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Brain Tumor Segmentation in MRI images Using Deep Learning – A Review

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ABSTRACT: Segmentation of brain tumor is the crucial task in medical image processing. In order to improve the treatment possibilities and to increase the survival rate of the patients, early diagnosis of brain tumors supposed to be an important role. Since the manual segmentation depends on the involvement of radiologist and their experience, it may cause some errors as the large volume of MRI (Magnetic Resonance Imaging) data is a difficult and time consuming task. This created the environment for automatic brain tumor segmentation. Now a day's machine learning techniques plays an indispensable role in medical imaging research. Recently, an extremely flexible machine learning approach known as deep learning has emerged as an upsetting technology to enhance the performance of existing machine learning techniques. This paper provides the survey of deep learning based MRI brain tumor segmentation methods and analyses its results.

KEYWORDS: Bain tumor, MRI, Segmentation, Deep learning.

I.INTRODUCTION

The brain is the managing center and is accountable for the execution of all activities throughout the human body. Formation of tumor in brain can threaten the human life directly. The early diagnosis of brain tumor will increase the patient's survival rate. Among the number of imaging modalities, Magnetic resonance (MR) imaging is extensively used by physicians in order to decide the existence of tumors or the specification of the tumors [1]. MRI is a non-invasive and good soft tissue contrast imaging modality, which provides important information about shape, size, and localization of brain tumors [2]. MRI is drawing more and more courtesy for the brain tumor diagnosis in the clinical [3].

In current clinical imaging, different MRI sequences are employed for the better diagnosis and accurate delineation of tumor extents. They include T1-weighted MRI (T1w), T1-weighted MRI with contrast enhancement (T1wc), T2-weighted MRI (T2w), FLuid- Attenuated Inversion Recovery (FLAIR), etc. Fig. 1 shows these four MRI sequences of brain [4]. The response of brain tumor treatment depends on the physician's experience and their knowledge [5].

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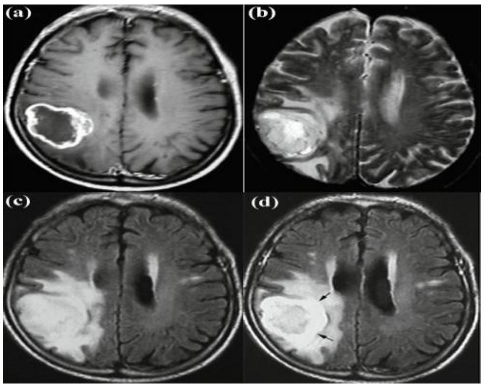

Fig. 1 Four imaging modalities: (a) T1-weighted MRI; (b) T2-weighted MRI; (c) FLAIR; and (d) FLAIR with contrast Enhancement [4]

This problem is the main reason, for the development of fully automated and flawless tumor detection system. In current scenario, there are many methods have been developed for automatically segmenting the tumor extents from brain MRI images. Recently, an extremely flexible machine learning approach known as deep learning has emerged as an upsetting technology to enhance the performance of existing machine learning techniques. Especially, CNNs (Convolutional Neural Network), are hastily gaining their attractiveness in the computer vision community. Various deep learning based brain tumor segmentation methods are discussed in this paper.

The rest of the paper is organized as follows: Section II discussed various deep learning based brain tumor segmentation methods and section III analyzed the results of various methods and concluded the discussion.

II. DEEP LEARNING BASED BRAIN TUMOR SEGMENTATION METHODS

In last decade, numerous methods have been projected to automatically segment the brain tumors from MRI images. In current scenario, deep learning based neural networks hastily gaining their magnetism in the computer vision community. The generic architecture of CNN based brain tumor segmentation is given in Fig. 2. In every image processing task, first step is the image acquisition. In majority of the brain tumor segmentation research, BRATS datasets are used since it has all four MRI modalities with ground truth images. BRATS are available in different forms such as BRATS 2013, BRATS 2015, BRATS 2017and BRATS 2018. Preprocessing should be done on the MRI images to avoid intensity related problems. Some of the preprocessing in MRI images may be may be intensity correction and intensity normalization. Then the preprocessed image is fed to the CNN which segments tumor extents through different layers such as convolution layer with ReLU activation layer, pooling layer and fully connected layers. The convolution layer is convolving an image with kernels to attain feature maps. The activation layer is accountable for non-linearly transforming the data. Rectifier linear units (ReLU) are found to attain superior results than the more conventional sigmoid, or hyperbolic tangent functions, and speed up training [6], [7]. Pooling layer joins the spatially nearby features in the feature maps. So that it decreases the computational load of the next stages. Max-pooling or average-pooling are the more commonly used pooling functions. In order to avoid the error classification of tumor tissues, post processing is applied on the segmented output.

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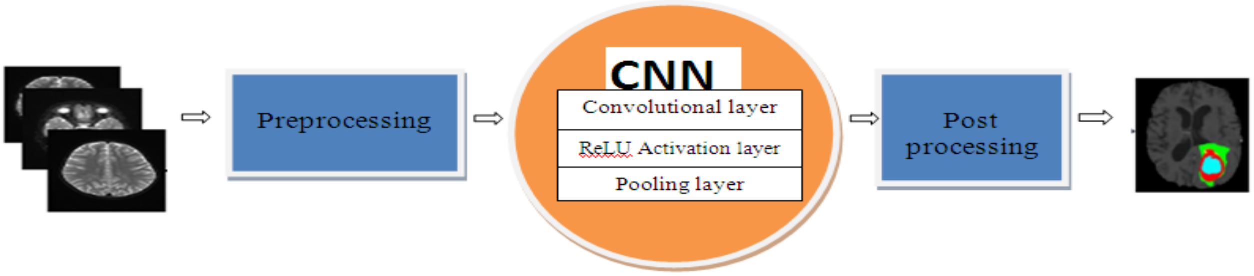

Fig. 2. Generic Architecture of deep learning based brain tumor segmentation

A. Types of CNN Architecture for Brain Tumor Segmentation

CNN are applied to attain some infiltrate results and succeed well-known contests [8], [9]. The convolution layer is convolving an image with kernels to attain feature maps. In order to improve certain characteristics of the input, the weights of the kernels are modified at some stage in the training phase by back propagation. Several convolution layers are heaped together, to extract more meaningful features. Numeral researchers have employ CNN for brain tumor segmentation. Some of the CNN based brain tumor segmentation method was discussed in this chapter.

Mohammad et al. [10] projected two architectures for CNN such as two-pathway architecture and cascaded architecture. In the two-pathway architecture, input is given to two CNNs; one named Local path CNN and other Global path CNN. Then the output of these CNNs is concatenated to produce the final value.

In the cascaded architecture, the output parameters of one CNN are provided as an input to second CNN. 2D patches are extracted and the training is done with this patches. Connected component-based method was used as a post processing method to remove a blob. The authors in [11] also proposed two separate architectures for brain tumor segmentation. One is implemented for segmenting high-grade glioma (HGG) which has depth of 11 layers and another one was implemented for low-grade glioma (LGG) which had 9-layer depth. 2D patches are extracted and given as an input after preprocessing such as intensity normalization and bias-field correction. For removing misclassified cluster, predefined threshold value is set.

Peter et.al [12] suggested the CNN architecture that accepts 2D patches as its input. For preprocessing they have used intensity normalization and histogram matching. They applied both normalization and bilinear interpolation at the hidden layer, which has ReLU and max pooling.

Konstantinos et.al.[13], used the two-pathway architecture that accepts 3D patches as its input to CNN. In preprocessing, the images are normalized with zero mean and unit variance. Conditional Random Field (CRF) is used for post processing which is used to reduce the imbalance between the tumor and the surroundings. Also the false positives are detached using morphological operations. In [14], the authors designed CNN that takes the 3D input patches as the input. Bias-field correction and normalization is completed as preprocessing only for T1 and T1c images. Closing operation is done as post processing step to remove small dark spots and connect all small bright cracks. Similarly Randhawa et.al.[15] proposed 8-layer CNN architecture that worked on 2D image patches.

III. DISCUSSION AND CONCLUSION

As such, manual tumor segmentation is time consuming process; the automated segmentation helps the radiologists to take a quick decision about the tumor progress. In this paper, we discussed various deep learning based tumor segmentation models. Table 1 summarizes the performance of those deep learning methods for automatic brain tumor segmentation and the comparison between various methods has been shown in Fig. 3.

All the methods discussed in this paper are almost use BRATS dataset as it is easily available to public along with its ground truth images. The automated method of segmentation needs validation.

Since BRATS databases are available with ground truth images, evaluation metric is enough for validation. Dice's Coefficient (DC) is one of the evaluation metrics for validation which is used as a similarity measure between two sets. This can be measured by using following formula.

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$$DC = \frac{2|A \cap B|}{|A| + |B|} \quad where 0 \le DC \le 1$$

Here, A is a set of ground truth voxels and B is a set of voxels labeled using segmentation method.

Table 1. Summary of deep-learning based brain tumor segmentation methods

S.No	Author	Database	Method Used	Performance (DICE)		
				Complete	Core	Enh
1	Mohammad et al. [10]	BRATS 2013	Two path-way CNN architecture	0.85	0.78	0.73
2	P. Sergio et al. [11]	BRATS 2013 and BRATS 2015	CNN with 11 layers for HGG and CNN with 9 layers for LGG	HGG/ 0.88	HGG/ 0.76	HGG/ 0.73
				LGG/ 0.65	LGG/ 0.53	LGG/ 0.00
3	Peter et.al., [12]	BRATS 2016	2D CNN	0.87	0.81	0.72
4	Konstantinos et.al., [13]	BRATS 2015	Deep CNN with CRF	0.898	0.75	0.721
5	Pandian et.al., [14]	BRATS 2016	3D CNN	0.725	0.611	0.572
6	Randhawa et.al., [15]	BRATS 2016	CNN with 8 layers	0.87	0.75	0.71
7	Urban et al. [16]	BRATS 2013	3D CNN	0.87	0.77	0.73
8	Zikic et al. [17]	BRATS 2013	3D CNN	0.84	0.74	0.69
9	Davy et al. [18]	BRATS 2013	A two pathway CNN	0.85	0.74	0.68
10	Dvorak and Menze [19]	BRATS 2013	CNN with structured prediction	0.83	0.75	0.77
11	Pereira et al. [20]	BRATS 2013	CNN with small kernals	0.88	0.83	0.77
12	Havaei et al. [21]	BRATS 2013	Cascaded CNN architecture	0.88	0.79	0.73
13	Lyksborg et al. [22]	BRATS 2014	2D CNN	0.80	0.64	0.59
14	Kamnitsas et al. [23]	BRATS 2015	3D CNN with CRF	0.85	0.67	0.63

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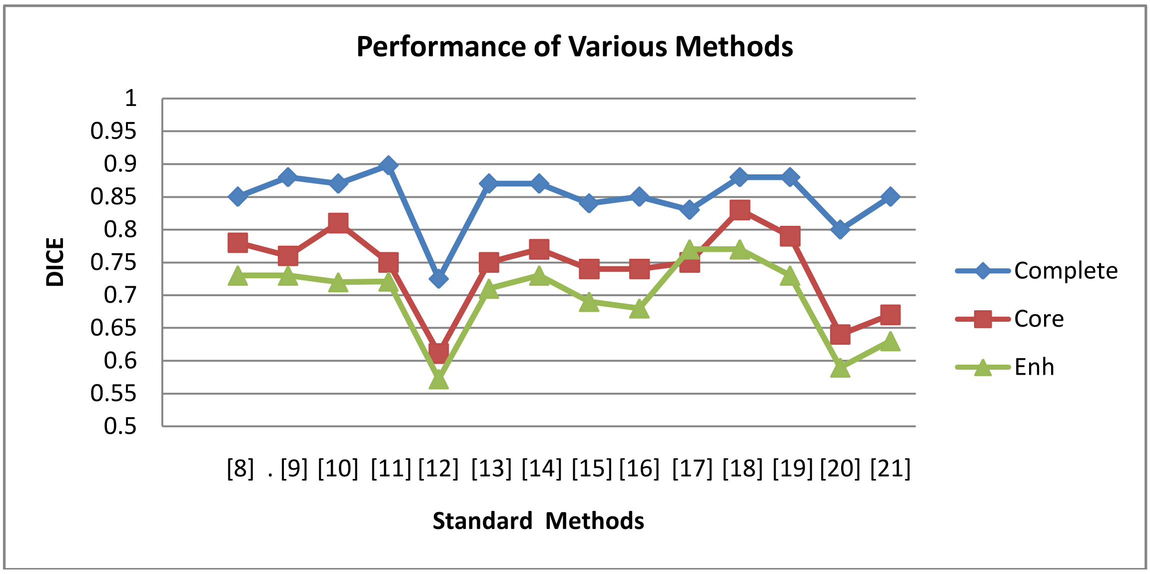

Fig.3. Dice Metric of Various Deep Learning based methods

In general, the manual segmentation recognizes four different types of intra-tumoral classes such as necrosis, edema, non-enhancing and enhancing tumor. Though, the evaluation is carry out for the enhancing tumor, the core (necrosis + non-enhancing tumor + enhancing tumor), and the complete tumor (all classes combined). Dice value should be calculated for each tumor regions. Dice metric of all these regions for various deep learning methods is shown in table1. Among various methods discussed in this paper, Konstantinos et.al., [11] achieves higher results in the dice metrics as it was shown in Fig. 3 that they reached 0.898 of dice for complete tumor, 0.75 of dice for core region and 0.721 of dice for enhancing region of tumor respectively. 3DCNN is used for segmentation with CRF as post processing in this work.

From this review it is inferred that the deep learning offers a very influential structure for brain image segmentation which provides considerable results compared to conventional methods. There are various CNN architectures for brain tumor segmentation. The CNN directly extracts the image features, where the conventional method extracts the hand-crafted features. However, once the training of CNN is completed, the testing requires reduced time. Nowadays with potent hardware, the response time for deep-learning methods is getting comparable to conventional methods. In future, the upgrading and variations in the architecture of CNN and the addition of balancing information from other modalities may perk up the current methods and causes the development of fast and fully automated tumor segmentation methods for enhanced diagnosis.

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BIOGRAPHY

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