Automated Brain Tumour Segmentation Techniques—A Review

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ABSTRACT: Automatic segmentation of brain tumour is the process of separating abnormal tissues from normal tissues, such as white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). The process of segmentation is still challenging due to the diversity of shape, location, and size of the tumour segmentation. The metabolic process, psychological process, and detailed information of the images, are obtained using positron emission tomography (PET) image, Computer Tomography (CT) image and Magnetic Resonance Image (MRI). Multimodal imaging techniques (such as PET/CT and PET/MRI) that combine the information from many imaging techniques contribute more for accurate brain tumour segmentation. In this article, a comprehensive overview of recent automatic brain tumour segmentation techniques of MRI, PET, CT, and multimodal imaging techniques has been provided. The methods, techniques, their working principle, advantages, their limitations, and their future challenges are discussed in this article. Int J Imaging Syst Technol, 27, 66–77, 2017; Published online in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/ima.22211

Key words: review; image segmentation; human brain tumour; medical imaging; computer-aided diagnosis

I. INTRODUCTION

The tumour is an abnormal growth of cells in the body. It is considered as a crucial disease as it affects the life of the human. However, early detection of the tumour is very important to save the life of people. The tumour occurs in various parts of the body in which the total system is collapsed, when it is in the brain. The brain tumour has different shape and size and requires different treatment (Gupta and Shringirishi, 2012). Over 120 different types of brain tumour exist and can be classified as primary and metastatic brain tumour. The primary tumours do not spread to another part of the body and stay within the brain. Statistically, it is found that primary tumour is found to be developed more in older adults and children. The metastatic tumour spreads to other parts of the body from where it is originated. It is more common in adults than in children. Based on the characteristics, tumours can be categorized as benign and malignant. The benign tumours are slowly growing and less aggressive. The malignant tumour is rapid growing and life threatening. American Brain Tumour Association has estimated that in the year 2015, nearly 78,000 new cases of primary brain tumours are diagnosed. This includes nearly 25,000 primary malignant and 53,000 nonmalignant brain tumours. The development of brain tumour among the people and people die out of brain tumour are increasing every year among the developed countries and it is estimated by National Brain Tumour Foundation (NBTF) (El-Dahshan et al., 2014). The World Health Organization (WHO) has issued a grading for brain tumours (Louis et al., 2007) in which Grade I (pilocytic astrocytoma) are least aggressive and grow slowly and Some Grade II (low-grade astrocytoma) reproduce and affect nearby tissues. Grade III (anaplastic astrocytoma) are the malignant tumour that reproduce cells and affect tissues. Grade IV glioblastoma) are the most malignant tumours which usually reproduce rapidly and affect nearby normal brain tissue.

The normal brain image contains various tissues, such as WM, GM, and CSF. The representation is shown in Figure 1. To diagnose human brain structure, safe imaging techniques are used throughout the world. CT, PET, MRI, and multimodal imaging techniques, such as MRI/CT and MRI/PET, are various imaging techniques that provide information from a variety of excitation sequences about brain tissues. The segmentation is the method of dividing an image into various regions, such that the pixels within the region have similar characteristics. In the specific case of MRI brain image, separation of different tumour tissues from normal tissues is labeled as segmentation process. In practical life, segmentation of brain tumour is done manually. The manual segmentation of tumour from the images involves huge processing time and may produce the inaccurate results. In order to help doctors for diagnosis and treatment of tumour and to help researcher for studying the brain activities, the research in automatic segmentation techniques of brain tumour are gaining more importance. Still, segmentation is challenging for the unpredictable shape and appearance of the brain tumour. The above points motivated us to do review on segmentation techniques of brain tumour. Every year, new brain automatic segmentation algorithms are published. In this article, review of automatic brain tumour segmentation using MRI, CT, PET, and multimodal segmentation techniques, such as PET/CT and PET/MRI, are emphasized. The survey has been done for the range of years from 2010 to 2016. The various

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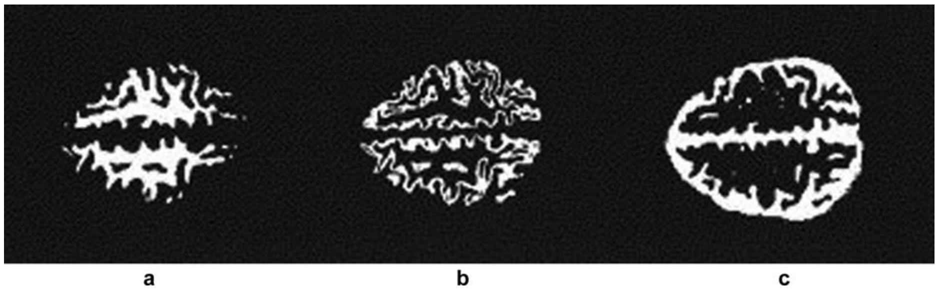

Figure 1. Tissues of human brain. (a) White matter (WM), (b) Gray matter (GM), and (c) Cerebrospinal fluid (CSF).

techniques, their advantages, limitations, and future challenges are discussed in the article. This article will be useful for researchers who are working in the field of development of CAD system for brain tumour segmentation. The rest of this article is organised as follows: Section II discusses the brain tumour segmentation techniques of MRI. Section III discusses the brain tumour segmentation techniques of PET. Section IV discusses the brain tumour segmentation techniques of CT. Section V discusses the multimodal brain tumour segmentation. Section VI discusses the evaluation measure of brain tumour segmentation. Section VII specifies the dataset for brain tumour, and finally, Section VIII discusses the conclusion and future challenges.

II. BRAIN TUMOUR SEGMENTATION TECHNIQUES OF MRI

MRI is mainly used for brain tumour diagnosis and treatment in the clinic. MRI offers various beneficial features like multiplanar capabilities, potential of tissue characterization and no bone and teeth artefacts.

A. Background. The detail images of different part of the body are obtained in MRI by using natural body's magnetic field. Under normal circumstances, the hydrogen atom spin like a bar magnet in the human body with the axis aligned. When the body is placed in the magnetic field under MRI scanner, a magnetic vector along the axis of MRI scanner is created. Magnetic vector is deflected, when the radio wave is passed through it. On switching off the radio wave, the signal is emitted, which is used for creation MRI images. T1 relaxation (spin lattice), T2 relaxation (transverse), and proton density (PD) are used to measure the spatial distribution of several soft tissues by varying radio frequency timing parameter. Most recently, the FLAIR (fluid attenuated inversion recovery) sequence has replaced the PD image. FLAIR images are T2-weighted when the CSF signals are suppressed. The representation of various tissues white matter, gray matter, and CSF in T1, T2, and FLAIR are listed in Table I. The FLAIR, T1, and T2 images of brain tumour are shown in Figure 2.

Many segmentation techniques are available in the literature survey. Some of the existing segmentation method for brain tumour from MRI is discussed in the following section.

B. Thresholding Method. Thresholding is one of the segmentation techniques which compare pixel intensities with one or more intensity thresholds. The major types of thresholding are local and global thresholding (Gordillo et al., 2013). The global thresholding technique works better for segmentation, if homogeneous intensity is available in an image. If the image contains more than one region with the different object, then local thresholding techniques works better for segmentation. The image can also be segmented using multiple thresholds also. In Saad et al. (2011) for preprocessing and enhancing the image, the global thresholding is used to form the binary image. Then brain tumour is segmented using morphological operation. Oversegmentation and undersegmentation are possible with threshold segmentation. Some part of the image may look dark and some part may look bright in global thresholding due to intensity inhomogeneity across the scene.

C. Edge-Based Method. The changes in the intensity of images are used for detecting edges. Edge pixels are those places where image function changes sharply. There are several methods for edge-based segmentation such as Sobel, Prewitt, Roberts, and Canny. In Aslam et al. (2015), an improved edge detection algorithm for tumour segmentation is proposed. An automatic image dependent thresholding is developed, which then combines with Sobel operator to detect edges of the brain tumour. The tumour region is then extracted using closed contour algorithm and object separation based segmentation. The results of the proposed method are better than the conventional method using Sobel. In Mathur et al. (2016), the process of edge detection for segmentation is performed with the help of Fuzzy Inference System. The Automatic thresholding is developed using K-means based fuzzy rule. Generally, the edge-based segmentation method is simple and easy. At some times produces open contour, and it is sensitive to the threshold. Much research work is carried out to overcome such issues.

D. Region Growing Method. Region growing method extracts regions with similar pixels. The process begins with seed selection of the given image. Automatic or manual seeds selection is performed. Neighbors of the seeds are added to the region if it is similar to the seed. The process is repeated until seeds cannot be added to the region (Gordillo et al., 2013). In Lina et al. (2013), Fuzzy Knowledge-Based Seeded Region Growing for multispectral MR images is proposed. Taking into account the advantages of spatial information and correlation from multispectral images, fuzzy edge and similarity are used for defining initial seed in modified seeded

Table I. Representation of white matter, gray matter and cerebrospinal fluid

	White Matter (WM)	Gray Matter (GM)	Cerebrospinal Fluid
T1	High	Intermediate	Low
T2	Low	Intermediate	High
FLAIR	Intermediate	High	low

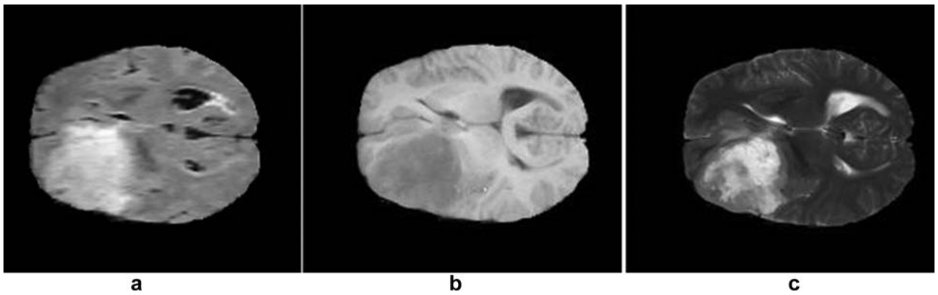

Figure 2. MRI brain tumour. (a) FLAIR image, (b) T1 image, and (c) T2 image.

region growing algorithm to segment tumour from MRI. In Viji and Jayakumari (2013), the texture based region growing is used. In the proposed method, local texture information of neighborhood pixel is extracted. Both intensity threshold and texture threshold for a pixel are considered for region growing to extract the brain tumour in MRI. The main advantage of region growing is that the regions with similar pixels are generated. The major limitations of region growing method (Gordillo et al., 2013) are the initial seed point selection and are more sensitive to noise

E. Watershed Algorithm. The watershed algorithm can be described with the help of the behavior of water on the land scape. The landscape is divided into various disjoint regions by dams. The dam is built at the point where water from different basins flow together. The process of building the dam is stopped, when water reaches the highest level in the land scape. Thus, each region in the landscape belongs to one dam. It leads to the production of a complete contour of the images, and no joining by contour is required. The main limitation of watershed segmentation is over segmentation (Gordillo et al., 2013). To overcome such limitation, pre- and post-processing is done to remove noise and to improve the reasonable segmentation result. In Pandav (2014), Marker-Controlled Watershed Segmentation used markers and floods. The gradient of image starting from these markers instead of regional minima is used. The proposed method produced the better result for larger image. The advantage of the watershed algorithm is that it can segment accurately multiple regions at the same time. Another benefit of this method is that contour joining is not required, as it produces complete contour of the segments. The major drawback of the method is over segmentation.

F. Morphological-Based Method. Morphology operation is based on the morphology of features of the image. It is mainly used for extraction of information from the image based on the representation of the shape. Dilation and erosion are two basic operations (Dougherty, 1992). Dilation is used for dilating the size of the image. Images are shrunk by erosion. In Sudharania et al. (2016), the proposed method is able to segment tumour even in low-intensity images. The method involves several steps to extract tumour from the image, which includes enhancement of image, resampling of image, color plane extraction, histogram application, an advanced morphological operation to extract tumour region. In the proposed method, morphological operations are mainly used as the filter to remove low-frequency pixels and boundary pixels. Area of tumour, length, and other parameters of the tumour are identified effectively for treatment and diagnosis of the tumour.

F. Genetic Algorithm. Genetic algorithm (GA) is based on natural evolution. The natural evolution in GA is based on search process that optimizes the structure that it generates. In GA, chromosomes are used for describing the population of individuals. The population of individuals is updated using mutation, cross over, and selection operator. The population of individuals is updated iteratively. Fitness function used for evaluating each population is to optimize it. In Chandra and Rao (2016), GA algorithm is used for optimizing the segmentation results of brain tumour from MRI image, through evaluation criteria. In the proposed method, clusters of K -means algorithm is used as initials population. Centers that are clustered are evaluated by a fitness function. The weaker chromosomes are then replaced by better one, using various selection criteria such as crossover and mutation. The main advantage of GA is its high efficiency in difficult search problem. In Holland (1992), some important aspects of GA are discussed.

G. Fuzzy Clustering. In fuzzy clustering, each pixel is allocated a membership function value to the available classes based on its attributes (Gordillo et al., 2013). Fuzzy membership function takes the value range of 0 to 1. This value gives the similarity between the pixel and its centroid. If the value is 1, then the pixel is close to the centroid. Thus clustering is done based on membership values. Some advanced concepts in fuzzy clustering are discussed in Oliveira and Pedrycz (2007). The neighborhood attraction, based on location and relation to neighboring pixels is introduced to increase the performance of Fuzzy C Means (FCM). The segmentation result depends on neighbors and their location. The intensity of the pixels and their neighbors' spatial position is used for determining the degree of the optimum value and degree of attraction is found using the combination of the Genetic algorithm (GA) and Particle Swam algorithm (PSW). In Aina et al. (2014), the author has proposed a multi-stage system. There are two stages namely, brain tumour diagnosis and tumour region extraction. In brain tumour diagnosis stage, texture features are extracted from the noise free brain MR images. Ensemble based Support Vector Machine (SVM) classification is used to classify tumours. In tumour region extraction stage, skull removal, brain region extraction and brain tumour extraction are done to extract the brain tumour. The drawback of standard fuzzy clustering is that it does not include any spatial information for segmentation. In Verma et al. (2015), an improved Intuitionistic FCM (IFCM) clustering algorithm, that incorporates the local spatial information and local gray level information in IFCM. The splitting techniques of Discrete Curve Evolution (DCE) techniques are used to find cluster for T1, T2 and PD MR Brain image segmentation. In Ji et al. (2014), adaptive scale FLGMM (AS-FLGMM) algorithm for brain MR image segmentation is proposed. The author has developed a local scale estimation method to estimate the variances of the local Gaussian mixture model. This is combined with FCM for segmentation. The initialisation of FCM is improved by the aforementioned method. In Dubey et al. (2016), rough set based intuitionistic fuzzy clustering is proposed. The initialisation of cluster centre is performed using intuitionistic rough set based measure. Membership of cluster center is updated using intuitionistic rough set similarity measure. The method used to segment an image into the CSF, WM, and GM, which is very useful for the diagnosis of brain diseases. The advantage of fuzzy clustering is that it converges to tumour boundary correctly. Many authors have developed the methods to overcome the drawbacks of FCM like reducing computation time, incorporating spatial information into clustering task to segment correctly, correlating neighbouring pixels for clustering to reduce noise effect and incorporated additional knowledge into clustering task to get better result.

H. K-Means Clustering. K-means is the easiest and the simplest way to cluster data. Initially k groups are identified to the cluster the data k groups. Then, k initial centres are identified randomly. The object is assigned to the centres that are close to them. The mean of all objects in each centre is identified and labelled as new centres. The process is repeated until all objects are converged in a cluster. In Nimeesha and Gowda (2013), evaluation of K-means and FCM have been modelled on T1 contrast axial plane MR images for segmentation of brain tumour with histogram guided initialization of cluster. K-means is able to cluster the regions comparatively better than FCM. FCM identifies only three tissue classes, whereas K-means identifies all the six classes.

J. Deformational Model. A deformable model forms a closed curve in 2D and a closed surface in 3D which moves under a speed function determined by local, global, and independent properties. The parametric and geometric deformable are the two types of deformation model. The parametric deformation model is known as active contour or snakes. The model defines the curves or surfaces which move under the influence of internal and external forces. The internal forces provide smoothness of the model and external forces push the model towards the boundary of the object (Gordillo et al., 2013). Handling the topological changes of the contour is difficult in the parametric deformation model. Hence geometric deformation model or level set is introduced. Computational complexity is high for geometric deformation model. In McInerney and Terzopoulos (2000), basic concepts of deformation model are discussed.

In Tandoori et al. (2011), the segmentation process is done with Vector Field Convolution (VFC) based active contour model to extract brain and nonbrain regions. The VFC move external forces quickly to strong edges. Finally, the SVM classifier is used to classify the nonbrain regions and, then, the tissues are separated effectively. In Sachdeva et al. (2012), the author proposed a method utilized, both the intensity and texture information with active contour model to segment the tumour. Gray Level Co-occurrence Matrix (GLCM) is used in a new way to extract texture space and the static and dynamic motion of the proposed method helps the active contour to move towards the accurate tumour boundary. In Thapaliyaa et al. (2013), region-based level set method along with modified Signed Pressure function (SPF) is used to segment tumour from MRI. The object is extracted irrespective of where contour evolves. The parameters are tuned automatically based on thresholding techniques without human intervention. In Ilunga-Mbuyamba et al. (2016), a multi-population Cuckoo Search Strategy (MCSS) is implemented for active contour model. In the proposed method, two different shape search window are used. The basic idea of MCSS is Cuckoo lays the egg and places it in the nest. Then, it removes eggs and places it in the next best nest. For given n number of the nest, a nest with the best solution is taken for next generation. Another nest has to be replaced with new eggs. The MCSS framework is applied for two search window to form active contour. The proposed method segments tumour more accurately. The major drawback of deformational models is that in the case of inhomogeneity, the model may converge to the wrong boundary and it is computationally expensive. The advantage of the models is that it accommodates to various biological structures across different individual at the different time.

K. Atlas. An atlas is developed, and it contains a combination of both an intensity image (template) and its segmented image (the atlas labels). The atlas template and the target image are registered. The atlas labels are then propagated to target image. In Rohlfing et al. (2005),some important aspects of atlas base segmentation is discussed. In Bauer et al. (2010), a mesh-free method is used to model atlas for healthy brain image and a modified atlas is used for pathological image. The tumour position and tumour growth simulating the tumour mass effect are seeded in the atlas to improve the registration accuracy. In Al-Shaikhli et al. (2014), the topological graph prior with atlas information is used in a modified multilevel set formulation for multiregion segmentation of brain tumour images. In Diaz and Boulanger (2015), mesh-free total Lagrangian explicit dynamic (TLED) method is used to deal simulation with atlas deformation and utilized the shape of the tumour segmented from multimodal MRI to derive a new tumour growth model. This method is able to handle large deformation without remeshing. The tumour growth models use actual shape of tumour instead of irregular shape and require no seed initialization. The method increased robustness to parameter variations and reduced computational time by means of parallel processing. The major drawback of atlas based segmentation is that it requires more time for atlas construction. The advantage of the method is that it can segment images with no better relation between pixels and region intensities.

L. Markov Random Field. Markov random field (MRF) model incorporates spatial information into clustering process. This reduces segmentation overlap and effect of noise in the segmentation. This feature motivated the researcher to use MRF in segmentation. In Subbanna and Arbel (2012), the author proposed a method that utilized the combined space feature to extract the pattern using Gabor decomposition, to separate tumour and nontumour region(including edema). Then the Bayesian classification with texture-based feature extraction is performed to segment tumour and edema. The results were further refined using MRF segmentation. An iterative MRF frame work (Subbanna et al., 2014) was proposed to include adopted MRF, voxel-based MRF, and regional MRF. The framework was also used to classify all the sub class of the brain image. The major limitation of Markov Random Feld is its computational complexity and selecting parameters effectively. However, it is used to model texture properties and intensity inhomogeneity effectively.

M. Artificial Neural Network. Artificial neural network (ANN) classifier consists of series of the node, such as input, intermediate, and hidden nodes. Intermediates can also be hidden nodes. The intermediate node performs processing by taking features as input from the input node and the final output can be reviewed in output node (Gordillo et al., 2013). The training is required in determining the

Table II. The advantage and disadvantage of human brain tumour segmentation methods through MRI

Methods	References	Advantages	Disadvantages
Thresholding	Saad et al. (2011)	Work well for homogeneous image	The selection of optimal threshold is difficult
Region growing	Lina et al. (2013)	Eliminates over and under segmentation	Seed selection is difficult
Region Growing	Viji and Jayakumari (2013)	Both the spatial overlap and coefficient of similarity are increased to increase sensitivity and specificity of tumor detection	The execution time is high
Edge based segmentation	Aslam et al. (2015)	The method is simple	More thickness on the boundary lines of the edges
Edge based segmentation	Mathur et al. (2016)	Thresholding setting capability is increased by fuzzy logic system with kmeans clustering	Complex computation is high
Watershed	Pandav (2014)	Large number of segmented region in edges is reduced by marker controlled watershed segmentation	Foreground objects and the background locations should be marked already to get better segmentation result
Morphological based segmentation	Sudharania et al. (2016)	High accuracy of segmentation result and less processing speed is obtained. Works well with low intensity image	The method involves many repeated steps for segmentation
GA	Chandra and Rao (2016)	Good at selecting optimal number of region for segmentation	Selection of fitness function is difficult
FCM	Ania (2014)	Advantages of different method are combined to produce accurate result	High computational complexity in combining different method
FCM	Ji et al. (2014)	This method helps to increase robustness of initialization of FCM	High computational complexity
FCM	Verma et al. (2015)	Reliable, fast, automatic and robust diagnosis system and handles uncertainty in segmentation effectively	Local spatial information is not included in segmentation process. Hence method is very much sustainable to noise image
FCM	Dubey et al. (2016)	Method works better in dealing with intensity inhomogeneity and noise image. Intuitionistic rough set based clustering method helps to reduce the randomness in selection of cluster center and mebershipvalues	Setting up of upper and lower approximation value for Rough ness measure is difficult
Kmeans	Nimeesha and Gowda (2013)	K-means is able to characterize the regions effectively. FCM identifies only three tissue classes whereas; K-means identifies all the six classes	Few WM is classified as edema and vice versa in using K-means algorithm. Intensify feature alone is not viable for MR classification
Contour-based segmentation	Tanoori (2011)	Simple method. Tissues are separated effectively	The result are nor satisfactory for noisy, nonuniform and high intensity images
Contour-based segmentation	Sachdeva et al. (2012)	The method is applied to segment both homogeneous and heterogeneous tumour	The limitation of the proposed method is that it does not support complete 3D segmentation and it is semiautomatic segmentation process
Contour-based segmentation	Dubey et al. (2016)	A multipopulation Cuckoo Search Strategy (MCSS) is implemented for active contour model. Accuracy of segmentation process is high	Computationally expensive compared to traditional ACM
Level set	Thapaliyaa et al. (2013)	Parameters of level set are tuned automatically based on thresholding	Computational complexity is high
Atlas-based segmentation	Bauer et al. (2010)	The proposed method is meshfree and hence removes the difficulty of handling meshes. This can be used clinically without knowledge of parameterization. The computation speed is high	The method is not completely automatic as initial seed selection for tumour is done manually
Atlas-based segmentation	Al-shaikhli et al. (2014)	The proposed method is able to perform segmentation and labeling of different regions in noisy, low resolution MRI brain images of different modalities	Accuracy of method depends on accuracy of topological graph priors
Atlas-based segmentation	Diaz and Boulanger (2015)	The proposed method does not depend on any deformation model to make it robust	No preprocessing done to enhance image
MRF	Subbann (2012)	The intensity distribution in all slides is captured and modeled using Gaussian mixture model. The technique is help to include all neighborhood relation in practical sense and mathematical sense. Tumour and edema is effectively segmented	Boundary information is not captured accurately since method is based only on texture information
MRF	Subbanna (2014)	The advantages of both a local, voxel-based MRF and a contextual, regional (nonlattice based) MRF are included in the process of	Computational complexity is high

TABLE II. *Continued*

Methods	References	Advantages	Disadvantages
		segmentation. Accuracy of tumour region extraction process is high	
PNN	Dahab et al. (2012)	PNN combined with LVQ helps to reduce processing time by reducing the size of hidden layer	ROI have to be identified for modeling network. Accuracy specified depends on ROI specified
SOM	Mei et al. (2015)	The method incorporates gray value and spatial data of pixels in segmentation process that helps to provides better accuracy	The computational complexity is high for training SOM and adaptive search algorithm
	De and Guo (2015)	Damaged tissues are separated well from normal tissues. The proposed method is able to cluster different areas with the tumour accurately	Obtaining perfect mapping is difficult in SOM
Deep neural network	Havaei et al. (2016)	The proposed method provides better accuracy for segmentation process	The GPU implementation required for more fast segmentation
Hybrid method	Demirhann and Guler (2011)	Multiple methods are combined to segment brain MRI image	The accuracy is very less for segmenting white matter in brain MRI image
Hybrid method	El-Sayed (2015)	The proposed method is hybrid, accurate and robust	Training phase required more time
Hybrid method	Sachdeva et al. (2016)	Multiclass classification of tumour is done efficiently. High accuracy is obtained using GA-ANN and high speed is obtained using GA-SVM	Complexity increases due to hybridization

values of parameters. In Dahab (2012), the specified region of interest (ROI) is classified using modified probabilistic neural network (PNN) with linear vector quantization (LVQ) modeling process. The set of features are extracted from each ROI to estimate brain tumour, each ROI is assigned a weight. These weights are used for modeling network based on LVQ. The major limitation of the neural network is that the complexity increases as the network size increases whereas more training is required in such cases. To overcome the abovementioned limitation, unsupervised neural network namely self-organizing map (SOM) is used. In SOM, the training is based on competitive learning and topological map. In Mei et al. (2015), the author proposed a method that showed the impact of SOM in brain tumour segmentation. The result shows that the damaged tissues are separated well from normal tissues. The method is capable to cluster different areas with the tumour. In De and Guo (2015), the author tries to incorporate both gray value and spatial data of pixels in segmentation process using LQV technique. An adaptive segmentation algorithm is used for search of the codebook (segment number). The codebook learning of LVQ is done by SOM. The general limitation of SOM is the lack of distance accuracy of input vectors and also obtaining the perfect mapping. In Havaei et al. (2016), the Deep neural network is implemented to segment tumour effectively. The method learns both local and global conceptual features to segment tumour.

Novel cascading architecture is implemented for dealing with imbalanced label distribution. In Haykin (2008), some important aspects neural networks are discussed.

N. Hybrid Method. The hybrid method combines the advantages of two or more methods for brain tumour segmentation. These methods are fast, robust, and accurate. The level of realism in network simulation is increased by pulse-coded neural network (PCNN). The segmentation of the region of interest is realised as region growing where neurons are selected as seed in primary firing. The region grows by adding seed during secondary firing feed forward back neural network (FFBNN) and sends back the input, until there is uniformity in their entire input. In Demirhann and Guler (2011), to obtain sub-images that contain multi-resolution information, stationary wavelet transform (SWT) is performed. Spatial filtering process is then applied to extract statistical features of sub images. A multidimensional feature vector is formed by combining SWT coefficients and their statistical features. This feature vector is used as input to the SOM. Finally, LVQ is applied to tune the result. In El-Sayed (2015), the author applied feedback PCNN technique for segmentation, DWT for feature extraction, principal component analysis for dimensionality reduction and feed forward back-propagation neural network to classify inputs into normal or abnormal. The proposed method is hybrid, accurate, fast, and robust. In Sachdeva et al. (2016), content-based active contour model is implemented to segment brain tumours. High-dimensional features are reduced using GA. GA-SVM and GA-ANN are implemented for brain tumour classification and compared. GA-SVM gives more advantage in terms of speed of processing, and GA-ANN is better at providing high accuracy. The advantage of hybrid method is that it combines the advantages of many different methods and provides the better result. The major drawback is high computational costs. The advantages and disadvantages of different MRI-based brain tumour segmentation methods that are listed in Table II.

O. Future Challenges of MRI. Now a day, segmentation methods are becoming more mature and are expected to be used in clinical applications. Despite of remarkable achievements obtained by MRI-based brain tumour segmentation techniques, many challenges are available to solve. The transparency and interpretability in the automatic segmentation process are very significant challenge for clinical acceptance. Other challenges of MRI-based brain tumour segmentation involve physical artifacts and motion artifacts. Partial volume effects and intensity inhomogeneity are also very common artifacts in MRI-based brain tumour segmentation. The lower the signal to Noise ratio, the higher resolution of the segmentation result. High-resolution imaging devices and better prefiltering techniques can be employed before segmentation to remove artifacts. So that fine anatomical structure is not lost in the image. Another challenge of segmentation of brain tumour is anatomical deviations due to diversity in shape, size, and location of the brain tumour. The tumour also influences nearby parts of the brain around the tumour exits. Segmentation of tumour, its edema and other parts are also important for treatment and diagnosis of the disease (Balafar et al., 2010). More attention can be paid to the robustness of segmentation algorithm along with precision, accuracy, and time of processing. The efficiency of the segmentation techniques can be proved by validating the results with state of art techniques using standard tumour image databases.

III. BRAIN TUMOUR SEGMENTATION TECHNIQUES OF PET IMAGE

Positron emission tomography (PET) is used for diagnosis, staging, treatment evaluation, and radiotherapy planning, for tumour disease, which requires accurate segmentation of the volume of interest (VOI). PET image helps in detecting early stage tumours which cannot be seen by human eyes. PET scanner can provide molecular information of biological diseases. The big challenge in the segmentation of PET image is its low spatial resolution and noisy data. The other factor like patient movement during scanning, partial volume effect, scatter, and attenuation is further included. The existence of large intensity range and overlap of intensity range make more difficult for proper segmentation.

A. Background. In this technique, a radioactive tracer is injected into a peripheral vein. Glucose is consumed by various parts of the body. This action emits a radioactivity signal based on the rate of consumption of glucose. The radioactive tracer contains oxygen-15, fluorine-18, carbon-11, or nitrogen-13. The rate of consumption of glucose is used to differentiate malignant and benign tumours. Faster metabolism of glucose is done by malignant tumour than benign tumours.

B. Segmentation Method of PET Image. Four types of segmentation techniques exist namely

- Image thresholding,
- Vibrational approaches,
- Learning methods,
- Stochastic modeling.

In image thresholding methods (Zaidi and El Naqa, 2010), a threshold is used to separate the tumour from foreground voxels with noise background in an image. Usually, standardized uptake values' (SUVs) conversion is done to PET voxels before thresholding. SUV is affected by many factors, such as noise and PVE. In vibrational approaches (Zaidi and El Naqa, 2010), intensity variation gives differences gradient between the foreground lesion and the background for the segmentation task. It is an efficient method for providing better sub-pixel accuracy and incorporating priors such as shape in the segmentation process. Active contour, level set, and gradient vector flow (GVF) snake model used the calculus of vibrational technique to solve PDF. Learning methods (Zaidi and El Naqa, 2010) are based on pattern recognition technique. Supervised and unsupervised are of two types. Here SVM, K-means, FCM, KNN, ANN, and EM are the methods used for segmentation of the image. Stochastic modeling-based techniques (Zaidi and El Naqa, 2010) are proposed, based on finding the statistical difference between the intensity of tumour, and their surrounding tissue is proposed.

In Zeng et al. (2012), segmentation errors are removed by using region-based active surface modeling in a hierarchical manner. The result is further tuned using an alpha mating technique which produces soft segmentation. In Zeng et al. (2013), the proposed method is used to remove noise by applying an improved anisotropic diffusion filter. The segmentation of volume of Interest is done using a hierarchical local and global intensity active surface modeling scheme followed by alpha matting step which helps to provide soft segmentation boundary. The limitation of traditional method is that it perform postprocessing step to remove artifact like PVE and 2D image for segmentation. The proposed method used 3D imaging techniques, which helped used whole context information of the image for VOI segmentation and integrated PVE correction in the segmentation process. This method combines both local and global intensity information leading global optimal subvoxel segmentation which results in less error. The limitation is that the alpha matting is extended for 3D images and dynamic range of intensity images are not taken to get fine details. In Mia et al. (2015), the joint method for tumour prediction and segmentation of tumour followed by the study of tumour therapy is discussed. The tumour growths models have been used to predict tumour growth and iterative segmentation method based on Random walk, which integrates information to segment tumour. In spite of remarkable of available researches, clinical application is one of the challenges faced by PET image segmentation process. The heterogeneity and tracer uptake or the combination of tracers are other challenges faced by PET image. Many research opportunities exist in connection with abov-mentioned challenges. The pros and cons of various segmentation techniques of PET image are shown in Table III.

C. Future Challenges of PET-Based Tumour Segmentation. In spite of much work carried in PET image segmentation techniques, there are many areas where still improvement is required. The heterogeneity or combination of tracer's uptake is one of the challenges faced by PET image. Heterogeneity in tracer's uptake may produce the diverse effect in segmentation algorithm. This may lead to setting up of inappropriate threshold in threshold-based segmentation. The tumour heterogeneity is also another challenge faced by PET image segmentation. The standard database images and hardware can be used for comparison of the result of segmentation to prove the efficiency of the method. Choosing an appropriate method for particular application is very much challenging. So the development of generalized framework is one of the significant challenges faced by PET image based brain tumour segmentation for clinical application. Combining anatomical information with metabolic activity such as PET-CT and PET-MRI will improve the accuracy and precision of segmentation and opened for further research investigation. High noise, high variability in location, texture, size of tumour are also added to the future challenges. High resolution and high sensitivity of PET image reconstruction are an ongoing project for improvement in PET image segmentation.

IV. BRAIN TUMOUR SEGMENTATION TECHNIQUES OF CT IMAGE

CT scanning is fast and simple, which helps to provide more detailed information on the head injury. For this reason, CT images are mainly used for radio therapy planning because it contains anatomical information which helps to apply radio therapy on tumour area. The second reason is that, it is obtained from X-rays. X-rays form the basis of radio therapy. Patients who are unable to be motionless for scan duration can effectively depend on CT for scanning. The low-contrast image and iodine-based contrast-enhanced (CE) image are

Table III. The advantage and disadvantage of human brain tumour segmentation methods through PET

Methods	References	Advantages	Disadvantages
Thresholding technique	Zaidi and El Naqa (2010)	Simple and highly efficient	Hard decision of threshold. very sensitive to noise
Variational approaches	Zaidi and El Naqa (2010)	Mathematically good and efficient in producing better sub pixel accuracy	Limitation of the method is that it is very much sensitive to noise and difficult to select parameters
Learning methods	Zaidi and El Naqa (2010)	Pattern recognition-based method	Computation complexity is high in unsupervised methods and large training time is required for supervised method
Stochastic models	Zaidi and El Naqa (2010)	Good in dealing with noise PET image	Initialization of parameter and convergence to local optimal has effect in the efficiency of the technique
Hierarchical local and global intensity active surface modeling scheme followed by alpha matting	Zeng et al. (2013)	The method combines both local and global intensity information. Global optimal sub voxel segmentation process produced better accuracy	Dynamic range of intensity of the images is not taken to get fine details
Random walk	Mi et al. (2015)	Joint method for tumour prediction and segmentation of tumour followed by study of tumour therapy is proposed	Complexity is high due to join of different methods

two types of CT images used for brain tumour segmentation. In the case of calcified tumours, CT image shows good contrast compared to the conventional MR images. A good contrast between tumours and parenchyma are provided by CT image. The advantage of the use of CT scanning is low cost, better classification detection of tissues, shortest imaging time and better wide spread availability. The limitations are partial volume effect and overlap of intensity.

A. Background. CT scan uses X-rays and computer system to provide cross-sectional view and 3D view to providing detailed information of body tissues and structure. X-rays are sent to body at various angles to get the data. Usually, patients are injected with contrast material to detect abnormal tissues. Sometimes dye is taken by the patient for better image. The CT image showing brain tumour is shown in Figure 3.

B. Segmentation Methods of CT. Some of the segmentation methods available for CT images are

- Threshold-based segmentation,
- Region-based segmentation,
- Deformable model-based segmentation,
- Fuzzy-based segmentation,
- Neural network-based segmentation.

In Padma and Sukanesh (2011a,b,c), the author has proposed a method that uses both wavelet statistical texture (WST) features and wavelet cooccurrence texture (WCT) features. These features are extracted for tumour segmentation. The selection of optimal features is done using GA and segmented using FFNN. The advantage of this method is that the different soft tissues, which have different texture features, are extracted using different extraction techniques. This helps to provide higher accuracy. In Padma and Sukanesh (2011a,b,c), the gray level cooccurrence feature extraction method is used for texture feature extraction and the classification of a tumour as malignant or benign is done by back propagation network (BPN). In Padma and Sukanesh (2013), the proposed method used dominant gray level run length matrix method, spatial gray level dependence matrix (SGLDM) method and wavelet based texture features are used to extract a feature from the ROI. The selection of optimal feature is done using GA, and the classification of tumours is performed using SVM classifier. In Padma and Sukanesh (2011a,b,c), the author used wavelet based Dominant gray level run length feature extraction techniques and SVM classifier to classify the image. The methods that work on boundary suffer from poor tissue contrast between the prostate gland and the surrounding tissues. Mostly, intensity-based segmentation algorithms, that is, gray level based, are available for CT images. In Abdulbaqi et al. (2015), a method Hidden Markov Random Field_Expected Maximisation (HMRF_EM) is proposed along with thresholding techniques to segment tumour from CT images.The proposed method effectively classifies all pixels from the same region. The information about the shape of tumour and positions are provided with good accuracy in the proposed method. The pros and cons of various segmentation techniques of CT image are listed in Table IV.

C. Future Challenges of CT. The result of segmentation of CT is affected by intensity in-homogeneities and partial volume effects.

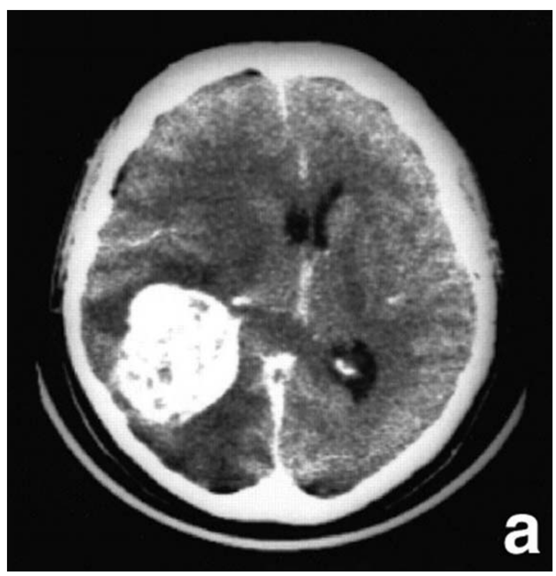

Figure 3. CT brain tumour image.

Table IV. The advantage and disadvantage of human brain tumour segmentation methods through CT

Methods	References	Advantages	Disadvantages
WST, WCT, GA, and FFNN	Padma and Sukanesh (2011)	Different soft tissues are extracted with better accuracy	Limitation of the method is that requires more training time for FFNN and high computational complexity
Gray level co-occurrence feature extraction method and BPN	Padma and Sukanesh (2011)	Better accuracy of segmentation process is produced. BPN method helps to reduce computational complexity	More training is require for BPN
Dominant gray level run length matrix method, SGLDM, and wavelet-based GA and SVM classifier	Padma and Sukanesh (2013)	The method yields good accuracy compared to other SVM based classifier	Complexity increases due to hybridization
Wavelet-based dominant gray level run length matrix method, and SVM classifier to classify the image	Padma and Sukanesh (2013)	The method yield good accuracy in segmentation of brain tumour	Poor tissue contrast between the prostate gland and the surrounding tissues in the boundary is produced
HMRF-EM	Abdulbaqi et al. (2015)	More accuracy and less noise is produced when compared to manual segmentation	Threshold setting for volume of tumour calculation is difficult

Much work has to be been done by the researchers to correct this problem. CT imaging system suffered from inaccurate matching superposition from different images taken at different time. CT–PET and CT–MRI multimodal techniques are opened for research investigation. Significant improvement has to be done for increasing sensitivity, reducing the number of false positives, increasing the speed of processing and to provide the high level of automation.

V. BRAIN TUMOUR SEGMENTATION OF MULTIMODAL IMAGING TECHNIQUES

Multimodel imaging techniques are the process of integrating images from same or different imaging modalities to increase the quality of the image and decrease randomness and reduce redundancy of information in the images. CT and MRI are mainly used for anatomical structure visualization. Metabolic and physiological processes are observed using PET. PET helps to provide more detailed information. Therefore researchers start to combine PET with CT and MRI imaging modularity to help in diagnosis and treatment. Since the anatomical structure of the head is easily obtained from MRI, PET with limited spatial resolution combined with MRI provides better information for detection of the brain tumour. CT imaging system suffered from inaccurate matching superposition from different images taken at different time. Here, CT and PET were combined in single scanner that helped to remove the above limitation of CT. However, MRI is mainly used for tumour diagnosis for the following advantages: (i) provides high-quality soft tissue contrast, (ii) emits no harmful radiation, and (iii) provides more complementary information to PET by measuring physiological and metabolic parameters. Bimodal imaging is more feasible in PET/MRI compared to PET/CT. The main feature of PET/MRI is the simultaneous measurement, which provides complementary information of two modularizes. Many works have been done on multimodal imaging techniques. In Setarehdan and Singh (2012), some advanced aspect multimodal imaging methodologies are discussed.

A. Multimodal Segmentation for Brain Tumour.

In Yu et al. (2009), textural feature extraction techniques named spatial gray-level dependence matrices (SGLDM) and neighborhood gray-tone-difference matrices (NGTDM) were used to differentiate

Table V. The advantage and disadvantage of human brain tumour segmentation methods through Multimodal imaging techniques

Multimodal Imaging Techniques	References	Advantages	Disadvantages
CT/PET	Yu (2009)	The accuracy is increased compared to simultaneous CT segmentation. It can provide better results than using features from one modality alone	Execution time was long
PET/CT	Han et al. (2011)	The superior contrast provided by PET and the superior spatial resolution of CT were combined to provide better accuracy	Requires user interaction and small uptake a region was not assessed for performance
PET/CT	Bagci et al. (2012)	No human interaction is required and method is fast and reproducible. Handles noise and low contrast images in effective way	The proposed method is not suitable to produce generalized solution
PET/CT and MRI/PET	Bagci et al. (2012)	The generalized algorithm for multifusion MRI–CT–PET segmentations is proposed	Weakness of Random walk method is that it is unable to encompass details, such as speculations
PET/CT and MRI/PET	Xu et al. (2015)	The method is more robust and fast compared to Random Walk algorithm	The method is not adopted for heterogeneous tumour segmentation
T1, T2, and FLAIR MRI	Li et al. (2016)	Segments edema, enhancing tumour, nonenhancing tumour and necrosis effectively. Adaptive dictionary and spatial information between voxels are used to segment tumour	Core tumour segmentation is still challenging

Table VI. Datasets for brain tumour segmentation methods.

National Biomedical Imaging Archive (NBIA)	https://imaging.nci.nih.gov/ncia/login.jsf
National Center for Image Guided Therapy, Harvard University	http://ncigt.org/downloads
Computer Vision and Image Analysis, Cornell University	http://www.via.cornell.edu/databases/
Brain web: Simulated Brain Database	http://brainweb.bic.mni.mcgill.c. . .
BRATS 2016 (Datasets are available from 2012)	http://www.via.cornell.edu/databases/

tumour tissues from CT images and PET information are included into task of tumour classification. In Han (2011), Markov random field algorithm on graph was formulated to segment tumour from joint PET/CT image. In Bagci et al. (2012), the automatic random walk cosegmentation method (PET/CT) is proposed, which is performs by taking regions from PET images and finding corresponding boundaries from CT images. In Bagci et al. (2012), a novel joint segmentation method for hybrid imaging PET/CT and MRI/CT techniques is proposed. A unique graph representation of each object is driven using extended random walk algorithm for jointly delineating multiple objects from multiple image modalities. In Xu et al. (2015), the author has proposed a hybrid method (PET/CT and MRI/PET) in 3D image domain to segment images under different conditions of visibility. The modality-specific visibility weighing scheme is built upon fuzzy connectedness (FC) image segmentation algorithm. The advantage of multimodal segmentation is that it combines the information from many modals and thereby increasing the accuracy of the segmentation result. However, the computational complexity and more execution time were considered as the major drawback of multimodal segmentation. In Li et al. (2016), sparse representation-based multimodal MR brain tumour segmentation is proposed. T1, T2, and flair modal of MRI image are used for the segmentation of edema, enhancing tumour, nonenhancing tumour, and necrosis. In the proposed method, probability maximization model uses a sparse representation-based framework to provide voxel-wise labeling through the likelihood estimation. Then, MRF is used for estimating MAP. Finally, graph cut is applied to MAP for obtaining optimal solution. Different multimodal brain tumour segmentation techniques are discussed and listed in Table V.

B. Future Challenges of Multimodal Imaging Techniques. In spite of various remarkable works done in imaging molarities's, many challenges are available for multimodal imaging techniques. Increased computational complexity in integrating different modal and attenuation correction are the major challenges of multimodal imaging techniques. The Motion correction that could be applied before segmentation to account for inter- and intrascan motions during imaging are also the areas where more research work need to be explored. Unique challenges brought by each imaging modularity, Clinical setup and finding expertise in cost effective way also have to paid more attention in future years.

VI. EVALUATION METHODS OF SEGMENTATION OF BRAIN TUMOUR

Evaluation method estimates the segmentation of medical images for a particular task. It validates the performance of a particular data and compares it with other methods. Some of the evaluation methods are discussed below. Dice's similarity coefficient (DSC) (Yeghiazaryan and Voiculescu, 2015) is popular evaluation measures and used frequently, for comparing overlap of segmented image and the ground truth image. It measures, the match of two set P1 and P2 by normalising the size of their intersection over the average of their sizes. The formula for DSC is given in the following equation:

$$\mathrm{DSC}=2\frac{|P1\cap P2|}{|P1|+|P2|}. \tag{1}$$

The symmetric volume difference (SVD) (Yeghiazaryan and Voiculescu, 2015) provides symmetric measures for the difference in volume of the segmented result and ground truth. The formula for calculating SVD is given in the following equation:

$$\mathrm{SVD}=1-\mathrm{DSC}. \tag{2}$$

Statistical decision theory measures are sensitivity, specificity, and accuracy and calculate using the following equations, respectively.

$$\mathrm{Sensitivity}=\mathrm{TP}/(\mathrm{TP}+\mathrm{FN}). \tag{3}$$
$$\mathrm{Specificity}=\mathrm{TN}/(\mathrm{TN}+\mathrm{FP}). \tag{4}$$
$$\mathrm{Accuracy}=(\mathrm{TN}+\mathrm{TP})/(\mathrm{TN}+\mathrm{TP}+\mathrm{FN}+\mathrm{FP}). \tag{5}$$

where TP (true positive) is the correctly classified positive cases, TN (true negative) is the correctly classified negative cases, FP (false positive) is the incorrectly classified negative cases, and FN (false negative) is the incorrectly classified positive cases respectively. The other popular methods are precision and recall measures. The precision normalises the volume of the correctly segmented shape (P1) over the volume of the result of the segmentation (P2). The formula is given in the following:

$$\mathrm{precision}=\frac{|P1\cap P2|}{|P1|} \tag{6}$$

The recall normalises the volume of the correctly segmented shape (P1) over the volume of the result of the segmentation (P2).The formula is given by the following equation:

$$\mathrm{Recall}=\frac{|P1\cap P2|}{|P2|}. \tag{7}$$

Other measures are Jaccard similarity coefficient (Jaccard) (Yeghiazaryan and Voiculescu, 2015) and volumetric overlap error (VOE). Jacquard measures the match of two set P1 and P2 by normalising the size of their intersection over their union is given by the following equation:

$$\mathrm{Jaccard}=\frac{|P1\cap P2|}{|P1\cup P2|}. \qquad \mathrm{VOE}=1-\mathrm{Jaccard}. \tag{8}$$

Root mean square symmetric surface distance (RMSD) (Yeghiazaryan and Voiculescu, 2015) and surface come under the category of surface distance based measures. Let $I(x,y)$ be an input image and $O(x,y)$ be an output image. The error between the images E is given by the following equation:

$$E=\sum_{i=1}^{m}\sum_{j=1}^{n}O(x,y)-I(x,y). \tag{9}$$

RMS of the E is given by the following equation:

$$\text{RMSD}{=}I/(E^2)^{1/2}. \quad (10)$$

These are some of the available evaluation method of segmentation for different imaging modularities.

VII. DATASET OF BRAIN TUMOUR SEGMENTATION TECHNIQUES

Some of the available datasets of human brain tumour image of different imaging modularity are given in Table VI. Some of the datasets are freely available, and some require registration to access the dataset.

VIII. CONCLUSION

In this article, various automated brain tumour segmentation techniques of MRI, CT, PET, and multimodal images have been reviewed. The methods, advantages, their limitations, and future challenges are discussed to provide insight into various techniques. MRI-based brain tumour segmentation methods are employed more for brain tumour segmentation due to the good soft tissue contrast and noninvasive of MRI. However, percentages of clinical application of automated brain tumour segmentation methods are significantly very low due to lack of interaction between developers and physicians. Technically sound algorithms are difficult to use in real time applications. In spite of the existence of many tools for tumour segmentation, manual segmentation is preferred in the day today life. Automatic segmentation performed in few minutes is not accepted clinically due to the lack of interpretability and easy handling of the tools. Hence more user-friendly tools should be embedded in the clinical environment in future. The failure of the system even for less number of times also affects clinical applicability. Hence, robustness and accuracy of the system are also another important factor to improve the confidence in the automated system.

The improvement in advanced tumour assessment, such as tumour volume estimation, tumour progression estimation in future, and multiclass tumour classification, will improve achievements in current techniques. The brain tumour segmentation techniques will undoubtedly show great potential in future, along with all specified remarkable advancement in this area.

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