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Advancements in hybrid approaches for brain tumor segmentation in MRI: a comprehensive review of machine learning and deep learning techniques

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Abstract

Magnetic resonance imaging (MRI) brain tumour segmentation is essential for the diagnosis, planning, and follow-up of patients with brain tumours. In an effort to increase efficiency and accuracy, a number of machine learning and deep learning algorithms have been developed over time to automate the segmentation process. Hybrid strategies, which include the advantages of both machine learning and deep learning, have become more and more popular as viable options. This in-depth analysis covers the developments in hybrid techniques for MRI segmentation of brain tumours. The essential ideas of machine learning and deep learning approaches are then covered, with an emphasis on their individual advantages and disadvantages. After that, the review explores the numerous hybrid strategies put out in the literature. In hybrid approaches, various phases of the segmentation pipeline are combined with machine learning and deep learning techniques. Pre-processing, feature extraction, and post-processing are examples of these phases. The paper examines at various combinations of methods utilised at these phases, such as segmentation using deep learning models and feature extraction utilising conventional machine learning algorithms. The implementation of ensemble approaches, which integrate forecasts from various models to improve segmentation accuracy, is also explored. The research study also examines the properties of freely accessible brain tumour datasets, which are essential for developing and testing hybrid models. To address the difficulties of generalisation and robustness in brain tumour segmentation, it emphasises the necessity of vast, varied, and annotated datasets. Additionally, by contrasting them with conventional machine learning and deep learning techniques, the review analyses the effectiveness of hybrid approaches reported in the literature. This comprehensive research provides information on recent advancements in hybrid techniques for MRI segmenting brain tumours. It emphasises the potential for merging deep learning and machine learning methods to enhance the precision and effectiveness of brain tumour segmentation, ultimately assisting in improving patient diagnosis and treatment planning.

Keywords Segmentation · Deep learning · Brain tumor · Magnetic resonance imaging · Machine learning

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1 Introduction

The brain seems to be a noteworthy organ that contains 100 billion neurons, often known as nerve cells. Brain cancers are listed as the tenth prominent reason of demise in developed nations including both children and adults [1]. In the USA, 18,280 adult fatalities from major brain tumors are projected to occur in 2022 [2]. Intracranial cancers, sometimes referred to as brain cancers, are malignant growths that originate in the brain's intracranial structures and could vary in severity from mild to severe [3, 4]. As cell reproduction rates rise and grow uncontrolled, brain tumors develop. Brain cancers can grow wherever in the skull or brain, along with the skull base, nasal cavity, brainstem sinuses, and numerous other locations. More than 150 different types of brain cancers exist. Brain cancers can be divided into two categories: malignant and non-tumor [5, 6]. Moreover, three distinct examinations and processes, involving imaging investigations, neurological examinations, and biopsies, are required to identify a brain cancer. The use of MRI has become a popular and commonly used model for diagnosing brain cancers [7]. A dye might be inserted into a vein while MRI scanning. On the basis of the MRI scan components, such as functional MRI, and perfusion MRI, MR-spectroscopy (MRS), experts evaluate the cancer and develop treatment recommendations. In certain cases, other imaging procedures like positron emission-tomography (PET) and computed tomography (CT) have been employed in conjunction with MRI. Any issue may indicate brain's which region is being damaged by the cancer [8]. Neurological testing in this situation can aid the expert in making a more accurate prognosis. The specialist performs a neurological assessment on the patient, testing their balance, reflexes, hearing, strength, coordination, and vision. A biopsy has been used to make a diagnosis that is more accurate. A sample of aberrant tissue is gathered and evaluated under a microscopy during this operation [9].

A variety of MR scans, including post-contrast T1-weighted (T1ce), T2-weighted, fluid-attenuated inversion recovery (FLAIR), and T1-weighted techniques [10] give further information that aids in segmenting the brain cancer and its neighbouring tissues. The 3 tumor areas that are utilized in the actual clinical system have been: (i) enhancing region (comprising of whole tumor's enhancing part), (ii) peritumoral edema area (comprising of whole tumor's edema region) and (iii) necrosis region (comprising of tumor's enhancing and non-enhancing part). Gliomas, which are brain tumors, develop from glial cells [11]. The two types of it are high-grade glioma (HGG) that has been extremely aggressive and possibly fatal, and low-grade glioma (LGG) that grows gradually. A patient's LGG may have a longer life time and be less intrusive due to the LGG's apparent high frequency. Sometimes HGG, more malignant gliomas, can survive for almost two years [12]. Even with the use of cutting-edge imaging, radiation, and surgical methods, HGG is often incurable. Because of cell abnormalities, uneven tissue development, and the complicated and varied character of HGG, segmenting HGG is a difficult process [13]. The fundamental goal of digitalized brain cancer detection has been to gather critical clinical statistics on the specific existence, kind, and location of the injury. Medical imaging results can direct and control any following therapies, guaranteeing a good cancer identification and treatment plan. The unregulated, irregular division and growth of bodily cells appears to be referred to as cancer. A brain tumor forms if there is aberrant cell division and multiplication in the brain tissue. Although their scarcity, brain cancers have historically been among the worst malignancies. Brain cancers can either be intrinsic or invasive, based on where they initially manifested. Although the cells that make up original tumors come from brain tissues, metastatic tumor may begin somewhere in the organ before extending to the brain.

Furthermore, diagnostic testing significantly improves the efficacy of glioma therapy. It might be tricky to detect and identify lesions using a lot of scanning and volumes since tumor features differ from patient-to-patient. This makes treatment complicated. Such images also include several artifacts [14], which were picked up by using numerous scanners and include abnormalities, pixel fluctuations, and non-uniformity. In order to manage binary (low and high) and numerous kinds of risk categories (e.g., weak, mild, medium, and high), a precise and quick brain tumor segmentation (BTS) approach is required. This will encourage early identification and cost-effective therapy. In addition, the standard technique was mostly used to describe the initial generations of BTS [15]. The majority of the 2nd and 3rd generations were made up of ML- and DL-predicated technology. In regards of how scientists extract characteristics from examples, DL and ML are different. ML classification algorithms frequently develop independently as analytical learning methods and make accurate forecasts employing retrieved attributes. Medical imaging systems have demonstrated to benefit from the usage of ML techniques for tissue characterisation. The effectiveness of ML approaches [16] totally rests on the researcher or radiologist skill in identifying the most persuasive aspects, leading to biased methodologies. Thus, DL methods [17] that use different statistical information layers and convolutional processes to acquire features and deploy forecasts [18] have attracted the attention of academics. The present responsibilities of clinicians and radiologists may be altered by DL-based medical image analysis, countenancing them to spend lesser time reviewing clinical images and far more time establishing diagnostic and therapy decisions. Hence, when applied to a large database, DL approaches give precise predictions while being more costly than other methods in regards of space and computing time.

Many scholars have previously evaluated BTS and highlighted ML methods such as K-Means Clustering, Support Vector Machine (SVM), or DL methods including CNN. For those new to the topic, Magadza and Viriri's [19] detailed discussion of DL techniques is helpful. Parvathy and Robert [20] present a good literature overview on DL algorithms and conventional automated BTS procedures. The many ML and DL segmentation algorithms used in brain tumour identification are not covered by these studies, though. A review paper on BTS has yet to link the most recent ML and DL methods with the tumor diagnostic paradigm, despite BTS being actively researched for recent years. This motivates to conduct a review on hybrid segmentation methods employing DL and ML technologies for brain tumor diagnosis. Over 100 academic research publications from the years 2015 to 2023 have been included in this study. A statistics report predicated on the "Scopus" repository is supplied to determine the number of studies on BTS conducted using ML and DL methods. The terms "BTS" and "ML technique" or "BTS" and "DL method" or "brain cancer" and "technique name" have been discovered in this repository.

Rest of the article is described as follows: Section 2 explains the BTS and commonly employed methods; Section 3 reviews the articles related to BTS; Section 4 summarizes the ML-based BTS; Section 5 summarizes the DL-based BTS; Section 6 reviews the hybrid methods employed for BTS; Section 7 compares the performance of different hybrid and commonly utilized BTS methods; Section 8 details the discussion of review; and Section 9 concludes this article.

2 Brain tumor segmentation (BTS)

Table 1 displays the various methods utilized for segmenting the image of a brain tumor. Image segmentation is frequently utilized in both glioma therapy and detection. In particular, an exact glioma segmentation mask might assist with surgery planning, postpartum monitoring, and raising success rates [21, 22]. To determine the image segmentation's effectiveness, researchers explain the chore of segmenting brain tumors as follows: By categorizing each input data voxel or pixels into a predetermined tumor region categorization, the system tries to automatically separate the region containing the tumor from the tissue that is healthy when given an input image from a variety of imaging techniques (for instance, numerous MRI segments). The structure then returns the associated data's segmentation map.

2.1 Types of segmentation

BTS can be broadly categorized into three categories predicated on the extent of human participation: manual segmentation, completely automated based segmentation, and semi-automatic depending segmentation. Detailed explanations of these methods are provided below:

- ***Manual segmentation***

A personal operator utilizes complex tools to physically designate or outline around tumor sites during manual segmentation. The segmentation outcome's precision has been significantly influenced by the training, experience, and knowledge of the human operator's analytical architecture. Regardless of being laborious and time-consuming; moreover, manual segmentation was often employed as the standard for entirely computerized and partially automated segmentation.

- ***Fully-automatic segmentation***

The segmentation of brain tumors has been completely mechanized, requiring no involvement from humans. Integrating artificial intelligence with previous information helped to answer the segmentation problems. For entirely computerized segmentation approaches, creative and discriminative approaches have been added as extra types. Discriminating methods commonly employ supervised learning, which entails discovering connections between an input image and the human-annotated information contained in a large amount of data. The organization has employed traditional ML methods that depend on hand generated characteristics extensively over the years. The complexity of clinical images may prevent these methods from completely utilizing the training data [29]. Due to their extraordinary effectiveness in computer-vision utilities and their capability to effectively derive attributes from images, DL methods have gained greater recognition recently. On the other hand, standard techniques depend on already-existing information regarding the pattern of distribution in addition to manifestations of different kinds of tissue.

- ***Semi-automatic based segmentation***

Table 1 Techniques for BTS and their views

References	Input data	Criteria	Image segmentation	Validation method	Components analysed	Results
[23]	Utilizing MR images in virtual imaging	Segmentation	For boundary-based object recognition, 3DACWE was created	When 3DAC is applying for segmentation, WE is intended to identify object boundaries	BTS	The precision as well as accuracy of the image segmentation are successfully attained
[24]	Method for random paths	Homogeneity-and Object-characteristics-based Random-Walks algorithm	The modelling of the image makes use of a graphs	When tumor-containing images have been identified and segmented, the HORW method is used	BTS	Shows the growth's intensity spread
[25]	MRI images	Level Set	Utilize Level Set for form descriptions	An adaptive method is used for the depiction of forms and tracks that have an effect on displays	Identification and dissection of brain tumors	Improvement in efficiency
[26]	Imaging functionality with MRI	Application of Conditional Random Fields	MRI image segmentation enhances in locating the damaged area	Small regions referred to as image patches have been retrieved from the brain image's segmented part	BTS	The splitting of images problem has been resolved
[27]	Brain MRI initial data	Clustering using kernelized fuzzy entropy	Utilizing Clustered Fuzzy Entropy, the images are divided accurately by clustering	The goal is optimized by employing the LHNPSO method	BTS	Improved brain images differentiation
[28]	MR structural images	Development of the BrainNetCNN	Edge-to-edge layers are utilized for data filtering	The BrainNetCNN structure in the illustration consists of layers of convolution and layers that are fully connected	Utilizing neuroimaging	Numerous variations of the BrainNetCNN design are being examined

This combines both machine and individual abilities. Users must be involved in starting the classification process, getting input, and evaluating the results is shown in Table 2. Semi-automatic methods of segmentation still require human intervention to produce the intended outcomes, regardless of requiring a shorter amount of time than manually segmenting techniques.

In order to separate and categorise brain tumours using various types of medical imaging data, the above table of references covers a variety of approaches, including saliency identification, CNNs, 3D CNNs, MFCM algorithm, and deep learning frameworks.

2.2 Segmentation techniques

There are additional areas where division methods are thoroughly discussed. Figure 1 illustrates the BTS techniques utilized. Additionally, a number of well-known division algorithms include the following:

- ***Method for thresholding***

Voxels that are greater than a particular threshold were identified as being a component of a tumor, as the titles suggest. Thresholding appears to be a useful segmentation technique that uses a number of threshold numbers for the corresponding histograms and the grey level along with a set of parameters based on their strength. It was a previous method for segmenting brain tumors [17]. Segmentation has been made feasible by applying intensity thresholding to images taken for medicinal purposes. The segmentation process yields certain common challenging activities in the domain of interest. Both local and worldwide methods are utilized to properly position the tumors. In which it was possible to complete the entire thresholding-based segmentation because there was a significant amount of consistent strength among the contextual and the item.

- ***Methods determined by regions***

The standardized behaviours of an image are employed as the foundation for the region-based segmentation, and the image pixels are confirmed. In the evaluation method, the neighbouring pixels produced by the various areas have been merged in accordance with similar known occurrences. Region and Watershed development appear to be two distinct kinds of segmentation depending on regions [39].

3 Technique for growing regions

The segmentation procedure begins with a seed voxel, from which similar voxels are determined to be a component of the tumor. The simplest and most popular technique of segmentation depending on areas has resulted in region growth. The method, that utilized a bonded region similar to an actual image pixel, only required one seed to get going. The neighbouring pixels obtained from that are reinforced into the region-based identical criterion in order to identify the connected regions. The seed utilized was chosen using either a human or automatic process. To divide tumors and organs in MRI images for clinical research, utilize region growth. The fundamental framework of the multispectral-image recognition is unique and involves prior comprehension, fuzzy traits, and modifications

Table 2 Techniques for BTS

References	Input data	Criteria	Image segmentation	Validation method	Components analysed	Results
[30]	Brain tumor images (original data)	Salient-map modifications	The colour difference between the sections has been specified using the location of the salient tumor	The saliency identification method is used to identify one or several more noticeable portions of an image	Segmentation of brain tumors	The summary of the patch variations in the colour has been created
[31]	Imaging functionality with MRI	3D- CNN	The separation of brain tumors with a 3D CNN	The Dice similarity-coefficient can be utilized to assess the success of segmentation	Segmenting brain tumors automatically	Multimodal MRI for the identification and localization of brain metastases
[32]	Diverse tumor kinds as examples	Features of clinical practice	Comprehensive sequencing of genomes was done quickly	The diagnosis selection criteria for the patients were established	Segmentation of brain tumors	Unique clinical and medicinal characteristics were found
[33]	CLE images (original data)	Method for collecting surgical data	CNN may help determine the affected region	A CLE imagery gathering tool is utilized in combination with a surgical CLE imagery technique to take CLE image	Segmentation of brain tumors	The surgical CLE-image's mapping for the biopsy's site
[34]	Imaging functionality with MRI	Tissue BOLD structure	The brain's neuron activity and spinal nerves is measured by fMRI	The ability to modulate several factors that influence deoxygenated hemoglobin is provided by BOLD signal generation	neurosurgical excision of brain tumors	Based on the realization that oxygen's mass is conserved

Table 2 (continued)

References	Input data	Criteria	Image segmentation	Validation method	Components analysed	Results
[35]	MRI scans (original data)	MFCM algorithm	MFCM optimizes classification	The pre-processed images have been organized using the MFCM method to find the function of membership	Segmentation of brain tumors	A membership function description is provided for every point of data in the collection
[36]	2D and 3D clinical visualization images	Creating the NiftyNet the supporting structure	It is feasible to collect the required data because of the innovative internet tool	The tensorflow architecture is utilized to create an interface and visualize 2D and 3D images	DL framework	Automating the educational environments to allow for further investigation
[37]	2D MR images with a patch-based technique	CNN programming	DNN are used to separate various tumor types	DCNN is being researched for categorizing and segmenting brain lesions	Segmentation of brain tumors	Brain tumors are divided into various types
[38]	MRI-derived multimodal brain images	Categorization of images	Characteristics have been recovered from the images by eliminating image fragments	The effectiveness of the image's categorization was used to evaluate the selection process	Segmentation of brain tumors	A substantial quantity of guided learning

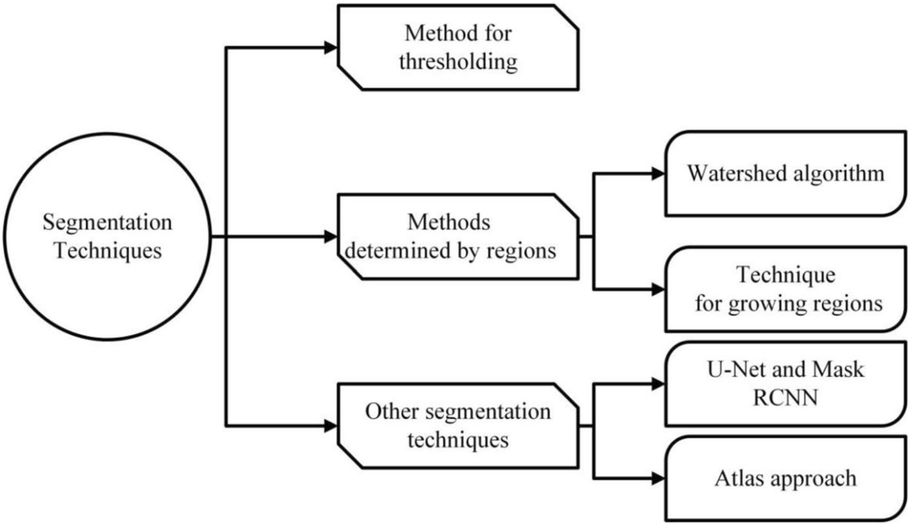


Fig. 1 Techniques used frequently for BTS

inside the fuzzy-region expansion. Utilizing FLAIR MRI, T1, and T2, quick multispectral cancer segmentation was made feasible by deterministic intensity form.

4 Watershed algorithm

With this, the voxel concentrations or slopes have been signified by a topographical chart comparable to those utilized in topography. The chart's "steepness" determines a boundary. Watershed appears to be a division method that considers both the geographic context and the hydrographic intellectual structure. The water drop descends the gradients in the image until it hits the close-by lower spot. The limits of neighbouring water drop in tributary areas eventually look like an involuntary watershed assistant. Over-segmentation might be prohibited by employing neither pre-processing nor post-processing techniques to enhance an item's architecture as an FCM clustering method. An innovative segmentation approach was outlined by fusing a watershed method with a procedure for expectation maximization (EM) [40]. When utilized in MRI, this produces effective gradient findings for separating the CSF from the gray tissue.

- ***Other segmentation techniques***

i. **Atlas approach**

Tumor tissue in the MRI is divided utilizing MRI technique; guidance Free of tumors. The technique determines the outcomes of fragmentation by creating a solitary-to-solitary correspondence between pre-segmented image and additional images using a registration-based technique. The examined material will be divided into non-typical brains and normal, allowing the brain atlases to provide the various variants. This tactic is based on a concept frequently used to describe brain regions.

ii. **Segmentation based on Mask RCNN and U-Net**

In recent years, UNet, culmination-to- culmination complete CNN for segmenting clinical images, was introduced. The device consists of a decoder and an encoder. The encoder was implemented to extract the spatial properties of the images, and the decoder was utilized for organizing the encoded data into a map. The sequence of double 3×3 convolutional algorithms that comprise up the encoder are followed by the max-pooling procedure. An evolution of double 3×3 convolutional algorithms has been utilized to link the decoder and encoder. Due to the robustness of the U-Net structure's system, training takes comparatively minimal duration and generates exact segmentation. It is possible to train extremely large amounts of samples while still getting superior outcomes with a smaller amount of data. The original development and application of UNet framework was in the cell tracking domain. Currently, utilizing this architectural approach, the brain tumor [41] can be separated from clinical imagery. To solve segmentation-related problems in the field of healthcare imaging, researchers created the S3D U-Net [42], and H-Dense U-Net [43], methods as enhanced variants of the U-Net approach.

To solve segmentation-related problems, a DNN based approach dubbed Mask-RCNN [44] is created. To accurately identify instances, the Mask-RCNN instance segmentation system has been created. The technique is utilized to identify various objects in a video or an image. If an illustration was allotted to Mask-RCNN, it characterizes the images in regards of masks, object-bounding boxes, and classes. Contrasted to U-Net, the Mask-RCNN generates fewer precise segmentation outlines. Mask-RCNN uses the dual-stage Regional-Proposal-Network and FastRCNN techniques. Characteristics were gathered from each potential box employing RoIPool, and in the following phase, the categorization process was carried out. Utilizing the Features Pyramid Network, Mask R-CNN improves the conventional character regaining pyramids, which employ high-level traits and transfer them to simpler levels. For object identification, the Region Proposal Network, that has been employed to separate the image into parts and identify areas holding items of interest, has been utilized. Bounding circles produced by RPN are then utilized to categorize ROIs. Last but not least, Mask R-CNN generates filters by employing extra regions from the ROI classification. These masks, which differ from binary masks in that they are defined by low resolution fluctuating numbers, may hold more detailed characteristics.

5 Review on BTS

In the area of medical imaging methods, the BTS in MRI scans seems to be a prominent issue. Finding the brain tumor's precise location and size requires a precise identification of the cancer. The K-means based clustering algorithm has been employed in the study [45] to detect tumors based on categorization and morphological assessment. Typically, the MRI scan picture is the initial pre-processed images. To retrieve the cancer from pre-processed MRI identified images, the image has been first processed to K-means cluster generation. The final stage is determining how much of the tumor was removed. The procedure in SciLab must be run several times, though, which proceeds more time. Recently, interest in the new ML field of "DL" has increased substantially. It was widely employed in many different applications and proved to be an efficient ML approach for many of the difficult problems. The authors of the study [46] categorize a database of 66 brain MRIs employing a DNN classifier, among the DL structures. Principal component analysis (PCA), a strong feature-based methodology, the wavelet decomposition, and the approach have all been employed to provide findings that were deemed to be quite acceptable across all process variables.

A DNN-based fully automated BTS approach was employed in the study [10]. The networks are made for glioblastomas found in MRI, both LGG and HGG. These tumors may grow anyplace in the brain and could take on almost any shape, structure, or severity due to their unique architecture. These characteristics motivate research of an extremely powerful ML method that makes use of a very adaptive, large capacity DNN. Below is a breakdown of a number of design options that were shown to be crucial for obtaining dependable performance. Many CNN-based architectures, or DNNs modified to picture data, are specifically explored in this paper. CNN architecture's state-of-art differs from some of the usual ones used in machine vision. In addition to local data, the network also employs extra global background data. Contrary to most conventional CNN paradigm implementations, systems employ an outer layer that seems to be a convolutional variant of a totally connected layer, consequential in a 40-fold enhance in speed. To overcome difficulties related to the disparity of tumour labels supplied, two-phase training technique is utilized. Last but not least, a sequence designs where a subsequent CNN takes basic system's output as a supplementary stream of data. The dependability and accuracy in the most current national whereas also being around 30 times quicker, according to findings from the 2013 BRATS test database. Automatic segmentation seems to be a difficult procedure since brain tumors have tentacles and distributed underlying addresses.

The study [47] utilized a variety of methods to raise the quality of the ingested hierarchical characteristics. Four different techniques have been implemented. In order to divide data more precisely, the Multi-Level Deep Medic approach of the widely recognized Deep Medic algorithm has been used. To enhance the standard of the multi-level characteristic derived from DN, a novel which doubles activity and learning has been described as well. It is an all-encompassing training tool that can be applied to a number of modern systems, which includes U-Net and Deep Medic. Third, extra classifiers that support deep networks' high-level phases, which are employed to gather more data, employing a label allocation loss function. An original MLP-based post-processing strategy was implemented to enhance the deep network's forecasting outcomes. Numerous studies have been performed on the two common recently released BTS databases, the BRATS 2015 and 2017 collections of data. Results from the two datasets demonstrate that the suggested methods increase the two widely recognized deep networks' segmentation methods efficiency. It has been tough to divide and category brain tumors because of their tentacles and scattered underlying structures.

The automation of BTS remains problematic because of their significant anatomical diversity. The study shows an automated BTS method predicated on DCN networks [48]. A patch-based method and a novel aspect have been employed to train the DN. It makes utilization of the capacity to extract two co-centric fragments of various dimensions from the original images. New Linear nexus design is developed using recent DNN events like batch normalization, non-linear stimulus, inception components and dropouts. The technique utilizes a dropout regularize to handle the over-fitting issue caused on by a lack of data. Images have been standardized and distortion field adjusted during pre-processing. The next stage is to process the gathered patches by using DCNN that allocates a result identifier to each patch's centre pixel. Segmentation methods have been implemented in post-processing to eradicate minimal FP at the borders. The BRATS 2015 and 2013 datasets are used to describe and evaluate a two-stage biased training technique that improves the effectiveness metrics of other methods in analogous settings. However, the computation duration has been long.

The precise division of brain tumors has been crucial for detection and therapy of tumors. The study demonstrated a novel method for segmenting brain tumors employing multicascaded CNN and completely linked conditional random fields. The greater part of the segmentation procedure is comprised of the following two stages. The original construction of the multi-cascaded complete network involved combining the intermediary outputs of different connected elements for the purpose to keep into consideration the regional reliance of tags and to benefit from multiple-scale characteristics for coarse segmentation. Secondly, CRFs were implemented for the better segmentation to account for the regional sources of data and remove some inaccurate findings. In addition, patches of images from the sagittal, coronal, and axial views were utilized for training three distinct segmentation simulations, which were subsequently merged to create the ultimate segmentation outcome. The effectiveness of the presented technique was assessed on three freely accessible databases. According to the trial findings, is more effective than existing techniques. However, the framework works more difficult whenever the data are considerably distinct [49].

For the development of trustworthy computer-aided diagnostic networks, collecting data and visualization are essential stages. The process is carried out to divide brain tumors in a systematic manner [50]. By combining OTSU and the customizable particle swarm optimization method, the optimal interrupted value is found. The noise reduction filtering is implemented in brain MRIs to minimize noise and improve picture clarity. The components that were found were utilized to teach CNN and perform tasks related to categorization. The study has a higher accuracy of 98% than analytical methods. Nevertheless, by additionally tuning the algorithm for a variety of sources of data and utilizing novel encountered heuristic methods, the diagnostic system's effectiveness will be increased. The study [51] utilized FLAIR Imaging methods for fully automatic major tumor segmentation and identification utilizing a universal DL design dubbed DeepSeg. The developed DeepSeg is an adaptable, detaching design. Its two linked central elements are built on the relationship between decoding and encoding. The transmission element is a CNN, which is in the position of retrieving spatial characteristics. The produced semantic map is delivered to the processing component, which integrates it to create the full-resolution probabilistic map. The study incorporates a variety of neural network designs developed around the modified U-Net design, which includes recurrent neural networks, NASNet, and DCNet. Utilizing MRI data of the brain tumour segmentation problem, the DL frameworks approach has been successfully investigated and tried online with 356 instances utilized as training data and 136 instances utilized as cross validation. Hausdorff separation and Dice values for the resulting segmentation methods vary from 0.82 to 0.85 and 9.7 to 18.7, correspondingly. The study has effectively demonstrated the viability and relative effectiveness of implementing numerous DL techniques in a novel DeepSeg structure to identify brain tumors inside FLAIR images utilizing technology. Yet, the examination of the DeepSeg design needs to take into account fresh image samples from different MRI methods.

The Fig. 2 shows the literature matrix includes papers from 2020 to 2023, distributed as 12 papers in 2020, no papers in 2021, 13 papers in 2022, and 1 paper in 2023. The papers from 2020 cover a range of methodologies, such as saliency identification, 3D CNNs, comprehensive genome sequencing, CNNs for confocal laser endomicroscopy (CLE) images, fMRI and BOLD signal generation, MFCM algorithm for MRI scans, NiftyNet as an internet tool, and CNN programming with DNNs for MR images. In 2022, the focus shifts to evaluating and improving segmentation techniques, including graph-based methods, deep learning models, and region-based approaches, with an emphasis on improved accuracy. Multimodal data, transfer learning techniques, and feature extraction methods are explored,

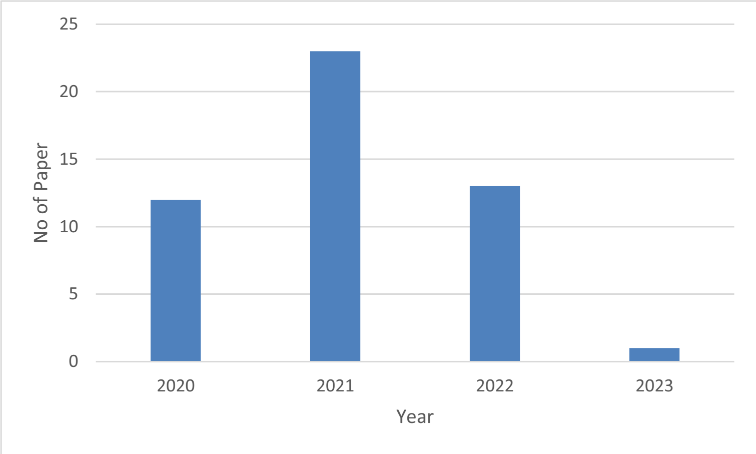


Fig. 2 Literature Matrix

alongside the development of automated segmentation frameworks. Finally, in 2023, one paper introduces a novel deep learning-based method for brain tumor segmentation, integrating advanced architectures and attention mechanisms while utilizing large-scale datasets for training and validation.

6 ML-based BTS

Image contraction in the type of segmentation offers several uses in the creation of CAD systems that rely on radiographic images like MRI. Broadly speaking, unsupervised and supervised image segmentation may be split into two groupings. Moreover, the borders of the targeted object in the images can be defined using unsupervised segmentation techniques such as edge detection, deformation, thresholding, and graph cutting. Contrarily, supervised segmentation methods use training examples that also take into account past knowledge of the image processing issue. The overview of unsupervised and supervised learning was indicated in Table 2.

6.1 Unsupervised learning

Unsupervised learning, sometimes referred to as unsupervised ML, uses ML methods to evaluate and organize unlabelled information. Without the assistance of a person, these techniques group data and identify obscure patterns. In other terms, unsupervised learning techniques detect correlations, spontaneously recurring tendencies and patterns, or comparable features within a database. In contrary to supervised learning methods, unsupervised learning techniques cannot be used to solve a prediction or categorization issue directly since the parameters of the outcome have been unknown. More complicated processing activities may be performed with unsupervised learning methods than with supervised learning. This method also makes it simple to decrease dimensionality. Understanding raw data could be aided by unsupervised learning. This learning becomes progressive and balances the outcome, similar to how human intellect functions. An unsupervised technique called clustering divides the input into many groupings. In the medical imaging domain, numerous clustering strategies were employed, particularly the grouping of healthy and aggressive brain cancers. Compared to supervised learning methods, unsupervised learning techniques are less sophisticated and don't need labeled dataset. The results, meanwhile, are frequently less accurate and can even be unexpected [52].

K-means clustering, morphology, and thresholding procedures were used by Khilkhal et al. [53] for BTS in MRI. To improve the ultimate accuracy of the findings, non-brain cells were eliminated during the morphological phase. The trials used LGG and HGG pictures from the BRATS databases. In attempt to identify brain cancers effectively, Islam et al. [54] suggested an enhanced design that combines Template-based K-means (TK) and PCA + superpixel approach. With less computational time, this technique might produce a usable segmentation outcome in MRI scans. For BTS in MR images, Kumar et al. [55] presented a five-stage technique. This goal was accomplished by using a crude K-means method. The results have been suggestive of the reality that the recommended technique got superior ratings in assessment in contrast with earlier efforts. Furthermore, K-means method has been straightforward, unpretentious to use, and ensures merging. Regrettably, it's indeed very reliant on the baseline numbers and grouping outliers. A technique for BTS in MR images was put out by Sheela et al. [56] and was predicated on rotational triangular portions with Fuzzy C-Means (FCM) method. Prior to thresholding, the image background ought to be primarily removed using two-level morphological reconstructive procedures. They used T1-a weighted contrast-improved image dataset—to assess the suggested structure's effectiveness. The final evaluation of the suggested approach is shown. The FCM model outperforms the k-means technique and yields the better consequence for example points that overlap. However, a lot depends on the predetermined number of clusters.

Modified mean-shift-predicated FCM segmentation was used by Singh et al. [57] to recognize brain cancers in MR images. The consequences exhibited that the recommended approach has a great extent of efficacy and precision. The number of clusters may be determined via the Mean-Shift clustering method automatically with no issues brought on by outliers. Nevertheless, when the number of clusters has been changed rapidly, this technique fails to perform effectively (higher dimension). Chaddad [58] proposed a novel method for retrieving Glioblastoma (GBM) characteristics from MR images using Gaussian Mixture-Models (GMM) to examine the GMM's efficacy in BTS. The T2-WI and T1-WI had accuracy performances of 97.05% each. Furthermore, in FLAIR setting, the accurateness diminished to 94.11%. Such experimental results offer hope for enhancing heterogeneity characteristics and, in turn, earlier GBM therapy. The MRI-predicated brain cancer was segmented by Pravitasari et al. [59] utilizing Reversible-Jump Markov Chain Monte-Carlo and GMM technique. Moreover, consequences of the investigation confirmed that the recommended model swiftly and effectively carried out the method. The GMM method was less dependent on the quantity of variables. However, this approach does have a sluggish rate of resolution and is delicate to starting settings.

6.2 Supervised learning

The term "supervised ML" refers to the popular subset of ML techniques known as supervised learning. This method uses labeled databases to teach computers how to accurately categorize inputs or forecast events. The cross-validation procedure involves the model changing its values till the structure is well fitted. In supervised learning, structures are taught to give the best outcomes using a training dataset. This training database's precise both output and input data (labels) allow the prototype to improve over time. The approach updates the loss function after evaluating accuracy in order to reduce error. Methods for supervised learning aid in locating comprehensive answers to problems encountered in the actual world, particularly those related to medicine. To identify a brain tumor, several supervised learning techniques have been used. An explanation of each approach is given below. The ability to generate data outputs or gather information from previous experiences is the main advantage of these strategies. These methods' primary drawback is their failure to appropriately categorize input statistics that didn't correspond to the relevant categories inside the training set.

FLAIR as well as T1-weighted brain images can be used to recognize and segment brain cancer, according to a technique proposed by Padlia et al. [60]. A fractional Sobel filter has been used to improve pictures and reduce noise. For the purpose of identifying asymmetries in brain images, mutual information and Bhattacharya coefficients were utilized. SVM was employed to categorizing the statistical characteristics to distinguish the tumor portion from the tumor zone after retrieving attributes of the targeted area via patches and windows. Their approach has a 98.03% mean accuracy rate. Employing Kernel SVM (KSVM)-Social Ski Driver (SSD) for far more precise categorization, Rao and Karunakara [61] emphasized on effective segmentation and categorization. After being identified as tumorous and benign using KSVM in this research, the malignant tumors have been further classified as a moderate, high, and low employing SSD optimization approach. With reliability scores of 99.15%, 99.36%, and 99.2% for the respective years of 2020, 2019, and 2018 BRATS databases, it is demonstrated that the suggested KSVM-SSD approach has been superior in terms of categorization accuracy measured on the BRATS databases. However, since SVM can effectively handle unstructured and semi-structured input with the use of the right kernel function, doing so is not always simple.

A discriminative Random Forest (RF) algorithm was created and improved by Lefkovits et al. [62] for BTS in multimodal MRI. The aim of tuning has been to identify the best parameter readings and the relevant significant restrictions of the discriminative algorithm. In regards of dice index, the suggested technique produced results for entire cancer is 75–91% and for central region is 71–82%. An RDF-predicated BTS method that was previously published by Ellwaa et al. [63] was extended. Instead of utilizing a randomly chosen training database, the RDF was trained by an iterative procedure in which specific patients have been exposed to the training examples employing heuristic methods. Approximately 80% has been given as the method's acquired dice score. Anitha and Raja [64] developed methods for segmenting and identifying brain tumors predicated on RF filters to divide the brain modalities into healthy and pathological. The specificity and sensitivity rates of the suggested method have been 98% and 97%, correspondingly. Smaller Kernels of Two-Path CNN (SK-TPCNN) with RF were used by Yang et al. [65] to develop an automatic segmentation method. The central tumor, expanding tumor, and whole tumor, each had sensitivity ratings of 92.2%, 83.2%, and 96%, correspondingly. Whereas RF performs effectively with both discrete and on-going input and aids to increase accuracy by reducing fitting problem in decision trees, it takes a long period to train.

Thayumanavan and Ramasamy [66] examined the effectiveness of RF Classifier (RFC), Decision Tree (DT), and SVM in developing a paradigm for malignancies identification and segmentation in brain-MR images. According to the research findings, RFC achieved the best outcome with a precision of 98.37%. Additionally, RFC demonstrated 99.09% specificity, accompanied by SVM and DT with 88.78%, and 95.68%, correspondingly. While normalization and data scaling are not necessary for DT, learning takes a long time. Moreover, a slight alteration in the source dataset causes a vast alteration in the method's architecture. One of the simplest and most effective classification techniques seems to be the Naïve Bayes Classifier (NBC). It facilitates the creation of ML algorithms that can anticipate outcomes accurately quickly. Many studies have used Naïve Bayes (NB) to detect brain tumors in medical imaging. To find brain cancers on MR images, Kaur and Oberoi [67] used an NBC, for instance. For BTS, the suggested method demonstrated 86% accuracy. Raju et al. [68] designed a Bayesian fuzz- clustering approach for BTS and Multiple-SV-Neural Network (multi-SVNN) classifiers predicated on the Harmony-Crow Search (HCS) evolutionary algorithms. The proposed approach, according to the researchers, has a 93% accuracy rate. The "zero-frequency issue" is when NB approaches provide zero likelihood to a categorizing example whose category in the testing examples wasn't present in the training examples, despite the fact that they have been suitable for handling multi-class forecasting issues and need far less training examples (Table 3).

7 BTS using DL methods

A kind of artificial intelligence (AI), and ML, known as DL imitates how people learn specialized subjects. DL seems to be important in data analytics that also includes statistical and prediction modeling. Owing to DL approaches, a number of visual analytic tasks, involving categorization, object identification, and monitoring, have shown considerable performance increases [75]. Also, despite demonstrating state-of-the-art reliability, DL approaches have had a substantial influence on medical imaging processing activities mechanisation. Numerous DL approaches were created and used in a variety of fields, especially the brain cancer's identification, over the past few decades [76]. For BTS, Nema et al. [77] created the RescueNet that has been trained using unpaired Generative-Adversarial-Network (GAN). For the BRaTS 2017 and BRaTS 2015 databases, the findings revealed Dice values of 94.63%, and 94.01%, correspondingly. Neelima et al. [78] suggested a model for categorizing brain cancers utilizing MR images was based on Optimal-DeepMRSeg technique, which was learned employing a developed Sailfish Political-Optimizer (SPO) method for BTS. This approach produced improved accuracy, specificity, segmentation accuracy, and sensitivity that have been, 91.7%, 92.5%, 90%, and 92.8%, correspondingly. Besides that, when segmenting cancers employing 3D brain CT or MR images, Rezaei et al. [79] presented an intelligent strategy predicated on an adversarial network termed voxel-GAN for addressing unbalanced data issues. Once the recommended strategy was examined on the ISLES database, the outcomes indicated 0.83 as Dice value, 9.3 as Hausdorff score, 0.81 as precision, and 0.78 as recall. The GAN networks have the ability to increase data generation, decrease expenses, and improve data examples. However, such algorithms call for sophisticated databases and solid technical expertise.

Raju et al. [80] suggested a strategy for dividing and classifying brain cancers using MR images used DBN and integrated active contour framework. The results showed that the suggested model has 94.5% accuracy, 96.95% sensitivity, and 99.35% specificity. Even with a massive quantity of input, the DBN algorithms may still deliver the greatest performance outcomes. To be more effective, these models need a ton of data and highly specialized understanding. Relying on MRI scans, Badža and Barjaktarović [81] constructed a convolutional autoencoder for BTS. According to the authors, the suggested strategy had 99.23% mean accuracy for pixel categorization and 99.28% mean accuracy for five-fold cross-validation and single test outcome. Moreover, the use of autoencoders may drastically minimize the data dimensionality, offer a suitable method for significantly reducing

Table 3 Summary of application of unsupervised and supervised techniques

Reference	Dataset	Segmentation Techniques	Demerits
[69]	BRATS 2015	Bayesian fuzzy clustering	1.Consumption of time 2.Extremely complicated system
[70]	BRaTS 2017	lattice Boltzmann + superpixel fuzzy clustering	1.Extremely complicated system 2.Disregarding the hazy borders
[16]	BRaTS 2013	Random Forest	1.Incredibly susceptible to sounds 2.New training sets are necessary
[71]	Clinical MR Images	Morphological Operation + Region of Interest + Region Growing	1.Class disparities not taken into account 2.Extremely complicated system
[72]	MRI images	FRFCM- BTS-ELM	1.Class disparities not taken into account 2.Employing only the T1 mode
[73]	BRATS 2015	Region of Growing algorithm	1.Required to choose a starting location
[74]	BRaTS 2015	VGG19 + k-means	1.Data is easily forgotten 2.There are several functions needed

source-data noise, and increase the developing DL system's efficacy. Autoencoders can only learn and replicate input attributes from the data they have been learned on; they cannot learn or reproduce input attributes from fresh data. An advanced CNN for BTS in MR images was presented by Sajid Iqbal et al. [82]. The segmentation challenging database for BRATS, which consists of images collected via four distinct modalities, has been used by the proposed scheme. In order to address the segmentation issue, an expanded version of the current network was also shown. Several neural network structures are interconnected in a consecutive manner in the system design, and Convolutional feature mappings are fed at the peer stage. Hence, experimental findings on BRATS 2015 standard database demonstrated the suggested approach's accessibility and superiority to competing methodologies in this field of study. For the purpose of segmenting gliomas within MRI images, Sun et al. [83] presented a multi-pathway 3D design predicated on a Fully Convolutional Network (FCN). Leveraging multi-modal MR images, the design uses 3D extended convolution throughout every route to extract various receptive regions of feature maps that have been subsequently spatially merged employing skip connections. This framework may make it easier for FCN algorithms to define the borders of tumour regions. Besides that, with the CNN methodology, Mohammad Havaei et al. [12] achieved a balance between performance and computational efficiency that has previously been difficult for other approaches to match. The CNN generates an attribute description instantly from the input because it is learned on image inputs. Furthermore, a cascaded structure with two routes—one concentrating on glioma's minute specifics and the other on the wider context—was suggested. Moreover, we provide a two-stage patch-wise learning method that enables us to learn methods in a matter of hours. By fully using the provided method's convolutional features, researchers can also segment whole brain imagery in 25 s to 180 s. The technique was one of the best reliable in the research and was also extremely computationally intensive, according to experimental findings on BTS challenges (BRATS 2013, and BRATS 2015). The CNN algorithms may automatically discover hidden outlines within the source dataset and distribute weights among stages. However, such frameworks are unable to represent the object's location and orientation.

Jalluri et al. [84] concentrated on the usages of several methods for brain tumor identification employing brain MRI. Moreover, an adaptive-bilateral filter (ABF) has been used in research's pre-processing to get rid of the sounds that have been prevalent in MR images. Next, for accurate tumor region recognition, fuzzy recurrent neural network (RNN) (FR-Net) and binary thresholding segmentation approaches were used. Datasets for testing, validation, and training are employed. The machine-based provided technique made a prediction about it or not the individual does have a brain cancer. Specificity, accuracy, and sensitivity are only a few of the performance indicators that were used to evaluate the final results. It has been hoped that the planned work would operate more admirably than its competitors. Each example can be thought to be reliant on earlier examples, and RNN algorithms can handle inputs of arbitrary length. Such approaches do, however, run into problems including Vanishing or Explosive Gradient. Long Short-Term Memory (LSTM) systems have been RNN that may learn order dependency in problems involving sequence prediction [85]. Among the most popular RNN models to date seems to be the LSTM. The most effective method for simulating sequence information, it has been used to understand the intricate complexities of individual action. Long-term memory is referred to as "cell state". To classify cancers employing multi-modal MRI, Xu et al. [86] presented an LSTM based Multi-modal-UNet (LSTM-UNet). The suggested LSTM-UNet beat the conventional U-Net with less model variables, according to empirical findings assessing the method's effectiveness on the BRATS-2015 database. Long-term relationships can be learned via LSTM networks. In order to capture both localised structural and worldwide contextual data, Cahall et al. [87] suggested the DIU-Net paradigm for end-to-end BTS predicated on U-Net. This architecture includes inception units with dilated convolutions along with widening and contracting routes. Every dilated inception component in this design consists of 3 1×1 convolution processes accompanied by a l-dilated convolutional filters. In a further work, Yang et al. [88] suggested a novel design (DCU-Net) predicated on the conventional U-Net but with dilated convolutions for BTS. By substituting elongated spatially pyramid pooling for max pooling towards the down-sampling procedure conclusion, the feature reception field may be increased while maintaining image resolution. During the training systems, both dilated convolutional residual cells and skip connections are coupled to enhance the network's capacity to detect tumour features more precisely. By retrieving a weighted patch within the tumor's boundary areas, Baid et al. [89] suggested a 3D fully automatic BTS structure centred on the U-Net framework that divides radiologically recognisable tumour subdivisions and tackles the class imbalance issue among tumor and non-tumor spots. The outcomes demonstrated that the segmentation based on weighted patch approach performs similarly to the pixel-based technique when there exists a thin border between tumour subparts. Guan et al. [90] suggested a 3D AGSE-VNet network incorporated segmentation layout predicated on V-net employing the attention guide filter (AG) for every decoder and an incorporated component of the squeeze and excites (SE) for every encoder, enhancing the helpful data consequently employing the channel relationship. This framework can be used for BTS employing 3D MR images. This algorithm's effectiveness was evaluated using the BraTS 2020 database, and it produced successful segmentation outcomes with the potential for clinical trials. Such algorithms require a variety of assets, a large memory capacity, and a long training period because they are susceptible to overfitting. Table 4 indicates the DL methods summary in BTS.

Table 4 Overview of BTS employing DL techniques

Reference	Dataset	Segmentation Techniques	Demerits
[91]	BRaTS 2020	CNN	1.New training sets are necessary 2. Interpretability is poor
[92]	Hospital databases + BRaTS2018 + CQ500	DTCWT + DRL	1.Spatial coherence is lacking 2. Extremely complicated system
[93]	BRaTS2013	FCRE + CNN	1.Utilizing only HGG sick individuals 2.New training sets are necessary
[94]	BRaTS 2018,2015 and 2017	3D CNN	1.Extremely complicated system 2.Neglect to identify the subtle and tiny brain tumor
[95]	BRaTS 2017 + 2015 + 2013	DDM+ DPGM	1.Extremely complicated system 2.A significant amount of training data is required
[96]	Radiopaedia dataset	VGG19-CNN	1.Employing only the T1 mode 2.Require to perform post-processing
[97]	MRI dataset	Faster R-CNN	1.Employing only the T1 mode 2.New training sets are necessary

8 Hybrid methods-based BTS

There have been two kinds of brain cancers: benign and aggressive. A brain cancer could be caused by an unchecked growth of aberrant cells within brain tissues. An innocuous brain cancer does not harm the nearby normal and healthy cells; however, a malignant cancer might affect the nearby brain cells and cause a person to pass away. To ensure the patients' life, a brain cancer may need to be found early. Often, MRI scanning has been used to find brain tumors. Because of the tumors' unusual shapes and locations inside the brain, radiographers have been unable to effectively segment them in MRI images. A precise BTS has been required to find the cancer, to diagnose a patient appropriately, and to offer the doctors the information necessary to carry out the patient's operation. To dynamically and effectively segment the cancer, Thillaikkarasi and Saravanan [98] introduced a unique DL technique (kernel-based CNN with M-SVM). The processes in the study that was being presented include pre-processing, attribute extraction, image categorization, and BTS. The Contrast Limited Adaptive Histrogram-Equalization (CLAHE) and Laplacian of Gaussian filtering method (LoG) are used to improve and flatten the MR image, and attributes may be derived from it depending on the tumor's location, size, and surface characteristics in the brain. In accordance with the chosen characteristics, M-SVM has been used to classify the images. With the aid of the kernel-based CNN approach, the tumor has been segmented from MR image. Moreover, the recommended method's empirical outcomes indicated that it can perform BTS with an accuracy of about 84% than existing strategies. However, the method needs higher computation time [99].

To build intelligent clinics, a segmentation method for brain cancers was necessary. Morphological diversity and major category mismatch need to be successfully addressed in order to classify brain tumors intelligently. Because of these problems, conventional DNN struggle to forecast higher-accuracy segmentation images. He-Xuan et al. [100] suggested employing multimodal brain cancer images along with LSTM and UNET frameworks in order to create new network architecture with a mixed gradient descent in order to address sample disparity and define an intellectual segmentation procedure to detect brain cancer as a solution to these issues. The open source BTS Challenge database has been utilized to learn and validate the suggested network in order to confirm the viability of this technique. In 3 tumor regions—enhanced, centre, and whole—the study found DSCs of 0.80, 0.82, and 0.91, specificities of 0.98, 0.99, and 0.99, and sensitivities of 0.82, 0.85, and 0.93. Also, findings demonstrated that the suggested method could segment various tumor regions more precisely than those of previous BTS approaches, demonstrating its possible application usefulness in the medical identification of brain cancers. However, the study was limited to a single tumor type, and this method requires a lot of computation time.

In order to achieve segmentation outcomes with visual and spatial coherence, Xiaomei et al. [26] introduced a revolutionary BTS approach that is built by merging Conditional Random-Fields (CRFs) and fully CNNs (FCNNs) in a coherent model. Employing 2D image patching and image segments, this study learns a DL-predicated segmentation algorithm as follows: FCNNs are trained employing image patches, CRFs are trained as RNN (CRF-RNN) employing image slicing with FCNN variables fixed, and CRF-RNN and FCNNs are fine-tuned employing image slices. In specifically, trained three segmentation algorithms were used to separate brain tumors employing a voting-based fusion technique employing 2D-image slice and patches collected in the radial, frontal, and sagittal perspectives, correspondingly. Slice-by-slice brain images segmentation using the proposed approach was substantially quicker than using image patches. Using imagery data from the

BRATS 2013, 2015, and 2016, the research tested the presented technique. The experimental findings have shown that the proposed technique is capable of creating segmentation models using T1c, Flair, and T2 scans and achieving comparable outcomes to models created using T1c, T2, Flair, and T1 scans. However, the method consumes more time.

A HTTU-Net model for BTS was proposed by Nagwa et al. [101]. This design makes advantage of activation and normalization function. It features two loops, each of which had a distinct kernel dimension and contains a distinct layer count. The ultimate segmentation will then be created by merging those two tracks. Furthermore, to tackle the issue of class imbalances, this study uses generalized Dice (GDL) loss mechanisms and focal losses. The BraTS'2018 databases were used to assess the suggested segmentation technique, and the consequences displayed mean Dice coefficients for 3 tumor regions-enhancement, core, and whole of 0.745, 0.808, and 0.865, correspondingly. The BTS may be done with the suggested HTTU-Net topology, and the findings are extremely accurate. Together with the article, several both qualitative and quantitative assessments have been discussed. It demonstrates that the findings of the provided model are extremely equivalent to professional human-level competence and might aid professionals in cutting down on diagnosis time. The study has limitations because of the numerous layers that make up its intricate design.

Conventional deep CNN for fully autonomous BTS has two issues: inadequate multi-scale tumor detection and spatial information loss due to recurrent pooling/striding. Zexun et al. [102] employed a 3D atrous-convolution along with a solitary stride to substitute striding/pooling as well as provide the framework for attribute learning to solve the first issue. A AFPNet+3D CRF has been created and appended to the backbone's end to address the second issue. This framework enhances the general model's capacity to discriminate between cancers of different sizes by adding contextual data. As a last stage in the network output's post-processing, a 3D fully-connected CRF has been built to achieve hierarchical segmentation of both spatial consistency and appearance. Several ablation tests performed on MRI databases show that the technique's multi-scale data acquisition and lossless attribute calculation are capable of solving the aforementioned issues. The suggested technique attains superior results and may be successfully incorporated into clinical applications when contrasted to state-of-the-art solutions on public standards. However, this model is not tested on challenge databases.

9 Results and discussion

9.1 Performance evaluation

There are numerous techniques to assess the effectiveness of segmentation or categorization systems. To display their verified outcomes, researchers employ a variety of approaches. The following commonly used performance metrics are examined in the present investigation: Confusion matrix, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Jaccard Index (Tanimoto Co-efficient), Dice-overlap-index (DOI) or Dice Similarity Coefficient (DSC), Accuracy metric, Specificity, Sensitivity, Recall, and Precision. The crucial data regarding the real outcome and the projected outcome given by segmentation or categorization techniques is provided by confusion matrices. Table 5 provides a demonstration of confusion matrix.

Table 5 Representation of Confusion Matrix

	Predicted Class 1	Predicted Class 2
Actual Class 1	T_P	F_N
Actual Class 2	F_P	T_N

9.1.1 Mean squared error

Mean Squared Error (MSE) is a statistic that expressed in Eq. (1) the average squared variation among the temperature values anticipated and observed. Higher values denote worse performance and provide an estimate of the entire prediction error.

$$MSE = \frac{1}{N} * \sum (Actual - Forecast)^2 \tag{1}$$

The segmentation techniques are shown in Table 6 along with the relevant Mean Squared Error (MSE) percentages. By evaluating the average squared difference between the predicted segmentation and the actual segmentation, the MSE is a frequently used statistic to evaluate the effectiveness of a segmentation method. Each segmentation method is represented by a row in the table, and the associated MSE percentage is given in the adjacent column. Lower MSE percentages suggest fewer errors between the anticipated and ground truth segmentations, indicating superior segmentation performance. Figure 3 depicts the Mean Square Error Ratio in graphic form.

9.1.2 Peak signal-to-noise ratio

A higher PSNR number denotes that the two pictures are more comparable or of greater quality. PSNR is frequently employed to assess how well image compression methods function or how faithfully reconstructed pictures compare to the originals. The PSNR equation is as follows in Eq. (2)

$$PSNR = \frac{10Log_{10}\left(peakval^2\right)}{MSE} \tag{2}$$

Different segmentation techniques are shown in Table 7 together with the Peak Signal-to-Noise Ratio (PSNR) values that correlate to them. The PSNR, which measures the ratio of the highest possible power of a signal to the strength of corrupting noise, is a commonly

Table 6 Comparison assessment of MSE

Reference	Method used for segmentation	MSE(%)
[30]	Salient-map modification	34
[37]	CNN	28
[38]	Image classification	58
[24]	HORW	45
[25]	Level Set	63
[27]	Kernelized Fuzzy Entropy Clustering	78

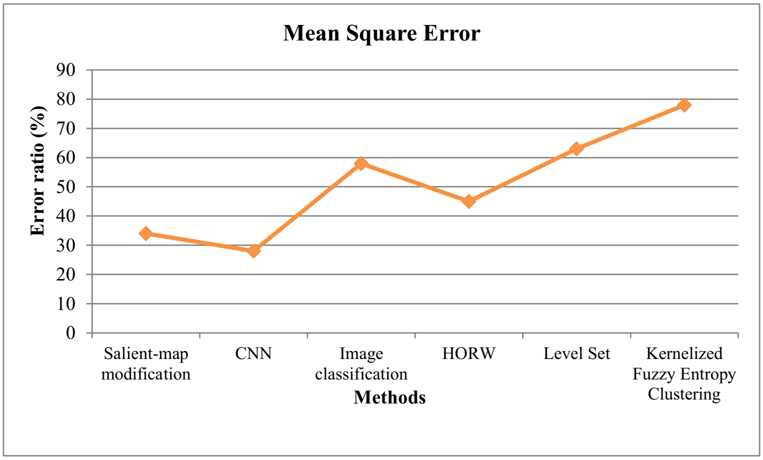


Fig. 3 Comparison assessment of MSE

Table 7 Comparison assessment of PSNR

Reference	Method used for segmentation	PSNR (db)
[30]	Salient-map modification	45.67
[37]	CNN	56.32
[38]	Image classification	62.15
[24]	HORW	38.92
[25]	Level Set	51.85
[27]	Kernelized Fuzzy Entropy Clustering	68.78

used metric to assess the quality of a picture that has been segmented or rebuilt. The comparison of PSNR values across segmentation techniques is shown in Fig. 4. greater bars denote greater PSNR values, which suggest segmentations of higher quality.

The effectiveness of frequently used BTS techniques is evaluated by taking each model's accuracy into account. Accuracy seems to be the percentage of correctly identified image pixels. This has been occasionally denoted to as complete pixel exactness. Whereas being the common fundamental effectiveness indicator, if there was a class conflict, the outcomes of detection process may be incorrect. When one of the specified categories performs higher compared to the other, there is a category disparity. In this scenario, findings would be skewed as a result of the superior accuracy of the dominant class outweighing the poorer precision of the competing cohort. If there hadn't been a class differences, the accuracy metric has been proposed for evaluating detection results utilizing images. Table 8 and Fig. 5 represented the segmentation accuracy of a widely used model is displayed.

Accuracy

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{3}$$

The segmentation result indicated that Salient-map modification [30] method has attained higher accuracy, while compared to other selected methods like CNN [37], Image

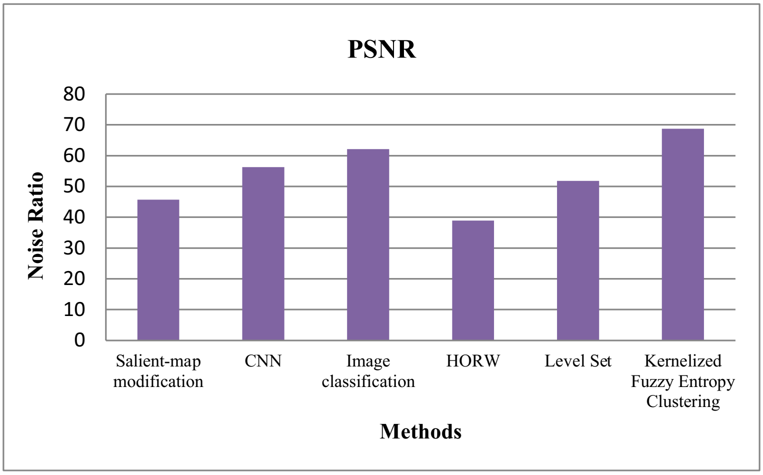


Fig. 4 Comparison assessment of PSNR

Table 8 Commonly used segmentation method's performance

Reference	Method used for segmentation	Accuracy (%)
[30]	Salient-map modification	98
[37]	CNN	95.1
[38]	Image classification	96.48
[24]	HORW	63
[25]	Level Set	89.5
[27]	Kernelized Fuzzy Entropy Clustering	90.19

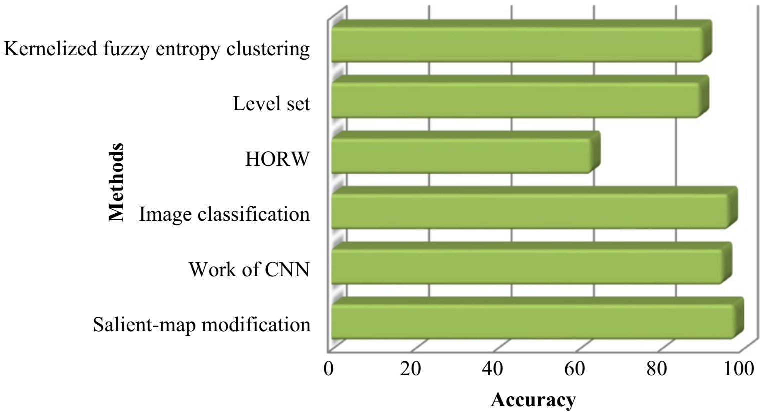


Fig. 5 Comparison of commonly used segmentation method's accuracy

classification [38], HORW [24], Level Set [25], and Kernelized Fuzzy Entropy Clustering [27].

Moreover, the hybrid segmentation method's performances are also compared that was shown in Table 9. The hybrid BTS methods employed in different databases are selected for this comparison process. The selected methods are lattice Boltzmann + super-pixel fuzzy clustering [70], Morphological Operation + ROI + Region Growing [71], FRFCM-BTS-ELM [72], VGG19 + k-means [74], FCRE+CNN [93], DDM + DPGM [95], VGG19-CNN [96], kernel-based CNN + M-SVM [98], LSTM + UNET [100], CRFs + FCNNs [26], HTTU-Net [101], and AFPNet+3D CRF [102].

Precision

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{4}$$

Recall

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{5}$$

Specificity

$$Specificity = \frac{T_{Neg}}{T_{Neg} + F_{Pos}} \tag{6}$$

The comparison of dice similarity and accuracy of the hybrid BTS method is shown in Fig. 6a and b, correspondingly. The result indicated that lattice Boltzmann + super-pixel fuzzy clustering [70] method has attained higher accuracy of 99.4% compared to other methods like VGG19 + k-means [74], VGG19-CNN [96], and kernel-based CNN + M-SVM [98].

The overlapping pixel among the segmentation outcome (n) and the ground truth (m) is provided by the Dice Similarity Coefficient (DSC).

$$DSC\,(m, n) = \frac{2|m \cap n|}{|m| + |n|} \tag{7}$$

The result indicated that lattice Boltzmann + super-pixel fuzzy clustering [70] method has attained higher dice of 93% compared to other methods like FRFCM- BTS-ELM [72], DDM + DPGM [95], LSTM + UNET [100], CRFs + FCNNs [26], HTTU-Net [101], and AFPNet+3D CRF [102].

9.1.3 Jaccard index

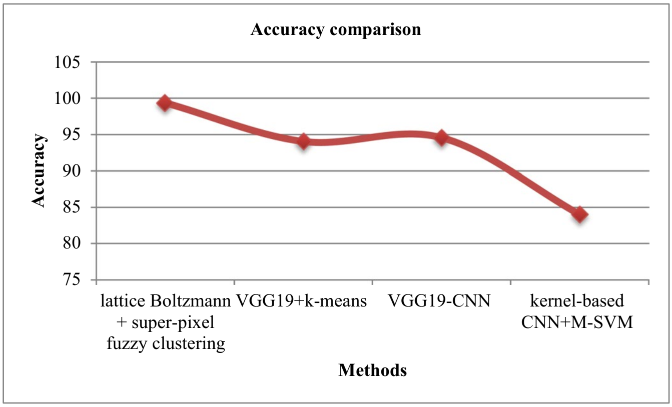
The Jaccard Index would demonstrate how closely the pixels in the segmented outcome (B) and the surface of the truth (A) match up. More accurate results are obtained when the Jaccard Index is high.

$$Jaccard_{Index}\,J\,(m, n) = \frac{|m \cap n|}{|m \cup n|} \tag{8}$$

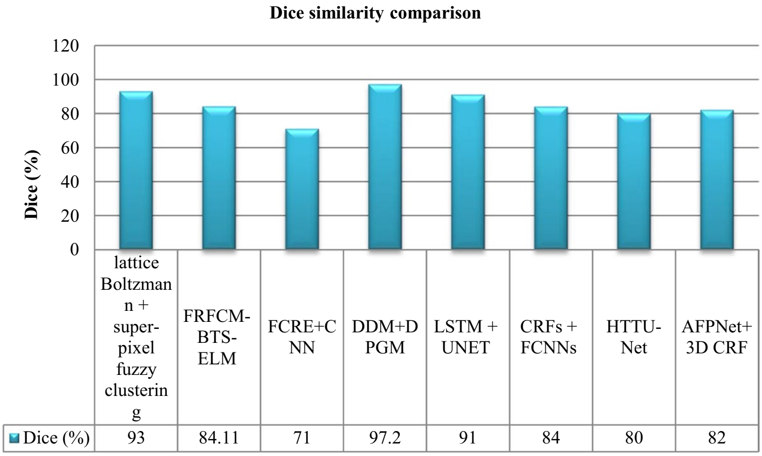
Based on their Jaccard Index scores, the segmentation techniques in Table 10 are compared. A popular metric for assessing the similarity between two sets—in this instance,

Table 9 Performances of hybrid BTS methods

References	Methods	Accuracy (%)	Specificity (%)	Sensitivity (%)	Dice (%)
[70]	lattice Boltzmann + super-pixel fuzzy clustering	99.4	99.72	91.83	93
[71]	Morphological Operation + ROI + Region Growing	–	77.9	86.98	–
[72]	FRFCM- BTS-ELM	–	–	–	84.11
[74]	VGG19 + k-means	94.06	–	–	–
[93]	FCRE+CNN	–	–	72	71
[95]	DDM + DPGM	–	–	–	97.2
[96]	VGG19-CNN	94.58	96.12	88.41	–
[98]	kernel-based CNN + M-SVM	84	–	–	–
[100]	LSTM + UNET	–	99	93	91
[26]	CRFs + FCNNs	–	–	82	84
[101]	HTTU-Net	–	99.9	80	80
[102]	AFPNet+3D CRF	–	–	–	82



(a)



(b)

Fig. 6 Hybrid BTS method performance comparison (**a**) Accuracy (**b**) Dice similarity

Table 10 Comparison of Jaccard Index

Reference	Method used for segmentation	Jaccard Index
[30]	Salient-map modification	0.85
[37]	CNN	0.92
[38]	Image classification	0.78
[24]	HORW	0.91
[25]	Level Set	0.88
[27]	Kernelized Fuzzy Entropy Clustering	0.80

the predicted and actual segmentations—is the Jaccard Index, commonly known as the Intersection over Union (IoU). Improved segmentation accuracy and similarity to the ground truth are shown by higher Jaccard Index values. The visual comparison of the

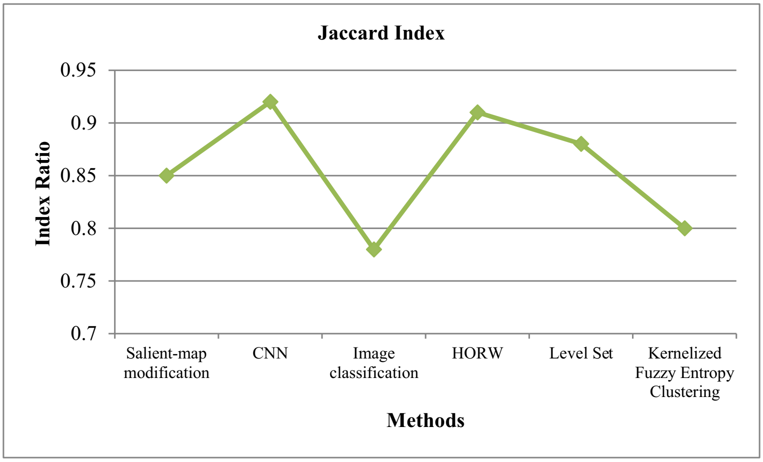


Fig. 7 Comparison of Jaccard Index

segmentation techniques based on their Jaccard Index values is presented in Fig. 7. It gives users and investigators an immediate, intuitive knowledge of the relative performance of each method, making it simpler for them to pinpoint the techniques that have the highest segmentation accuracy.

10 Discussion

Brain tumors remain to be a hot topic for study in the medical-image processing domain. The brain cancer is among the deadliest disease that arises when the proliferation of tissues in the brain has been out of bounds. The death incidence of this malignancy motivated experts examines ways for earlier brain cancer detection. MRI images remain among the greatest methods to identify tumor by offering a view of soft matter inside the brain. Numerous ML- and DL-based techniques were created during the past few decades. But because so many articles used these strategies, it's critical to review the most recent research and techniques. In addition to reviewing frequently used BTS methodologies, BTS articles, ML-based BTS techniques, DL-based BTS techniques, and hybrid BTS articles, this work compared the performance of the various approaches when used on databases that were made accessible to the public. According to analyses of earlier studies, MRI remains the most effective imaging method for diagnosing brain tumors (Tables 2 and 3). The primary rationale that MRI has been used so often is that it offers more information than other imaging methods including CT scans. Furthermore, DL approaches have been applied substantially more recently than ML methods. Nonetheless, the amount of research that employed ML algorithms or hybrid strategies was still larger than DL-predicated hybrid BTS strategies. The most popular ML and DL techniques for BTS were SVM and CNN. Furthermore, BRATS databases have been used in the majority of studies. However, the CNN integrated with other methods have attained less accuracy for segmentation process. Thus, the accuracy needs improvement in future work while integrating CNN with other methods.

11 Conclusion

BTS have benefited greatly from advances in AI. For example, pathology, anomaly identification, brain cancer diagnosis, tissue density computation, therapy planning, and computer-assisted surgery all have benefited from the use of ML and DL techniques and methodologies by researchers. These methods have been efficient for tasks involving the BTS because their characteristics make it possible to tell aberrant tissues apart from healthy ones. This essay provides an overview of approaches used in BTS. This research covers a wide range of commonly employed BTS, ML-based BTS, and DL-based BTS techniques for brain tumors identification. In order to assist scholars and medical professionals in developing prospective research paths and, more crucially, in identifying the most efficient and accurate tactics for BTS, the present work objectively evaluates the existing methodologies based on numerous assessment parameters. Despite CNN's widespread popularity, it can be difficult to separate brain structures using DL approaches. The efficiency of particular models is impacted by the images captured by diverse scanners. Deep CNN performs poorly because to insufficient training data and resolution. Conventional strategies have been still applied in real-world circumstances, and training time remains an important consideration. This research makes numerous suggestions for future research that might be used to improve the functionality of the existing BTS processes: (i) Greater databases of 3D MRI should be gathered, (ii) segmentation accuracy should be improved by creating a unique hybrid CNN-UNet approach, and (iii) incorporated multi-head attention layers should be created for the hybrid DL models.

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

Declarations

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

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