



A systematic analysis of magnetic resonance images and deep learning methods used for diagnosis of brain tumor

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Abstract

Accurate classification and segmentation of brain tumors is a critical task to perform. The term classification is the process of grading tumors i.e., whether the tumor is Malignant (cancerous) and Benign (not cancerous), and segmentation is the process of extracting the region of interest. In the last few years, with the development of approaches like computer vision, deep learning, and machine learning algorithms, Magnetic Resonance Images (MRI) are the most widely used modality for the purpose of tumor screening and diagnosing. This process is automated in nature and also attain higher accuracy. Nowadays, physicians also practice MRI automated diagnosis systems, so that the diagnosis is faster, reliable, automated, reproducible, and more prominently less expensive. So here in this paper, we present an extensive survey of brain tumor classification and segmentation approaches based on MRI images. This manuscript mainly explores recently used deep learning methods and approaches. Finally, the paper concludes with various state-of-the-art findings.

Keywords Brain tumor · Classification · Deep learning · Segmentation · Magnetic resonance image

1 Introduction

The development of non-interfering brain imaging technologies has opened new horizons to study and analyze brain anatomy, structure, and functions. Over the last few decades, MRI imaging has facilitated a number of medical applications. MRI for the brain

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has been put forward for visualizing and measuring the surgical planning, learning brain anatomical structure, analyzing changes in the brain, pre-post-treatment analysis, etc. Data presented is with high accuracy, quality, and quantity level due to the advancement in MRI technologies [15, 21].

MRI plays an important role in analyzing some critical issues; sometimes the entire clinical application results depend on it. Extracting and finding accurate information from complex and tedious images becomes multifaceted for most clinicians to deal with it manually. Magnetic resonance imaging plays an important role to find tumors by creating detailed and cross-sectional images of the brain. It distinguishes tissues that are normal and get affected by cancerous cells. MRI also defines whether a tumor is cancerous or not, the size of the tumor, location of the tumor, and helps in treatment such as radiation or surgery and monitoring the treatment. MRIs are generally executed and interpreted by a radiologist who is specially trained and certified to conduct this job. Manual procedures are quite often time-consuming and due to inter or intra-operator variability can cause errors. So, to assist doctors, nowadays automatic or computerized methods have been developed, helping them in making decisions and qualitative diagnoses [4, 20, 27, 31, 32, 53, 63].

With the rapid development in Computer Vision and Deep Learning theories and models, the process of image segmentation and classification becomes easier when compared with the traditional approaches. Image segmentation and classification depend on each other as segmentation is the process of subdivision. On the other hand, classification is the process of aggregating those subdivisions into some predefined classes based on similar characteristics. The result of segmentation is a set of homogenous regions or contours. It is a part of the preprocessing step in image processing, quite often done on the basis of some attributes of the object like the intensity value of pixels, color, etc. Image segmentation serves as to be the most crucial and vital step in the number of clinical applications [15, 21]. MRI image segmentation can be performed for both 2D and 3D images [16–18, 20, 31]. The steps involved in MRI segmentation are given in Fig. 1. Normally after the segmentation process, MRIs are classified on the basis of

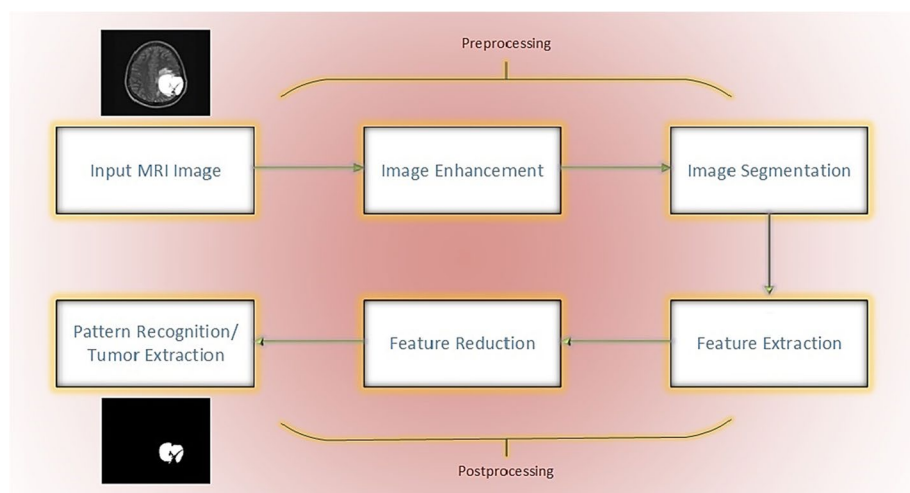


Fig. 1 Steps for MRI segmentation

three categories of tissue given as 1. White Matter (WM) 2. Gray Matter (GM) and 3. Cerebrospinal Fluid (CSF) is shown in Fig. 2.

Classification of brain tumors malignant and benign using machine learning and deep learning algorithms is a very critical and important task. The analysis has to be precise as one's life hinges on the outcomes of diagnosis. As stated, tumors can be cancerous or not, once a tumor is identified this stage of classification, generally depends upon the quality of the MRI images and the learning algorithm which has been used for. Nowadays, it has been observed that with the availability of high-end computing devices and availability of large databases deep learning algorithms are most widely used among. These deep learning algorithms also prove their efficacy in providing accurate solutions. Basic steps involved in classification is depicted by Fig. 3. It involves data collection, preprocessing of the data if required, splitting the dataset randomly among training and testing dataset, training of model using training data, further testing trained model on the unseen data i.e., testing dataset, and finally this process ends up with validating and evaluating the performance of the model.

In this article, our aim is to present various aspects associated with the study of MRI images: their types, characteristics, categories, scanning procedures, MRI examination process, and so on. For a better understanding, the various facts associated with a brain tumor are also presented in this article. Further, an extensive survey is then carried out introducing the various deep learning models used in the past few years for the purpose of segmentation and classification of brain tumors. Followed by findings including methodologies used, the dataset used, performance metrics, etc. Finally, the article concludes with a conclusion and proposed future work.

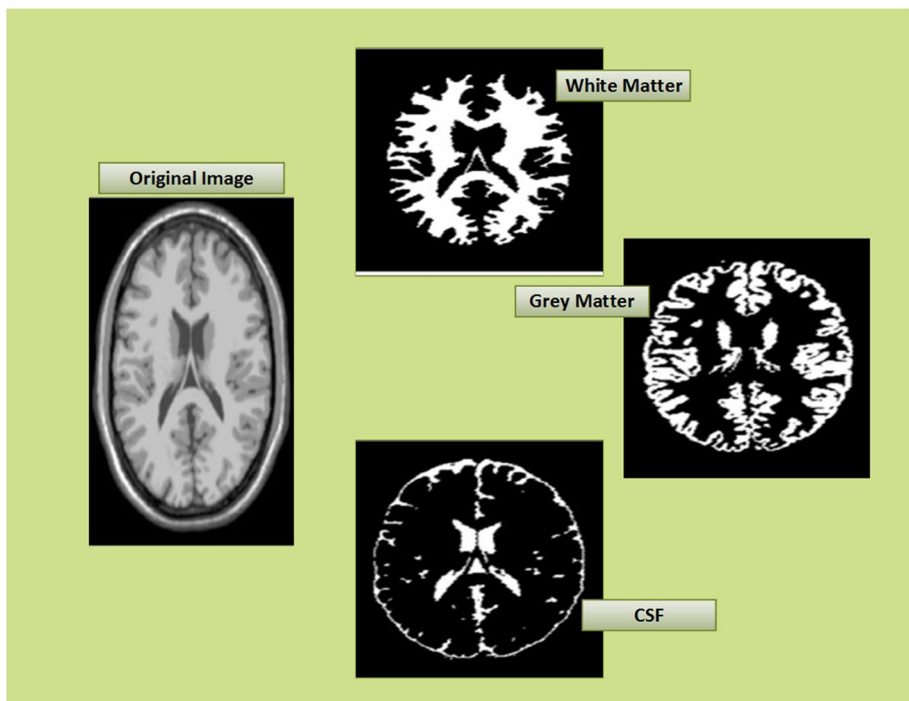


Fig. 2 Post segmentation

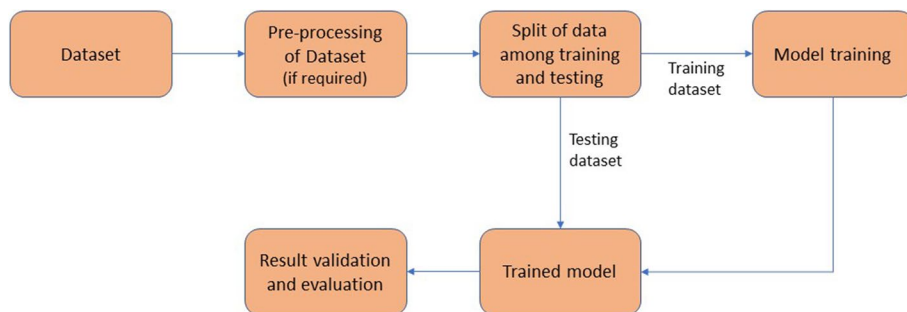


Fig. 3 Steps involved in classification process

Some of the research questionnaire that our manuscript stabs to answer are given as:

RQ1: Offer information about various terms related to brain tumors and MRI images investigation.

RQ2: Conduct a detailed literature study of the recent work carried out for brain tumor segmentation and classification.

RQ3: To present different findings including intelligent models, databases, evaluation parameters, future research direction among all.

RQ4: To make a critical analysis and discussing the impacts of various studies.

2 Brain tumors

Brain tumors arise when there is the development of abnormal cells anywhere within the brain or the Central Nervous System (CNS). It can be of any size, or type, and located in any part of the brain. Generally, brain tumors are classified among Primary and Metastatic (secondary) compromises of about 120 different forms of tumors. Primary tumors grow within the brain, and can spread to other parts of the brain or spine but not to the other body parts, on the other hand, Metastatic tumors can grow in the other part of the body as well [20, 31]. These types of tumors are the most common brain tumors. Both primary and metastatic tumors can be either malignant (cancer) or benign (not cancer). Neurologists and Oncologists are two categories of physicians who handle the diagnosis of tumors [20, 31, 53]. Various factors associated with brain tumor study are given below

- (i) Symptoms for brain tumors
 - a. Headaches
 - b. Seizures
 - c. Behavioral and cognitive (thinking) loss
 - d. Endocrine dysfunction
 - e. Vision loss, hearing loss
 - f. DVT (Deep venous thrombosis) or blood clot
 - g. Fatigue
 - h. Drowsiness

(ii) Risk factors for brain tumors

- a. Environmental Risk
- b. Genetic Risk

(iii) Brain Tumor Diagnosis measures

- a. Magnetic resonance imaging (MRI)
- b. Computed tomography (CT)
- c. Positron emission tomography (PET) or PET-CT scan
- d. Neurologic exam
- e. Biopsy
- f. Lumbar puncture or spinal tap
- g. Electroencephalography (EEG)
- h. Myelogram

(iv) **Most common tumor types:** In 2016, World Health Organization (WHO) have classified tumors of CNS based upon the categorization of the year 2007 [51]. Table 1 summarizes common brain tumors and their classification

(v) Brain Tumor Treatment

- a. Surgery
- b. Chemotherapy
- c. Radiotherapy
- d. Steroids
- e. Anti-seizure medication
- f. Ventricular peritoneal shunt

(vi) Grading of tumors

Generally, tumors were graded among four categories. Depending upon the structures of the cell under microscopic vision the doctors assign grades to the tumors. That is if cells having a structure similar to the normal cell are termed as to be well-differentiated tumors and others are known to be undifferentiated. The differentiated tumors grow slowly and there is the possibility of diagnosis for the same, but on the other hand, undifferentiated ones are critical ones. Thus, based on this tumor were classified among grades form I, II, III, and IV. Grade I tend to be normal and curable whereas grade IV is less curable [26]. In 2016 the World Health Organization published a list of graded tumors. The taxonomy is given in Fig. 4 [51].

3 Magnetic resonance imaging (MRI)

Magnetic resonance imaging plays an important role to find tumors by creating detailed and cross-sectional images of the brain. It distinguishes tissues that are normal and which get affected by cancerous cells. MRI defines whether a tumor is cancerous or not, the size of the tumor, location of the tumor, helps in treatment such as radiation or surgery and monitoring the treatment. The credit for using MRI as a diagnostic tool goes to Paul C.

Table 1 The details of most common tumor types

Tumor type	Type	Description	Symptoms	Cause	Incidence	Treatment
Meningioma	Benign (B)	Slow growing Grows inwardly toward spinal cord or grows outward towards the skull	Headache, weakness in arm or leg	Chromosome22 or PDGFR and EGFR for about 40 to 80%	Rarely in children, in adults age > 60 for about 36.1% and ratio is 2:1 for men and women	Surgery, Radiotherapy
Glioma	B	Occurs in a tissue named “glio” having 3 types of cells 1. Astrocytes 2. Oligodendrocytes 3. Ependymal and mixed glioma are known to be oligoastrocytoma	Headache	The exact cause is not known	Varies	Radiotherapy, chemotherapy, surgery
Glioblastoma (GBM)	B/ Malign-ant (M)	Arrives form astrocytes and generally found in cerebral hemispheres of the brain, but can be at other parts of the brain or spinal cord, are of two types primary and secondary	Headache, vomiting, drowsiness, nausea, and depends on the location of tumors	Not known	3% for the child, more in men than women and about 15.4% is primary tumors and 60–70% are astrocytomas	Radiotherapy, chemotherapy, surgery
Astrocytoma	B	Present in four grades and arises from astrocytes grade I = Pilocytic, II = Diffuse, III = Anaplastic, IV =	Memory loss, headache, seizures, change in behavior	Not known	More in males than females, rarely in young and children’s, generally for age above 45	Chemotherapy, surgery
		Astrocytoma, can be at any part of brain				

Table 1 (continued)

Tumor type	Type	Description	Symptoms	Cause	Incidence	Treatment
Pituitary tumors	B/M	Also known as adenomas or carcinomas, mostly found in the front two third of pituitary, are of two types secreting and non-secreting	Headache, visual impairment, behavior changes, changes in hormones and many more	Not known	Higher in women than men, most common at old age and about 9–12% in adults	Surgery, drug therapies, radiation, hormone replacement therapy
Lymphoma	B	Known as primary CNS lymphoma (PCNSL), can be present in eyes, spinal cord, cerebral hemisphere or CSF	Behavior change, eyesight loss, confusion, weakness, seizures	Originates from B lymphocytes classified as non-Hodgkin's	Healthy immune system or immune system that does not works well	Steroids, Chemotherapy, radiation
Oligodendroglioma	B	Originates from oligodendrocytes, found on cerebral hemisphere or frontal or temporal lobe, they look like fried egg shapes, and pink in colors	Dependent on location, headache, seizures, personality change	Chromosomal abnormalities but exact cause is not known	More in men than women, adults for about 50–60% and children's for bout 4–6%	Radiotherapy, chemotherapy, surgery
Medulloblastoma	B	They are of different types, generally found in cerebellum, are high grade tumors	Headache, behavior changes, vomiting, drowsiness	Not known	More in men than women, more than 70% in children under 10	Radiotherapy, chemotherapy, surgery

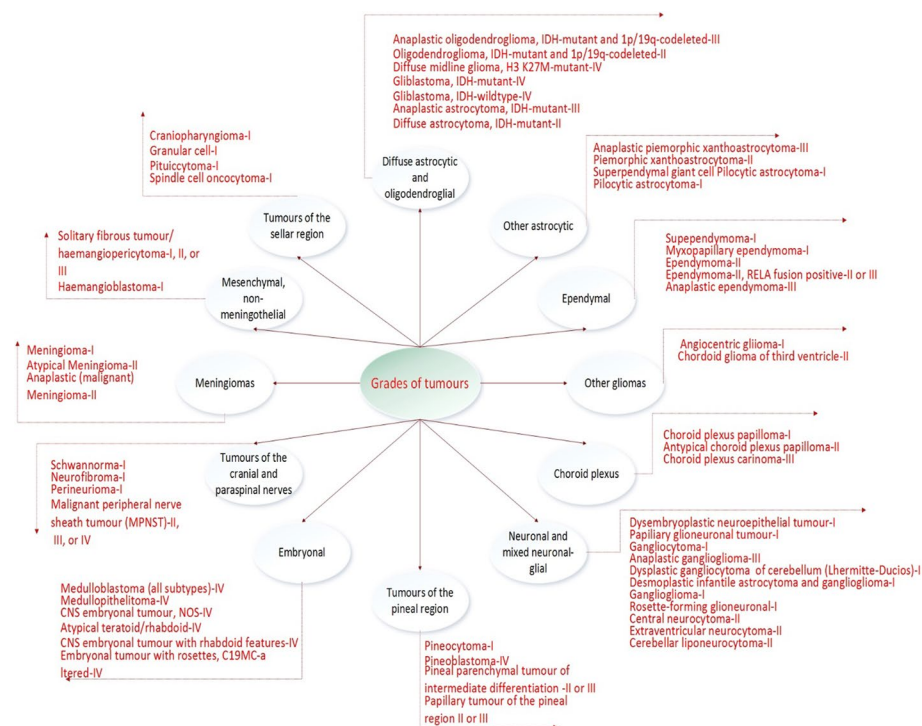


Fig. 4 Taxonomy of tumor taken from [51]

Lauterbur and Peter Mansfield the two Nobel laureates who received the Nobel in 2003 for their remarkable job. But the phenomena of magnetic resonance were developed in the year 1946 by Felix Bloch and Edward Purcell working individually and got a Nobel in 1952. From then to 1970 MRI was used for chemical and physical examination. But in the year 1971, Raymond Damadian suggested that they can also be used for medical diagnosis because of the property of visualizing the internal structure of the body. “Indomitable” a full-body scanner was also created by him. With the development of computed tomography (CT) by Hounsfield in 1973 and echo-planar imaging by Mansfield in 1977, when compared, MRI has proven to be an effective tool for diagnosis since then.

MRI can be done for a number of reasons such as locating tumors, blood vessel diseases, bleeding, musculoskeletal or female pelvic problems, and many more. It is both a harmless and painless procedure because of the reason that it does not use ionizing radiation used in X-rays and CT scans. MRI scan is avoided in some cases such as pregnancy, a cardiac pacemaker, head injury (done recently), etc. Japan is at the top in countries with about 46.5 per one million citizens MRI scanners.

MRI scan uses pulses of radio waves and magnetism to take pictures of internal structures or parts of the body that are quite detailed in nature. MRI scanner looks like a tube that is surrounded by a giant circular magnet. The patient under observation is positioned on a moveable bed that is implanted into the magnet. The protons of hydrogen atoms (also known as proton density or PD weighted) are aligned by the strong magnetic field, which is then exposed to a beam of radio waves that spins the various

protons of the body, which produces a faint signal that is detected by the receiver portion of the MRI scanner. The greater the proton content the brighter the image. Radiologists or radiographers are responsible for programming MRI machines to pick up a convincing direction of proton movement. This information is processed by computer and saved for further investigation or monitoring treatment in the form of an image. MRI scanners come in different magnet field strengths measured in Tesla or “T”, usually between 0.5 T and 3.0 T. Higher the strength of the signal and magnetic field higher the accuracy of an image. But these values are often a deciding factor for the type of diagnosis done for example neurological MRI, breast MRI, etc. so not always a 3 T MRI has been considered. Whereas quite often 1.2 T and 1.5 T are considered to be of the same type but 1.5 T with more features and advantages is preferably used.

Normally while having an MRI scan three types of images are generated: T1-weighted, T2 weighted, and Proton density (PD) images as shown in Fig. 5.

Other than these two a third one is known as Proton density MRI images which are based on the proton density. High proton density tissues are bright areas in the image as well as high signal intensity whereas regions with low proton density tissues are dark areas in the image as well as with low signal intensity. The difference between T1 weighted and T2 weighted is given in Table 2.

- (i) There are three types of MRI machines used namely
 - a. Extremity MRI: This type of machine is specially designed for arms and legs useful in detecting injuries, tumors, tissue injuries, etc.
 - b. Open MRI: This type of machine reduces the chance of claustrophobia (enclosed spaces). This process is comfortable for the patients but it gets lesser information when compared to an enclosed MRI. Ranges from 0.2 T to 1.5 T.
 - c. Tesla MRI: This is faster and more efficient than the conventional MRI because of its ability to produce a magnetic field twice the conventional value. It is more effective to find abnormal developments as compared with 1.5 T MRI.
- (ii) The most common MRI examinations depending on diagnosis can be customized as follows:

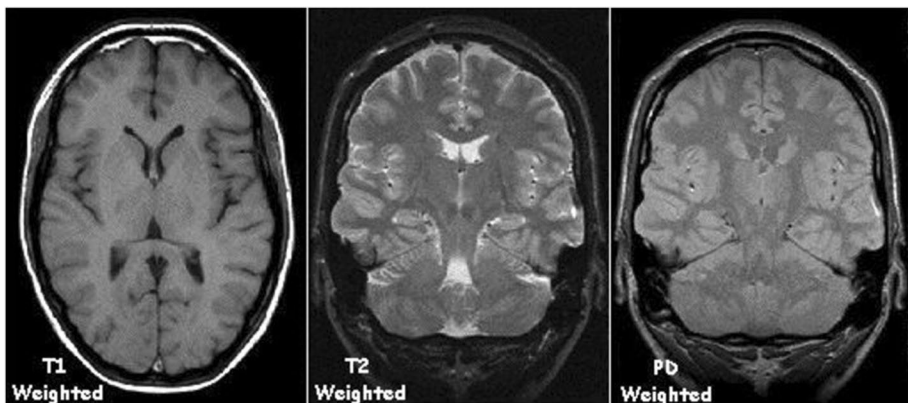


Fig. 5 T1, T2, and PD MRI images

Table 2 Difference between most commonly used MRI scans are as follows

S No.	Attributes	T1 weighted	T2 weighted
1.	Movement of protons	Longitudinal	Transverse
2.	Fat	Bright	Dark
3.	Grey matter	Grey	Grey
4.	Cerebrospinal fluid (CSF) or water	Black	White
5.	White matter	Light grey	White grey
6.	 shows	Fat, fatty bone marrow, slow-flowing blood, contrast agents, blood products	CSF, blood products, proteinaceous tissue
7.	 shows	Proteinaceous tissue	Fat, fatty bone marrow, or high-bound water tissues
8.	 shows	CSF, high-bound water tissues, collagenous tissue	Collagenous tissue, high-bound water tissues
9.	 shows	Air, mineral-rich tissue and fast-flowing blood	Air, mineral-rich tissue and fast-flowing blood
10.	Applications	Anatomic detail (CSF spaces), vascular changes + C, disruption of BBB+C	Anatomic detail (CSF spaces), lesions

- a. Functional MRI (fMRI): Used to observe the blood flow within the nervous system.
 - b. Diffusion MRI: Used to govern the direction of nerve fibers in the brain, especially white matter.
 - c. Magnetic resonance angiography (MRA): Used for the analysis of irregularities of blood vessels from the brain, legs, chest etc. There are 2 types of MRA namely:
 1. Flow independent: Independent on the flow of blood-based on T1, T2, and chemical shifts of dissimilar tissues. Better for patients having slow blood flow.
 2. Flow dependent: Dependent on the flow of blood. Diagnosis has to be done on the basis of static tissues and vessels' blood flow comparison.
 - d. Magnetic resonance venography (MRV): Used to observe the blood flow within the veins.
 - e. Cardiac MRI: Also known as cardiovascular magnetic resonance (CMR) used for the analysis of the heart in detail. The important aspect of this MRI is that it can be correlated with ECG simultaneously.
- (iii) Other than above, there is the number of MRI examinations specified for particular diagnoses some of them are:
- a. Fluid Attenuated Inversion Recovery (FLAIR)
 - b. Neuromelanin Imaging
 - c. Proton Density Weighted
 - d. Susceptibility Weighted Imaging (SWI)
 - e. Breast scan
 - f. T1rho MRI
 - g. Real-time MRI
 - h. Magnetization Transfer MRI
 - i. Magnetic Resonance Spectroscopy
 - j. Multinuclear Imaging

4 Literature survey

In the past few years, with the advent of high computing devices and efficient algorithms, an accurate segmentation and classification of brain tumors from MRI images has accelerated the diagnosis process. This process has resulted in timely treatment, because of which a number of human lives are saved. Though MRI images are very difficult to process, with the availability of deep learning models known for handling large and complex data this task can be done effectively. So, in this study, our major focus is on presenting various deep-learning approaches used for the purpose of brain tumor segmentation. A detailed analysis has been carried out and the various facts associated including the model used, the feature extraction process, the dataset used, results, research gaps, and future enhancement for the related work are presented in Table 3.

It has been observed from the literature that the deep models like UNet or its hybrid amalgamation with the other state-of-the-arts algorithm has been widely used for the purpose of tumor region segmentation. This methodology has been majorly deployed on the BRATS dataset. The unique feature of this dataset lies in its better-quality High-Grade Gliomas (HGG) MRIs and 54 Low Grade Gliomas (LGG) MRIs. This dataset is publicly available collection of MRIs, specifically used for the purpose of tumor segmentation. Finally, accuracy is the evaluation parameter that is commonly being used to validate the performance of the models.

Further, to carry on with the related study has been directed towards introduction the various contributions made in the past for the purpose of tumor classification or grading them. The following Table 4 presents the related research work, name of the model used, the feature learning methodology used, dataset used, result, research gaps of the studies, and future works.

Further, we have experience from the literature study that dataset plays an important role for accurately segmenting and classifying the brain tumor region. The quality and quantity of images present in the dataset allow us to conveniently select the deep learning model. A number of data repository of MRI images are available publicly. Tables 5 and 6 presents the results comparison for segmentation and classification data separately.

5 Findings

The motivation behind this article is to present the various terms allied with brain tumor segmentation and classification using MRI images.

5.1 Approaches

Despite the number of techniques that have proven supremacy in the past years, deep learning models with their ability to work with complex data have overpowered them. The earlier approaches encountered with a lack of flexibility or multitasking, variability in the dataset, overfitting, the small size of the dataset, corrupted or noisy data, etc. [22, 23, 85]. When we were in the process of collecting manuscripts for conducting this survey, we observed that probably out of ten articles, 80% to 90% of authors have used deep learning models in recent years, a comparative graph is given in Fig. 6. This also shows that Deep Learning approaches have overpowered the machine learning algorithms. Deep neural networks (DNNs) or Convolutional neural networks (CNNs) are recent neural networks

Table 3 Related work for brain tumor segmentation

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Douglas N. Greve et. al. [33]	Automatic segmentation of subcortical limbic structure	U-Net Model	Convolutional layer	MRI dataset with 39 trained Images and focuses on 698 various databases	Accuracy =99%	Toolbox is not effectively useful for mammillary bodies	With addition of deep learning algorithm tools can be used for Mammillary body parts
Mina Ghaffari et al [29]	Classification of brain tumor and its sub-region	3D densely connected U-net	Decoder	BRATS database	Dice score for whole tumor =0.83, tumor core =0.77, enhancing tumor =0.60	Low performance. The training dataset is small	Performance can be increased with the large training dataset
Gokay Karayegen a and, Mehmet Feyzi Aksahin [38]	Finding tumor location and dimension	Deep learning network and 3D images	Convolutional layer	BRATS dataset with 253 training images	Mean prediction ratio =91.718 Mean IOU =86.946 BF score =92.938	Performance and training dataset is restricted	Performance can be increased by adding more class identifications and adding test data
Kareem A. Wahid et al. [88]	Detection of oropharyngeal cancer primary tumor	3D residual U-net model.	Convolutional layer	MRI images with 30 patient data	Hausdroff distance = 95%	Robustness and generalizability of the tested model are restricted, Analysis of Input image is based on the previous survey, and analysis is limited to primary tumor only	In addition to mpMRI DL auto-segmentation algorithms, look into the role of additional OPC-specific registration algorithms and geometric distortion correction

Table 3 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Andreanne Lemay et.al [46]	Finding the location, size, and growth rate of tumor	U-Net, CNN	Convolutional layer	T1 and T2 weighted MRI with 343 patient data	High true positive detection rate for every class >87% Average Dice score = 76.7%	Poor performance for Edema classification and the system is only trained for intramedullary tumor	Should focus on missing images by learning tools or by adding better model
Muhammad Irfan Sharif et.al [75]	Classification and segmentation of Glioma	Active deep learning.	Convolutional layer	BRATS 2013, 2014, 2017, 2018	Accuracy = 92%	While improving classification time, overall accuracy reduces	Implementation on Capsule net is possible to get improvement in general accuracy
P. Ramya et al [67]	Detection and localization of abnormal tissues in the brain	Deep super learner, K-means, Self-organization map, Gaussian mixture model	Laplacian Automata	BRATS image database with 384 patient data where 220 cases are HGG and 54 are LGG, 110 patient database is used for testing	Accuracy = 98% for ensemble 1 and 97% for ensemble 2	Time and space complexity is high because of the size of the image	Optimal selection can solution to reduce the size of the image and time complexity
Arkapravo Chatopadhyay & Mausumi Maitra [14]	Classification and localization, identification of brain tissues	Deep learning, CNN, SVM classifier	Convolutional layer	BRATS 2020 with 2892 images where 2473 with training data and 273 with testing data	Accuracy = 99.74	Computation is with multiple task	If all processes will be with single module computation will be faster

Table 3 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Sakshi Ahuja [5]	Classifying and locating tumors from MRI	Dark-Nets –53 model, super pixel segmentation techniques	Convolutional layer	BRATS2018 T1W-CE MRI dataset with 80% training data and 10% testing data.	Accuracy = 98.54	Implemented only for 2D radiographic images. Accuracy is less	Volumetric data can be used for 3D radiography and for real-time clinical application computer-aided technology needed to implement
P. Harish & S. Baskar [34]	Classification and detection of benign and malignant	Deep learning, Enhanced based R-CNN, Alex net model	Convolutional layer	Dataset is of different MRI images	Accuracy = 99.25%	Accuracy is obtained with the different model so computation costs increases	Computation costs can be decreased by combining different modules into one.
Weijin Xu et. al. [90]	Inter-slice area information extraction from tumor data	Corner attention module, CH-UNet	Corner attention module	BRATS 2018, BRATS2019 and BRATS2020 database with MRI images	The average dice coefficient improved by = 3.01	As tumor shape design is complicated challenge remains for classification. As a limited-size database getting ground truth results is also difficult	Ground truth results can be possible by increasing size of the database

Table 3 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Zheng Huang et. al [36]	Finding out fine details of brain tumors	GCAUnet, Gross channel attention module, Multiscale input path	Convolutional layer	BRATS 2017 and BRATS2018	Avg Dice score BRATS2017 Whole tumor = 87.2% Tumor core = 79.6% Enhancing tumot = 78.1% And for BRATS2018 Whole tumor = 90.9% Tumor core = 84.5% Enhancing tumor = 81.3% Accuracy = 90.42	As model is generic but performance validation task has not done for all medical image segmentation	In future performance can be validated for other medical classification like liver tumor, lung cancer
D. Yuvaraj et.al [95]	Finding out abnormal tissues in the brain	Multi-perspective scaling-CNN	Convolutional layer	Self-acquired	Accuracy = 90.42	Stability is not generalized	By adding an optimization model Generalized model can be achieved

Table 4 Related work for brain tumor classification

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
O Fasihi Shirehjini [26]	Grading of tumors	Convolutional neural network	Convolutional layer	Self-acquired dataset of 1061 images	Accuracy = 99.38%	To develop glioma grading systems	Incorporating high end computing device
Tiejun Yang et. al. [94]	To classify MRI image voxel into normal brain tissues and in various parts of the tumor	Small kernel two-path CNN and Random Forest	Convolutional layer	BRATS2015 Database with image block 33 × 33 training and with size 25 × 25 and 41 × 41 for comparison.	Increase classification accuracy and reduces redundancy	Segmentation was not performed on the lesion dataset	Using proper structure and well-trained dataset lesion segmentation can be possible
R. Thillaikarasi and S. Saravanan [86]	To classify Benign and Malignant tumors	Kernel-based CNN, M-SVM	Convolutional layer	MRI images with 15 normal and 10 abnormal as test cases and for training 9 normal and 6 abnormal	Accuracy = 84%	All parameters for the result are calculated with a very less dataset.	The addition of a large number of the dataset will provide realistic results
Mohamed A. Naser a and M. Jamal Deen [57]	To classify Benign and Malignant tumors	U-Net, Deep Neural Network	Convolutional layer	MRI images with 110 patients' data	For MRI Image level Accuracy = 0.89 Sensitivity = 0.87 Specificity = 0.92 For Patient level Accuracy = 0.95, Sensitivity = 0.97, Specificity = 0.98	Data used for LGG validation are small And for testing only the dependent dataset is available only	Cross-validation approach can solve the problem and performance can be increased

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
T. Ruba et.al [70]	Classification of brain tumor	Local symmetry inter sign, Deep neural network, 3 D U-net	Convolutional layer	BRATS2015 Dataset with 210 training data, 29 validation data and 96 testing data.	DC- complete=0.9147, Core=0.86, Enhanced=0.831 PPV- complete=0.9261, Core=0.86, Enhanced=0.831 Sensitivity- complete=0.9014, Core=0.8450, Enhanced=0.8394	Segmentation is limited to HGG images	By changing the algorithm and flow of the method segmentation is possible for LGG images
Tongxue Zhou et.al [96]	Classification of tumor	Deep neural network, Encoder, U-net	Convolutional layer	BRATS 2018 database with 285 ground truth cases	Average dice score of WHOLE TUMOE = 82.9 TC = 74.9 ET = 59.1	The analysis is only with multi-MR modalities; the public brain tumor dataset is used for the classification	Expansion with multimodal segmentation problem
Mostefa Ben naceur et.al [60]	Classification of Glioblastomas	Deep neural network, CNN	Convolutional layer	BRATS 2017 with 11 tumor regions	Average dice score = 0.88	Results are with multiclassification	Changing of classification from multi to binary we can get 2 outputs instead of 4
G. Neelima et.al [61]	Categorizing of brain tumor tissues	Sailfish optimization algorithm, Sailfish political optimizer, Political optimizer, Generative Adversal network, CNN	Convolutional layer	BRATS 2018 with 30 patient brain images	Elevated Accuracy = 91.7% Segmentation accuracy = 90.0% Sensitivity = 92.8% Specificity = 92.5%	With the present dataset reliability validation is not performed.	By adding dataset reliability can be validated

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
M.O. Khairandish et al. [39]	To classify Benign and Malignant tumors	Hybrid CNN-SVM	Convolution layer	BRATS 2015 database with 110 training cases and 220 testing cases	Accuracy = 98.4959%	The focus must be on exact location and size of the tumor	Using novel optimization methods for improving the efficiency of the hybrid model
Yanming sun and Chunyan Wang [81]	To classify pixels for mono modality and cross-modality for tumor localization	Application specific CNN	Convolution layer	BRATS2018 database with 285 patient cases, 75 training, and 56 testing cases	Reproducibility-Enhancing tumor = 77.2%, whole tumor = 89.2% for tumor core = 76.3%	Functions with only 2D slice and training quality are affected because of restricted information in training tasters	Using CNN of 3D slice to improve quality and quantity in training data
P. Takacs et. al. [83]	Classification of potential tumors with multiple MRI sensory	Deep learning with salient handcrafted model	Convolution layer	BRATS2015 and BRATS2018 with training and testing on 28 brain images	High performance in segmentation with retained network capacity increased by 8%	Post-training data generates time complexity as pseudo-color saliency map is not implanted in the network model	Fixing with Pseudo color saliency map in the network model will result in the training of data itself
Suchismita Das et.al [79]	Classification of brain lesion	CNN, encoder-decoder, transfer learning and hybrid DL	Convolution layer	BRATS database with 75 studies in BLS	For all attributes Bias cutoff = 1.0	CNN, ED, TL, HDL needs more inner analysis of Risk of bias	The BTS technique can be extended by using big data to improve general performance and validation

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Dhiraj Maji et.al [52]	Classification of brain tumors	Generator architecture with guided decoder	Guided decoder	BRATS 2019 data set with training set 4700 images, validation set 775 images and testing set 1000 images	Dice score for whole tumor = 0.911, tumor core = 0.876, enhancing tumor = 0.801. Mean Intersection over union for whole tumor = 0.838, tumor core = 0.781, enhancing tumor = 0.668 DCS = 89.76 Sensitivity = 89.19 PPV = 90.65	High-time complexity, Heavyweight computation, not suitable for 3D MRI input	Time complexity can be reduced by adding memory requirement
Motahareh Aghalari et.al [3]	Classification of Glioma brain tumors	U-Net based architecture	Residual U-Net	BRATS2018	DCS = 89.76 Sensitivity = 89.19 PPV = 90.65	Skill-stripped MRI images are not considered	Analysis of deep neural networks can be used for proper structure design
Mohammad Aminian & Hassan Khotanlou [7]	Classification of Glioma	Capsnet with Inhomogeneous voxel technique	Convolutional layer	BRATS2015 and BRATS2013 database	Dice similarity for the whole tumor = 0.90 and for entire tumor = 0.88	Conversion of MRI into voxel and reconstruction results in high time complexity. And because of data loss in MRI creates more false rate	The false rate can be reduced by adding a post-processing module and modification in a deep neural network by using vector space performance can be better
Pin Tang et.al [84]	Classification of Head and neck tumor	Dual attention-based dense SU-net, encoder, decoder	Convolutional layer	In-house MRI images of 95 patients' data.	Dice similarity coefficient = 0.8050 prevent match = 0.8026 correspondence ratio = 0.7065	Training samples are limited processed with only 2D	Using multimodal concept result in better segmentation

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Jingjing Wang et.al [89]	Classification of enhancing tumor, whole tumor, and tumor core	Dilated Feature pyramid-ResU-net, CNN with pyramid feature	Convolutional layer	BRATS 2018 and BRATS 2019	For 2018 mean dice score of Enhancing tumor = 0.8431 Whole tumor = 0.897 Tumor core = 0.9068 For 2019 Enhancing tumor = 0.7985 Whole tumor = 0.90281 Tumor core = 0.8453	Performance in the WT region is not satisfactory	Network post-processing can overcome limitations of WT region performance
A. Srinivasa Reddy [78]	Classification of tumor in MRI	CNN, Modified spider optimization-CNN	Convolutional layer	MRI images database with 500 images of 250 training and 250 validation set	Accuracy = 1 Sensitivity = 0.99 Specificity = 0.99	Less optimization	By determining weight values of CNN better optimization. Can possible
Adam Budai et.al [11]	Classification of right and left ventricle classification	The deep learning algorithm, Cardiac magnetic resonance imaging	Convolutional layer	ACDC dataset with 5570 patients	Average dice index for left endocardium = 0.927 Right endocardium: 0.873	Results are less accurate in basal and apical regions	Acquiring techniques to handle different data generations
Thuy Xuan Pham et.al [65]	Classification of abnormal brain tissues with fuzzy clustering	Kernelized fuzzy entropy clustering with local spatial information and bias correction with PSO	Convolutional layer	Simulated and real time brain images	Jaccard Index = 0.90% Hausdorff distance = 46.80%	Performance of the method may decrease when high-level noise is added to image	By using a multi-objective optimization algorithm

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Siyu Xiong et.al [93]	Classification of brain tumor	Field programmable gate way neural network	Convolutional layer	BRATS2019 and BRATS2020	Performance 5.21 faster than CPU and 44.47 than GPU Energy efficiency ratio = 11.22 greater than GPU 82.63 greater than CPU	Computational-ly not efficient	By using sparse characteristics of the input image in an algorithm or in the hardware we can save the time of computation
Zhiyong Xiao et. al. [91]	Classification of tumor tissues	U-net, Multi view hierarchical -net	Convolutional layer	BRATS 2018	Dice score for WHOLE TUMOE = 89.55 ET = 85.24 TC = 80.22 Hausdorff distance WHOLE TUMOE = 2.32 ET = 5.21 TC = 5.71	Redundancy in feature of 3D images	Training of MVHS network with deep learning
Hao Gong et. al. [30]	Classification of multiple spinal structures	ResAttenGAN, Adversal learning module, residual refinement attention module	Full-feature fusion module	169 T2-weighted MRI images with 62 clinical patients 38 male and 24 female	Mean IOU = 89.2% + -1.8% Positive predictive value = 94.2% + -2.3% Specificity = 94.4 + -2.4%	Reliability is poor as fewer MRI images are collected	Collection of more MRI images for high reliability
Yujian Liu et. al. [47]	Classification of tumor tissues	Metric U-net	Super Voxel-level feature	BRATS2019	Dice score TC = 3.38% ET = 3.82%	Work with only 2D images.	By using volumetric data technique can be used with 3D images

Table 4 (continued)

Author	Related research work	Name of model used	Feature extraction method	Dataset used	Result	Research gap	Future work
Jindong Sun et. al. [82]	Classification of brain tissues	3D FCN	Convolutional layer	BRATS 2018 and Brats2019	Dice similarity coefficient Complete Core Enhanced	Not Defined	An application can be used with current medical technologies
Xinheng Wu et. al. [92]	Non-linear mapping of left and right brain images	SD-GAN	Convolutional layer	BRATS 2012 and 2018	Dice score is less than 3% than supervised U-net	As working with asymmetric region so result is not accurate with symmetric region of Brain	By using post processing with unsupervised learning algorithm

Table 5 Results comparison of segmentation methods based on datasets

Datasets	Approaches used	Results
Figshare and Harvard	Gaussian Filter (GF), and SynthStrip [59]	99.8% accuracy, 99.3% recall, 99.4% precision, 99.5% F1 score, and 0.989 AUC
BraTS2015, BraTS2018, BraTS2019, BraTS2020, and BraTS2021	Deep multimodal network [48] U-Net Architecture [72]	Dice similarity coefficient (DSC) is 0.800, 0.930, and 0.857 Test accuracy of 99.4%
	Deep hybrid representation learning [25]	98.81% pixel-level and 98.93% classification accuracy
	3D convolutional neural network with 3D multi-branch attention – MBANet [12]	Dice coefficient (DC) of ET, WT and TC reach 80.18%, 89.80%, 85.47% and 78.21%, 89.79%, 83.04%
	Deep residual network and U-Net model (dResU-Net) [69]	Dice score on the BraTS 2020 dataset of 0.8357, 0.8660, and 0.8004, dice scores on the external cohort are 0.8400, 0.8601, and 0.8221 for BraTS 2021
	Automatic weighted dilated convolutional network (AD-Net) [64]	Dice scores of 0.90, 0.80, and 0.76
	Multi-input Unet model [24]	Precision of 0.92 and 0.90
	JGate-AttResUNet network [71]	Dice values of 0.896 and 0.913
	ADHDC-Net [49]	Dice coefficients of 77.91%, 89.94%, and 83.89%
	DPAFNet [13]	Dice score of 79.5%, 90.0% and 83.9% on BraTS2018 and Dice score of 78.2%, 89.0% and 81.2% on BraTS2019
	2D U-net architecture [58]	Accuracy of 99.41% and dice similarity coefficient (DSC) of 93%
Publicly available dataset created by Cheng et al.	Deep convolution neural network (DCNN), named the Edge U-Net model [28]	Dice scores of 88.8% for meningioma, 91.76% for glioma, and 87.28% for pituitary tumors.
The Kaggle LGG dataset	ResUnet [43]	Dice coefficient of 0.9056 and a Jaccard index/ IOU of 0.8293
Clinical BT datasets (Bakas et al., 2019, Bakas et al., 2017, Clark et al., 2013, Menze et al., 2015, Schmainda and Prah, 2019)	MDFU-Net [80]	DC of 82.96%, IoU of 74.94%, Specificity of 99.89%, and Sensitivity of 68.05%
MSCOCO dataset	‘You Only Look Once’ v3 (YOLOv3) [37]	Average precision of 94.14%, a precision of 91.34%, recall of 90.58%, and an F1-Score of 92.55%

Table 6 Results comparison of classification methods based on datasets

Datasets	Approaches used	Results
BMIBT dataset	Res-Net 50 [44]	Classification accuracy of 99.30 and 98.40%
Brats-large-2c, Brats-small-2c, and Brats-large-4c datasets, Cheng dataset, BraTS2015, BraTS2017, BraTS2019	PCANet [73] Hybrid DCNN-DH [40]	An average accuracy of 0.99% Accuracy (99.8%), sensitivity (98.1%), specificity (99.6%), precision (97.4%), and F-measure (98.6%)
https://www.kaggle.com/datasets/sartajbhuwaji/brain-tumor-classification-mri	Hierarchical Residual VGGNet19 (HR-VGGNet19) [41]	Accuracy of 99.4%
https://www.kaggle.com/jarvisgroot/brain-tumor-classification-mri-images	Deep learning-based ResNet architecture [54]	Accuracy of 0.98694
Binary tumor identification dataset-I, Figshare dataset-II, and Multiclass Kaggle dataset-III	Parallel deep convolutional neural network (PDCNN) [66]	Accuracy of 97.33%, 97.60%, and 98.12%
Figshare dataset	Deep learning model [1] EfficientNetB2 [97]	Classification accuracy of 98.95% Accuracy, precision, recall/sensitivity, and F1-score of 98.86%, 98.65%, 98.77%, and 98.71%
MRI images with 3064, 3264, and 4292 were used	Deep Convolutional Neural Networks (CNN) [8]	Average accuracy of 99.13%
BRATS 2018 and Figshare dataset	FASMO-based SqueezeNet [62]	92.2% testing accuracy, 94.3% sensitivity, 90.8% specificity and 0.089 prediction error.
Self-acquired dataset of 1000 images	An automatic optimized hybrid deep neural network (OHDNN) [74]	Average accuracy of 97.5%
Self-acquired dataset	Graph Attention AutoEncoder-Convolution Neural Network (GATE-CNN) [56]	Accuracy of 98.27% for first dataset, 99.83% for second dataset, and 98.78% for third dataset

having a very deep network, which learns through several phases and does have the ability to solve critical tasks like MRI segmentation and classification. It has been seen from the survey that using deep learning models gives more accurate results when compared to traditional methods and algorithms. The CNN network consists of a stack of layers like convolution, pooling, and fully connected layers with various hyperparameters like learning rate, epoch, activation, loss function, etc. The most important factor affecting the deep learning models are learning rate and momentum. More often the value of the learning rate lies between 0.01 to 0.03 and 0.001 to 0.003 and the value of momentum has been selected to 0.9 usually. The other parameters like batch size (varies), weight decay (varies), and dropout (0.3) are also important for any deep learning model. Having a combination of a perfect number of layers while selecting appropriate values of hyperparameters of models, makes them expedient to accomplish such a complicated job [85].

When compared with traditional approaches, the deep learning consortium still needs to formulate mechanisms in lowering the computational cost, processing time, resources, interpretability, and understandability [68, 85]. The potential of deep learning models is still to be explored, especially when there is variability in the resolution and intensity of the acquired images [85]. Therefore, a significant study has to be put forward in selecting the convolutions. Also, with the use of SGD variants, Fast Fourier Transform algorithms, and quicker matrix multiplication the computational speed of deep models can be enhanced [85]. One of the possible solutions to enhance the performance of deep learning models is to introduce cascade and two-pathway networks. In the first, the dependency of labeling of pixels is taken into consideration, where two CNN models are stacked in which the segmented image as an output of one CNN becomes the input to the other. Wherein the two-pathway the local and global contextual features are modeled simultaneously [2, 68, 85, 87]. Further Table 7. presents pros and cons of some methods.

5.2 Dataset

The other and most vital fact related to the automaton in the segmentation and classification of MRI images is the dataset. The impact of selecting in the database is directly proportional to the performance of the model. Appropriate, non-redundant, conservative data is the first step in selecting the model. There is a number of publicly available databases like Brain Web, Internet Brain Segmentation Repository (IBSR), Brain Tumor Segmentation (BRATS), MIDAS, openfMRI (a project which collaborates databases) [35], Open Access Series of Imaging Studies (OASIS), Kennedy Krieger Institute database, Center

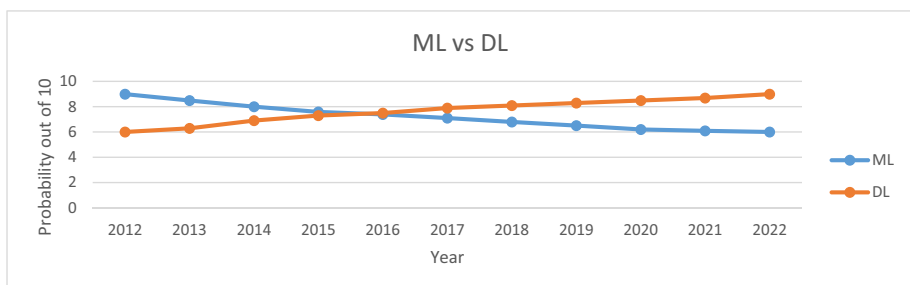


Fig. 6 Comparison between ML and DL

Table 7 Pros and Cons of some methods

S. no.	Method name	Pros	Cons
1	Two-path CNN and Random forest	Method is effective with non-linear data. Little chance of over-fitting. Operates effectively on a huge dataset. Superior than other categorization algorithms in accuracy	It has been discovered that when dealing with categorical variables, random forests are biased. Slow Training For linear approaches with a lot of sparse features, it is not appropriate
2	U-Net Model	The U-Net approach has various benefits for segmentation tasks, starting with the simultaneous use of global location and context. Second, it performs better for segmentation tasks even with a small number of training examples	Due to the skip connections and additional layers in the growing path, U Net includes numerous parameters. This could increase the likelihood of the model overfitting, especially when using limited datasets
3	SVM	In situations where there are more dimensions than samples, SVM is successful Memory efficient	There is no probabilistic justification for the classification because the support vector classifier works by placing data points above and below the classifying hyperplane Performance is poor when the data set has added noise Not applicable in real CT clinical cases.
4	3D densely connected U-net	Maintain low-level traits and yield useful outcomes	When clusters fluctuate in size and density, k-means has problems clustering the data.
5	K-Means	broadens to include clusters of various sizes and shapes, such as elliptical clusters. Easily implement with large dataset	Problem of multi-objective and practical optimization
6	Sailfish Optimization algorithm	Creating the swarm variety, avoiding local optima, ensuring high convergence speed, and ensuring a dynamic balance between the exploration and exploitation phases are all achieved using a straightforward method	
7	Hybrid CNN	Dual-channel data input is used by HYBRID-CNN to extract useful features from 1D and 2D flow data, fuse important features using the self-attention process, and then perform detection using a fully connected neural network	Optimal number of clusters are not known. Hybrid CNN architecture is complicated
8	R-CNN	It generates area proposals using a novel region proposal network (RPN). It extracts a fixed-length feature vector from each region suggestion using the ROI Pooling layer	It is a multi-stage model with independent components at each stage. As a result, it cannot be trained completely. In order to later train the SVMs, it caches the pre-trained CNN's extracted features on disc
9	Alex-net model	Faster training model. It uses 8-layer deeper architecture because of that it gives better performance for feature extraction	Gradient vanishing problem is not solved and model working is complex

Table 7 (continued)

S. no.	Method name	Pros	Cons
10	Capsnet	Retaining geographical information, minimizing feature loss owing to pooling, requiring less training data, and training more quickly	Slow, not suitable for large dataset
11	ResUnet CNN	Improves efficiency with more layers. Training of Deeper network is possible because of the skip connections, which combine the outputs from earlier layers with the outputs of stacked layers	Error detection is tough. Network is Shallow, Learning is ineffective
12	Metric U-net	High accuracy, Adequate to work with inconsistent dataset	Their optimal depth is unknown a priori, necessitating a thorough architecture search or an ineffective ensemble of models with different depths; also, their skip connections impose an unduly constrained fusion technique that limits aggregation to the same size

for Imaging Science are some of them. The most widely used databases in the literature are Brain Web and Internet Brain Segmentation Repository (IBSR). Brain Web: Simulated Brain Database (SBD) is available free for educational purposes. The database contains realistic MRI data volumes that are produced by an MRI simulator and available in 2 categories (i) Normal Brain (ii) MS Lesion Brain Database. The SBD was generated using different parameters like 1. Pulse sequence as in the ICBM {T1, T2, PD} template of custom simulations 2. Noise as the reference tissue for the noise computation: White Matter (WM) for T1 and Cerebrospinal fluid (CSF) for T2 and PD images. 3. Intensity Non-Uniformity (INU) as the field A was used for T1 images, field B for T2 images, and field C for PD images. The Internet Brain Segmentation Repository (IBSR): is a freely available database for non-commercial research use for MRI brain image segmentation. Supported by the NIH under Grant number 1 R01 NS34189–01 from the National Institute of Neurological Disorders and Stroke (NINDS), IBSR consists of images for different subjects, like an Adult Male and 5-year-old Child: T1-weighted MRI data with complete expert segmentations, 20 Normal Subjects: T1-weighted MRI data with gray/white/other expert segmentations (3.1 mm slice thickness), 2 Tumor patients: various scans over time, 18 Scans: T1-weighted MRI data with expert segmentations of 43 individual structures (1.5 mm slice thickness), Registered multi-echo scans. Further, some of the datasets are given by Table 8.

5.3 Evaluation parameters

Finally, evaluation parameters are the basis to authenticate the accuracy of the method. Manual interpretation of the segmentation outcomes is a time-consuming task. There are a number of evaluation parameters used to verify the segmentation results automatically. Amongst the following parameters Dice Similarity coefficient (DSC), Jaccard Similarity (JS), Specificity, Sensitivity, and Accuracy are the most common ones. DSC provides a measure of the degree of overlap between two segmentations if R and S are images where R=segmenting contour and S=ground truth resulting from manual segmentation. If DSC=1 perfect segmentation, DSC=0 imperfect segmentation results. JS is used to compare the similarity and diversity of image given by an intersection to the union, JS generally lies between 0 and 1. A higher JS value better segmentation results. Specificity, Sensitivity, and Accuracy are used to verify the quality of segmented images. This is done on the basis of ground truth image and segmented image. Based upon TP=True Positive is the exact classification, TN=True Negative is the exact misclassification, FP=False positive is misclassification, and FN=False Negative is region misclassified. Specificity defines the competence of an algorithm to segment the normal regions present in the input image, which lies between 0 and 1, a segmented value near 1 shows better segmentation. Sensitivity values define the proper classification or segmentation of the input image, lie between 0 and 1, and a segmented value near 1 shows better segmentation. Accuracy is an evaluation parameter used to assess the efficacy of the segmentation algorithm, lies between 0 and 1, and a segmented value near 1 shows better segmentation [16, 17, 19, 76, 77]. Some of the commonly used mathematical equation for evaluation parameters are:

$$\text{Dice Similarity Coefficient (DSC)} = D(R, S) = \frac{2 |R \cap S|}{|R| + |S|} \quad (1)$$

Table 8 Data set details

Dataset name	Description	Available at
Brain Web { Simulated Brain Database (SBD) } (https://www.mcgill.ca/bic) [45]	Available free for educational purposes. Contain realistic MRI data Available in 2 categories • Normal Brain • MS lesion brain database SBD is still considered “ <i>under development</i> ”, both in terms of the anatomical model and the simulation itself.	https://www.mcgill.ca/bic & https://brainweb.bic.mni.mcgill.ca/ & https://brainwebskills.in/
Internet Brain Segmentation Repository { IBSR }	Available free for non-commercial research provides manually-guided expert segmentation results along with magnetic resonance brain image data. The purpose is to encourage the evaluation and development of segmentation methods. This data set includes 1.5 mm data. Eighteen subjects aged 7–71 are currently available.	https://www.nitrc.org/projects/ibsr & https://scholarship.miami.edu/esploro/outputs/dataset/Internet-Brain-Segmentation-Repository-IBSR-15mm/991031560233802976
Brain tumor segmentation	Medical image analysis task that involves the separation of brain tumors from normal brain tissue in magnetic resonance imaging (MRI) scans. In brain tumor segmentation, region growing, and clustering algorithms are the most commonly used region-based segmentation technique. The goal of brain tumor segmentation is to produce a binary or multi-class segmentation map that accurately reflects the location and extent of the tumor.	https://paperswithcode.com/task/brain-tumor-segmentation#:~:text=Brain%20Tumor%20Segmentation%20is%20a,resonance%20imaging%20(MRI)%20scans.

Table 8 (continued)

Dataset name	Description	Available at
BRATS [9, 10, 55]	In the realm of medical image analysis, the Brain Tumor Segmentation (BrATS) dataset is a frequently used benchmark dataset. It includes segmented MRI scans of the brain with related tumors. The dataset is divided into four tumor sub-regions: necrotic core, non-enhancing tumor, enhancing tumor and edema. The BrATS dataset offers specialists and academics a standardized dataset to create and test brain tumor segmentation algorithms. It has advanced the creation of automatic tumor detection, classification, and treatment planning techniques. A variety of MRI modalities, including T1-weighted, T1-weighted contrast-enhanced, T2-weighted, and fluid-attenuated inversion recovery (FLAIR) images, are included in the collection, which is made up of scans obtained from numerous centers. Each image comes with manual segmentations done by professionals to identify the tumor locations. The performance of different methods is assessed using metrics like Dice similarity coefficient (DSC), sensitivity, specificity and Hausdorff distance. This dataset can be used by researchers and clinicians to enhance brain tumor patient diagnosis and treatment planning.	https://www.smir.ch/BRATS/Start2013 https://www.med.upenn.edu/cbica/brats2020/data.html
MIDAS openfMRI [35]	OpenfMRI database (Poldrack et al. 2013; Poldrack & Gorewolski 2015) is a repository of human brain imaging data collected using MRI and EEG techniques. Data deposited in OpenfMRI can be used to address or validate many questions concerning the human brain structure and function. OpenfMRI has also been listed as a recommended repository by some academic journals such as Nature Scientific Data, PloS One, and F1000Research.	https://openfmri.org/dataset/ & https://openfmri.org/ & https://www.aylward.org/notes/open-access-medical-image-repositories

Table 8 (continued)

Dataset name	Description	Available at
Open access series of imaging studies	Open Access Series of Imaging Studies (OASIS) is a project aimed at making neuroimaging data sets of the brain freely available to the scientific community. The present MRI data set consists of a longitudinal collection of 150 subjects aged 60 to 96 all acquired on the same scanner using identical sequences.	https://www.oasis-brains.org/ & https://dash.harvard.edu/bitstream/handle/1/33896768/Buckner_OpenAccess.pdf?sessionid=8E41DD0A0D4CB31F83EA3BD60311EC8B?sequence=2
Kennedy kriegler institute database	It is a public <i>database</i> , open to registered users. Its purpose is to facilitate research in <i>DTI data</i> processing and analysis, to study specific biological	https://www.kennedykrieger.org/national-resource-for-quantitative-functional-mri/databases
Center for imaging science	Center for Imaging Science (CIS) sits at the intersection of mathematics, computer science, biomedical engineering, and electrical engineering. Its members are developing tools to extract patterns and meaning from various types of large-scale datasets, and are applying this knowledge to guide new advances in facial recognition software, vision-based navigation systems for robots and self-driving cars, disease diagnosis and treatment, and more. Using mathematical and computational approaches, CIS researchers are pioneering new discoveries in four major areas: medical image analysis, computer vision, computational biology, and statistical learning.	https://www.cis.jhu.edu/ & https://www.rit.edu/science/chester-f-carlson-center-imaging-science

Provides a measure of degree of overlap between two segmentations, if R and S are images where R =segmenting contour and S =ground truth resulted from manual segmentation.

$$\text{Jaccard similarity (JS) or Jaccard coefficient (JC)} = J(R, S) = \frac{|R \cap S|}{|R \cup S|} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3)$$

$$\text{Sensitivity or Recall} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6)$$

5.4 Future research directions

Nowadays, with the availability of high computing devices and accessibility of the large volume database, the research has been directed towards the implication of deep models for attaining higher accuracy. This has uplifted the interest of academicians and researchers in developing and experimenting with newer deep-learning models. Also, the processes including semantic segmentation, instance segmentation, and panoptic segmentation help in a better understanding of the region of interest. Some of the possible future work the researchers could direct their work includes [6, 42, 50]:

- (i) For the comprehensive understanding of the MRI images one can adopt the process of panoptic segmentation. It contributes the features of both semantic and instance segmentation. Certainly, a more detailed and accuracy can be achieved.
- (ii) Evolutionary optimization algorithms play a vital role in the fine-tuning of hyper-parameters for a deep learning model. This hybridization model reduces the computational efforts.
- (iii) Further, the researchers can also focus on task that involves segmentation with less supervision, neural network search-based segmentation including domain knowledge i.e., tumor morphology and tumor degree, and protecting patients' privacy is an essential.
- (iv) Brain tumor grade classification helps in diagnosing the severity of them, a deep learning model-based CAD system will be helpful.
- (v) Use of second order optimization approaches can be also useful in enhancing the performance of deep models for detecting and classifying tumors with higher accuracy.
- (vi) 3D volumetric dataset and other measures of data acquisition process like scanners should be incorporated.

- (vii) Lightweighted approaches such as quantum machine learning can be very useful in order to reduce the computational time and cost.

6 Conclusion

In the last decade, a lot of research has been directed toward introducing various new concepts and theories towards the segmentation and classification of brain tumors from MRI images. Among them, deep learning models have emerged to be the most efficient tool when compared with the other learning algorithms. With an extensive feature of working with complex data and providing high accuracy these models accumulated widespread popularity. Also, with the availability of high-end computing devices supports this learning process. Therefore, in this article, a survey has been carried out in incorporating the literature mainly focusing upon the recent deep learning models used for the purpose of segmentation and classification of brain tumors from MRI images. Though these models achieve higher performance, still there are certain factors toward which future research can be directed, especially the high-performance cost and complexity of the model structures. Finally, for the proposed work we aim to perform instance segmentation to identify tumors using deep learning models like MASKRCNN or UNET.

Author's contributions Author 1 is responsible for the collection of data and literature, Author 2 and Author 3 are engaged in writing the manuscript, preparing figures, and tables, and Author 4 helps with conceptualization and guidance. Authors 2, 3, and 4 review the manuscript.

Data availability Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest On behalf of all the authors corresponding author declares that there is no conflict of interest to disclose.

Ethical approval Ethical approval is not required for this study.

Informed consent Informed consent is not required.

References

1. Aamir M, Rahman Z, Dayo ZA, Abro WA, Irfan Uddin M, Khan I, Imran AS, Ali Z, Ishfaq M, Guan Y, Zhihua H (2022) A deep learning approach for brain tumor classification using MRI images. *Comput Electr Eng* 101:108105, ISSN 0045-7906. <https://doi.org/10.1016/j.compeleceng.2022.108105>
2. Abd-Ellah MK, Awad AI, Khalaf AAM, Hamed HFA (2019) A review on brain tumor diagnosis from MRI images: practical implications, key achievements, and lessons learned. *Magn Reson Imaging* 61:300–318. <https://doi.org/10.1016/j.mri.2019.05.028>
3. Aghalari M, Aghagolzadeh A, Ezoji M (2021) Brain tumor image segmentation via asymmetric/symmetric UNet based on two-pathway-residual blocks. *Biomed Signal Process Control* 69:102841. <https://doi.org/10.1016/j.bspc.2021.102841>

4. Agrawal S et al (2014) A study on fuzzy clustering for magnetic resonance brain image segmentation using soft computing approaches. *Appl Soft Comput* 24:522–533. <https://doi.org/10.1016/j.asoc.2014.08.011>
5. Ahuja S, Panigrahi BK, Gandhi TK (2022) Enhanced performance of Dark-Nets for brain tumor classification and segmentation using colormap-based superpixel techniques. *Mach Learn Appl* 7:100212. <https://doi.org/10.1016/j.mlwa.2021.100212>
6. Amin J, Sharif M, Haldorai A et al (2022) Brain tumor detection and classification using machine learning: a comprehensive survey. *Complex Intell Syst* 8:3161–3183. <https://doi.org/10.1007/s40747-021-00563-y>
7. Aminian M, Khotanlou H (2022) CapsNet-based brain tumor segmentation in multimodal MRI images using inhomogeneous voxels in Del vector domain. *Multimed Tools Appl*. <https://doi.org/10.1007/s11042-022-12403-3>
8. Aurna NF, Yousuf MA, Taher KA, Azad AKM, Moni MA (2022) A classification of MRI brain tumor based on two stage feature level ensemble of deep CNN models. *Comput Biol Med* 146:105539, ISSN 0010-4825. <https://doi.org/10.1016/j.combiomed.2022.105539>
9. Bakas S, Akbari H, Sotiras A, Bilello M, Rozycki M, Kirby JS et al (2017) Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features. *Nat Sci Data* 4:170117. <https://doi.org/10.1038/sdata.2017.117>
10. Bakas S, Reyes M, Jakab A, Bauer S, Rempfler M, Crimi A et al (2018) Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge. *arXiv preprint arXiv:1811.02629*
11. Budai A, Suhai FI, Csorba K, Toth A, Szabo L, Vago H, Merkely B (2020) Fully automatic segmentation of right and left ventricle on short-axis cardiac MRI images. *Comput Med Imaging Graph* 85:101786. <https://doi.org/10.1016/j.compmedimag.2020.101786>
12. Cao Y, Zhou W, Zang M, An D, Feng Y, Bin Y (2023) MBANet: A 3D convolutional neural network with multi-branch attention for brain tumor segmentation from MRI images. *Biomed Signal Process Control* 80(Part 1):104296, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.104296>
13. Chang Y, Zheng S, Sun Y, Zhao M, Yao L, Zhang Y (2023) DPAFNet: a residual dual-path attention-fusion convolutional neural network for multimodal brain tumor segmentation. *Biomed Signal Process Control* 79(Part 1):104037, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.104037>
14. Chattopadhyay A, Maitra M (2022) MRI-based brain tumour image detection using CNN based deep learning method. *Neurosci Inform* 2(4). <https://doi.org/10.1016/j.neuri.2022.100060>
15. Chen Y et al (2016) Non-local-based spatially constrained hierarchical fuzzy C-means method for brain magnetic resonance imaging segmentation. *IET Image Process*. <https://doi.org/10.1049/iet-ipr.2016.0271>
16. Chouhan SS, Koul A, Singh UP (2018) Soft computing approaches for image segmentation: a survey. *Multimed Tools Appl* 77:28483
17. Chouhan SS, Koul A, Singh UP (2019) Image segmentation using computational intelligence techniques: review. *Arch Comput Methods Eng* 26:533–596
18. Chouhan SS, Singh UP, Jain S (2020) Applications of computer vision in plant pathology: a survey. *Arch Computat Methods Eng* 27:611–632. <https://doi.org/10.1007/s11831-019-09324-0>
19. Chouhan SS, Singh UP, Sharma U, Jain S (2021) Leaf disease segmentation and classification of *Jatropha Curcas* L. and *Pongamia Pinnata* L. biofuel plants using computer vision based approaches. *Measurement* 171:108796, ISSN 0263-2241. <https://doi.org/10.1016/j.measurement.2020.108796>
20. Devi CN et al (2015) Neonatal brain MRI segmentation: a review. *Comput Biol Med* 64:163–178. <https://doi.org/10.1016/j.combiomed.2015.06.016>
21. Dhole NV et al (2022) Review of brain tumor detection from MRI images with hybrid approaches. *Multimed Tools Appl* 81:10189–10220. <https://doi.org/10.1007/s11042-022-12162-1>
22. Ding Y, Zhang C, Cao M, Wang Y, Chen D, Zhang N, Qin Z (2021) ToStaGAN: An end-to-end two-stage generative adversarial network for brain tumor segmentation. *Neurocomputing* 462:141–153. <https://doi.org/10.1016/j.neucom.2021.07.066>
23. Fang L, Wang X (2022) Brain tumor segmentation based on the dual-path network of multi-modal MRI images. *Pattern Recogn* 124:108434. <https://doi.org/10.1016/j.patcog.2021.108434>
24. Fang L, Wang X (2023) Multi-input Unet model based on the integrated block and the aggregation connection for MRI brain tumor segmentation. *Biomed Signal Process Control* 79(Part 1):104027, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.104027>
25. Farajzadeh N, Sadeghzadeh N, Hashemzadeh M (2023) Brain tumor segmentation and classification on MRI via deep hybrid representation learning. *Expert Systems with Applications* 224:119963, ISSN 0957-4174. <https://doi.org/10.1016/j.eswa.2023.119963>

26. Fasihi Shirehjini O, Mofrad FB, Shahmohammadi M et al (2023) Grading of gliomas using transfer learning on MRI images. *Magn Reson Mater Phy* 36:43–53. <https://doi.org/10.1007/s10334-022-01046-y>
27. Feng Y et al (2016) Segmentation fusion based on neighboring information for MR brain images. *Multimed Tools Appl*. <https://doi.org/10.1007/s11042-016-4098-3>
28. Gab AM, Allah AM, Sarhan NM, Elshennawy E (2023) U-Net: Brain tumor segmentation using MRI based on deep U-Net model with boundary information. *Exp Syst Appl* 213(Part A):118833, ISSN 0957-4174. <https://doi.org/10.1016/j.eswa.2022.118833>
29. Ghaffari M, Samarasinghe G, Jameson M, Aly F, Holloway L, Chlap P, Koh ES, Sowmya A, Oliver R (2022) Automated post-operative brain tumour segmentation: a deep learning model based on transfer learning from pre-operative images. *Magn Reson Imaging*:28–36. <https://doi.org/10.1016/j.mri.2021.10.012>
30. Gong H, Liu J, Chen B, Li S (2022) ResAttenGAN: simultaneous segmentation of multiple spinal structures on axial lumbar MRI image using residual attention and adversarial learning. *Artif Intell Med* 124:102243. <https://doi.org/10.1016/j.artmed.2022.102243>
31. González S et al (2016) A review on brain structures segmentation in magnetic resonance imaging. *Artif Intell Med* 73:45–69. <https://doi.org/10.1016/j.artmed.2016.09.0010933-3657>
32. Gordillo N et al (2017) State of the art survey on MRI brain tumor segmentation. *Magn Reson Imaging*. <https://doi.org/10.1016/j.mri.2013.05.002>
33. Greve DN, Billot B, Cordero D, Hoopes A, Hoffmann M, Dalca AV, Fischl B, Iglesias JE, Augustinack JC (2021) A deep learning toolbox for automatic segmentation of subcortical limbic structures from MRI images. *NeuroImage* 244. <https://doi.org/10.1016/j.neuroimage.2021.118610>
34. Harish P, Baskar S (2020) MRI based detection and classification of brain tumor using enhanced faster R-CNN and Alex net model. *Mater Today*. <https://doi.org/10.1016/j.matpr.2020.11.495>
35. <http://openfmri.org/dataset/>
36. Huang Z, Zhao Y, Liu Y, Song G (2021) GCAUNet: a group cross-channel attention residual UNet for slice based brain tumor segmentation. *Biomed Signal Process Control* 70:102958. <https://doi.org/10.1016/j.bspc.2021.102958>
37. Kalyani BJD, Meena K, Murali E et al (2023) Analysis of MRI brain tumor images using deep learning techniques. *Soft Comput* 27:7535–7542. <https://doi.org/10.1007/s00500-023-07921-7>
38. Karayegen G, Aksahin MF (2021) Brain tumor prediction on MR images with semantic segmentation by using deep learning network and 3D imaging of tumor region. *Biomed Signal Process Control* 66:102458. <https://doi.org/10.1016/j.bspc.2021.102458>
39. Khairandish MO, Sharma M, Jain V, Chatterjee JM, Jhanjhi NZ (2021) A hybrid CNN-SVM threshold segmentation approach for tumor detection and classification of MRI brain images. *IRBM*. <https://doi.org/10.1016/j.irbm.2021.06.003>
40. Kishanrao SA, Jondhale KC (2023) An improved grade based MRI brain tumor classification using hybrid DCNN-DH framework. *Biomed Signal Process Control* 85:104973, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2023.104973>
41. Krishna PR, Prasad VVKDV, Battula TK (2023) Optimization empowered hierarchical residual VGGNet19 network for multi-class brain tumour classification. *Multimed Tools Appl* 82:16691–16716. <https://doi.org/10.1007/s11042-022-13994-7>
42. Krishnapriya S, Karuna Y (2023) A survey of deep learning for MRI brain tumor segmentation methods: trends, challenges, and future directions. *Health Technol* 13:181–201. <https://doi.org/10.1007/s12553-023-00737-3>
43. Kumar PS, Sakthivel VP, Raju M, Sathya PD (2023) Brain tumor segmentation of the FLAIR MRI images using novel ResUnet. *Biomed Signal Process Control* 82:104586, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2023.104586>
44. Kumar S, Choudhary S, Jain A et al (2023) Brain tumor classification using deep neural network and transfer learning. *Brain Topogr* 36:305–318. <https://doi.org/10.1007/s10548-023-00953-0>
45. Kwan RK-S, Evans AC, Pike GB (1999) MRI simulation-based evaluation of image-processing and classification methods. *IEEE Trans Med Imaging* 18(11):1085–1097
46. Lemay A, Gros C, Zhuo Z, Zhang J, Duan Y, Cohen-Adad J, Liu Y (2021) Automatic multiclass intramedullary spinal cord tumor segmentation on MRI with deep learning. *Neuroimage Clin*. <https://doi.org/10.1016/j.nicl.2021.102766>
47. Liu Y, Jie D, Vong C-M, Yue G, Juan Y, Wang Y, Lei B, Wang T (2022) Scale-adaptive super-feature based MetricUNet for brain tumor segmentation. *Biomed Signal Process Control* 73:103442. <https://doi.org/10.1016/j.bspc.2021.103442>

48. Liu Z, Cheng Y, Tan T, Shinichi T (2023) MimicNet: mimicking manual delineation of human expert for brain tumor segmentation from multimodal MRIs. *Appl Soft Comput* 110394. <https://doi.org/10.1016/j.asoc.2023.110394>
49. Liu H, Huo G, Li Q, Guan X, Tseng M-L (2023) Multiscale lightweight 3D segmentation algorithm with attention mechanism: Brain tumor image segmentation. *Expert Syst Appl* 214:119166, ISSN 0957-4174. <https://doi.org/10.1016/j.eswa.2022.119166>
50. Liu Z, Tong L, Chen L et al (2023) Deep learning-based brain tumor segmentation: a survey. *Complex Intell Syst* 9:1001–1026. <https://doi.org/10.1007/s40747-022-00815-5>
51. Louis DN et al (2016) The 2016 World Health Organization classification of tumors of the central nervous system: a summary. *Acta Neuropathol* 131:803–820. <https://doi.org/10.1007/s00401-016-1545-1>
52. Maji D, Sigedat P, Singh M (2022) Attention res-U-Net with guided decoder for semantic segmentation of brain tumors. *Biomed Signal Process Control* 71:103077. <https://doi.org/10.1016/j.bspc.2021.103077>
53. Manoj KC et al (2022) Automated brain tumor malignancy detection via 3D MRI using adaptive-3-D U-Net and heuristic-based deep neural network. *Multimedia Systems*. <https://doi.org/10.1007/s00530-022-00952-4>
54. Mehnatkesh H, Jalali SMJ, Khosravi A, Nahavandi S (2023) An intelligent driven deep residual learning framework for brain tumor classification using MRI images. *Expert Syst Appl* 213(Part C):119087, ISSN 0957-4174. <https://doi.org/10.1016/j.eswa.2022.119087>
55. Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J et al (2015) The multimodal brain tumor image segmentation benchmark (BRATS). *IEEE Trans Med Imaging* 34(10):1993–2024. <https://doi.org/10.1109/TMI.2014.2377694>
56. Mishra L, Verma S (2022) Graph attention autoencoder inspired CNN based brain tumor classification using MRI. *Neurocomputing* 503:236–247. <https://doi.org/10.1016/j.neucom.2022.06.107>
57. Mohamed A, Naser M, Deen J (2020) Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images. *Comput Biol Med* 121. <https://doi.org/10.1016/j.combiomed.2020.103758>
58. Montaha S, Azam S, Rakibul Haque Rafid AKM et al (2023) Brain tumor segmentation from 3D MRI scans using U-net. *SN Comput Sci* 4:386. <https://doi.org/10.1007/s42979-023-01854-6>
59. Mostafa AM, El-Meligy MA, Alkhayyal MA, Alnuaim A, Sharaf M (2023) A framework for brain tumor detection based on segmentation and features fusion using MRI images. *Brain Res* 1806:148300. <https://doi.org/10.1016/j.brainres.2023.148300>
60. Naceur MB, Saouli R, Akil M, Kachouri R (2018) Fully automatic brain tumor segmentation using End-To-End incremental deep neural networks in MRI images. *Comput Methods Prog Biomed* 166:39–49. <https://doi.org/10.1016/j.cmpb.2018.09.007>
61. Neelima G, Chigurukota DR, Maram B, Girirajan B (2022) Optimal DeepMRSeg based tumor segmentation with GAN for brain tumor classification. *Biomed Signal Process Control* 74:103537. <https://doi.org/10.1016/j.bspc.2022.103537>
62. Nirmalapriya G, Agalya V, Rajeshkannan Regunathan M, Ananth BJ (2023) Fractional Aquila spider monkey optimization based deep learning network for classification of brain tumor. *Biomed Signal Process Control* 79(Part 1):104017, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.104017>
63. Panda R et al (2017) An evolutionary gray gradient algorithm for multilevel thresholding of brain MR images using soft computing techniques. *Appl Soft Comput* 50:94–108. <https://doi.org/10.1016/j.asoc.2016.11.011>
64. Peng Y, Sun J (2023) The multimodal MRI brain tumor segmentation based on AD-Net. *Biomed Signal Process Control* 80(Part 2):104336, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.104336>
65. Pham TX, Siarry P, Oulhadj H (2018) Integrating fuzzy entropy clustering with an improved PSO for MRI brain image segmentation. *Appl Soft Comput* 65:230–242. <https://doi.org/10.1016/j.asoc.2018.01.003>
66. Rahman T, Islam MS (2023) MRI brain tumor detection and classification using parallel deep convolutional neural networks. *Meas Sens* 26:100694, ISSN 2665-9174. <https://doi.org/10.1016/j.measen.2023.100694>
67. Ramya P, Thanabal MS, Dharmaraja (2021) Brain tumor segmentation using cluster ensemble and deep super learner for classification of MRI. *J Ambient Intell Human Comput* 12:9939–9952. <https://doi.org/10.1007/s12652-021-03390-8>
68. Rao CS, Karunakara K (2021) A comprehensive review on brain tumor segmentation and classification of MRI images. *Multimed Tools Appl* 80:17611–17643. <https://doi.org/10.1007/s11042-020-10443-1>
69. Raza R, Bajwa UI, Mehmood Y, Anwar MW, Hassan Jamal M (2023) dResU-Net: 3D deep residual U-Net based brain tumor segmentation from multimodal MRI. *Biomed Signal Process Control* 79(Part 1):103861, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2022.103861>

70. Ruba T, Tamilselvi R, Beham Mp (2022) Brain tumor segmentation in multimodal MRI images using novel LSIS operator and deep learning. *J Ambient Intell Human Comput*. <https://doi.org/10.1007/s12652-022-03773-5>
71. Ruba T, Tamilselvi R, Parisa Beham M (2023) Brain tumor segmentation using JGate-AttResUNet – A novel deep learning approach. *Biomed Signal Process Control* 84:104926, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2023.104926>
72. Sangui S, Iqbal T, Chandra PC, Ghosh SK, Ghosh A (2023) 3D MRI segmentation using U-net architecture for the detection of brain tumor. *Proced Comput Sci* 218:542–553, ISSN 1877-0509. <https://doi.org/10.1016/j.procs.2023.01.036>
73. Shahin AI, Aly S, Aly W (2023) A novel multi-class brain tumor classification method based on unsupervised PCANet features. *Neural Comput Appl* 35:11043–11059. <https://doi.org/10.1007/s00521-023-08281-x>
74. Shanthi S, Saradha S, Smitha JA, Prasath N, Anandakumar H (2022) An efficient automatic brain tumor classification using optimized hybrid deep neural network. *Int J Intell Netw* 3:188–196. <https://doi.org/10.1016/j.ijin.2022.11.003>
75. Sharif MI, Li JP, Khan MA, Saleem MA (2020) Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images. *Pattern Recogn Lett* 129:181–189. <https://doi.org/10.1016/j.patrec.2019.11.019>
76. Solanki S, Singh UP, Chouhan SS, Jain S (2023) Brain tumor detection and classification using intelligence techniques: an overview. *IEEE Access* 11:12870–12886. <https://doi.org/10.1109/ACCESS.2023.3242666>
77. Solanki S, Singh UP, Chouhan SS, Jain S (2023) Brain tumour detection and classification by using deep learning classifier. *Int J Intell Syst Appl Eng* 11(2s):279
78. Srinivasa Reddy A (2022) Effective CNN-MSO method for brain tumor detection and segmentation. *Mater Today: Proc* 57(5):1969–1974. <https://doi.org/10.1016/j.matpr.2021.10.145>
79. Suchismita Das GK, Nayak LS, Kalra M, Suri JS, Saxena S (2022) An artificial intelligence framework and its bias for brain tumor segmentation: a narrative review. *Comput Biol Med* 143:105273. <https://doi.org/10.1016/j.compbiomed.2022.105273>
80. Sultan H, Owais M, Nam SH, Haider A, Akram R, Usman M, Park KR (2023) MDFU-net: multiscale dilated features up-sampling network for accurate segmentation of tumor from heterogeneous brain data. *J King Saud Univ Comput Inf Sci* 35(5):101560, ISSN 1319-1578. <https://doi.org/10.1016/j.jksuci.2023.101560>
81. Sun Y, Wang C (2022) A computation-efficient CNN system for high-quality brain tumor segmentation. *Biomedical Signal Processing and Control* 74:103475. <https://doi.org/10.1016/j.bspc.2021.103475>
82. Sun J, Peng Y, Guo Y, Li D (2021) Segmentation of the multimodal brain tumor image used the multipathway architecture method based on 3D FCN. *Neurocomputing* 423:34–45. <https://doi.org/10.1016/j.neucom.2020.10.031>
83. Takacs P, Kovacs L, Manno-Kovacs A (2021) A fusion of salient and convolutional features applying healthy templates for MRI brain tumor segmentation. *Multimed Tools Appl* 80:22533–22550. <https://doi.org/10.1007/s11042-020-09871-w>
84. Tang P, Chen Z, Hong M, Yan R, Peng X, Xiao J, Xi W, Zhou J, Zhou L, Wang Y (2021) DA-DSUnet: dual attention-based dense SU-net for automatic head-and-neck tumor segmentation in MRI images. *Neurocomputing* 435:103–113. <https://doi.org/10.1016/j.neucom.2020.12.085>
85. Thaha MM, Kumar KPM, Murugan BS, Dhanasekaran S, Vijayakarthish P, Selvi AS (2019) Brain tumor segmentation using convolutional neural networks in MRI images. *J Med Syst* 43(9). <https://doi.org/10.1007/s10916-019-1416-0>
86. Thillaikkarasi R, Saravanan S (2019) An enhancement of deep learning algorithm for brain tumor segmentation using kernel based CNN with M-SVM. *J Med Syst* 43(84). <https://doi.org/10.1007/s10916-019-1223-7>
87. Wadhwa A, Bhardwaj A, Verma VS (2019) A review on brain tumor segmentation of MRI images. *Magn Reson Imaging* 61:247–259. <https://doi.org/10.1016/j.mri.2019.05.043>
88. Wahid KA, Ahmed S, He R, van Dijk LV, Teuwen J, McDonald BA, Salama V, Mohamed ASR, Salzillo T, Dede C, Taku N, Lai SY, Fuller CD, Naser MA (2022) Evaluation of deep learning-based multiparametric MRI oropharyngeal primary tumor auto-segmentation and investigation of input channel effects: Results from a prospective imaging registry. *Clin Transl Radiat Oncol* 32:6–14. <https://doi.org/10.1016/j.ctro.2021.10.003>
89. Wang J, Gao J, Ren J, Luan Z, Yu Z, Zhao Y, Zhao Y (2021) DFP-ResUNet: Convolutional neural network with a dilated convolutional feature pyramid for multimodal brain tumor segmentation. *Comput Methods Prog Biomed* 208:106208. <https://doi.org/10.1016/j.cmpb.2021.106208>

90. Weijin X, Yang H, Zhang M, Cao Z, Pan X, Liu W (2022) Brain tumor segmentation with corner attention and high-dimensional perceptual loss. *Biomed Signal Process Control* 73:103438. <https://doi.org/10.1016/j.bspc.2021.103438>
91. Xiao Z, He K, Liu J, Zhang W (2021) Multi-view hierarchical split network for brain tumor segmentation. *Biomed Signal Process Control* 69:102897. <https://doi.org/10.1016/j.bspc.2021.102897>
92. Xinheng W, Bi L, Fulham M, Feng DD, Zhou L, Kim J (2021) Unsupervised brain tumor segmentation using a symmetric-driven adversarial network. *Neurocomputing* 455:242–254. <https://doi.org/10.1016/j.neucom.2021.05.073>
93. Xiong S, Wu G, Fan X et al (2021) MRI-based brain tumor segmentation using FPGA-accelerated neural network. *BMC Bioinformatics* 22. <https://doi.org/10.1186/s12859-021-04347-6>
94. Yang T, Song J, Li L (2019) A deep learning model integrating SK-TPCNN and random forests for brain tumor segmentation in MRI. *Biocybern Biomed Eng* 39(3):613–623. <https://doi.org/10.1016/j.bbe.2019.06.003>
95. Yuvaraj D, Noori SF, Swaminathan S Multi-perspective scaling convolutional neural networks for high-resolution MRI brain image segmentation. *Mater Today*. <https://doi.org/10.1016/j.matpr.2020.12.199>
96. Zhou T, Canu S, Vera P, Ruan S (2021) Feature-enhanced generation and multi-modality fusion based deep neural network for brain tumor segmentation with missing MR modalities. *Neurocomputing* 466:102–112. <https://doi.org/10.1016/j.neucom.2021.09.032>
97. Zulfiqar F, Bajwa UI, Mehmood Y (2023) Multi-class classification of brain tumor types from MR images using EfficientNets. *Biomed Signal Process Control* 84:104777, ISSN 1746-8094. <https://doi.org/10.1016/j.bspc.2023.104777>

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