchiaro, E. Lamperti, and A. Salmaggi, "Living with a brain tumor," *Supportive Care in Cancer 2012 21:4*, vol. 21, no. 4, pp. 1105–1111, Oct. 2012, doi: 10.1007/S00520-012-1632-3.

[2]   C. Kruchko, Q. T. Ostrom, H. Gittleman, and J. S. Barnholtz-Sloan, "The CBTRUS story: providing accurate population-based statistics on brain and other central nervous system tumors for everyone," *Neuro Oncol*, vol. 20, no. 3, pp. 295–298, Feb. 2018, doi: 10.1093/NEUONC/NOY006.

[3]   A. Tahir, M. Asif, M. Bin Ahmad, T. Mahmood, M. A. Khan, and M. Ali, "Brain Tumor Detection using Decision-Based Fusion Empowered with Fuzzy Logic," *Math Probl Eng*, vol. 2022, pp. 1–13, Aug. 2022, doi: 10.1155/2022/2710285.

[4]   K. D. Miller *et al.*, "Brain and other central nervous system tumor statistics, 2021," *CA Cancer J Clin*, vol. 71, no. 5, pp. 381–406, Sep. 2021, doi: 10.3322/CAAC.21693.

[5]   J. B. Iorgulescu *et al.*, "Molecular biomarker-defined brain tumors: Epidemiology, validity, and completeness in the United States," *Neuro Oncol*, Apr. 2022, doi: 10.1093/NEUONC/NOAC113.

[6]   P. A. McKinney, "Brain tumours: incidence, survival, and aetiology," *J Neurol Neurosurg Psychiatry*, vol. 75, no. suppl 2, pp. ii12–ii17, Jun. 2004, doi: 10.1136/JNNP.2004.040741.

[7]   F. Özyurt, E. Sert, and D. Avcı, "An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine," *Med Hypotheses*, vol. 134, p. 109433, Jan. 2020, doi: 10.1016/J.MEHY.2019.109433.

[8]   N. Tataei Sarshar *et al.*, "Glioma Brain Tumor Segmentation in Four MRI Modalities Using a Convolutional Neural Network and Based on a Transfer Learning Method," pp. 386–402, 2023, doi: 10.1007/978-3-031-04435-9_39.

[9]   N. A. Charles, E. C. Holland, R. Gilbertson, R. Glass, and H. Kettenmann, "The brain tumor microenvironment," *Glia*, vol. 59, no. 8, pp. 1169–1180, Aug. 2011, doi: 10.1002/GLIA.21136.

[10] B. Cacho-Díaz, D. R. García-Botello, T. Wegman-Ostrosky, G. Reyes-Soto, E. Ortiz-Sánchez, and L. A. Herrera-Montalvo, "Tumor microenvironment differences between primary tumor and brain metastases," *Journal of Translational Medicine 2020 18:1*, vol. 18, no. 1, pp. 1–12, Jan. 2020, doi: 10.1186/S12967-019-02189-8.

[11] I. Koh and P. Kim, "In Vitro Reconstruction of Brain Tumor Microenvironment," *BioChip Journal 2019 13:1*, vol. 13, no. 1, pp. 1–7, Mar. 2019, doi: 10.1007/S13206-018-3102-6.

[12] J. Kotia, A. Kotwal, and R. Bharti, "Risk Susceptibility of Brain Tumor Classification to Adversarial Attacks," *Advances in Intelligent Systems and Computing*, vol. 1061, pp. 181–187, 2020, doi: 10.1007/978-3-030-31964-9_17/COVER/.

[13] L. Desjardins *et al.*, "Predicting social withdrawal, anxiety and depression symptoms in pediatric brain tumor survivors," *https://doi.org/10.1080/07347332.2018.1535531*, vol. 37, no. 1, pp. 22–36, Jan. 2019, doi: 10.1080/07347332.2018.1535531.

[14] A. Wadhwa, A. Bhardwaj, and V. Singh Verma, "A review on brain tumor segmentation of MRI images," *Magn Reson Imaging*, vol. 61, pp. 247–259, Sep. 2019, doi: 10.1016/J.MRI.2019.05.043.

[15] W. Zhang, Y. Wu, B. Yang, S. Hu, L. Wu, and S. Dhelimd, "Overview of Multi-Modal Brain Tumor MR Image Segmentation," *Healthcare 2021, Vol. 9, Page 1051*, vol. 9, no. 8, p. 1051, Aug. 2021, doi: 10.3390/HEALTHCARE9081051.

[16] P. K. Chahal, S. Pandey, and S. Goel, "A survey on brain tumor detection techniques for MR images," *Multimedia Tools and Applications 2020 79:29*, vol. 79, no. 29, pp. 21771–21814, May 2020, doi: 10.1007/S11042-020-08898-3.

[17] W. L. Bi *et al.*, "Artificial intelligence in cancer imaging: Clinical challenges and applications," *CA Cancer J Clin*, vol. 69, no. 2, pp. 127–157, Mar. 2019, doi: 10.3322/CAAC.21552.

[18]   R. Ranjbarzadeh, A. Bagherian Kasgari, S. Jafarzadeh Ghoushchi, S. Anari, M. Naseri, and M. Bendechache, "Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images," *Sci Rep*, vol. 11, no. 1, p. 10930, Dec. 2021, doi: 10.1038/s41598-021-90428-8.

[19]   M. Afridi, A. Jain, M. Aboian, and S. Payabvash, "Brain Tumor Imaging: Applications of Artificial Intelligence," *Seminars in Ultrasound, CT and MRI*, vol. 43, no. 2, pp. 153–169, Apr. 2022, doi: 10.1053/J.SULT.2022.02.005.

[20]   R. Singh, A. Goel, and D. K. Raghuvanshi, "Computer-aided diagnostic network for brain tumor classification employing modulated Gabor filter banks," *The Visual Computer 2020 37:8*, vol. 37, no. 8, pp. 2157–2171, Sep. 2020, doi: 10.1007/S00371-020-01977-4.

[21]   A. Aghamohammadi, R. Ranjbarzadeh, F. Naiemi, M. Mogharrebi, S. Dorosti, and M. Bendechache, "TPCNN: Two-path convolutional neural network for tumor and liver segmentation in CT images using a novel encoding approach," *Expert Syst Appl*, vol. 183, p. 115406, Nov. 2021, doi: 10.1016/J.ESWA.2021.115406.

[22]   R. Ranjbarzadeh and S. Baseri Saadi, "Corrigendum to 'Automated liver and tumor segmentation based on concave and convex points using fuzzy c-means and mean shift clustering' [Measurement 150 (2020) 107086]," *Measurement*, vol. 151, p. 107230, Feb. 2020, doi: 10.1016/J.MEASUREMENT.2019.107230.

[23]   S. B. Saadi *et al.*, "Osteolysis: A Literature Review of Basic Science and Potential Computer-Based Image Processing Detection Methods," *Comput Intell Neurosci*, vol. 2021, 2021, doi: 10.1155/2021/4196241.

[24]   J. Nalepa, M. Marcinkiewicz, and M. Kawulok, "Data Augmentation for Brain-Tumor Segmentation: A Review," *Front Comput Neurosci*, vol. 13, p. 83, Dec. 2019, doi: 10.3389/FNCOM.2019.00083/BIBTEX.

[25]   N. J. Shafana and A. Senthilselvi, "Analysis of AI based Brain Tumor Detection and Diagnosis," *Proceedings of the 2021 4th International Conference on Computing and Communications Technologies, ICCCT 2021*, pp. 627–633, 2021, doi: 10.1109/ICCCT53315.2021.9711914.

[26]   S. J. Ghoushchi, R. Ranjbarzadeh, A. H. Dadkhah, Y. Pourasad, and M. Bendechache, "An Extended Approach to Predict Retinopathy in Diabetic Patients Using the Genetic Algorithm and Fuzzy C-Means," *Biomed Res Int*, vol. 2021, pp. 1–13, Jun. 2021, doi: 10.1155/2021/5597222.

[27]   A. Naseer, T. Yasir, A. Azhar, T. Shakeel, and K. Zafar, "Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI," *Int J Biomed Imaging*, vol. 2021, 2021, doi: 10.1155/2021/5513500.

[28]   S. Razzaq, M. A. Asghar, and M. J. Khan, "An Improved AI Inspired Brain Tumor Detection," *3rd International Conference on Communication Technologies, ComTech 2021*, pp. 1–6, 2021, doi: 10.1109/COMTECH52583.2021.9616648.

[29]   H. E. M. Abdalla and M. Y. Esmail, "Brain Tumor Detection by using Artificial Neural Network," *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering, ICCCEEE 2018*, Oct. 2018, doi: 10.1109/ICCCEEE.2018.8515763.

[30]   S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," *Phys Med Biol*, vol. 58, no. 13, p. R97, Jun. 2013, doi: 10.1088/0031-9155/58/13/R97.

[31]   F. Fraioli and S. Punwani, "Clinical and research applications of simultaneous positron emission tomography and MRI," *British Journal of Radiology*, vol. 87, no. 1033. British Institute of Radiology, Jan. 2014. doi: 10.1259/bjr.20130464.

[32]   A. Tiwari, S. Srivastava, and M. Pant, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019," *Pattern Recognit Lett*, vol. 131, pp. 244–260, Mar. 2020, doi: 10.1016/J.PATREC.2019.11.020.

[33]   A. Wadhwa, A. Bhardwaj, and V. Singh Verma, "A review on brain tumor segmentation of MRI images," *Magn Reson Imaging*, vol. 61, pp. 247–259, Sep. 2019, doi: 10.1016/J.MRI.2019.05.043.

[34]   S.-G. Choi, C.-B. Sohn, and P. D. Candidate, "Detection of HGG and LGG Brain Tumors using U-Net," *Medico Legal Update*, vol. 19, no. 1, pp. 560–565, Feb. 2019, doi: 10.37506/MLU.V19I1.978.

[35]   S. Lapointe, A. Perry, and N. A. Butowski, "Primary brain tumours in adults," *The Lancet*, vol. 392, no. 10145, pp. 432–446, Aug. 2018, doi: 10.1016/S0140-6736(18)30990-5.

[36]   C. J. Valvona, H. L. Fillmore, P. B. Nunn, and G. J. Pilkington, "The Regulation and Function of Lactate Dehydrogenase A: Therapeutic Potential in Brain Tumor," *Brain Pathology*, vol. 26, no. 1, pp. 3–17, Jan. 2016, doi: 10.1111/BPA.12299.

[37]   S.-G. Choi, C.-B. Sohn, and P. D. Candidate, "Detection of HGG and LGG Brain Tumors using U-Net," *Medico Legal Update*, vol. 19, no. 1, pp. 560–565, Feb. 2019, doi: 10.37506/MLU.V19I1.978.

[38]   C. I. Hill, C. S. Nixon, J. L. Ruehmeier, and L. M. Wolf, "Brain Tumors," *Phys Ther*, vol. 82, no. 5, pp. 496–502, May 2002, doi: 10.1093/PTJ/82.5.496.

[39]   S. Saman and S. Jamjala Narayanan, "Survey on brain tumor segmentation and feature extraction of MR images," *International Journal of Multimedia Information Retrieval 2018 8:2*, vol. 8, no. 2, pp. 79–99, Dec. 2018, doi: 10.1007/S13735-018-0162-2.

[40]   S. Bacchi *et al.*, "Deep learning in the detection of high-grade glioma recurrence using multiple MRI sequences: A pilot study," *Journal of Clinical Neuroscience*, vol. 70, pp. 11–13, Dec. 2019, doi: 10.1016/J.JOCN.2019.10.003.

[41]   D. A. Hormuth *et al.*, "Translating preclinical MRI methods to clinical oncology," *Journal of Magnetic Resonance Imaging*, vol. 50, no. 5, pp. 1377–1392, Nov. 2019, doi: 10.1002/JMRI.26731.

[42]   J. Amin, M. Sharif, N. Gul, M. Yasmin, and S. A. Shad, "Brain tumor classification based on DWT fusion of MRI sequences using convolutional neural network," *Pattern Recognit Lett*, vol. 129, pp. 115–122, Jan. 2020, doi: 10.1016/J.PATREC.2019.11.016.

[43]   S. Saman and S. Jamjala Narayanan, "Survey on brain tumor segmentation and feature extraction of MR images," *International Journal of Multimedia Information Retrieval 2018 8:2*, vol. 8, no. 2, pp. 79–99, Dec. 2018, doi: 10.1007/S13735-018-0162-2.

[44]   R. Schettini, "A segmentation algorithm for color images," *Pattern Recognit Lett*, vol. 14, no. 6, pp. 499–506, Jun. 1993, doi: 10.1016/0167-8655(93)90030-H.

[45]   T. Kumar, J. Park, M. S. Ali, A. F. M. Shahab Uddin, J. H. Ko, and S.-H. Bae, "Binary-Classifiers-Enabled Filters for Semi-Supervised Learning," *IEEE Access*, pp. 1–1, 2021, doi: 10.1109/ACCESS.2021.3124200.

[46]   M. Turab, T. Kumar, M. Bendechache, and T. Saber, "Investigating Multi-Feature Selection and Ensembling for Audio Classification," Jun. 2022, doi: 10.48550/arxiv.2206.07511.

[47]   S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," *Phys Med Biol*, vol. 58, no. 13, p. R97, Jun. 2013, doi: 10.1088/0031-9155/58/13/R97.

[48]   A. Baghban, M. Kahani, M. A. Nazari, M. H. Ahmadi, and W. M. Yan, "Sensitivity analysis and application of machine learning methods to predict the heat transfer performance of CNT/water nanofluid flows through coils," *Int J Heat Mass Transf*, vol. 128, pp. 825–835, Jan. 2019, doi: 10.1016/J.IJHEATMASSTRANSFER.2018.09.041.

[49]   Z. Liu and A. Baghban, "Application of LSSVM for biodiesel production using supercritical ethanol solvent," *http://dx.doi.org/10.1080/15567036.2017.1380732*, vol. 39, no. 17, pp. 1869–1874, Oct. 2017, doi: 10.1080/15567036.2017.1380732.

[50]   S. Baseri Saadi, N. Tataei Sarshar, S. Sadeghi, R. Ranjbarzadeh, M. Kooshki Forooshani, and M. Bendechache, "Investigation of Effectiveness of Shuffled Frog-Leaping Optimizer in Training a Convolution Neural Network," *J Healthc Eng*, vol. 2022, pp. 1–11, Mar. 2022, doi: 10.1155/2022/4703682.

[51]   R. Ranjbarzadeh *et al.*, "MRFE-CNN: multi-route feature extraction model for breast tumor segmentation in Mammograms using a convolutional neural network," *Annals of Operations Research 2022*, pp. 1–22, May 2022, doi: 10.1007/S10479-022-04755-8.

[52]   J. Dougherty, R. Kohavi, and M. Sahami, "Supervised and Unsupervised Discretization of Continuous Features," *Machine Learning Proceedings 1995*, pp. 194–202, Jan. 1995, doi: 10.1016/B978-1-55860-377-6.50032-3.

[53]   A. Qi *et al.*, "Directional mutation and crossover boosted ant colony optimization with application to COVID-19 X-ray image segmentation," *Comput Biol Med*, vol. 148, p. 105810, Sep. 2022, doi: 10.1016/J.COMPBIOMED.2022.105810.

[54]   N. H. Rajini and R. Bhavani, "Classification of MRI brain images using k-nearest neighbor and artificial neural network," *International Conference on Recent Trends in Information Technology, ICRTIT 2011*, pp. 563–568, 2011, doi: 10.1109/ICRTIT.2011.5972341.

[55]   S. Sun and R. Huang, "An adaptive k-nearest neighbor algorithm," *Proceedings - 2010 7th International Conference on Fuzzy Systems and Knowledge Discovery, FSKD 2010*, vol. 1, pp. 91–94, 2010, doi: 10.1109/FSKD.2010.5569740.

[56]   M. Havaei, H. Larochelle, P. Poulin, and P. M. Jodoin, "Within-brain classification for brain tumor segmentation," *International Journal of Computer Assisted Radiology and Surgery 2015 11:5*, vol. 11, no. 5, pp. 777–788, Nov. 2015, doi: 10.1007/S11548-015-1311-1.

[57]   G. Cinarer and B. G. Emiroglu, "Classificatin of Brain Tumors by Machine Learning Algorithms," *3rd International Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT 2019 - Proceedings*, Oct. 2019, doi: 10.1109/ISMSIT.2019.8932878.

[58] D. M. Kumar, D. Satyanarayana, and M. N. G. Prasad, "MRI brain tumor detection using optimal possibilistic fuzzy C-means clustering algorithm and adaptive k-nearest neighbor classifier," *Journal of Ambient Intelligence and Humanized Computing 2020 12:2*, vol. 12, no. 2, pp. 2867–2880, Sep. 2020, doi: 10.1007/S12652-020-02444-7.

[59] A. S. Remya Ajai and S. Gopalan, "Analysis of active contours without edge-based segmentation technique for brain tumor classification using svm and knn classifiers," *Lecture Notes in Electrical Engineering*, vol. 656, pp. 1–10, 2020, doi: 10.1007/978-981-15-3992-3_1/COVER/.

[60] R. H. Ramdlon, E. Martiana Kusumaningtyas, and T. Karlita, "Brain Tumor Classification Using MRI Images with K-Nearest Neighbor Method," *IES 2019 - International Electronics Symposium: The Role of Techno-Intelligence in Creating an Open Energy System Towards Energy Democracy, Proceedings*, pp. 660–667, Sep. 2019, doi: 10.1109/ELECSYM.2019.8901560.

[61] V. V. P. Wibowo, Z. Rustam, and J. Pandelaki, "Classification of Brain Tumor Using K-Nearest Neighbor-Genetic Algorithm and Support Vector Machine-Genetic Algorithm Methods," *2021 International Conference on Decision Aid Sciences and Application, DASA 2021*, pp. 1077–1081, 2021, doi: 10.1109/DASA53625.2021.9682341.

[62] A. Shmilovici, "Support Vector Machines," *Data Mining and Knowledge Discovery Handbook*, pp. 231–247, 2009, doi: 10.1007/978-0-387-09823-4_12.

[63] H. B. Nandpuru, S. S. Salankar, and V. R. Bora, "MRI brain cancer classification using support vector machine," *2014 IEEE Students' Conference on Electrical, Electronics and Computer Science, SCEECS 2014*, 2014, doi: 10.1109/SCEECS.2014.6804439.

[64] J. Amin, M. Sharif, M. Yasmin, and S. L. Fernandes, "A distinctive approach in brain tumor detection and classification using MRI," *Pattern Recognit Lett*, vol. 139, pp. 118–127, Nov. 2020, doi: 10.1016/J.PATREC.2017.10.036.

[65] M. Padlia and J. Sharma, "Fractional sobel filter based brain tumor detection and segmentation using statistical features and SVM," *Lecture Notes in Electrical Engineering*, vol. 511, pp. 161–175, 2019, doi: 10.1007/978-981-13-0776-8_15/COVER/.

[66] M. O. Khairandish, M. Sharma, V. Jain, J. M. Chatterjee, and N. Z. Jhanjhi, "A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images," *IRBM*, Jun. 2021, doi: 10.1016/J.IRBM.2021.06.003.

[67] C. S. Rao and K. Karunakara, "Efficient Detection and Classification of Brain Tumor using Kernel based SVM for MRI," *Multimedia Tools and Applications 2022 81:5*, vol. 81, no. 5, pp. 7393–7417, Jan. 2022, doi: 10.1007/S11042-021-11821-Z.

[68] M. H. O. Rashid, M. A. Mamun, M. A. Hossain, and M. P. Uddin, "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images," *International Conference on Computer, Communication, Chemical, Material and Electronic Engineering, IC4ME2 2018*, Sep. 2018, doi: 10.1109/IC4ME2.2018.8465613.

[69] S. Deepak and P. M. Ameer, "Automated Categorization of Brain Tumor from MRI Using CNN features and SVM," *Journal of Ambient Intelligence and Humanized Computing 2020 12:8*, vol. 12, no. 8, pp. 8357–8369, Oct. 2020, doi: 10.1007/S12652-020-02568-W.

[70]   Y. Qi, "Random Forest for Bioinformatics," *Ensemble Machine Learning*, pp. 307–323, 2012, doi: 10.1007/978-1-4419-9326-7_11.

[71]   T. M. Oshiro, P. S. Perez, and J. A. Baranauskas, "How many trees in a random forest?," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7376 LNAI, pp. 154–168, 2012, doi: 10.1007/978-3-642-31537-4_13/COVER.

[72]   L. Lefkovits, S. Lefkovits, and L. Szilágyi, "Brain Tumor Segmentation with Optimized Random Forest," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10154 LNCS, pp. 88–99, Oct. 2016, doi: 10.1007/978-3-319-55524-9_9.

[73]   A. Ellwaa *et al.*, "Brain tumor segmantation using random forest trained on iteratively selected patients," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10154 LNCS, pp. 129–137, 2016, doi: 10.1007/978-3-319-55524-9_13/COVER/.

[74]   R. Anitha and D. Siva Sundhara Raja, "Development of computer-aided approach for brain tumor detection using random forest classifier," *Int J Imaging Syst Technol*, vol. 28, no. 1, pp. 48–53, Mar. 2018, doi: 10.1002/IMA.22255.

[75]   T. Yang, J. Song, and L. Li, "A deep learning model integrating SK-TPCNN and random forests for brain tumor segmentation in MRI," *Biocybern Biomed Eng*, vol. 39, no. 3, pp. 613–623, Jul. 2019, doi: 10.1016/J.BBE.2019.06.003.

[76]   R. Rajagopal, "Glioma brain tumor detection and segmentation using weighting random forest classifier with optimized ant colony features," *Int J Imaging Syst Technol*, vol. 29, no. 3, pp. 353–359, Sep. 2019, doi: 10.1002/IMA.22331.

[77]   A. J. Myles, R. N. Feudale, Y. Liu, N. A. Woody, and S. D. Brown, "An introduction to decision tree modeling," *J Chemom*, vol. 18, no. 6, pp. 275–285, Jun. 2004, doi: 10.1002/CEM.873.

[78]   W. Wang, A. Tu, and F. Bergholm, "Improved Minimum Spanning Tree based Image Segmentation with Guided Matting," *KSII Transactions on Internet and Information Systems (TIIS)*, vol. 16, no. 1, pp. 211–230, Jan. 2022, doi: 10.3837/TIIS.2022.01.012.

[79]   Y. Y. Song and Y. Lu, "Decision tree methods: applications for classification and prediction," *Shanghai Arch Psychiatry*, vol. 27, no. 2, p. 130, Apr. 2015, doi: 10.11919/J.ISSN.1002-0829.215044.

[80]   "Tumor Detection and Classification using Decision Tree in Brain MRI | Semantic Scholar."

[81]   A. Chaddad, P. O. Zinn, and R. R. Colen, "Brain tumor identification using Gaussian Mixture Model features and Decision Trees classifier," *2014 48th Annual Conference on Information Sciences and Systems, CISS 2014*, 2014, doi: 10.1109/CISS.2014.6814077.

[82]   L. Hussain, S. Saeed, I. A. Awan, A. Idris, M. S. A. Nadeem, and Q.-A. Chaudhry, "Detecting Brain Tumor using Machines Learning Techniques Based on Different Features Extracting Strategies," *Current Medical Imaging Formerly Current Medical Imaging Reviews*, vol. 15, no. 6, pp. 595–606, Jul. 2019, doi: 10.2174/1573405614666180718123533.

[83]   M. Thayumanavan and A. Ramasamy, "An efficient approach for brain tumor detection and segmentation in MR brain images using random forest classifier:," *https://doi.org/10.1177/1063293X211010542*, vol. 29, no. 3, pp. 266–274, Apr. 2021, doi: 10.1177/1063293X211010542.

[84]   P. Rajendran and M. Madheswaran, "Hybrid Medical Image Classification Using Association Rule Mining with Decision Tree Algorithm," vol. 2, Jan. 2010, doi: 10.48550/arxiv.1001.3503.

[85]   Z. Zhang, "Artificial Neural Network," *Multivariate Time Series Analysis in Climate and Environmental Research*, pp. 1–35, 2018, doi: 10.1007/978-3-319-67340-0_1.

[86]   S. Tang and F. Yu, "Construction and verification of retinal vessel segmentation algorithm for color fundus image under BP neural network model," *Journal of Supercomputing*, vol. 77, no. 4, pp. 3870–3884, Apr. 2021, doi: 10.1007/S11227-020-03422-8/FIGURES/4.

[87]   B. He *et al.*, "Image segmentation algorithm of lung cancer based on neural network model," *Expert Syst*, vol. 39, no. 3, p. e12822, Mar. 2022, doi: 10.1111/EXSY.12822.

[88]   M. Mishra and M. Srivastava, "A view of Artificial Neural Network," *2014 International Conference on Advances in Engineering and Technology Research, ICAETR 2014*, 2014, doi: 10.1109/ICAETR.2014.7012785.

[89]   T. Chithambaram and K. Perumal, "Brain tumor segmentation using genetic algorithm and ANN techniques," *IEEE International Conference on Power, Control, Signals and Instrumentation Engineering, ICPCSI 2017*, pp. 970–982, Jun. 2018, doi: 10.1109/ICPCSI.2017.8391855.

[90]   Virupakshappa and B. Amarapur, "Computer-aided diagnosis applied to MRI images of brain tumor using cognition based modified level set and optimized ANN classifier," *Multimedia Tools and Applications 2018 79:5*, vol. 79, no. 5, pp. 3571–3599, Jun. 2018, doi: 10.1007/S11042-018-6176-1.

[91]   Virupakshappa and B. Amarapur, "An Automated Approach for Brain Tumor Identification using ANN Classifier," *International Conference on Current Trends in Computer, Electrical, Electronics and Communication, CTCEEC 2017*, pp. 1011–1016, Sep. 2018, doi: 10.1109/CTCEEC.2017.8455154.

[92]   G. I. Webb, "Naïve Bayes," *Encyclopedia of Machine Learning and Data Mining*, pp. 1–2, 2016, doi: 10.1007/978-1-4899-7502-7_581-1.

[93]   W. Li, G. G. Wang, and A. H. Gandomi, "A Survey of Learning-Based Intelligent Optimization Algorithms," *Archives of Computational Methods in Engineering 2021 28:5*, vol. 28, no. 5, pp. 3781–3799, Feb. 2021, doi: 10.1007/S11831-021-09562-1.

[94]   L. Jiang, H. Zhang, and Z. Cai, "A novel bayes model: Hidden naive bayes," *IEEE Trans Knowl Data Eng*, vol. 21, no. 10, pp. 1361–1371, Oct. 2009, doi: 10.1109/TKDE.2008.234.

[95]   G. Kaur and A. Oberoi, "Novel Approach for Brain Tumor Detection Based on Naïve Bayes Classification," *Advances in Intelligent Systems and Computing*, vol. 1042, pp. 451–462, 2020, doi: 10.1007/978-981-32-9949-8_31/COVER/.

[96] A. R. Raju, P. Suresh, and R. R. Rao, "Bayesian HCS-based multi-SVNN: A classification approach for brain tumor segmentation and classification using Bayesian fuzzy clustering," *Biocybern Biomed Eng*, vol. 38, no. 3, pp. 646–660, Jan. 2018, doi: 10.1016/J.BBE.2018.05.001.

[97] E. E. Ulku and A. Y. Camurcu, "Computer aided brain tumor detection with histogram equalization and morphological image processing techniques," *2013 International Conference on Electronics, Computer and Computation, ICECCO 2013*, pp. 48–51, 2013, doi: 10.1109/ICECCO.2013.6718225.

[98] T. Kohonen, "Learning Vector Quantization," pp. 245–261, 2001, doi: 10.1007/978-3-642-56927-2_6.

[99] D. Nova and P. A. Estévez, "A review of learning vector quantization classifiers," *Neural Computing and Applications 2013 25:3*, vol. 25, no. 3, pp. 511–524, Dec. 2013, doi: 10.1007/S00521-013-1535-3.

[100] T. Liu, C. Chen, X. Shi, and C. Liu, "Evaluation of Raman spectra of human brain tumor tissue using the learning vector quantization neural network," *Laser Phys*, vol. 26, no. 5, p. 055606, Apr. 2016, doi: 10.1088/1054-660X/26/5/055606.

[101] R. Sonavane, P. Sonar, and S. Sutar, "Classification of MRI brain tumor and mammogram images using learning vector quantization neural network," *Proceedings of 2017 3rd IEEE International Conference on Sensing, Signal Processing and Security, ICSSS 2017*, pp. 301–307, Oct. 2017, doi: 10.1109/SSPS.2017.8071610.

[102] R. S. Sonavane and A. S. Sonavane, "Classification of MRI brain tumor and mammogram images using adaboost and learning vector quantization neural network," *2020 International Conference on Convergence to Digital World - Quo Vadis, ICCDW 2020*, Feb. 2020, doi: 10.1109/ICCDW45521.2020.9318645.

[103] T. Hastie, R. Tibshirani, and J. Friedman, "Unsupervised Learning," Springer, New York, NY, 2009, pp. 485–585. doi: 10.1007/978-0-387-84858-7_14.

[104] H. Su *et al.*, "Multilevel threshold image segmentation for COVID-19 chest radiography: A framework using horizontal and vertical multiverse optimization," *Comput Biol Med*, vol. 146, p. 105618, Jul. 2022, doi: 10.1016/J.COMPBIOMED.2022.105618.

[105] S. Anari, N. Tataei Sarshar, N. Mahjoori, S. Dorosti, and A. Rezaie, "Review of Deep Learning Approaches for Thyroid Cancer Diagnosis," *Math Probl Eng*, vol. 2022, pp. 1–8, Aug. 2022, doi: 10.1155/2022/5052435.

[106] D. Gao, G. G. Wang, and W. Pedrycz, "Solving Fuzzy Job-Shop Scheduling Problem Using de Algorithm Improved by a Selection Mechanism," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 12, pp. 3265–3275, Dec. 2020, doi: 10.1109/TFUZZ.2020.3003506.

[107] G. G. Wang, D. Gao, and W. Pedrycz, "Solving Multi-Objective Fuzzy Job-shop Scheduling Problem by a Hybrid Adaptive Differential Evolution Algorithm," *IEEE Trans Industr Inform*, Dec. 2022, doi: 10.1109/TII.2022.3165636.

[108] M. A. T. Figueiredo and A. K. Jain, "Unsupervised learning of finite mixture models," *IEEE Trans Pattern Anal Mach Intell*, vol. 24, no. 3, pp. 381–396, Mar. 2002, doi: 10.1109/34.990138.

[109] K. Krishna and M. N. Murty, "Genetic K-means algorithm," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 29, no. 3, pp. 433–439, 1999, doi: 10.1109/3477.764879.

[110] A. Likas, N. Vlassis, and J. J. Verbeek, "The global k-means clustering algorithm," *Pattern Recognit*, vol. 36, no. 2, pp. 451–461, Feb. 2003, doi: 10.1016/S0031-3203(02)00060-2.

[111] R. Khilkhal and M. Ismael, "Brain Tumor Segmentation Utilizing Thresholding and K-Means Clustering," pp. 43–48, Jun. 2022, doi: 10.1109/MICEST54286.2022.9790103.

[112] M. K. Islam, M. S. Ali, M. S. Miah, M. M. Rahman, M. S. Alam, and M. A. Hossain, "Brain tumor detection in MR image using superpixels, principal component analysis and template based K-means clustering algorithm," *Machine Learning with Applications*, vol. 5, p. 100044, Sep. 2021, doi: 10.1016/J.MLWA.2021.100044.

[113] D. M. Kumar, D. Satyanarayana, and M. N. G. Prasad, "An improved Gabor wavelet transform and rough K-means clustering algorithm for MRI brain tumor image segmentation," *Multimedia Tools and Applications 2020 80:5*, vol. 80, no. 5, pp. 6939–6957, Oct. 2020, doi: 10.1007/S11042-020-09635-6.

[114] T. C. Havens, J. C. Bezdek, C. Leckie, L. O. Hall, and M. Palaniswami, "Fuzzy c-Means algorithms for very large data," *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 6, pp. 1130–1146, 2012, doi: 10.1109/TFUZZ.2012.2201485.

[115] S. Askari, "Fuzzy C-Means clustering algorithm for data with unequal cluster sizes and contaminated with noise and outliers: Review and development," *Expert Syst Appl*, vol. 165, p. 113856, Mar. 2021, doi: 10.1016/J.ESWA.2020.113856.

[116] H. Izakian and A. Abraham, "Fuzzy C-means and fuzzy swarm for fuzzy clustering problem," *Expert Syst Appl*, vol. 38, no. 3, pp. 1835–1838, Mar. 2011, doi: 10.1016/J.ESWA.2010.07.112.

[117] R. Sindhiya Devi, B. Perumal, and M. Pallikonda Rajasekaran, "A hybrid deep learning based brain tumor classification and segmentation by stationary wavelet packet transform and adaptive kernel fuzzy c means clustering," *Advances in Engineering Software*, vol. 170, p. 103146, Aug. 2022, doi: 10.1016/J.ADVENGSOFT.2022.103146.

[118] S. Debnath, F. A. Talukdar, and M. Islam, "Combination of contrast enhanced fuzzy c-means (CEFCM) clustering and pixel based voxel mapping technique (PBVMT) for three dimensional brain tumour detection," *Journal of Ambient Intelligence and Humanized Computing 2020 12:2*, vol. 12, no. 2, pp. 2421–2433, Aug. 2020, doi: 10.1007/S12652-020-02366-4.

[119] C. J. J. Sheela and G. Suganthi, "Accurate MRI brain tumor segmentation based on rotating triangular section with fuzzy C- means optimization," *Sādhanā 2021 46:4*, vol. 46, no. 4, pp. 1–20, Oct. 2021, doi: 10.1007/S12046-021-01744-8.

[120] M. Soleymanifard and M. Hamghalam, "Multi-stage glioma segmentation for tumour grade classification based on multiscale fuzzy C-means," *Multimedia Tools and Applications 2022 81:6*, vol. 81, no. 6, pp. 8451–8470, Feb. 2022, doi: 10.1007/S11042-022-12326-Z.

[121] X. T. Yuan, B. G. Hu, and R. He, "Agglomerative mean-shift clustering," *IEEE Trans Knowl Data Eng*, vol. 24, no. 2, pp. 209–219, 2012, doi: 10.1109/TKDE.2010.232.

[122] R. Ranjbarzadeh and S. B. Saadi, "Automated liver and tumor segmentation based on concave and convex points using fuzzy c-means and mean shift clustering," *Measurement*, vol. 150, p. 107086, Jan. 2020, doi: 10.1016/J.MEASUREMENT.2019.107086.

[123] K. L. Wu and M. S. Yang, "Mean shift-based clustering," *Pattern Recognit*, vol. 40, no. 11, pp. 3035–3052, Nov. 2007, doi: 10.1016/J.PATCOG.2007.02.006.

[124] R. B. Vallabhaneni and V. Rajesh, "Brain tumour detection using mean shift clustering and GLCM features with edge adaptive total variation denoising technique," *Alexandria Engineering Journal*, vol. 57, no. 4, pp. 2387–2392, Dec. 2018, doi: 10.1016/J.AEJ.2017.09.011.

[125] B. Singh and P. Aggarwal, "Detection of brain tumor using modified mean-shift based fuzzy c-mean segmentation from MRI Images," *2017 8th IEEE Annual Information Technology, Electronics and Mobile Communication Conference, IEMCON 2017*, pp. 536–545, Nov. 2017, doi: 10.1109/IEMCON.2017.8117123.

[126] J. H. Kim, S. Lee, G. S. Lee, Y. S. Park, and Y. P. Hong, "Using a Method Based on a Modified K-Means Clustering and Mean Shift Segmentation to Reduce File Sizes and Detect Brain Tumors from Magnetic Resonance (MRI) Images," *Wireless Personal Communications 2016 89:3*, vol. 89, no. 3, pp. 993–1008, Jun. 2016, doi: 10.1007/S11277-016-3420-8.

[127] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: an overview," *Wiley Interdiscip Rev Data Min Knowl Discov*, vol. 2, no. 1, pp. 86–97, Jan. 2012, doi: 10.1002/WIDM.53.

[128] F. Nielsen, "Hierarchical Clustering," pp. 195–211, 2016, doi: 10.1007/978-3-319-21903-5_8.

[129] T. Hiratsuka *et al.*, "Hierarchical Cluster and Region of Interest Analyses Based on Mass Spectrometry Imaging of Human Brain Tumours," *Scientific Reports 2020 10:1*, vol. 10, no. 1, pp. 1–11, Apr. 2020, doi: 10.1038/s41598-020-62176-8.

[130] G. Tamilmani and S. Sivakumari, "Early detection of brain cancer using association allotment hierarchical clustering," *Int J Imaging Syst Technol*, vol. 29, no. 4, pp. 617–632, Dec. 2019, doi: 10.1002/IMA.22346.

[131] K. Khan, S. U. Rehman, K. Aziz, S. Fong, S. Sarasvady, and A. Vishwa, "DBSCAN: Past, present and future," *5th International Conference on the Applications of Digital Information and Web Technologies, ICADIWT 2014*, pp. 232–238, 2014, doi: 10.1109/ICADIWT.2014.6814687.

[132] E. Schubert, J. Sander, M. Ester, H. P. Kriegel, and X. Xu, "DBSCAN Revisited, Revisited," *ACM Transactions on Database Systems (TODS)*, vol. 42, no. 3, Jul. 2017, doi: 10.1145/3068335.

[133] "ANALYSIS OF BRAIN TUMOR CLASSIFICATION BY USING MULTIPLE CLUSTERING ALGORITHMS | Semantic Scholar."

[134] "[PDF] Segmentation of Brain Tumour from MRI image – Analysis of K-means and DBSCAN Clustering | Semantic Scholar."

[135] M. A. T. Figueiredo and A. K. Jain, "Unsupervised learning of finite mixture models," *IEEE Trans Pattern Anal Mach Intell*, vol. 24, no. 3, pp. 381–396, Mar. 2002, doi: 10.1109/34.990138.

[136] A. Chaddad, "Automated feature extraction in brain tumor by magnetic resonance imaging using Gaussian mixture models," *Journal of Biomedical Imaging*, vol. 2015, Jan. 2015, doi: 10.1155/2015/868031.

[137] A. A. Pravitasari *et al.*, "MRI-based brain tumor segmentation using Gaussian mixture model with reversible jump Markov chain Monte Carlo algorithm," *AIP Conf Proc*, vol. 2194, no. 1, p. 020085, Dec. 2019, doi: 10.1063/1.5139817.

[138] S. Bonte, I. Goethals, and R. Van Holen, "Machine learning based brain tumour segmentation on limited data using local texture and abnormality," *Comput Biol Med*, vol. 98, pp. 39–47, Jul. 2018, doi: 10.1016/J.COMPBIOMED.2018.05.005.

[139] N. B. Bahadure, A. K. Ray, and H. P. Thethi, "Comparative Approach of MRI-Based Brain Tumor Segmentation and Classification Using Genetic Algorithm," *Journal of Digital Imaging 2018 31:4*, vol. 31, no. 4, pp. 477–489, Jan. 2018, doi: 10.1007/S10278-018-0050-6.

[140] A. Srinivasa Reddy and P. Chenna Reddy, "MRI brain tumor segmentation and prediction using modified region growing and adaptive SVM," *Soft Computing 2021 25:5*, vol. 25, no. 5, pp. 4135–4148, Jan. 2021, doi: 10.1007/S00500-020-05493-4.

[141] X. Xie, "A K-Nearest Neighbor Technique for Brain Tumor Segmentation Using Minkowski Distance," *J Med Imaging Health Inform*, vol. 8, no. 2, pp. 180–185, Jan. 2018, doi: 10.1166/JMIHI.2018.2285.

[142] P. M. Siva Raja and A. V. rani, "Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach," *Biocybern Biomed Eng*, vol. 40, no. 1, pp. 440–453, Jan. 2020, doi: 10.1016/J.BBE.2020.01.006.

[143] U. Ilhan and A. Ilhan, "Brain tumor segmentation based on a new threshold approach," *Procedia Comput Sci*, vol. 120, pp. 580–587, Jan. 2017, doi: 10.1016/J.PROCS.2017.11.282.

[144] A. Aslam, E. Khan, and M. M. S. Beg, "Improved Edge Detection Algorithm for Brain Tumor Segmentation," *Procedia Comput Sci*, vol. 58, pp. 430–437, Jan. 2015, doi: 10.1016/J.PROCS.2015.08.057.

[145] A. Kermi, K. Andjouh, and F. Zidane, "Fully automated brain tumour segmentation system in 3D-MRI using symmetry analysis of brain and level sets," *IET Image Process*, vol. 12, no. 11, pp. 1964–1971, Nov. 2018, doi: 10.1049/IET-IPR.2017.1124.

[146] C. J. J. Sheela and G. Suganthi, "Morphological edge detection and brain tumor segmentation in Magnetic Resonance (MR) images based on region growing and performance evaluation of modified Fuzzy C-Means (FCM) algorithm," *Multimedia Tools and Applications 2020 79:25*, vol. 79, no. 25, pp. 17483–17496, Feb. 2020, doi: 10.1007/S11042-020-08636-9.

[147] A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, and Z. Mehmood, "Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification," *Microsc Res Tech*, vol. 84, no. 7, pp. 1389–1399, Jul. 2021, doi: 10.1002/JEMT.23694.

[148] F. ŞİŞİK and E. SERT, "Brain tumor segmentation approach based on the extreme learning machine and significantly fast and robust fuzzy C-means clustering algorithms running on Raspberry Pi hardware," *Med Hypotheses*, vol. 136, p. 109507, Mar. 2020, doi: 10.1016/J.MEHY.2019.109507.

[149] A. Khosravanian, M. Rahmanimanesh, P. Keshavarzi, and S. Mozaffari, "Fast Level set Method for Glioma Brain Tumor Segmentation based on Superpixel Fuzzy Clustering and Lattice Boltzmann Method," *Comput Methods Programs Biomed*, vol. 198, p. 105809, Oct. 2020, doi: 10.1016/j.cmpb.2020.105809.

[150] K. Suzuki, "Overview of deep learning in medical imaging," *Radiological Physics and Technology 2017 10:3*, vol. 10, no. 3, pp. 257–273, Jul. 2017, doi: 10.1007/S12194-017-0406-5.

[151] M. T. S. T. R. B. and M. B. Teerath Kumar *et al.*, "Forged Character Detection Datasets: Passports, Driving Licences and Visa Stickers," *InternationalJournal of ArtificialIntelligence Applications(IJAIA), Vol.13,No.2*, vol. 13, no. 2, p. 21, Mar. 2022, doi: 10.5121/IJAIA.2022.13202.

[152] A. Aiman, Y. Shen, M. Bendechache, I. Inayat, and T. Kumar, "AUDD: Audio Urdu Digits Dataset for Automatic Audio Urdu Digit Recognition," *Applied Sciences 2021, Vol. 11, Page 8842*, vol. 11, no. 19, p. 8842, Sep. 2021, doi: 10.3390/APP11198842.

[153] 박진배*, T. Kumar, 경희대학교배성호, J. Park, and S.-H. Bae, "Search of an Optimal Sound Augmentation Policy for Environmental Sound Classification with Deep Neural Networks," *Proceedings of the Korean Society of Broadcast Engineers Conference*, pp. 18–21, 2020.

[154] S. Aleem, T. Kumar, S. Little, M. Bendechache, R. Brennan, and K. McGuinness, "Random Data Augmentation based Enhancement: AGeneralized Enhancement Approach for Medical Datasets." Dec. 17, 2021.

[155] M. I. Razzak, S. Naz, and A. Zaib, "Deep Learning for Medical Image Processing: Overview, Challenges and the Future BT - Classification in BioApps: Automation of Decision Making," *Springer*, vol. 26, pp. 323–350, 2018.

[156] R. Ranjbarzadeh *et al.*, "Nerve optic segmentation in CT images using a deep learning model and a texture descriptor," *Complex & Intelligent Systems 2022*, pp. 1–15, Feb. 2022, doi: 10.1007/S40747-022-00694-W.

[157] S. Wang *et al.*, "Multi-Scale Context-Guided Deep Network for Automated Lesion Segmentation with Endoscopy Images of Gastrointestinal Tract," *IEEE J Biomed Health Inform*, vol. 25, no. 2, pp. 514–525, Feb. 2021, doi: 10.1109/JBHI.2020.2997760.

[158] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *Proceedings of 2017 International Conference on Engineering and Technology, ICET 2017*, Mar. 2018, vol. 2018-Janua, pp. 1–6. doi: 10.1109/ICEngTechnol.2017.8308186.

[159] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights into Imaging*, vol. 9, no. 4. Springer Verlag, pp. 611–629, Aug. 2018. doi: 10.1007/s13244-018-0639-9.

[160] I. A. El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. S. Ahmad, "Differential Deep Convolutional Neural Network Model for Brain Tumor Classification," *Brain Sciences 2021, Vol. 11, Page 352*, vol. 11, no. 3, p. 352, Mar. 2021, doi: 10.3390/BRAINSCI11030352.

[161] N. Bacanin, T. Bezdan, K. Venkatachalam, and F. Al-Turjman, "Optimized convolutional neural network by firefly algorithm for magnetic resonance image classification of glioma brain tumor grade," *Journal of Real-Time Image Processing 2021 18:4*, vol. 18, no. 4, pp. 1085–1098, Apr. 2021, doi: 10.1007/S11554-021-01106-X.

[162] J. Wang *et al.*, "DFP-ResUNet:Convolutional Neural Network with a Dilated Convolutional Feature Pyramid for Multimodal Brain Tumor Segmentation," *Comput Methods Programs Biomed*, vol. 208, p. 106208, Sep. 2021, doi: 10.1016/J.CMPB.2021.106208.

[163] A. Gurunathan and B. Krishnan, "Detection and diagnosis of brain tumors using deep learning convolutional neural networks," *Int J Imaging Syst Technol*, vol. 31, no. 3, pp. 1174–1184, Sep. 2021, doi: 10.1002/IMA.22532.

[164] T. Mikolov, S. Kombrink, L. Burget, J. Černocký, and S. Khudanpur, "Extensions of recurrent neural network language model," *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, pp. 5528–5531, 2011, doi: 10.1109/ICASSP.2011.5947611.

[165] M. Lukoševičius and H. Jaeger, "Reservoir computing approaches to recurrent neural network training," *Comput Sci Rev*, vol. 3, no. 3, pp. 127–149, Aug. 2009, doi: 10.1016/J.COSREV.2009.03.005.

[166] A. C. Tsoi, "Recurrent neural network architectures: An overview," pp. 1–26, 1998, doi: 10.1007/BFB0053993.

[167] J. G. SivaSai, P. N. Srinivasu, M. N. Sindhuri, K. Rohitha, and S. Deepika, "An automated segmentation of brain MR image through fuzzy recurrent neural network," *Studies in Computational Intelligence*, vol. 903, pp. 163–179, 2021, doi: 10.1007/978-981-15-5495-7_9/COVER/.

[168] Y. Zhou *et al.*, "Holistic brain tumor screening and classification based on densenet and recurrent neural network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11383 LNCS, pp. 208–217, 2019, doi: 10.1007/978-3-030-11723-8_21/COVER/.

[169] S. S. Begum and D. R. Lakshmi, "Combining optimal wavelet statistical texture and recurrent neural network for tumour detection and classification over MRI," *Multimedia Tools and Applications 2020 79:19*, vol. 79, no. 19, pp. 14009–14030, Feb. 2020, doi: 10.1007/S11042-020-08643-W.

[170] G. Van Houdt, C. Mosquera, and G. Nápoles, "A review on the long short-term memory model," *Artificial Intelligence Review 2020 53:8*, vol. 53, no. 8, pp. 5929–5955, May 2020, doi: 10.1007/S10462-020-09838-1.

[171] A. Graves, "Long Short-Term Memory," pp. 37–45, 2012, doi: 10.1007/978-3-642-24797-2_4.

[172] E. Dandıl and S. Karaca, "Detection of pseudo brain tumors via stacked LSTM neural networks using MR spectroscopy signals," *Biocybern Biomed Eng*, vol. 41, no. 1, pp. 173–195, Jan. 2021, doi: 10.1016/J.BBE.2020.12.003.

[173] F. Xu, H. Ma, J. Sun, R. Wu, X. Liu, and Y. Kong, "LSTM Multi-modal UNet for Brain Tumor Segmentation," *2019 IEEE 4th International Conference on Image, Vision and Computing, ICIVC 2019*, pp. 236–240, Jul. 2019, doi: 10.1109/ICIVC47709.2019.8981027.

[174] I. Shahzadi, F. Meriadeau, T. B. Tang, and A. Quyyum, "CNN-LSTM: Cascaded framework for brain tumour classification," *2018 IEEE EMBS Conference on Biomedical Engineering and Sciences, IECBES 2018 - Proceedings*, pp. 633–637, Jan. 2019, doi: 10.1109/IECBES.2018.8626704.

[175] A. Creswell, T. White, V. Dumoulin, K. Arulkumaran, B. Sengupta, and A. A. Bharath, "Generative Adversarial Networks: An Overview," *IEEE Signal Process Mag*, vol. 35, no. 1, pp. 53–65, Jan. 2018, doi: 10.1109/MSP.2017.2765202.

[176] K. Wang, C. Gou, Y. Duan, Y. Lin, X. Zheng, and F. Y. Wang, "Generative adversarial networks: Introduction and outlook," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 4, pp. 588–598, Oct. 2017, doi: 10.1109/JAS.2017.7510583.

[177] S. Nema, A. Dudhane, S. Murala, and S. Naidu, "RescueNet: An unpaired GAN for brain tumor segmentation," *Biomed Signal Process Control*, vol. 55, p. 101641, Jan. 2020, doi: 10.1016/J.BSPC.2019.101641.

[178] G. Neelima, D. R. Chigurukota, B. Maram, and B. Girirajan, "Optimal DeepMRSeg based tumor segmentation with GAN for brain tumor classification," *Biomed Signal Process Control*, vol. 74, p. 103537, Apr. 2022, doi: 10.1016/J.BSPC.2022.103537.

[179] M. Rezaei, H. Yang, and C. Meinel, "Voxel-GAN: Adversarial framework for learning imbalanced brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 321–333, 2019, doi: 10.1007/978-3-030-11726-9_29/COVER/.

[180] Y. Hua, J. Guo, and H. Zhao, "Deep Belief Networks and deep learning," *Proceedings of 2015 International Conference on Intelligent Computing and Internet of Things, ICIT 2015*, pp. 1–4, May 2015, doi: 10.1109/ICAIOT.2015.7111524.

[181] A. Kharrat and M. Néji, "Classification of brain tumors using personalized deep belief networks on MRImages: PDBN-MRI," *https://doi.org/10.1117/12.2522848*, vol. 11041, pp. 713–721, Mar. 2019, doi: 10.1117/12.2522848.

[182] A. Ratna Raju, S. Pabboju, and R. Rajeswara Rao, "Hybrid active contour model and deep belief network based approach for brain tumor segmentation and classification," *Sensor Review*, vol. 39, no. 4, pp. 473–487, Jul. 2019, doi: 10.1108/SR-01-2018-0008/FULL/XML.

[183] M. Tschannen, O. Bachem, and M. Lucic, "Recent Advances in Autoencoder-Based Representation Learning," Dec. 2018, doi: 10.48550/arxiv.1812.05069.

[184] M. Tschannen, O. Bachem, and M. Lucic, "Recent Advances in Autoencoder-Based Representation Learning," Dec. 2018, doi: 10.48550/arxiv.1812.05069.

[185] J. Amin *et al.*, "Brain Tumor Detection by Using Stacked Autoencoders in Deep Learning," *Journal of Medical Systems 2019 44:2*, vol. 44, no. 2, pp. 1–12, Dec. 2019, doi: 10.1007/S10916-019-1483-2.

[186] M. M. Badža and M. Barjaktarović, "Segmentation of Brain Tumors from MRI Images Using Convolutional Autoencoder," *Applied Sciences 2021, Vol. 11, Page 4317*, vol. 11, no. 9, p. 4317, May 2021, doi: 10.3390/APP11094317.

[187] J. N. Stember and H. Shalu, "Deep Reinforcement Learning with Automated Label Extraction from Clinical Reports Accurately Classifies 3D MRI Brain Volumes," *Journal of Digital Imaging 2022*, pp. 1–10, May 2022, doi: 10.1007/S10278-022-00644-5.

[188] R. Dey and F. M. Salemt, "Gate-variants of Gated Recurrent Unit (GRU) neural networks," *Midwest Symposium on Circuits and Systems*, vol. 2017-Augus, pp. 1597–1600, Sep. 2017, doi: 10.1109/MWSCAS.2017.8053243.

[189] A. M. G. Allah, A. M. Sarhan, and N. M. Elshennawy, "Classification of Brain MRI Tumor Images Based on Deep Learning PGGAN Augmentation," *Diagnostics 2021, Vol. 11, Page 2343*, vol. 11, no. 12, p. 2343, Dec. 2021, doi: 10.3390/DIAGNOSTICS11122343.

[190] J. Chang *et al.*, "A mix-pooling CNN architecture with FCRF for brain tumor segmentation," *J Vis Commun Image Represent*, vol. 58, pp. 316–322, Jan. 2019, doi: 10.1016/J.JVCIR.2018.11.047.

[191] H. N. T. K. Kaldera, S. R. Gunasekara, and M. B. DIssanayake, "Brain tumor Classification and Segmentation using Faster R-CNN," *2019 Advances in Science and Engineering Technology International Conferences, ASET 2019*, May 2019, doi: 10.1109/ICASET.2019.8714263.

[192] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *J Comput Sci*, vol. 30, pp. 174–182, Jan. 2019, doi: 10.1016/J.JOCS.2018.12.003.

[193] M. Y. B. Murthy, A. Koteswararao, and M. S. Babu, "Adaptive fuzzy deformable fusion and optimized CNN with ensemble classification for automated brain tumor diagnosis," *Biomedical Engineering Letters 2021 12:1*, vol. 12, no. 1, pp. 37–58, Nov. 2021, doi: 10.1007/S13534-021-00209-5.

[194] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," *Microsc Res Tech*, vol. 84, no. 1, pp. 133–149, Jan. 2021, doi: 10.1002/JEMT.23597.

[195] J. Amin, M. Sharif, M. Raza, T. Saba, R. Sial, and S. A. Shad, "Brain tumor detection: a long short-term memory (LSTM)-based learning model," *Neural Computing and Applications 2019 32:20*, vol. 32, no. 20, pp. 15965–15973, Dec. 2019, doi: 10.1007/S00521-019-04650-7.

[196] G. Liu, X. Li, and Y. Cai, "Segmentation for Multimodal Brain Tumor Images Using Dual-Tree Complex Wavelet Transform and Deep Reinforcement Learning," *Comput Intell Neurosci*, vol. 2022, pp. 1–11, May 2022, doi: 10.1155/2022/5369516.

[197] T. Sathies Kumar, C. Arun, and P. Ezhumalai, "An approach for brain tumor detection using optimal feature selection and optimized deep belief network," *Biomed Signal Process Control*, vol. 73, p. 103440, Mar. 2022, doi: 10.1016/J.BSPC.2021.103440.

[198] P. Harish and S. Baskar, "MRI based detection and classification of brain tumor using enhanced faster R-CNN and Alex Net model," *Mater Today Proc*, Dec. 2020, doi: 10.1016/J.MATPR.2020.11.495.

[199] B. Ahmad, J. Sun, Q. You, V. Palade, and Z. Mao, "Brain Tumor Classification Using a Combination of Variational Autoencoders and Generative Adversarial Networks," *Biomedicines 2022, Vol. 10, Page 223*, vol. 10, no. 2, p. 223, Jan. 2022, doi: 10.3390/BIOMEDICINES10020223.

[200] D. Mukherkjee, P. Saha, D. Kaplun, A. Sinitca, and R. Sarkar, "Brain tumor image generation using an aggregation of GAN models with style transfer," *Scientific Reports 2022 12:1*, vol. 12, no. 1, pp. 1–16, Jun. 2022, doi: 10.1038/s41598-022-12646-y.

[201] W. Takrouni and A. Douik, "Improving geometric P-norm-based glioma segmentation through deep convolutional autoencoder encapsulation," *Biomed Signal Process Control*, vol. 71, p. 103232, Jan. 2022, doi: 10.1016/J.BSPC.2021.103232.

[202] A. Chattopadhyay and M. Maitra, "MRI-based brain tumour image detection using CNN based deep learning method," *Neuroscience Informatics*, vol. 2, no. 4, p. 100060, Dec. 2022, doi: 10.1016/J.NEURI.2022.100060.

[203] N. Kesav and M. G. Jibukumar, "Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN," *Journal of King Saud University - Computer and Information Sciences*, May 2021, doi: 10.1016/J.JKSUCI.2021.05.008.

[204] R. Vankdothu, M. A. Hameed, and H. Fatima, "A Brain Tumor Identification and Classification Using Deep Learning based on CNN-LSTM Method," *Computers and Electrical Engineering*, vol. 101, p. 107960, Jul. 2022, doi: 10.1016/J.COMPELECENG.2022.107960.

[205] L. Fidon, S. Ourselin, and T. Vercauteren, "Generalized Wasserstein Dice Score, Distributionally Robust Deep Learning, and Ranger for Brain Tumor Segmentation: BraTS 2020 Challenge," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 200–214, 2021, doi: 10.1007/978-3-030-72087-2_18/COVER/.

[206] F. Isensee, P. F. Jäger, P. M. Full, P. Vollmuth, and K. H. Maier-Hein, "nnU-Net for Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 118–132, 2021, doi: 10.1007/978-3-030-72087-2_11/COVER/.

[207] T. Henry *et al.*, "Brain Tumor Segmentation with Self-ensembled, Deeply-Supervised 3D U-Net Neural Networks: A BraTS 2020 Challenge Solution," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12658 LNCS, pp. 327–339, 2021, doi: 10.1007/978-3-030-72084-1_30/COVER/.

[208] Y. Yuan, "Automatic Brain Tumor Segmentation with Scale Attention Network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12658 LNCS, pp. 285–294, 2021, doi: 10.1007/978-3-030-72084-1_26/COVER/.

[209] J. Tang, T. Li, H. Shu, and H. Zhu, "Variational-Autoencoder Regularized 3D MultiResUNet for the BraTS 2020 Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 431–440, 2021, doi: 10.1007/978-3-030-72087-2_38/COVER/.

[210] C. A. Silva, A. Pinto, S. Pereira, and A. Lopes, "Multi-stage Deep Layer Aggregation for Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 179–188, 2021, doi: 10.1007/978-3-030-72087-2_16/COVER/.

[211] T. Tarasiewicz, M. Kawulok, and J. Nalepa, "Lightweight U-Nets for Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 3–14, 2021, doi: 10.1007/978-3-030-72087-2_1/COVER/.

[212] S. Qamar, P. Ahmad, and L. Shen, "HI-Net: Hyperdense Inception 3D UNet for Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial*

Intelligence and Lecture Notes in Bioinformatics), vol. 12659 LNCS, pp. 50–57, 2021, doi: 10.1007/978-3-030-72087-2_5/COVER/.

[213] P. Ahmad, S. Qamar, L. Shen, and A. Saeed, "Context Aware 3D UNet for Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12658 LNCS, pp. 207–218, 2021, doi: 10.1007/978-3-030-72084-1_19/COVER/.

[214] J. Colman, L. Zhang, W. Duan, and X. Ye, "DR-Unet104 for Multimodal MRI Brain Tumor Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12659 LNCS, pp. 410–419, 2021, doi: 10.1007/978-3-030-72087-2_36/COVER/.

[215] Z. Jiang, C. Ding, M. Liu, and D. Tao, "Two-stage cascaded u-net: 1st place solution to brats challenge 2019 segmentation task," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11992 LNCS, pp. 231–241, 2020, doi: 10.1007/978-3-030-46640-4_22/COVER/.

[216] A. Myronenko and A. Hatamizadeh, "Robust semantic segmentation of brain tumor regions from 3D MRIs," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11993 LNCS, pp. 82–89, 2020, doi: 10.1007/978-3-030-46643-5_8/COVER/.

[217] R. R. Agravat and M. S. Raval, "Brain tumor segmentation and survival prediction," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11992 LNCS, pp. 338–348, 2020, doi: 10.1007/978-3-030-46640-4_32/COVER/.

[218] F. Wang, R. Jiang, L. Zheng, C. Meng, and B. Biswal, "3d u-net based brain tumor segmentation and survival days prediction," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11992 LNCS, pp. 131–141, 2020, doi: 10.1007/978-3-030-46640-4_13/COVER/.

[219] M. U. Saeed *et al.*, "RMU-Net: A Novel Residual Mobile U-Net Model for Brain Tumor Segmentation from MR Images," *Electronics 2021, Vol. 10, Page 1962*, vol. 10, no. 16, p. 1962, Aug. 2021, doi: 10.3390/ELECTRONICS10161962.

[220] G. K. Murugesan *et al.*, "Multidimensional and multiresolution ensemble networks for brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11993 LNCS, pp. 148–157, 2020, doi: 10.1007/978-3-030-46643-5_14/COVER/.

[221] Y. X. Zhao, Y. M. Zhang, and C. L. Liu, "Bag of tricks for 3d mri brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11992 LNCS, pp. 210–220, 2020, doi: 10.1007/978-3-030-46640-4_20/COVER/.

[222] M. Amian and M. Soltaninejad, "Multi-resolution 3d cnn for mri brain tumor segmentation and survival prediction," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11992 LNCS, pp. 221–230, 2020, doi: 10.1007/978-3-030-46640-4_21/COVER/.

[223] M. Bhalerao and S. Thakur, "Brain tumor segmentation based on 3D residual U-Net," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11993 LNCS, pp. 218–225, 2020, doi: 10.1007/978-3-030-46643-5_21/COVER/.

[224] J. Sun, Y. Peng, Y. Guo, and D. Li, "Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN," *Neurocomputing*, vol. 423, pp. 34–45, Jan. 2021, doi: 10.1016/J.NEUCOM.2020.10.031.

[225] L. Weninger, O. Rippel, S. Koppers, and D. Merhof, "Segmentation of brain tumors and patient survival prediction: Methods for the braTS 2018 challenge," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 3–12, 2019, doi: 10.1007/978-3-030-11726-9_1/COVER/.

[226] C. Zhou, S. Chen, C. Ding, and D. Tao, "Learning contextual and attentive information for brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 497–507, 2019, doi: 10.1007/978-3-030-11726-9_44/COVER/.

[227] R. Mehta and T. Arbel, "3D U-Net for brain tumour segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 254–266, 2019, doi: 10.1007/978-3-030-11726-9_23/COVER/.

[228] H. Y. Yang and J. Yang, "Automatic brain tumor segmentation with contour aware residual network and adversarial training," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 267–278, 2019, doi: 10.1007/978-3-030-11726-9_24/COVER/.

[229] W. Chen, B. Liu, S. Peng, J. Sun, and X. Qiao, "S3D-UNET: Separable 3D U-Net for brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 358–368, 2019, doi: 10.1007/978-3-030-11726-9_32/COVER/.

[230] N. M. Aboelenein, P. Songhao, A. Koubaa, A. Noor, and A. Afifi, "HTTU-Net: Hybrid Two Track U-Net for Automatic Brain Tumor Segmentation," *IEEE Access*, vol. 8, pp. 101406–101415, 2020, doi: 10.1109/ACCESS.2020.2998601.

[231] A. Myronenko, "3D MRI brain tumor segmentation using autoencoder regularization," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 311–320, 2019, doi: 10.1007/978-3-030-11726-9_28/COVER/.

[232] D. Lachinov, E. Vasiliev, and V. Turlapov, "Glioma segmentation with cascaded UNet," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 189–198, 2019, doi: 10.1007/978-3-030-11726-9_17/COVER/.

[233] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic Brain Tumor Segmentation Based on Cascaded Convolutional Neural Networks With Uncertainty Estimation," *Front Comput Neurosci*, vol. 13, p. 56, Aug. 2019, doi: 10.3389/FNCOM.2019.00056/BIBTEX.

[234] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using convolutional neural networks with test-time augmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11384 LNCS, pp. 61–72, 2019, doi: 10.1007/978-3-030-11726-9_6/COVER/.

[235] F. Isensee, P. Kickingereder, W. Wick, M. Bendszus, and K. H. Maier-Hein, "Brain tumor segmentation and radiomics survival prediction: Contribution to the BRATS 2017 challenge," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 287–297, 2018, doi: 10.1007/978-3-319-75238-9_25/COVER/.

[236] M. Soltaninejad, L. Zhang, T. Lambrou, G. Yang, N. Allinson, and X. Ye, "MRI brain tumor segmentation and patient survival prediction using random forests and fully convolutional networks," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 204–215, 2018, doi: 10.1007/978-3-319-75238-9_18/COVER/.

[237] M. Rezaei *et al.*, "A conditional adversarial network for semantic segmentation of brain tumor," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 241–252, 2018, doi: 10.1007/978-3-319-75238-9_21/COVER/.

[238] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 178–190, 2018, doi: 10.1007/978-3-319-75238-9_16/COVER/.

[239] K. Kamnitsas *et al.*, "Ensembles of multiple models and architectures for robust brain tumour segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 450–462, 2018, doi: 10.1007/978-3-319-75238-9_38/COVER/.

[240] M. Shaikh, G. Anand, G. Acharya, A. Amrutkar, V. Alex, and G. Krishnamurthi, "Brain tumor segmentation using dense fully convolutional neural network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 309–319, 2018, doi: 10.1007/978-3-319-75238-9_27/COVER/.

[241] H. Li, A. Li, and M. Wang, "A novel end-to-end brain tumor segmentation method using improved fully convolutional networks," *Comput Biol Med*, vol. 108, pp. 150–160, May 2019, doi: 10.1016/J.COMPBIOMED.2019.03.014.

[242] M. Islam and H. Ren, "Multi-modal PixelNet for brain tumor segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 298–308, 2018, doi: 10.1007/978-3-319-75238-9_26/COVER/.

[243] S. Sedlar, "Brain tumor segmentation using a multi-path CNN based method," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 403–422, 2018, doi: 10.1007/978-3-319-75238-9_35/COVER/.

1618   [244] A. Phophalia and P. Maji, "Multimodal brain tumor segmentation using ensemble of forest method,"
1619   *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and*
1620   *Lecture Notes in Bioinformatics)*, vol. 10670 LNCS, pp. 159–168, 2018, doi: 10.1007/978-3-319-
1621   75238-9_14/COVER/.

1622