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A Review on Typical and Modern Brain MRI Image Segmentation Methods and Challenges

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Abstract:- Background: Brain image segmentation is one of the essential tasks in medical image analysis. Digital Brain MR Images usually contain Noise, inhomogeneity, and sometimes deviation due to the capturing device's configuration. Therefore, accurate segmentation of brain MRI images is deployed to measure and visualize the brain's anatomical structures, analyze brain changes, delineate pathological regions, and for surgical planning and image-guided interventions. During the past few decades, various segmentation techniques of different accuracy and degree of complexity have been developed and reported in the literature. In this paper, several popular methods are used for brain MRI segmentation and focus on their capabilities, advantages, and pitfalls. Likewise, we also discuss modern image segmentation techniques by Deep Learning Technology and deliberate the metrics to evaluate the brain tumor segmentation and dataset availability performance. Eventually, we suggest future research challenges among brain tumor multimodal imaging techniques.

Keywords: Magnetic Resonance Imaging (MRI), Deep Learning, Segmentation techniques, Convolutional Neural Network (CNN.

1. Introduction

In recent times, the introduction of information technology and the e-health care system in the medical field helps clinical experts provide better health care. A brain tumor is a mass or growth of abnormal cells in the brain. Many different types of brain tumors exist. Primary brain tumors originate in our minds. They can develop from some brain tumors such as noncancerous, i.e. brain cells, the membranes that surround your brain, called meninges, nerve cells and glands (benign), and some brain tumors cancerous (malignant). Brain tumors can, in your brain (primary brain tumors), or cancer can begin in other parts of our body, i.e,

Lung cancer, breast cancer, kidney cancer, and skin cancer spread to your brain (secondary, or metastatic, brain tumors).

A brain tumor's signs and symptoms vary greatly and depend on the brain tumor's size, location, and rate of growth. The diagnosis of a brain tumor begins with a physical exam and looks at our medical history. In continuation, we also recommend more tests after they finish the physical exam. The various types of medical imaging technologies based on noninvasive approaches like; these could include C.T. scan of the head, MRI, Angiography, Skull X-rays [1], and Biopsy. Compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is majorly used, and it provides more magnificent contrast images of the brain and cancerous tissues. Therefore, brain tumor identification can be made through MRI images [2]. This paper emphasizes the identification of brain tumor using image processing techniques. The detection of a brain tumor at an early stage is a key issue for providing improved treatment.

Modern Computer Vision technology, based on A.I. and deep learning methods, has evolved dramatically in the past decade. Today it is used for applications like image classification, face recognition, identifying objects in images, video analysis and classification, and image processing in robots and autonomous vehicles.

Many computer vision tasks require intelligent segmentation of an image, to understand what is in the image and enable a more straightforward analysis of each part. Today's image segmentation techniques use deep learning models for computer vision to understand, at a level unimaginable only a decade ago, accurately which real-world object is represented by each pixel of an image.

Deep learning can learn patterns in visual inputs to predict object classes that make up an image. The central deep learning architecture used for image processing is a Convolutional Neural Network (CNN), or specific CNN frameworks like AlexNet, VGG, Inception, and ResNet. Models of deep learning for computer vision are typically trained and executed on specialized graphics processing units (GPUs) to reduce computation time.

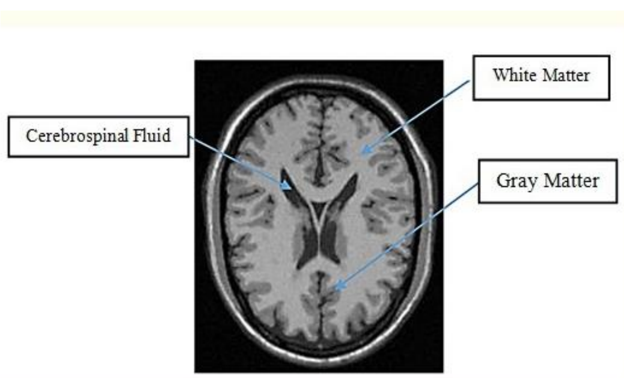

Figure 1. Anatomy of MRI brain Image

Contribution of the paper is

- To explore the Brain Tumour Segmentation Techniques of MRI and its future challenges.
- Image Segmentation in Deep Learning: Methods and Applications
- To explore the Assessment Metrics of Brain Tumour Segmentation and Source of available Datasets for further investigations.

The remainder of this paper consists of section II. Brain Tumour Segmentation Techniques of MRI, Section III. Describes the Modern Image Segmentation techniques by Deep Learning Technology. Section IV. describes Evaluation Metrics of Segmentation of Brain Tumour; Section V. presents the MRI image data source. And Section V. describes the future challenges finally concludes the paper with Section VI.

2. Brain Tumour Segmentation Techniques of MRI

2.1 Background:

Image segmentation is a critical process in computer vision. It involves dividing a visual input into segments to simplify image analysis. Segments represent objects or parts of objects, and comprise sets of pixels, or "super-pixels". Image segmentation sorts pixels into more significant components, eliminating the need to consider individual pixels as observation units. There are three levels of image analysis shown in figure 2:

Classification: categorizing the entire image into a class such as "Skull," "brain", "tumors."

Object detection: detecting objects within an image and drawing a rectangle around them, such as tumors.

Segmentation: identifying parts of the image and understanding what object they belong to. Segmentation lays the basis for performing object detection and classification.

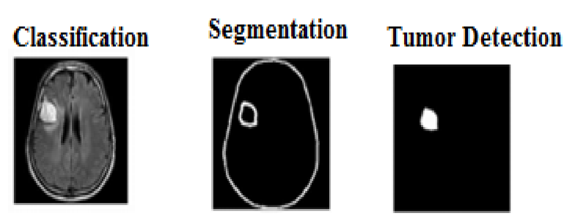

Figure 2. MRI image Three Level of analysis

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

a. **Thresholding Method:** Thresholding is the simplest segmentation method. The pixels are partitioned depending on their intensity value. Peaks and valleys of the image histogram can help choose the appropriate value for the threshold(s). Image thresholding is a simple, yet effective way of partitioning an image into a foreground and background. This image analysis technique is a type of image segmentation that isolates objects by converting grayscale images into binary images. Image thresholding is most effective in models with high levels of contrast. Thresholding is one of the segmentation techniques which compare pixel intensities with one or more intensity thresholds. The significant types of thresholding are local and global thresholding [3]. The comprehensive thresholding technique works better for segmentation if the homogeneous intensity is available in an image. If the image contains more than one region with a different object, then local thresholding techniques work better for segmentation.

b. **Ostu's Segmentation:** One of the well-known and widely accepted global thresholding methods, Otsu's thresholding method [4], is based on discriminant analysis to find the maximum separability of classes and is used to automatically perform histogram shape-based image thresholding. The original Otsu's algorithm assumes that the image is composed of two basic classes, foreground (Co) and background (C1). It constructs a normalized histogram using the discrete probability density function and is given by Using weighted class variance it divides the image into two categories Extracted image contains an extra part with tumor and required to reprocess for proper output Does no work properly with all type of MRI images Required to select weighted variance value.

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 [5] Edge image thresholding represents the Non-maximal suppression, and hysteresis, which supports the Edge relaxation, Border tracing, Border detection as graph searching and Border detection as dynamic programming

d. **Histogram-based image segmentation**—uses a histogram to group pixels based on "gray levels". Simple images consist of an object and a background. The background is usually one gray Level and is the larger entity. Thus, a broad peak represents the background gray level in the histogram. A smaller peak represents the object, which is another gray level.

e. **Region Growing Method:** Region-based segmentation is a technique for determining the region directly. Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves selecting initial seed points. This method's applications are Finding tumors , veins, etc. in medical images, finding targets in satellite/aerial images, finding people in surveillance images, summarizing video, etc. Region growing is a procedure that groups pixels or sub-regions into more significant regions. The simplest of these approaches is pixel aggregation, which starts with a set of seed points. These grow areas by appending to each seed point those neighboring pixels with similar properties (such as grey Level, texture, color, shape). Region growing based techniques are better than the edge-based methods in noisy images where edges are difficult to detect.

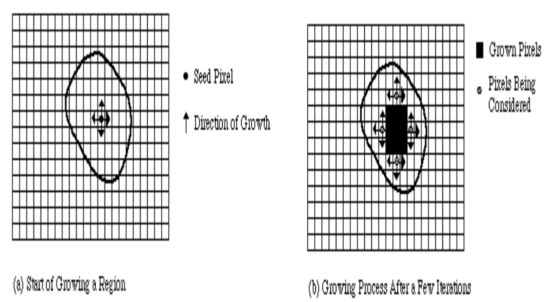

Figure 3.Illustrations of Region Growing Method

Advantages and Disadvantages of Region Growth:

Advantages:

- Regions having desired specifications are correctly separated.
- Good segmentation results for image have a distinctive edge.
- It is simple and develops only by some initial grains.
- One can select initial grains and desired criteria.
- Several criteria can be used simultaneously.
- There is an excellent performance concerning Noise.

Disadvantages

- It is time-consuming.
- This method may lead to additional segmentation or the whole creation of images having high fluctuations in intensity.

f. **Genetic Algorithm:** Initial point selection to start region growth segmentation was performed using a genetic algorithm, which is an inspiration of genetics and Darwin's theory of evaluation, based on tap survival or natural selection. One common application of a genetic algorithm is using it as an optimization function. A genetic algorithm is a useful tool in pattern recognition, property selection, image identification, and machine learning. G.A. algorithm is used for optimizing the segmentation results of brain tumour from MRI images through evaluation criteria. In the proposed method, clusters of K -means algorithm is used as an initials population. A fitness function evaluates centers that are clustered. The weaker chromosomes are then replaced by a better one, using various selection criteria such as crossover and mutation.

g. **Morphological-Based Method:** Morphological operations are used to identify the boundaries and skeleton of objects in an image. Morphological operations create a window called a structural element on an image [6]. This window is placed in all possible locations on the image and the corresponding pixel is compared with the neighborhood. The most commonly morphological operations are dilation and erosion. Dilation is a morphological operation that can be applied to binary and grayscale images. Dilation operation grows objects by expanding the boundaries [7]. With this operation's effect, the small holes in the regions that begin to expand become even smaller.

h. **Fuzzy Clustering:** Clustering approach is widely used in biomedical applications, particularly for brain tumor detection in abnormal magnetic resonance (MRI) images. Fuzzy clustering using the fuzzy C-means (FCM) algorithm proved superior over the other clustering approaches in terms of segmentation efficiency. But the major drawback of the FCM algorithm is the substantial computational time required for convergence. The effectiveness of the FCM algorithm in terms of computational rate. Randomly select centroid and assign membership value to each pixel. Pixels are assigned to clusters based on membership value and distances from centroid. Its result is highly accurate and extracts the exact edges of tumor in the segmented image.

i. **K-Means Clustering:** K-Means clustering algorithm is an unsupervised algorithm, and it is used to segment the interest area from the background. It clusters or partitions the given data into K-clusters or parts based on the K-centroids. Divides all pixels randomly in K clusters and iteratively finds the mean for each cluster center and repeats the same until it matches with the previous one. Its result is more accurate and requires less run time.

j. **Markov Random Field:** A natural way of incorporating spatial correlations into a segmentation process is to use Markov random fields as a priori models. The MRF is a stochastic process that specifies an image's local characteristics and is combined with the given data to reconstruct the true image. Markov random field (MRF) theory has been widely used in image segmentation and analysis. It can facilitate the modeling of spatial or contextual dependencies in images. [8] Proposed a method based on MRF and a hybrid of social algorithms, including an ant colony optimization and a Gossiping algorithm, which can be used for segmenting MRIs in real-time environments. 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.

k. **Artificial Neural Network:** Since 1990, artificial neural networks have come to be used as a different approach for image segmentation. Their properties, such as graceful degradation in the presence of Noise, their ability to be used in real-time applications, and the ease of implementing them with VLSI processors, led to a booming of ANN-based methods for segmentation. Almost all types of neural networks have been applied with a different degree of success.

Table 1.Comparison of Segmentation Methods

Author(s)	**Proposed Methods**	**Advantages**	**Remarks**
Gordillo et al. [3]	Thresholding Method:	• Work well for homogeneous image • Extracted image contains an extra part with tumor and required to reprocess for proper output	• Does not work correctly with all type of MRI images • Required to select weighted variance value
N. Otsu et al. [4]	Ostu's Segmentation:	Extracted image contains extra part with tumor and required to reprocess for proper output	Does not work properly with all type of MRI images Required to select weighted variance value
Aslam et al. [5]	Edge-Based Method:	The method is simple The fuzzy logic system increases thresholding setting capability with K-means clustering	Complex computation is high
Easha Noureen et al. [7]	Histogram-based image segmentation	Extracted image contain tumor with some part of MRI image which can be removed by required feature extraction	Required to apply correct threshold value to achieve proper result
Viji and Jayakumari et al. [9]	Region Growing Method:	Extract the required region of interest from Noise-free input brain MRI region	Seed points are manually Selected Noise creates holes in extracted image or discontinuities in it.
Chandra and Rao et.al[11]	Genetic Algorithm.	Good at selecting an optimal number of the region for segmentation	Selection of fitness function is difficult
Radha R et al. [8]	Morphological-Based Method:	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
M Shasidhar et al. [12]	Fuzzy Clustering:	Its result is highly accurate and extracts the exact edges of the tumor in the segmented image.	Sensitive to Noise and more time required to segment the image.
Shweta A. et.al [13]	K-Means Clustering.	Its result is more accurate and requires less run time.	Need to understand K-values Not works for global cluster More sensitive to Noise
Yousefi S et.al[14]	Markov Random Field.	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.
Gordillo et al. [3]	Artificial Neural Network.	The intermediate the node performs processing by taking features as input from the input node and the final output can be reviewed in output node the specified region of interest	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.

		(ROI) is classified using a modified probabilistic neural network (PNN) with linear vector quantization (LVQ) modelling process. The set of features are extracted from each ROI to estimate brain tumour, and each ROI is assigned a weight. These weights are used for modeling Network-based on LVQ.	

3. Modern Image Segmentation techniques by Deep Learning Technology

Modern image segmentation techniques are powered by deep learning technology. Here are several deep learning architectures used for segmentation:

Convolutional Neural Networks (CNNs) Image segmentation with CNN involves feeding segments of an image as input to a convolutional neural network, which labels the pixels. CNN cannot process the whole image at once. It scans the image, looking at a small "filter" of several pixels each time until it has mapped the entire image. To learn more, see our in-depth guide about Convolutional Neural Networks.

Fully Convolutional Networks (FCNs) Traditional CNNs have fully-connected layers, which can't manage different input sizes. FCNs use convolutional layers to process varying input sizes and can work faster. The final output layer has a large receptive field and corresponds to the image's height and width, while the number of channels corresponds to the number of classes. The convolutional layers classify every pixel to determine the context of the image, including objects' location.

Ensemble learning synthesizes the results of two or more related analytical models into a single spread. Ensemble learning can improve prediction accuracy and reduce generalization error. This enables accurate classification and segmentation of images. Segmentation via ensemble learning attempts to generate a set of weak base-learners that classify parts of the image and combine their output instead of creating one single optimal learner.

DeepLab One main motivation for DeepLab is to perform image segmentation while helping control signal decimation—reducing the number of samples and the amount of data that the network must process. Another motivation is to enable multi-scale contextual feature learning—aggregating features from images at different scales. DeepLab uses an ImageNet pre-trained residual neural network (ResNet) for feature extraction. DeepLab uses atrous (dilated) convolutions instead of regular convolutions. The varying dilution rates of each convolution enable the ResNet block to capture multi-scale contextual information. DeepLab is comprised of three components:

- **Atrous convolutions**—with a factor that expands or contracts the convolutional filter's field of view.
- **ResNet**—a deep convolutional network (DCNN) from Microsoft. It provides a framework that enables training of thousands of layers while maintaining performance. The powerful representational ability of ResNet boosts computer vision applications like object detection and face recognition.
- **Atrous spatial pyramid pooling (ASPP)**—provides multi-scale information. It uses a set of atrous convolutions with varying dilution rates to capture long-range context. ASPP also uses global average pooling (GAP) to incorporate image-level features and add global context information.

SegNet neural network architecture based on deep encoders and decoders, also known as semantic pixel-wise segmentation. It involves encoding the input image into low dimensions and then recovering it with orientation invariance capabilities in the decoder. This generates a segmented image at the decoder end.

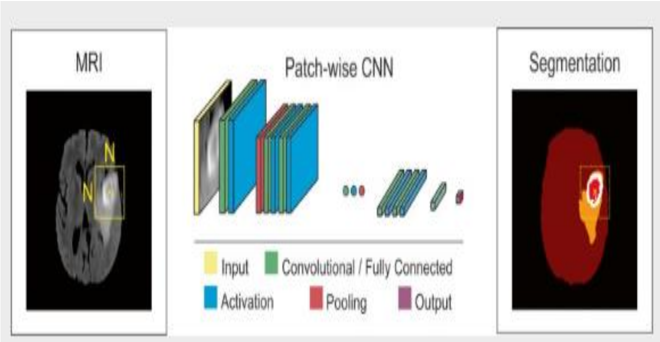

Figure 4. Deep learning-based Architecture

4. Evaluation Metrics of Segmentation of Brain Tumour

To evaluate brain tumors' performance, segmentation usually uses five metrics such as Accuracy, Sensitivity, Specificity, Dice Coefficient, and Jaccard coefficient, which are computed according to the following.

$$Accuracy = \frac{TP + FN}{TP + FP + TN + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Dice = \frac{2TP}{2TP + FP + FN}$$

$$Jaccard = \frac{TP}{TP + FP + FN}$$

T.P. "True Positive" counts the number of correctly segmented pixels as a tumor, and F.P. "False Positive" represents the number of pixels in the image that are incorrectly segmented as a tumor. F.N. "False Negative" gives the number of pixels that are improperly segmented as healthy pixels. T.N. stands for "True Positive" denotes the number of pixels that are correctly segmented as healthy pixels.

5. Dataset of Brain Tumour Segmentation Techniques

Dataset details: Some of the available datasets of human brain tumor image of different imaging modularity are given in Table 2. Some of the datasets are freely available, and some require registration to access the dataset. There are so many sources of brain MRI image data sources such as

Table 2. Dataset for MRI Image Brain tumor Segmentation

Name of the Source	URL
kaggle	https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection
BRATS MICCAI BRAIN TUMOR DATASET	https://ieee-dataport.org/competitions/brats-miccai-brain-tumor-dataset
Figshare	https://figshare.com/articles/brain_tumor_dataset/1512427
Brain web: Simulated Brain Database	http://brainweb.bic.mni.mcgill.c..
BRATS 2016 (Datasets are available from 2012)	http://www.via.cornell.edu/databases/

6. Future challenges

Despite various remarkable works done in imaging molarities, many challenges are available for multimodal imaging techniques. Increased computational complexity in integrating different modal and attenuation corrections is the significant challenge of multimodal imaging techniques. The Motion correction that could be applied before segmentation to account for inter- and inters can 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 ways also have to pay more attention in future years.

7. Conclusion

In this article, various automated brain tumour segmentation techniques of MRI images have been reviewed. The methods, advantages, limitations, and future challenges are discussed to provide insight into different technologies. MRI-based brain tumour segmentation methods are engaged more in brain tumour segmentation due to the good soft-tissue contrast and noninvasive MRI. However, the 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. Despite the existence of many tools for tumour segmentation, manual segmentation is preferred in the day today life. Automatic segmentation performed in a few minutes is not accepted clinically due to the lack of interpretability and secure 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, the system's robustness and accuracy are also other essential factors to improve 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 current techniques' achievements. The brain tumour segmentation techniques are undoubtedly showing great potential in the future and all specified remarkable advancement in this area.

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