A Review of Brain Tumor Image Segmentation of MR Images Using Deep Learning Methods

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Abstract

A significant analysis is routine for Brain Tumor patients and it depends on accurate segmentation of Region of Interest. In automatic segmentation, field deep learning algorithms are attaining interest after they have performed very well in various ImageNet competitions. This review focuses on state-of-the-art Deep Learning Algorithms which are applied to Brain Tumor Segmentation. First, we review the methods of brain tumor segmentation, next the different deep learning algorithms and their performance measures like sensitivity, specificity and Dice similarity Coefficient (DSC) are discussed and finally, we discuss and summarize the current deep learning techniques and identify future scope and trends.

Keywords: Deep Learning, MRI, CNN, Brain Tumor Segmentation

1 Introduction

An uncontrolled growth of abnormal cells in a body is called Cancer. Mass composed by cluster of such abnormal cells in brain is called brain tumor. There are two types of tumors Malignant (Cancerous) and Benign (Non- Cancerous). On the basis of their origin, brain tumors are divided into Primary and Secondary or Metastatic tumor. Tumors which originate in brain are Primary Tumors. They can develop from brain cells, meninges, nerve cells or glands. Whereas metastatic tumor can spread from different areas of body affected by cancer cells. In primary tumors gliomas and meningiomas are the most common types of brain tumor. Gliomas are the most prevalent type of tumors in adults. It originates in glial cells and pervades in neighboring tissues [1]. According to World Health Organization, Gliomas affect children aged 5 to 10 years and adults aged 40 to 65 years, respectively [2]. Additionally, these tumors account for 81% of all malignant brain tumors and 45% of all primary brain tumors [4]. Around 120 tumor types are identified and graded by WHO. Brain tumors are graded from grade I to grade IV, as reported by WHO. The classification and grade system of the tumor helps to predict the nature of the tumor and its stage, which may help diagnose it.

Tumor cell nature, however, can also affect diagnosis, such as complex cell structure, heterogeneous distribution of strength, tumor dynamic location, and tumor artifacts. Heterogeneity in the growth of cancer cells poses major challenges in the design of cost-effective and efficient methods of treatment. Different modalities for biomedical imaging are X-Ray, Computed Tomography (CT), Positron Emission Tomography (PET). Amongst all, MRI is a prominent modality used in brain structure analysis, as it offers high contrast images for soft tissues and high spatial resolution.

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2 Background

2.1 Magnetic Resonance Imaging

The MRI scan is used to visualize the detailed features of the brain and other components of the cranium. In three different planes, it results from visualizing the anatomy; axial, coronal, and sagittal. The Axial, Sagittal and Coronal planes of the brain taken from the Magnetic Resonance image are shown in Fig.1

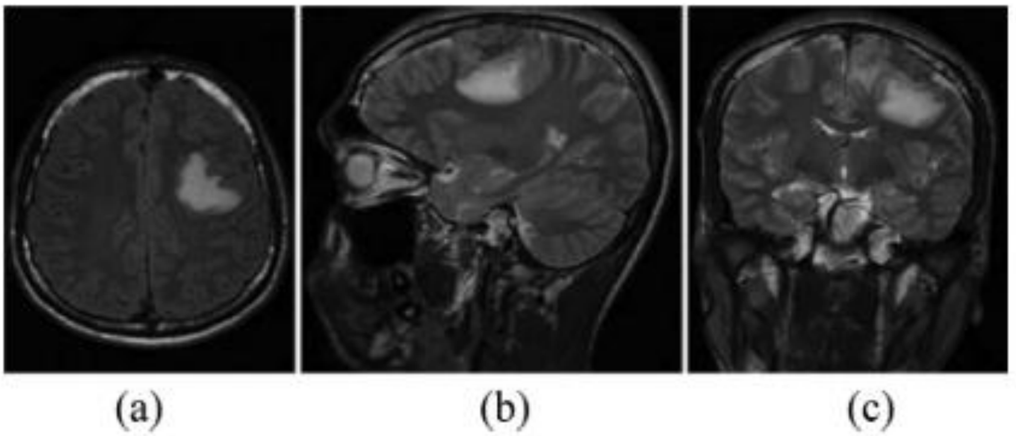

Fig.1 (a) Axial plane, (b) Sagittal plane and (c) Coronal plane of the brain observed by MRI.

The MRI scan is a highly sensitive test used to measure net magnetization. A circular coil is fixed around the head that generates and transmits electromagnetic waves within the brain. Later, electromagnetic waves are released and the receiver coil tests them. The gradient coil is used for the signal's spatial localization. Eventually, the machine rebuilds this signal and the human brain is captured. The MRI image pre-diagnosis process involves numerous image sequences:T1-weighted, T2-weighted, T1CE-weighted and FLAIR. Fig.2 shows the images of different sequences.

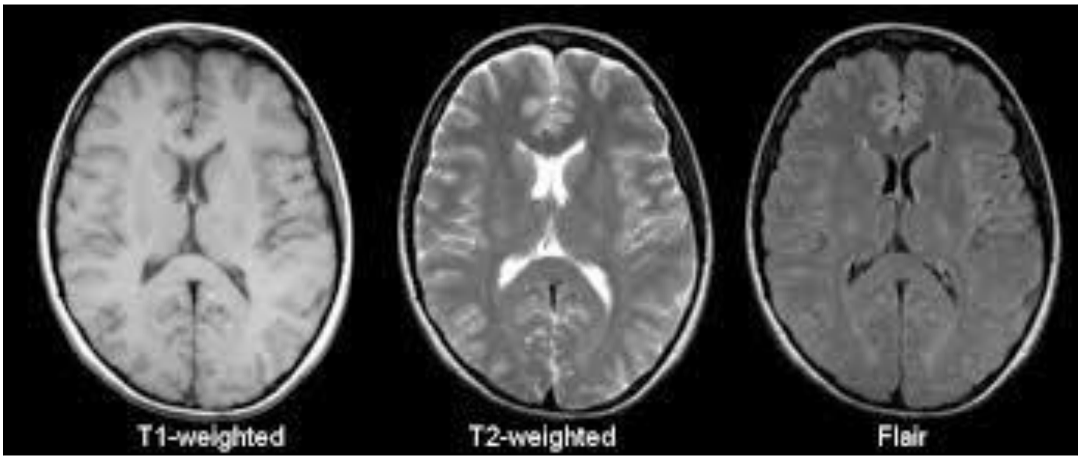

Fig.2 Images of different sequences.

2.2 Image Segmentation

Separating the meaningful pixels or essential parts from an image is called as Image segmentation. Medical image segmentation is segmenting the region of interest and locate the boundaries and objects. In brain tumor it is used in delineation, detection and separation of tumor tissues like edema, necrotic core and active cells from normal tissues like white matter, grey matter and Cerebrospinal Fluid. Segmentation is very important step in brain tumor detection. In multimodal 3D images it is very tough task to segment the image due to tumors' heterogeneous nature and variability in shape, size, location and frequency. Manual segmentation shows most accurate result but it is very tedious topic. The major focus of research is automatic segmentation methods which give potential quantitative assessments of brain tumors.

3 Methods of Brain Tumor Segmentation

3.1 Manual Segmentation

It is a process in which an expert physician or radiologist labels and segments the image in a slice-by-slice manner by hand. Although this method is very accurate but it is very time taking and difficult process. It is also an expert dependent process. However, it is used in evaluating the results of other two methods.

3.2 Semi-Automatic segmentation

Semi- Automatic method involves user interaction for defining initial region of interest, giving regular feedback, for evaluation of results and for further modification or repeating the process if needed [6]. It requires manual labeling on automatically chosen slices.

Xiaoli et. al. used the multiscale Otsu based multilevel thresholding for the segmentation. This method first smoothens the original image with edge- aware filter then Otsu based thresholding is done on both smoothed and original image. Two segmentation maps are then fused by KNN to obtain segmented results then a region growing method is used to segment the tumorous region nearby seeds which are inserted by the user. This approach is applied on T2- MRI modality [7].

Compared to manual segmentation methods, semi-automatic brain tumor segmentation methods consume less time and can achieve accurate results but it still depends upon inter and intra user variability which leads to the need of Fully- Automatic segmentation Methods.

3.3 Fully-Automatic Segmentation

Evaluating the huge information from an MRI image is very tedious and difficult also it needs an expert to perform the task which leads to the need for fully automatic methods. It doesn't require any human intervention for evaluation and training. Fully automatic methods are further categorized into two methods: Generative and Discriminative methods. In Generative method knowledge of location and spatial extent of healthy tissues are required to generate probabilistic models. In Discriminative methods large datasets and valid ground truth is required for training the model. learning is based on the relationship between ground truth and input images. Several techniques for fully automatic methods are proposed. G. Manogaran et. al. [7] used an edge-based segmentation with automatic detection of Region of Interest. Orthogonal gamma distribution model with machine learning approach is defined to implement this. Edge analysis and machine learning approach is used to train and identify the edge coordinates.

Soltaninejad et.al. [8][9] proposed a 3D super voxel-based learning method for tumor segmentation in which an image is partitioned into 3D Patch volumes which reduces the classification computation. A set of 3D Gabor filters with different orientation and sizes are used to calculate histogram of Textron descriptors which are extracted on each super voxel. RF classifiers are used to handle large unbalanced dataset. To reduce the computational burden of processing 3D multiple scans Kamnitsas et. al. suggested a dual pathway, 11 layers deep 3D CNN which is processing images at multiple scales and also removing false positives.

3.4 DeepLearning Algorithms forsegmentation

Deep Learning is a type of Machine Learning which is inspired from the human brain. A neural network is design in the same manner as the structure of human brain. Just like human brain, neural networks analyze the data and give conclusions on the basis of logics given to the network. A simple neural network consists of input layer, hidden layer and output layer. In deep learnings neural networks with many layers are used. In deep learning algorithms, CNN achieves the best result among all the neural networks. Many state-of-the-art algorithms like Unet, Resnet etc. are based on CNNs. They achieve very good results in various ImageNet competitions.

Y. LeCun et. al. [10] first introduced the CNNs in 1989 but it obtained attention after its spectacular results in ImageNet [12][13] competition in 2012[11]. It halved the error rates best computing approaches which were previously used. It was applied on about a million images with 1000 different classes [11].

CNN is made up of 3 type of layers: Input layers, Hidden layers and Output layers. Its architecture has successive layers of convolution, pooling, activation and classification (Fully connected). By convolving kernel across input image, Convolutional layers extracts features. Pooling layers is used to reduce the dimensions of the output of previous convolutional layer. There are two types of pooling operation: Max pooling which uses maximum value of each cluster and Average pooling which uses average value of each cluster. ReLU and Leaky ReLU are the most commonly used activation functions. Rectified linear activation function is a piecewise activation function which clips negative value to zero and simply pass the positive inputs. Leaky ReLU is its modified version where negative values are not zero instead, they have very small slope which is regularized by a small constant alpha. Different loss functions are then connected by output scores to get the prediction of an input data. Finally, Losses are minimized between ground truth labels and prediction to get the parameters of the network, and the weights are being updated in each iteration using backpropagation until convergence.

4 Performance Measures:

There are 3 types of performance measures in brain tumor segmentation: Sensitivity, specificity and Dice similarity coefficient (DSC).

a) Sensitivity: It is the ratio of positive labeled which are correctly predicted and the total positive.

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

b) Specificity: It is the ratio of negative labeled which are correctly predicted and the total negative.

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

c) DSC: It is a measure of spatial overlap between label and automatic segmentation.

$$\text{DSC} =\frac{2TP}{FP+2TP+FN}$$

Authors	**Journal/ conference, year**	**Title**	**Dataset used**	**Architecture Utilized**	**Performance Measure**	**Features**
Paul et. al. [37]	IET, Computer vision,2014	Brain Tumor classification using two tier classifiers with adaptive	3 MRI datasets	K- means algorithm, KNN, DWT	Sensitivity= 0.1 Specificity= 0.5 Accuracy= 0.966	Initial training is based on self-organizing map.

		segmentation technique				
Soltanineja d et. al. [8]	Springer,2016	Automated brain tumor detection and segmentation using super pixel based extremely randomized trees in FLAIR MRI	BRATS 2012 dataset and 19 FLAIR MRI images	Extremely randomized tree classifier, simple linear iterative clustering	Sensitivity-0.89 Dice score-0.91	Similar sized patches are partitioned from an image through SLIC method. 20 extra trees in ensemble are used to perform the random splits.
Pereira et. al. [20]	IEEE, 2016	Brain Tumor Segmentation using CNNS in MRI images	BRATS 2013 and 2015	N4ITK Algorithm, CNN	DSC- 0.75	Use of 3*3 kernels for fewer weights in the network. Heterogeneity caused by multi scanner acquisitions of MRI images using intensity Normalization.
Alfonse et. al.[15]	Egyptian computer science Journal,2016	An Automatic Classification of Brain Tumors through MRI using SVM	100 MRI images	Expectation Maximization Algorithm, FFT, SVM	Accuracy= 0.989	Median filter is used for denoising. 3*3 square neighborhood is used.
Bahadure et. al.[30]	International Journal of Biomedical Imaging,2017	Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction using Biologically Inspired BWT and SVM	MRI images	SVM, BWT	DSC= 0.82	SVM is used to increase the accuracy. To reduce the complexity in feature reduction BWT is used.
Kamnitsas et. al. [31]	ScienceDirect , 2017	Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation	BRATS 2015	3D CNNs	DSC= 0.66	Parallel convolutional pathways are used to incorporate both local and contextual information for better segmentation. Utilization of small kernels.
Soltanineja d et. al. [9]	Computer methods and programs in Biomedicine, 2018	Supervised Learning Based multimodal MRI brain tumor segmentation using texture	BRATS 2013	Random forest classifier,Supe r pixel based extremely randomized trees with	Sensitivity= 0.86 Dice score = 0.84	FLAIR image is partitioned into irregular patches with appx. similar size and intensity values.

		features from super voxels		support vector machines.		Use of Feature selection to increase the computational speed.
Abd Ellah et. al. [16]	EURASIP Journal on Image processing,2018	Two phase multi-modal automatic brain tumor diagnosis system from MRI images using CNN	BRATS 2013	CNN and error correcting output codes svm.	DSC= 0.87	Two phases are used, first for detection and second for localization. Over fitting is reduced. ECOC is used to correct the data error.
Manogaran et. al [7]	IEEE,2019	Machine Learning Based Gamma Distribution for Brain tumor detection and data sample imbalance analysis	994 MRI images	Orthogonal gamma distribution in the Machine Learning model.	Accuracy= 0.99	Region of Interest is self-identified using this approach. Edge analysis and ML is used to train edge coordinates.
Mano et. al. [36]	IET Image Processing,2020	Method of multi region tumor segmentation in brain MRI images using grid-based segmentation and weighted bee swarm optimization	MRI images	Gamma correction, k-means clustering, weighted bee swarm optimization	Accuracy- 0.93	Use of gamma correction to control gamma correction.
Li et. al. [18]	IEEE ,2019	Brain tumor detection based on Multimodal information fusion and CNN	BRATS 2018	Multimodal Information fusion, CNN	DCS= 0.927 SN= 0.928 SE= 0.998	Multi Kernel convolution is used to extract richer image features. Local perception and Parameter sharing is used to reduce the number of network model parameters.
Mahesh et. al. [21]	IET Image processing, 2020	Deep joint Segmentation for the classification of severity-levels of glioma tumor using multimodal MRI images	BRATS 2018	Fractional jaya whale optimiser, DCNN	Accuracy 0.96	Fractional jayaoptimiser and whale optimisation algorithm is integrated for deep joint segmentation. Use of threshold value to extract ROI.
Ali et. al. [34]	IEEE,2020	Brain tumor image segmentation using deep networks	BRATS 2019	3D CNN, U-Net	Dice score-0.846	Enhancing tumor segmentation is better done by CNNs.

Naceur et. al. [2]	Medical Image Analysis,2020	Fully Automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-class weighted cross-entropy	BRATS 2018	CNN, Sparse and dense connection OCM	DSC- 0.9	CNNs internal structure's design is inspired from internal structure of human face.
Paul et. al. [5]	Springer, 2020	Computer aided diagnostics of brain tumor using novel classification techniques	BRATS 2016	Gray level co-occurrence matrix, Support Vector Machine, Bag of visual words, K-means clustering	Accuracy- 0.95 Sensitivity- 0.91 Specificity- 0.94	Use of non-linear and linear radial basis function classifier. False segmented pixel is removed by tumor masking.
Chen et. al. [35]	Computer method and programs in biomedicine, 2020	A novel extended Kalman filter with support vector machine-based method for the automatic diagnosis and segmentation of brain tumors	120 MRI Images	EKF-SVM, gray level co-occurrence matrix, k-means clustering	Accuracy- 0.96	EKF-SVM is used for better results in images of positive brain tumor. Use of K- means clustering and region growth for automatic segmentation.
Sun et. al. [4]	Neurocomputing,2021	Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN	BRATS 2018	3D FCN,	DSC-0.9	Multi-pathway convolutional layers are used to extract features. Use of FCN for segmentation.

5 Conclusion

With the increasing demand of AI and automation, Deep Learning Algorithms are gaining attention. Automatic systems are now becoming the major research area. This review focuseson currently used different state-of-the-art deep learning algorithms which gives a review of the methods used in brain tumor segmentation. As there is a lack of dataset, different techniques should be explored for handling data or class imbalance problem. Most of the techniques are based on supervised Learning which needs manual intervention for ground truth labels. Therefore, we need unsupervised learning-based algorithm to resolve this issue.

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