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Machine Learning-based Brain Tumor Segmentation: A Comprehensive Review

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Abstract

Segmentation of Brain tumors refers to a crucial function in medical image processing. Despite a lot of main attempts and satisfactory results in such a field, appropriate classification and segmentation remain an important function. Segmentation of an image is a hard task in the processing of an image. In order to improve the efficiency of processing, analysis, and detection, hospitals have already begun to use machine learning (ML). To increase the speed of the recovery process started, doctors could get help with detection. In the last few years, techniques of machine learning have illustrated satisfactory performance in solving different issues of computer vision like semantic segmentation, image classification as well as object diagnosis. Several ML-based methods have been successfully applied to the problem of brain tumor segmentation. The present paper shows an overview of recent ML and deep learning techniques to diagnose and group brain illnesses from MRI images. More than 60 scientific studies are chosen and discussed here, covering technical features like network architecture design, and segmentation.

Keywords: Brain tumor segmentation, Classification, Deep learning, Machine Learning, Region Growing.

1. Introduction

The human brain is where all of the body's controls are located, it is the nervous system's important element that contains the spinal cord and wide nerves and neurons system. Everything in the body, from the senses to the muscles, is monitored by the nervous system. A lot of things could go wrong when the brain is damaged such as personality, memory, and sensation. Each ailment/disability influencing your brain is considered a brain disorder. Brain disorders contain each situation/disorder that influences the brain. They contain genetics, diseases, and trauma-related issues. There are various brain diseases' kinds such as brain injuries induced by forceful

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trauma. Brain tissue, nerves as well as neurons could be harmed by trauma [1]. Modalities of Brain imaging like Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) have an important role in brain abnormalities detection. The majority of CNS illnesses can be diagnosed with brain MRI, a noninvasive diagnostic test. General practitioners (GPs) may view the brain in large slices thanks to brain MRI. Magnetic Resonance Imaging (MRI) is the most precise imaging technique for identifying central nervous system (CNS) diseases and providing valuable information to educate patients about the results. Better picture contrast and real-time brain structure recognition during scanning are two advantages of MRI over CT. Medical experts can read medical imaging papers with ease and have a broad interest in them. With its many imaging orders for different purposes, MRI requires more time to become implemented. The diagnosis of appropriate CNS illnesses is mostly dependent on the experience of medical professionals; this could be a labor- and time-intensive procedure [2]. Brain image instances seen by different imaging techniques are shown in Fig 1.

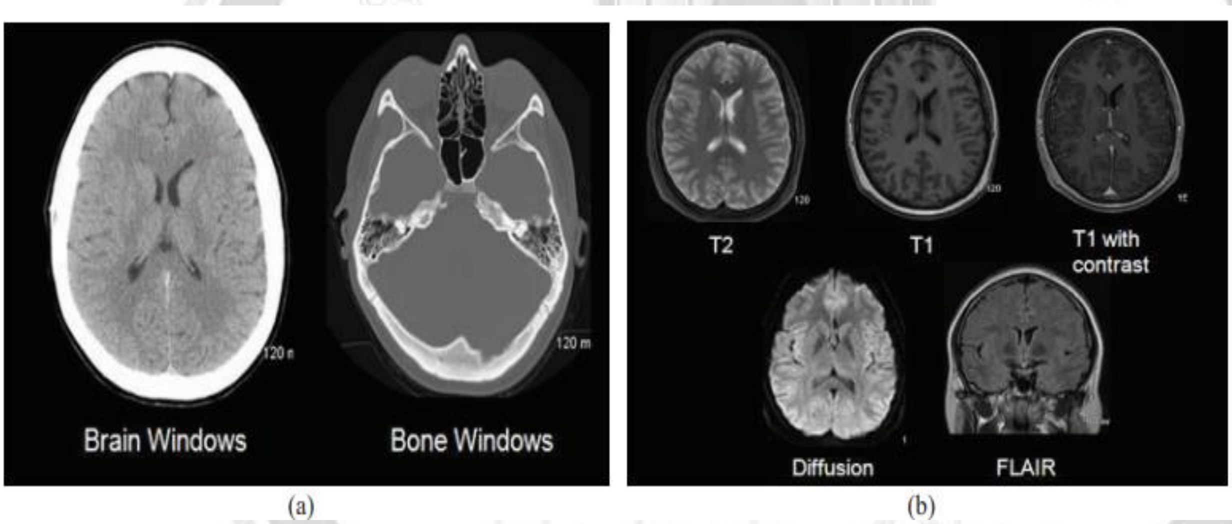

Figure. 1. Brain images' sample created by various methods of imaging. (a) CT, (b) MRI [1].

The underlying cause of tumour formation remains elusive, as there is currently no definitive explanation for its development. Furthermore, there is no morphological structure that can accurately identify the type of tumour and its grade according to the WHO scale. The unpredictable locations, variable size, and unstructured shape of tumours pose a significant challenge for radiologists in detecting them in MR images without the use of technology. Image Segmentation is a machine learning procedure that identifies and isolates a specific Region of Interest (ROI) from an input image. The segmentation process algorithm identifies and groups together similar subjects in a picture. The subject of interest involves two standard algorithms: one for determining the similarity between items and categorising them based on their level of similarity, and another for finding the dissimilarity between objects and separating the most dissimilar ones in space [3]. One of the most significant steps in the process of developing clinical trials, detecting illness, planning therapy, and exercising control is the segmentation of brain tumours using neuroimaging modalities. To diagnose the location and extent of a brain tumor, accurate brain tumor segmentation is required. Nonetheless, certain characteristics of brain tumors make it difficult to categorize them appropriately [4]. These tumors could manifest in any form and size at specific places. Moreover, there could be a convergence between the intensity value of the tumour and the intensity value of normal brain tissue because of their low contrast. Hence, distinguishing between healthy tissue and a tumour is challenging. Typically, to solve such an issue, information required from several MR modalities is combined, like Fluid-Attenuated Inversion Recovery (FLAIR) MRI, T1-weighted MRI (T1), T1-weighted MRI with contrast (T1c), T2-weighted MRI (T2). The present study targets making a full study of various techniques that apply ML and deep learning strategies for aiding in different brain illnesses from MRI and CT images. Although, even literature includes some relevant to MRI, a minimal study exists which takes CT scan brain images into account.

The present study's remaining parts are structured as part 2 defines challenges, data sets and measures of performance, part 3 clarifies brain tumor image segmentation techniques, part 4 displays related work, and part 5 summarizes the present study work.

2. Challenges, Datasets and Performance measures

2.1 Challenges of Brain Tumor Segmentation

Even while brain tumor segmentation has advanced significantly, there are still certain problems that modern deep-learning approaches cannot seem to solve. The following categories would contain the difficulties associated with brain tumor segmentation [5]:

1. **Uncertainty about location**: The gluey cells that envelop nerve cells are the source of glioma mutations. Owing to the extended spatial gluey cell sharing, a brain's locations may exhibit either Low-Grade Glioma (LGG) or High-Grade Glioma (HGG).
2. **Morphological uncertainty:** Differentiating from a rigid item, there is considerable uncertainty regarding the shape and size of different brain tumors. The edema tissues, which compose the outer layer of a brain tumour, exhibit various fluid patterns that do not offer sufficient information to distinguish between different tumour types. Tumour sub-regions can exhibit variations in both size and shape.
3. **Low contrast**: Diverse information is anticipated to be included in photographs with high resolution and strong contrast. An image's projection and the tomography procedure can result in low-contrast and quality MRI pictures. The distinction between biological tissues is sometimes hazy and challenging to make. Accurate segmentation is more difficult to achieve when cells close to the boundary are difficult to group.
4. **Annotation bias:** The definition of annotation bias in data labeling is mostly dependent on individual experience when it comes to manual annotation.
5. **Unbalanced problem**: Different tumor regions have unequal voxel counts. The size of the necrotic/non-enhancing tumour core (NCR/ECT) area is significantly less compared to the other two areas. The issue of imbalance has a negative impact on the data-driven learning technique as it can greatly influence the derived attributes, especially in cases when there are big tumour regions.

6. **Automated Segmentation**: Glioma segmentation by automation is a challenging problem. Brain MRI data containing tumors is three-dimensional information; each patient's tumor may vary greatly in size, shape, and placement. Furthermore, tumor limits are typically ill-defined, irregular, and fraught with difficulties, especially when compared to more established edge-based approaches. Furthermore, brain tumor MRI data either from synthetic databases or clinical scans are intrinsically complex. The MRI equipment and procedures used to obtain results might vary significantly from scan to scan, introducing biases in intensity and other variances for each different image slice in a dataset. Such a problem is further increased by certain modalities' requirements to segment tumor sub-regions efficiently [6].

2.2. Datasets

In recent years, there has been a notable surge in research focused on the automated segmentation of brain tumors. As the study's results kept increasing, it became challenging to evaluate the goals of various algorithms because the investigators used different sets of private data with distinct characteristics. As a result, benchmarking issues like Multi-modal Brain Tumor Segmentation (BraTS) emerged to establish a consistent way of evaluating performance using easily accessible datasets. The summary of frequently used datasets for brain tumor segmentation is shown in Table 1. The BraTS Challenge has been the primary benchmarking source for brain tumor segmentation since the year of 2012, in collaboration with (MICCAI) the International Conference on Medical Image Computing and Computer Assisted Interventions. This provides the use of publicly available data sets from the medical research society for training and validation, as well as the use of standard criteria to objectively evaluate model performance through an online evaluation platform. Although the number of glioma patient scans has grown over the years, the first batch of data only included 30 scans [7–10].

Table 1. Summary of usually applied general data sets for brain tumor segmentation

Name	Total	Training Data	Validation Data	Testing Data
BraTS 2012	50	35	-	15
BraTS 2013	60	35	-	25
BraTS 2014	238	200	-	38
BraTS 2015	253	200	-	53
BraTS 2016	391	200	-	191
BraTS 2017	477	285	46	146
BraTS 2018	542	285	66	191
BraTS 2019	653	335	127	191
BraTS 2020	660	369	125	166
BraTS 2021	2040	1251	219	570
Decathlon [11]	750	484	-	266
FeTS 2021 [12]	447	336	111	-
Masoud 2021 [13]	7023	5712	-	1311
Fshare [14]	3064	-	-	-
Dataset-255 [15]	255	204	-	51

As illustrated in Fig. 2, which displays three separate patients' worth of data, the datasets contain all four modalities for each patient. The datasets contain the following four labels:

• Enhancing Tumor

• Necrosis and Non-enhancing Tumor

• Edema

• Healthy Tissue

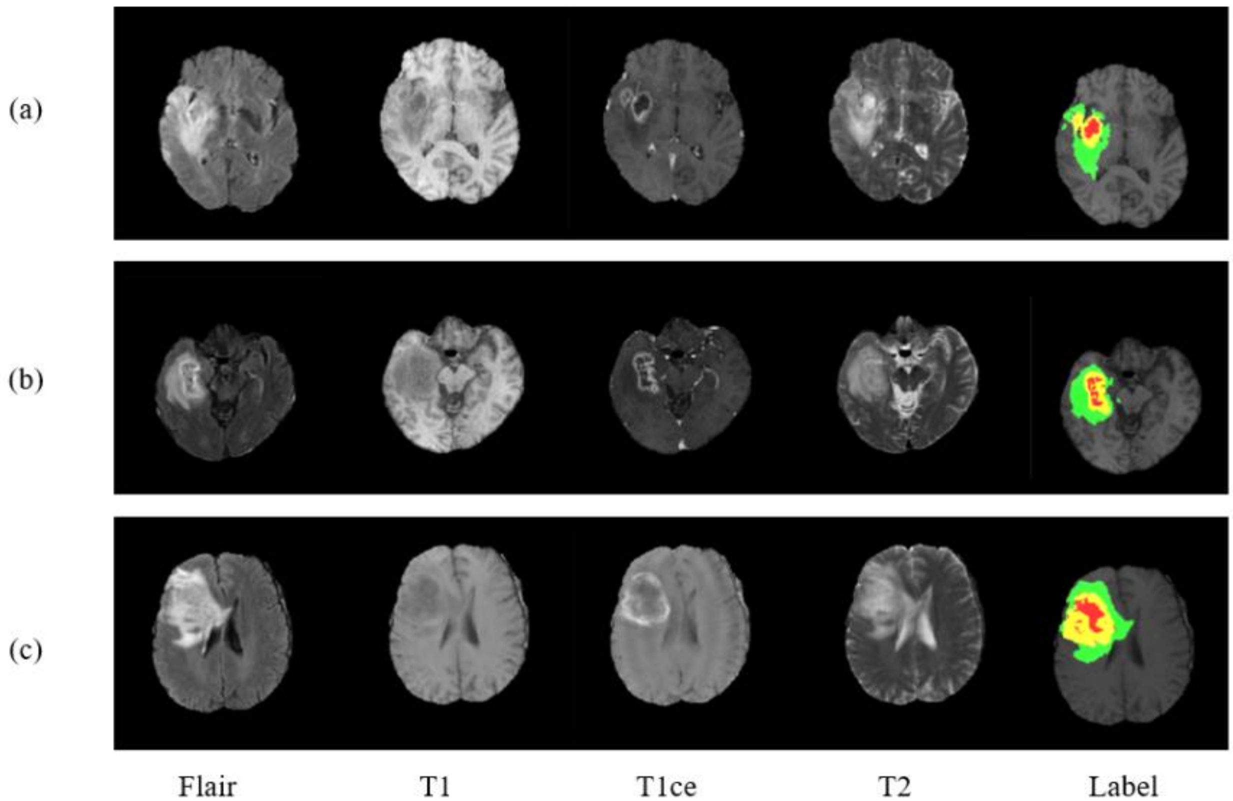

Figure 2 shows four modalities and label plots for three MRI instances (a–c) of brain tumors. These are Flair, T1, T1ce, T2, and Label, going left to right. Each color in the ground truth image corresponds to a distinct tumor class. Edema is shown as green, necrosis and non-enhancing tumors as red, and enhancing tumors as yellow.

2.3 Performance measures

Classification/segmentation approaches' performance evaluation could be acquired by applying various techniques. Investigators use different approaches to validate the achieved results. The most famous and broadly applied performance measures contain Sensitivity (True Positive Rate/Recall), Confusion matrix, Dice Similarity, Specificity, Accuracy as well as Precision. The mentioned variables could be described as a matrix of confusion applied for presenting important info on certain and estimated results made by methods of classification/segmentation. The second table is an example of a 2-level classification function.

Now, False Negative (FN), True Positive (TP), True Negative (TN), and False Positive (FP) are defined below:

TP: accurately grouped/segmented brain tumor.

TN: accurately grouped/segmented of Ordinary tissue as Ordinary tissue.

FN: inappropriately grouped/segmented of certain tumor tissue as Ordinary tissue.

FP: inappropriately grouped/segmented of an ordinary tissue.

Table 2. Classification variables' details for 2 levels.

Category	Estimated Brain tumor	Ordinary tissue
Brain tumor	TP	FN
Ordinary tissue	FP	TN

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

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

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

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

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

3. Methods for Brain Tumor Image Segmentation

Normally, medical images achieved for cancer classification pass via some stages. The presented method includes four basic stages: (i) data preprocessing, (ii) segmenting images using a variety of computer vision and machine learning techniques; (iii) extracting features through the use of two local and global level algorithms; and (iv) classification using multiple strategies based on ML. Fig. 2 displays a standard block diagram that shows the medical data categorization process. The data is typically obtained from pathology laboratories, which contain both healthy subjects and malignant case data. Preprocessing medical images is frequently advised to improve classification accuracy, which reduces errors and overall costs. Other functions are taken into consideration to improve the accuracy and efficacy of the machine learning model after the preprocessing stage. Such operations contain classification, segmentation, and feature extraction. An intentional procedure called "image segmentation" divides the incoming image into discrete pixel groups, making entity identification and analysis simple. Applying techniques of feature extraction will make prominent retrieval features like average/mean, standard deviation, peak signal-to-noise ratio, entropy, and so on. The obtained features include distinct info on images of input. After performing segmentation, investigators used two main methods of grouping medical images: strategies based on (a) ML, and (b) deep learning.

In strategies based on ML, the segmented region is processed using custom feature extraction methods that display feature vectors and preserve their associated labels. To create mathematical models, ML techniques are also used for the aforementioned feature vectors and the associated labels. In the stage of testing to show labels, these models are then utilized to group the unknown image feature vectors. Here, we have focused on research on machine learning and deep learning techniques.

The methods based on Deep learning are not in such study domain. In a wide sense, such a system broadly speaking, classifies cancerous cells into the malignant or benign group according to the cancer component. Machine learning is emerging as a critical method for classifying cancer images, revolutionizing the way medical professionals identify and handle different forms of cancer. Through the application of data and algorithmic analysis, this interprets medical images, simplifying the process of medical assessment, therapeutic planning, and prognosis while achieving significant accuracy and efficacy. Using ML for grouping images of cancer has shown multiple important advantages. Algorithms for ML thrive at controlling wide intricate data quantities such as medical pictures, quickly and accurately. These techniques improve precision by detecting microscopic conditions and models that are difficult for the human eye to see, which benefits radiologists and physicians. Early diagnosis may help increase the likelihood that cancer therapy may have positive results. By using medical imaging to identify distinguishable cancer indicators, machine learning patterns could be trained to diagnose tumors and anomalies early and more effectively. Due to fatigue and inexperience, human mistakes can occur when interpreting medical imaging. Because machine learning algorithms are trained to analyze several sets of data, they can continually examine photos without becoming tired and provide more reliable, accurate, and steady diagnosis results.

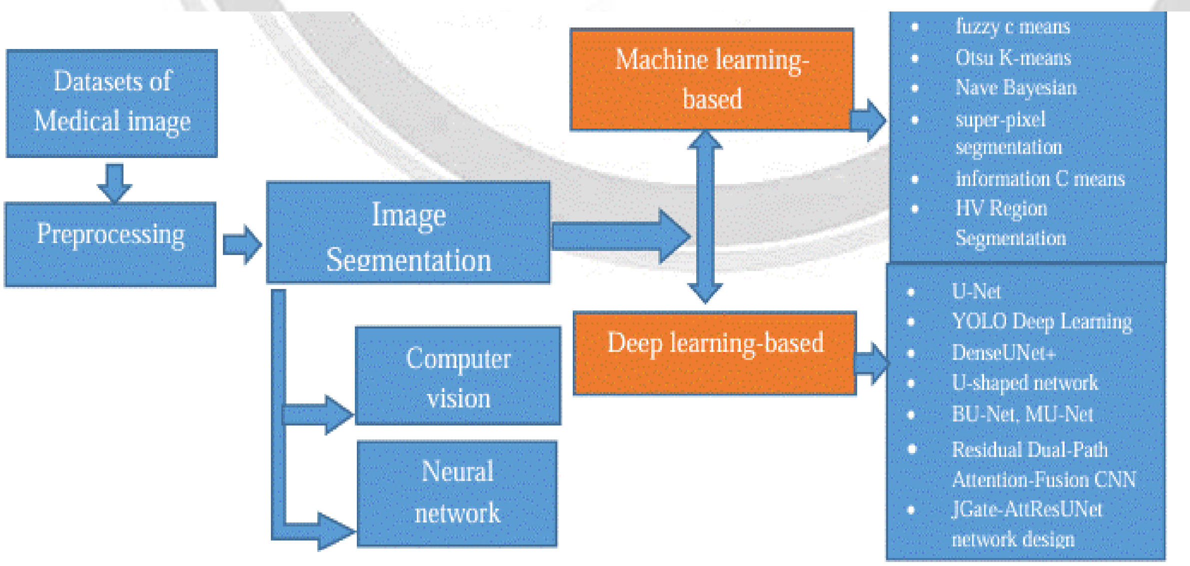

Figure. 2 Generic flow schematic representation for medical info classification

4. Related works

In this survey, papers published in journals indexed by Scopus and Web of Science between 2021 and 2024 are analyzed to verify techniques for deep learning, region growth, and machine learning-based brain tumor classification and deep segmentation. Throughout this research project, the following databases were extensively searched for: (1) Science Direct; (2) IEEE Xplore Digital Library; (3) MDPI; (4) PubMed; and Google Scholar (5). The search variable includes the terms "Brain Tumor," "Classification," "Deep Learning," "Machine Learning," "Region Growing," and "Segmentation."

A lot of techniques of ML and DL have been offered to detect and diagnose tumors in the brain via CT and MRI.

4.1. Machine Learning Methods

In [16], there is the base random forest (RF)-based solution study for tumor part segmentation issues applying multi-spectral MRI data. Glioma records are preprocessed to remove noise effects and to produce 100 additional attributes to 4 monitored ones. RF classifier result is straightly fed to statistical assessment for investigating straight RF contribution to an appropriate segmentation.

In [17], a completely automatic system is improved to detect the brain tumor from brain MR images. It combines an automatic framework that diagnoses FLAIR MR images including tumor and tumorous region segmentation. This system carries out detection in 3 steps. The first step is applied to diagnose the tumorous brain MRI. The second step includes tumorous region localization by applying the sliding window algorithm pursued by fuzzy c means.

In [18], two ML models, SVM and CNN, are used for LGG MR image segmentation. SVM model Training needs just 1 image for each patient which importantly decreases the time of computation to a few seconds. The model of CNN performs better than the SVM model in recall, accuracy, F1 score, and precision. However, the model of CNN training is slow, usually taking a few hours with high-performance computers, and also needs an importantly enlarged set of data that often is not readily accessible practically.

In [19], the researchers offer the strategy of OKM to perform the function of segmentation. The strategy of OKM is the integration of basically 2 well-known terms Kmeans clustering, and Otsu thresholding. The function is not just to segment the tumor portion but also elements of the tumor-like edema, Necrosis, and increasing and non-increasing tumor.

In [20], tissue cluster class graph cut (TisCut), an unsupervised method to segment histological pictures into informative compartments to assist with histological annotations for supervised models that come after. TisCut comes with three modules. First, morphological characteristics and geographic proximity are used to organize histological tissue objects. Given the tissue object clustering, a Voronoi diagram is constructed. An area adjacency graph is created in the final module by combining morphological traits that were determined using the Voronoi diagram. By using a graph cut technique, image partitioning divides an image into understandable sections.

In [21], the researchers demonstrate the efficient automated segmentation of brain tumors using the Greedy Snake Model and fuzzy CMeans optimization. This technique employs 2-class morphological reconstruction, specifically dilatation and erosion, to accurately detect the approximate Region Of Interest (ROI) and eliminate the non-tumor section. The Greedy Snake algorithm shapes a mask by thresholding reconstructed pictures, which are then degraded to improve segmentation accuracy. To estimate unique tumor borders, the greedy snake model uses the mask boundary as a fundamental snake contour. These kinds of boundaries work well in places with sharp edges and less well near ramp edges. To attain adequate segmentation results, the improper borders are then optimized through the application of the Fuzzy C-Means algorithm. An area that has a big perimeter is selected lastly, to remove inappropriate segmented areas.

In [22], the researchers provide an automatic method for segmenting brain tumors based on shape using topological data and rough-fuzzy C-means (RFCM). Rough-fuzzy C-means algorithm utilises lower and upper rough set bounds to handle uncertainty in data sets and employs fuzzy membership to efficiently manage overlapping partitions. The segmentation of brain tumours on MR images is significantly improved by utilising the precise lower approximation and fuzzy border in RFCM. The fundamental problem in C-means algorithms is the selection of centroids. The current study has defined a technique for basic centroids choice by which RFCM run time is decreased in comparison with random basic centroids. K-means technique based on patch is performed for skull stripping as a preprocessing stage.

In [23], the researchers present the method given the Nave Bayesian classification strategy which could effectively recognize and segment brain tumors. Noises are recognized and filtered out in the preprocessing tumor recognition stage. After preprocessing the brain image, GLCM and probabilistic features are extracted. A naive Bayesian classifier is applied for training and labeling the retrieved properties. While tumors in a brain picture have been grouped, the watershed segmentation strategy is applied for isolating tumors.

In [24], the eXtreme Gradient Boosting (XGBoost) approach is optimized by feature selection and image processing for accurate brain tumor identification. The Contrast-Limited Adaptive Histogram Equalization (CLAHE) approach is used to produce images. Parts of the K-Means algorithm share pictures. This division facilitates identifying a certain topic of interest. To choose features, Particle Swarm Optimization (PSO) is used. XGBoost, Iterative Dichotomiser 3 (ID3), and Naive Bayes classify the data.

In [25], using a combination of features, a potent method for identifying brain tumors has been proposed. The proposed approach first employs Gaussian filtering as a preprocessing step to decrease the noise present in the brain samples. In order to improve the localization results on MRIs, the researchers employed open-source tools such as SynthStrip for the process of brain skull stripping. The tumor was then located using a brain MRI image segmentation technique. DarkNet 19 was then used for key-feature extraction, whereas HOG was used for local feature extraction. Ultimately, the LSTM classifier was employed to amalgamate characteristics for the tripartite classification of brain tumours: glioma, pituitary, and meningioma.

In [26], a novel method is introduced to improve the distinction between different areas of a tumour for both region-wise and voxel-wise segmentation techniques. The system relies on

conditional generative adversarial networks (cGANs). The authors provide two models: Enhancement and Segmentation GAN (ESGAN), which merge classifier loss and adversarial loss to forecast core labels of input patches, and Enhancement GAN (EnhGAN), which produces high-contrast synthetic images with minimal overlap between different classes. The synthetic images are used with complementing modalities to obscure less significant tissues and highlight key ones.
The authors also present a novel generator that utilises fully convolutional networks to dynamically adjust voxel values inside input patches. Both methods utilise a multi-scale Markovian network as a GAN to analyse local patch data and forecast the distribution of MR images in intricate situations.

In [27], along with pixel segmentation, the researchers propose a normalizing preprocessing approach. Then, generative adversarial networks (GANs) have made it favorable to create synthetic images in numerous sectors. On the other hand, merging many GANs can help comprehend scattered features, but it can also complicate and confuse the model. Only the localized features in an image's latent version can be retrieved by a standalone GAN. The authors have employed a vision transformer (ViT) in conjunction with a standalone GAN to accomplish both global and local feature extraction in a single model. This will enhance picture similarity and potentially boost the model's tumor detection ability.

In [28], the research stated that brain tumors that have been mixed with pancreatic cancers are identified using the PG-DBCWMF, the HV area approach, and CTSIFT extraction. In therapeutic settings, these tactics perform better in terms of efficiency, precision, originality, and other aspects. The proposed method combines the three techniques: PG-DBCWMF, HV region algorithm, and CTSIFT extraction.

In [29], the researchers described using a partial differential equation, by first eliminating the noise from the MRI brain image. The contourlet transform, which operates based on multiscale image decomposition, receives those previously processed images as input. The contourlet transform generates a sparse representation of the smooth contour of an image by using a double filter bank structure consisting of a directional filter bank and the Laplacian pyramid. A new Possibilistic Fuzzy C-Means clustering approach was used to segment these retrieved bands. A Grey Wolf Optimization technique based on opposition is used to determine the optimal parameters of an Optimized Support Vector Machine, which is then used to classify the various parts of brain tissue into white matter, grey matter, cerebrospinal fluid, edema, and tumor tissues.

In [30], the study introduced a unique method that integrates an Adaptive Dense Neural Network (ADNN) classifier and a Segmentation-based Kernel Fuzzy C-Mean (SKFCM) using the Penguin Search Optimisation Algorithm (PeSOA). The pre-processing of the MRI images involves the use of Bright-contrast Dynamic Histogram Equalisation (BCDHE) and a weighted median filter. Modular linear discriminant analysis (MLDA) is subsequently employed to extract the many features. The segmentation of brain tumours (PeSOA) was performed utilising a machine learning-based Penguin Search Optimisation Algorithm and an Adaptive Dense Neural Network (ADNN) with a unique SKFCM.

In [31], the pre-processing of MR images, which involves cranium stripping and other procedures, corresponds to the first phase of the proposed method. The next step of brain MRI is feature extraction (FE), which is distinct from MR imaging of brain tumors and involves the use of a histogram and a local binary pattern. The Support Vector Machine (SVM) classifies brain tumors according to a variety of features. In the third stage, a decision compound is used to classify Support Vector Machines and Ant Colony Optimization (ACO). ACO depends on decision rates related to confidence criteria to support the final unique outcome.

In [32], this study introduces a method for detecting and categorising brain tumours using an enhanced version of the fuzzy factor fuzzy local information C means (IFF-FLICM) segmentation approach and a hybrid modified harmony search and sine cosine algorithm (MHSSCA) optimised extreme learning machine (ELM). The IFF-FLICM approach is used to accurately segment magnetic resonance imaging (MR) of the brain in order to identify the locations of tumours. The Mexican hat wavelet transform is employed to extract characteristics from the segmented pictures. The MHS-SCA-ELM classifier receives the extracted features from the segmented regions and uses them to classify data. In order to improve the accuracy of classification, the weights of the ELM model are optimised using the MHS-SCA algorithm. In order to demonstrate resilience, the optimisation process considers five distinct benchmark functions that incorporate both multimodal and unimodal characteristics.

Table 3. ML techniques' summary is reviewed in this paper.

Reference	Year	Type	Methods	Database	Accuracy/Dice
[16]	2021	Automatic Segmentation	random forest (RF)	BraTS 2015	82 Dice
[17]	2021	fuzzy c means,	PCA, SVM with linear, and RBF	NCI-MICCAI 2017	97.89 Acc
[18]	2021	SVM and U-Net	Support vector machine	The Cancer Imaging Archive (TCIA)	99.8 Acc
[19]	2021	Otsu K-means Method	K-means	BraTS 2013	91.89 Dice
[20]	2021	Cluster Level Graph Cut (TisCut)	graph cut algorithm	35 H&E stained brain histological images, 30 Ki-67 stained skin histological images	91.82 Dice
[21]	2022	greedy snake algorithm	FuzzyC-Means optimization	T1-weighted contrast-enhanced image database	78 Dice
[22]	2022	rough-fuzzy C-means (RFCM)	shape-based topological properties, patch-based K-means method	BraTS 2013, BraTS 2017	-
[23]	2023	Nave Bayesian classification	Nave Bayesian classification	BraTS 2015	98.25 Acc
[24]	2023	Fuzzy K-means algorithm	XGBoost, Naive Bayes, and the Iterative Dichotomiser 3	total 250 images	97 Acc

			(ID3), Particle Swarm Optimization (PSO)		
[25]	2023	an enhanced threshold method utilizing binomial mean, standard deviation, and variance	DarkNet19 + HOG + LSTM	Figshare	99.8 Acc
[26]	2024	conditional generative adversarial networks (cGANs)	combines classifier loss with adversarial loss	BraTS 2013 BraTS 2018	89 Dice
[27]	2024	super-pixel segmentation (SPS) method	GAN with ViT	Masoud2021 BraTS2020	95.82 Acc
[28]	2024	HV Region Segmentation Algorithm	Patch Group Decision Couple Window Median Filter, Scale Invariant characteristic remodel	-	96 Acc
[29]	2024	Interval-Valued Possibilistic Fuzzy C-Means (IIPFCM)	FOPDE method, optimized support vector machine (OSVM), the opposition of the grey wolf optimizer (OGWO)	BraTS2021 Figshare	99.9 ACcc
[30]	2024	Kernel Fuzzy C-Mean (SKFCM)	Penguin Search Optimization Algorithm (PeSOA), Adaptive Dense Neural Network (ADNN)	BraTS 2020	98.4 Acc
[31]	2024	fuzzy c-means clustering (FCM)	SVM (Support Vector Machine), (ACO) Ant colony optimization	BraTS 2019–2020–2021 MR brain images from 2013, 2015, and 2018	98.99 Acc
[32]	2024	n an improved fuzzy factor fuzzy local information C means (IFF-FLICM)	hybrid modified harmony search and sine cosine algorithm (MHSSCA) optimized extreme learning machine (ELM)	Dataset-255	99.12 Acc

4.2. Deep Learning Methods

In [33], the proposed method presents a 3D Center-crop Dense Block for medical images. It achieves this by employing a parallel route network attention and context pathways framework. Additionally, it incorporates high-level supervision into the lower neural network layers. The context pathway has a lower level of detail and is primarily concerned with the surrounding information, whereas the attention pathway has a higher level of detail and is focused on the individual details of each voxel. In order to compensate for the loss of detailed information caused by down sampling, the authors of the study have included cross-pathway links. These linkages involve a weighted fusion structure that connects the attention pathway to the context pathway.

In [34], the research offers the 3D fully convolutional network-based model. In particular, the writers use the multi-pathway framework for feature extraction to efficiently extract features from multi-modal MRI images. Various receptive feature domains have been extracted by adopting 3D dilated convolution in every pathway.

In [35], TRIU-Nets, which are triple intersecting U-Nets, are designed to facilitate the segmentation of brain gliomas. The initial TIU-Nets provided are BU-Net, which implements binary-class segmentation, and MU-Net, which implements multi-class segmentation. MU-Net once more makes use of the multi-resolution capabilities of BU-Net. Furthermore, in order to facilitate weighted multi-category MU-Net segmentation, the authors establish the segmentation soft-mask anticipated by BU-Net. This soft-mask consists of background images that are predominantly devoid of gliomas and is a candidate glioma region. Thirdly, glioma substructure boundary information is enhanced by the edge branch in MU-Net, which facilitates the development of segmentation accuracy and ease of detecting glioma real boundaries. Finally, they recommend using polarization cross-entropy loss (S-CE) based on sigmoid evolution to address the class unbalance issue. In addition, S-CE loss can be applied to edge prediction, multi-class segmentation loss in MU-Net, and soft-mask prediction loss in BU-Net.

In [36], the researchers provide the semantic segmentation technique using CNN to automatically segment brain tumors on 3D Brain Tumor Segmentation (BraTS) data sets of an image which comprise 4 various imaging modalities (T1, T1C, T2, and Flair). Additionally, this paper contains 3D imaging of the entire brain and a comparison among ground truth and predicted labels in 3D. for achieving certain tumor area and dimensions like depth, height as well as width and such technique was successfully used and images showed various programs containing axial, sagittal, coronal.

In [36], the paper provides the fully automatic brain tumor segmentation technique given the mathematical model and deep neural networks (DNNs). Every 3D picture part is increased by the offered mathematical model that is transferred via 3D attention U-Net to present the tumor segmented result. This paper contains the detailed mathematical model for tumor pixel increment and a 3D attention U-Net to accurately divide the pixels.

In [38], by using YOLO with T1C+ grade and FLAIR low-grade tumor pictures from the BraTS dataset, this paper enhanced the deep network for brain tumor segmentation. To find the ideal hyperparameters, a thorough search is conducted because hyperparameters are crucial to CNN efficacy. To determine the ideal numbers, the mini-batch size, the learning algorithm, and the number of anchor boxes are carefully evaluated.

In [39], researchers improve the novel region-of-interest-aided (ROI-aided) deep learning method for automated brain tumor MRI segmentation. Such technique includes 2 main stages.

Stage 1 uses the 2D network with the U-Net framework for localizing tumor ROI that decreases normal tissue's disturbance effect. After that, a 3D U-Net is done in step 2 for tumor segmentation in recognized ROI.

In [40], this study introduces a highly efficient method for accurately segmenting brain tumours from MRI data. The method utilises tumour localization and increment approaches within a deep learning framework called U-net. A nonparametric technique that utilises histograms is employed to localise tumour locations. The proposed technique for modifying the localised areas involves increasing the visibility of indistinct or low-contrast tumour appearances. The resulting images are inputted into the fundamental U-net architecture for the purpose of segmenting the entire brain tumours.

In [41], the paper offers a novel segmentation strategy applying deep learning. The novel segmentation model is offered by applying CNN.

In [42], the researchers presented BTSwin-Unet which is a 3D U-shaped symmetrical Swin Transformer-based network for brain tumor segmentation. In addition, the researchers build the self-supervised learning framework to pre-train the model encoder via a reconstruction function.

In [43], the enhanced deep learning-based MRI image segmentation strategy for brain tumors was presented. Before patch extraction, the input MRI images are pre-processed using filtering and contrast increment techniques. The Enhanced U-Net model processes image segmentation in pre-processed images; the created Coyote Optimization Algorithm (COA), also known as Adaptive Searched Coyote Optimization Algorithm (AS-COA), then optimally tunes the framework.

In [44], the paper displays the Edge U-Net model, sometimes referred to as the deep convolution neural network (DCNN), the architecture is constructed as an encoder-decoder framework, taking inspiration from the design of U-Net. The Edge U-Net approach has the potential to accurately locate tumours by integrating essential data from brain MRIs with boundary-based MRI information. The decoder stage combines boundary-based information obtained from basic MRIs of various scales with accurate neighbouring contextual information. A novel loss function was included in this segmentation technique to enhance its performance. By utilising boundary information to formulate this loss function, the learning process might yield more precise outcomes.

In [45], the research presents the light-automated 3D algorithm with the attention algorithm for brain-tumor image segmentation. Appropriate brain-tumor area segmentation in medical images is important for patient detection by applying 3D U-Net. The present paper replaces the standard convolutions with hierarchical decoupled convolutions to decrease parameter number; the present paper adds dilated convolutions to increase the network's ability to express multiscale info in the bottom convolution module; the present work defines the attention mechanism to layer of result so the network could automatically concentrate on tumor area and apply relations between tumor core, increasing tumor, entire tumor to develop accuracy of segmentation.

In [46], the research offers a thorough structure for the automatic segmentation of brain tumours in three dimensions (3D). The given model is a fusion of the U-Net and deep residual networks, known as dResU-Net. The given architecture utilises the residual network as an encoder together with a U-Net model decoder to address the issue of gradient vanishing. The suggested technique aims to utilise both high-level and low-level features concurrently for prediction. In addition, residual networks utilise shortcut connections to preserve low-level characteristics across all layers. Moreover, the architecture utilises skip connections between convolutional and residual blocks to accelerate the training process.

In [47], the new architecture based on encoder–decoder is presented for the efficient brain tumor areas' segmentation. To make model training easier, z-score, N4 bias field correction, and 0 to 1 resampling are used in data pre-processing. The residual spatial pyramid pooling (RASPP) module is proposed to mitigate location information loss in several modules. A collection of parallel layers using dilated convolution is called RASPP. Additionally, the extracted characteristic map segmented result is effectively focused and restored by applying the attention gate (AG) module. The modules that are being described aim to obtain rich characteristic representations by combining information from various feature maps while keeping their local details.

In [48], the 3D CNN with 3D multi-branch attention, MBANet, is shown. First, the MBANet basic unit (BU) module is shaped using the optimized shuffle component. After the input channel is divided, the BU module uses set convolution to perform the convolution operation, and channel shuffle to scramble the convolutional channels following fusion. Subsequently, MBANet uses a novel multi-branch 3D Shuffle Attention (SA) module as the encoder's attention layer. The channel dimension is determined in the 3D SA module, which also shares characteristic maps in tiny attributes. When the 3D SA module accepts the BU module, it generates spatial attention and two-channel attention for each small characteristic. Additionally, a 3D SA module can improve recovering up sampling semantic feature resolution.

In [49], the researchers present the automated weighted dilated convolutional network (AD-Net) to learn multimodal brain tumor characteristics via channel feature separation learning. Particularly, the auto-weight dilated convolutional unit (AD unit) uses dual-scale convolutional characteristic maps to gain channel separation attributes. The writers use 2 learnable parameters for fusing dual-scale convolutional attribute encoding layers maps automatically, the two learnable parameters are set with gradient backpropagation. They adopted Jensen–Shannon divergence to limit feature map share that regularizes whole down-sampling weights in turn. Also, they apply deep supervision training methods for obtaining quick fitting.

In [50], the paper shows how DenseUNet+, a ground-breaking deep learning-based method, employs multimodal photos to accurately segment data. In the DenseUNet+ model, information from four distinct modalities was combined in dense block structures. After that, linear operations were applied to this kind of data to produce a concatenate function. The decoder's layer received the results that were acquired in this way.

In [51], researchers suggest brain tumor MR image classification and segmentation in 1 solid framework. Integrates hyperkernel for convolution layers with attention layers for segmentation. Presents a hybrid neural network with the automated feature weighing module for extracted features effect regulation.

In [52], the integrated inception v2 net and Fast Fuzzy C-means method is beneficial for the tumor core, whole tumor, and edema segmentation. To get a more accurate diagnosis of the whole tumor region, Inception v2 net is used. Compared to other models, Inception v2 uses fewer parameters, requiring less memory and computing power and offering an improvement in training efficiency. Furthermore, this might regulate larger input sizes, which would make it useful in applications that use high-resolution photos.

In [53], the multi-scale attention fusion (MAF) and dual-path (DP) modules are provided by the effective 3D segmentation model (DPAFNet). The residual connection is detailed in DPAFNet to prevent network deterioration, and dual-path convolution is employed to increase the network's scalability. To collect channel-level global and local data, the attention fusion module is given. Various scales feature maps are fused to obtain attributes that are richer in meaningful data.

In [54], the simple and new JGate-AttResUNet network model is built in the suggested work to create a strong and trustworthy system of brain tumor segmentation. Such a technique presents more efficient and accurate tumor localization in comparison to other models. So, the J-Gate attention technique is applied to increase the localization of the tumor.

In [55], the novel Shuffled-YOLO network was introduced and is used to separate brain cancers from multimodal MRI pictures. Using the scalable range-based adaptive bilateral filter (SCRAB) pre-processing approach, noise artifacts from MRIs were eliminated while maintaining edge integrity. In the step of segmentation, the writers suggest a new deep Shuffled-YOLO framework to segment internal tumor structures which contain necrosis, growing, non-growing, and edema tumors from multi-modality MRI orders.

In [56], the researchers improved the method of neuroimaging synthesis to supplement data for fully convolutional networks (U-nets) training in automatic segmentation of gliomas. The authors simultaneously generated associated glioma segmentation masks and fluid-attenuated inversion recovery (FLAIR) magnetic resonance images using StyleGAN2-ada. To train U-nets, artificial data was gradually added to real training data over the course of fourteen rounds of 1000. Test sets and held-out validation were used to assess the results. U-nets were trained with and without shear, translation, and zoom geometric augmentation. To evaluate the segmentation performance, dice coefficients were also computed. To determine the computing expenses associated with training each U-net, they managed the number of training iterations before the whole training duration, pausing, and timing each iteration. Augmentation of Synthetic data showed marginal developments in Dice coefficients while geometric augmentation developed generalization.

In [57], four 2D GANs (progressive GAN, StyleGAN 1-3) and a 2D diffusion technique are evaluated to generate brain tumor images and tumor annotations using two publicly available datasets. According to the authors, using synthetic images to train segmentation networks (a U-Net and a Swin transformer) results in performance measures that are marginally lower than when training with real photos. They also demonstrate that sharing synthetic images can serve as a means of exchanging real images.

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In [58], the researchers investigate the feasibility of using conditional generative adversarial network (GAN) strategy to synthesize multi-modal images for neural networks training based on deep learning targeted in high-grade glioma (HGG) segmentation. The presented GAN is conditioned on auxiliary brain tissue and tumor segmentation masks, letting us get better tissue appearance accuracy and control in synthesis. To decrease the field change among synthetic and actual MR images, the writers also adapt low-frequency Fourier space synthetic data elements, showing image style, to those of actual data.

In [59], references to MRI are analyzed to recognize and highlight cancers applying Deep Convolutional Generative Adversarial Network (DCGAN), the strategy for info increment used for preliminary data processing. In addition, malignancies are grouped into one of four types, such as pituitary, meningioma, tumors, and glioma. Such increased technique of R-CNN is preferred as categorization is performed more readily and reliably than with usual R-CNN.

In [60], the paper presented the deep Convolutional Neural Network (CNN)-based framework for automated brain image classification in 4 levels and a segmentation model based on U-Net. A model of segmentation that confirms input MRIs and makes masked pictures has been offered. While a model was trained to apply the manually created mask from the Merged set of data 1, this could create masks for other sets of data.

In [61], DAUnet is a U-shaped network that combines convolutional attention and deep supervision for brain tumor MRI image segmentation. The first step is modeling the bottleneck and attention (BA) module. These days, attention includes residual connection in addition to spatial and channel (SC) attention; this is referred to as 3D SC attention. Second, a module for extending the feature map receptive domain without changing resolution is modeled by combining an atrous spatial pyramid (CASP) module with ordinary convolution. Ordinary convolution sets the information in the feature map; hence, the feature map is sent as an input to the ASP module. The module of CASP fuses attributes extracted by down-sampling and does an up-sampling function that makes correlation strong among various network layers. Using deep supervision as the U-shaped network auxiliary branch, which combines regularization and deep learning techniques to oversee a model during training, refine parameters, and improve model fit automatically, is the final step.

In [62], the ensemble strategy which presents strong segmentation, has a simple framework, needs less computation also could be widely used in clinical practice. The main framework was created on 2D U-Net. This paper undoubtedly offers attention to algorithms to raise the discriminating ability of models between complicated lesions.

Table 4. DL techniques' summary is reviewed in this paper.

Reference	Year	Type	Methods	Database	Accuracy/ Dice
[33]	2021	Weighted fusion structure	parallel pathway dense neural network	BraTS 2015 and BraTS 2017	88.7 Dice
[34]	2021	FCN and U-Net	3D fully convolutional network	BraTS 2018 and BraTS 2019	90 Dice
[35]	2021	BU-Net, MU-Net	sigmoid-evolution-based polarized cross-entropy loss (S-CE)	BraTS 2015	85 Dice
[36]	2021	a semantic segmentation method	CNN model	FLAIR, (T1T1C, and T2) weighted	95.7 ACC
[37]	2022	3D attention U-Net	Deep neural networks (DNNs)	BraTS 2019	98.9 Acc
[38]	2022	YOLO Deep Learning	CNN	BraTS 2013 And REL	89 Dice
[39]	2022	3D U-Net	ROI-based cascading network	BraTS 2015	87.7 Dice
[40]	2022	U-Net	Tumor localization and enhancement	RATS 2012, BraTS 2019, and BraTS 2020	94 Dice
[41]	2022	CNN for glioma segmentation	CNN	BraTS 2017, BraTS 2018, and BraTS 2020	86 Dice
[42]	2022	BTS win-Unet	Swin Transformer	BraTS 2018 BraTS 2019	91.74 Dice
[43]	2023	Enhanced U-Net model	Adaptive Searched Coyote Optimization Algorithm (AS-COA)	BraTS 2019	96.4 Dice
[44]	2023	Edge U-Net model	Deep convolution neural network	a public dataset with 3064	91.76 Dice

[45]	2023	3D U-Net	a lightweight automatic 3D algorithm with an attention mechanism	BraTS 2018 BraTS 2019 BraTS 2020	89.94 Dice
[46]	2023	3D U-Net model	deep residual network	BraTS 2020 BraTS 2021	86.01 Dice
[47]	2023	recursive residual (R2) block termed RAAGR2-Net	CNN	BraTS 2017 BraTS 2018 BraTS 2019	89.6 Dice
[48]	2023	3D Shuffle Attention (SA)	3D convolutional neural network	BraTS 2018 BraTS 2019	89.80 Dice
[49]	2023	automatic weighted dilated convolutional network (AD-Net)	DNN	BraTS 2019 BraTS 2020 FeTS 2021	90 Dice
[50]	2023	DenseUNet+	preferred CNN	BraTS 2021 FeTS 2021	95 Dice
[51]	2023	hybrid U-Net	six shallow CNNs	BraTS 2020	98.93 Acc
[52]	2023	Fast fuzzy C-means method	inception v2 net	BraTs 2020 BraTs 2017	99.45 Acc 89.74 Dice
[53]	2023	Residual Dual-Path Attention-Fusion Convolutional Neural Network (DPAFNet)	dual-path (DP) module and multi-scale attention fusion (MAF) module	BraTS 2018 BraTS 2019 BraTS 2020	90 Dice
[54]	2023	JGate-AttResUNet network design		BraTS 2015 BraTS 2019	91.3 Dice
[55]	2023	deep Shuffled-YOLO	scalable range-based adaptive bilateral filer (SCRAB) technique	BraTS 2020	98.07 Acc
[56]	2024	automatic glioma segmentation	fully-convolutional networks (U-nets)	Cancer Imaging Archive (TCIA)	87.7 Dice

[57]	2024	U-Net and a Swin transformer	progressive GAN, StyleGAN 1–3	BraTS 2020 BraTS 2021	80%–90% Dice
[58]	2024	3D net	generative adversarial network (GAN)	BraTS2020	97.8 Dice
[59]	2024	K-Means clustering (KMC) algorithm	Deep Convolutional Generative Adversarial Network (DCGAN), Region-based Convolutional Neural Network (R-CNN)	3064 brain MRI	97.25 Acc
[60]	2024	U-Net	Deep CNN	total of 6 classification datasets	96.7 Acc
[61]	2024	U-shaped network	deep supervision and attention	BraTS 2020 FeTS 2021	89.8 Dice
[62]	2024	2D U-Net-based Triplanar Models and Attention Mechanisms	ResNet-like structure	BraTS2020	87.3 Dice

4. Conclusions

Segmentation of Brain tumors has broadly taken advantage of developments in AI. Investigators have been using AI mechanisms and methods to diagnose brain tumors, calculate abnormality diagnosis, computer-aided surgery, tissue volumes, treatment planning, and pathology. The aforementioned techniques perform better than those linked to brain tumor segmentation because of their characteristics, which make differentiating between aberrant and normal tissues easy. The present study suggests the public techniques survey used for brain tumor segmentation. A long array of classification, automated and semi-automated brain tumor segmentation is covered here. To help readers and medical professionals identify the most effective and precise methods for segmenting brain tumors—as well as to improve future study directions—the current study statistically evaluates current tactics in light of hybrid assessment measures.

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تجزئة أورام الدماغ القائمة على التعلم الآلي: مراجعة شاملة

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الخلاصة

يشير تجزئة أورام المخ إلى وظيفة حاسمة في معالجة الصور الطبية. وعلى الرغم من المحاولات الرئيسية الكثيرة والنتائج المرضية في هذا المجال، إلا أن التصنيف والتجزئة المناسبين يظلان وظيفة مهمة. يعد تجزئة الصورة مهمة صعبة في معالجة الصورة. من أجل تحسين كفاءة المعالجة والتحليل والكشف، بدأت المستشفيات بالفعل في استخدام .MLالتعلم الالي

ولزيادة سرعة بدء عملية التعافي، يمكن للأطباء الحصول على المساعدة في الكشف في السنوات القليلة الماضية، أظهرت تقنيات التعلم الآلي أداءً مرضيًا في حل مشكلات مختلفة تتعلق برؤية الكمبيوتر مثل التجزئة الدلالية وتصنيف الصور بالإضافة إلى تشخيص الكائنات. تم تطبيق العديد من الأساليب المعتمدة على التعلم الآلي بنجاح على مشكلة تجزئة ورم الدماغ. تعرض هذه الورقة نظرة عامة على تقنيات التعلم الآلي والتعلم العميق الحديثة لتشخيص أمراض الدماغ وتجميعها من صور التصوير بالرنين المغناطيسي. تم اختيار ومناقشة أكثر من 60 دراسة علمية هنا، والتي تغطي الميزات التقنية مثل تصميم بنية الشبكة، والتجزئة.

الكلمات الدالة:– تجزئة ورم الدماغ تصنيف، التعلم العميق، التعلم الآلي، المنطقة المتنامية.