Brain Tumor Segmentation using Pattern Neural Networks with MRI Images

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Abstract

Image segmentation is the method widely applied in images for diagnosing kind of diseases in medical field. In which pixels are grouped together that have similar attributes. In this paper segmentation has an important role for segmenting brain tumor. Uncontrolled growth of cells in brain is called brain tumor. Gliomas are the brain tumor which has high mortality rate. Magnetic resonance imaging (MRI) is used to get informations about the tumor level accurately. This paper depicts the Pattern neural network (PNN) for tumor segmentation. It is a feedforward network PNN uses small kernals to avoid overfitting. The work of this segmentation method provide very good result in terms of time consumption and accuracy over soft tissue in brain with the help of MRI images.

Keywords: Image segmentation, Brain tumor, Gliomas, Pattern neural network, MRI images

I. INTRODUCTION

Brain tumor is a mass of abnormal cells which grows uncontrollably in our brain. Early detection of these abnormality is essential because the growth may leads to Gliomas. These are brain tumor having highest mortality rate. Mainly the brain tumor can be classified into malignant (cancerous tumors) and benign tumors. Magnetic resonance imaging is better than Computer tomography (CT) for scanning the brain to get the contrast of affected area of brain, because MRI scan does not cause radiation which is harmful for the human body. Fig 1 shows the MRI image of brain affected with tumor. The dark round with white border shows the tumor region. The Gliomas can be classified into two level one is Low Grade Gliomas (LGG) and High Grade Gliomas (HGG). The segmentation process consume more time and produce inaccurate result in some irregular condition like variation in shape and location of tumor tissue. So there is the need of automatic methods for segmentation. MRI images has the problem that, sometimes it will show inhomogeneity ie, for the same sequence it produces different intensity in the scanned image[5]. In this paper we are using a novel segmentation techniques such as Pattern neural network (PNN) tumor classifier. PPN and artificial neural network are structurally similar. The difference between them is set of activation function used. Merits of the segmentation with PNN gives its better classification efficiency. This paper starts with preprocessing step. Normalization is the main part in preprocessing step. Here using normalization method proposed by Nyúl et al. It will helps to avoid intensity variation produced by MRI images. After preprocessing the features are extracted from normalized image. In our proposed method bayasien learning method is used to train the network. Small kernel used will provide deep network structure and also avoid over fitting.

Fig. 1: MRI of brain with tumor

The remaining of this paper cover the following sections. Section II discusses the review on the papers related to the method going to be done. Section III depicts the proposed method. In section IV discuss about expected outcome. Finally according to the expected result Vth section concluded about the novelty.
II. RELATED WORK

There are many techniques for MRI segmentation have been developed over the years. Meena and Raja [9] proposed an approach called Spatial Fuzzy C-means (PET-SFCM) clustering algorithm on Positron Emission Tomography (PET) scan image datasets. The algorithm is joining the classical FCM to spatial neighborhood information and updating the objective function of each cluster.

Another one is proposed by Tatiraju and Mehta [10]. They introduced K-means clustering, Expectation Maximization (EM), and Normalized Cuts (NC). They proceeded with two former unsupervised learning methods and compared them with a graph-based algorithm, the Normalized Cut algorithm. With varying value of k (number of clusters) they applied the partitioning algorithm to gray-scaled images. When the k value is small, the K-means and EM algorithms give good results. When value of k is large, the segmentation is very coarse.

For image segmentation several other researchers have suggested number of hybrid algorithms such as an efficient segmentation approach using K-means clustering technique joined with Fuzzy C-means algorithm. For providing an accurate brain tumor detection the method then followed by thresholding and level set segmentation stages.

Moumen T El-Melegy and Hashim M Mokhtar[8] proposed fuzzy approach with class center priors. Here prior information is used for the segmentation process. Information about the class centers of the data helps to regularize the clusters produced by the FCM algorithm. Thus it improves performance of the algorithm by increasing the convergence rate.

Glavan and Holban [11] introduced a system that using convolution neural network (CNN) as pixel classifier for image segmentation process. Some X-ray images are used for the system. Here each pixel is analyzed from the image and tries to classify them into two classes called bone and non-bone. Then the bone tissue area is separated from the remaining of the image. CNN shows the best results compared to other configurations. To reduce training time they used only interested area from the image. The system detect bone area but, when the irregularities presented which take more execution time.

Marcel Prastawa a, Elizabeth Bullitt c, Sean Ho et.al.[17] proposed a method, which describes a method for automatic brain tumor segmentation from MR images. In addition to tumor segmentation the detection of edema is also done simultaneously. The segmentation framework is composed of three stages. First, using a registered brain atlas as a model for healthy brains they detected abnormal regions. In second stage, they determined intensities whether edema appears together with tumor in the abnormal regions from the second weighted image. Atlast they applied geometric and spatial constraints to the detected tumor and edema regions.

Funmilola et al. [18] proposed the Fuzzy K-C-means method, which carries more of Fuzzy C-means properties than that of K-means. The algorithm reads the image, determines the iterations, by using distance checker reduces the iterations, gets the size of the image, concatenates the dimension, generates large data items with distance calculation, and reduces repetition when possible distance has been attained. The iteration begins by identifying significant component of data then it stops when possible identification elapses. Fuzzy K-C-means works on grayscale images like Fuzzy C-means. It generates the same number of iterations as in Fuzzy C-means. The authors reduced the iterations by checking the distances only. The demerits of the proposed method is that the result of their proposed method is similar to the outcome of the Fuzzy C-means algorithm except in some images. The time of Fuzzy C-means is greater than by maximum 2 s than their proposed method.

III. METHOD

Proposed method can be mainly divided into three parts pre-processing, segmentation through pattern network (PPN) and finally post processing. The Fig 5 shows the over view of proposed model with different steps for segmentation.

A. Pre-Processing

Compared to other medical images brain images are more sensitive, they should have minimum noise and maximum quality. To achieve this requirement MRI images are used. This type of image will have some variations in there intensity when take more samples on same images. This problem is solved by using normalization method. N4ITK method [2] is applied for normalization. In normalization method the intensity values are trained from each MRI sequence as described in [14]. The normalized image of Fig 1 is shown in Fig 2.

Fig. 2: Normalized image
Fig. 3: Mean calculated from Fig 2
Fig. 4: Varience calculated from Fig 2
After normalization method the images are divided into different patches of 3x3 kernel. From each patch the value of mean and variance are calculated. Fig 3 and Fig 4 show the mean and variance computed by using normalized MRI image respectively.

### Pattern Recognition Neural Network

Pattern recognition networks are feedforward networks that can be trained to classify inputs according to target classes. The two-layer feedforward network with sigmoid hidden and softmax output neurons (patternet), can classify the vectors arbitrarily well. The network will be trained with scaled conjugate gradient backpropagation. The target data for pattern recognition networks should consist of vectors of all zero values except for a 1 in element $i$, where $i$ is the class they are to represent.

1) **Initialization**

Initialization is an important step in any neural network here also we start with initialization method. For initialization, Xavier initialization method is used [5]. If the weights start too small, the image shrinks when it passes through each layer of the network. If the weights start too large, then the image enlarges as it passes through each layer in network. By keeping the image with in a reasonable values of weight through many layers, Xavier initialization method makes the weights just right.

2) **Activation Function**

The sigmoid function is used as activation function, and is given by the weighted sum over activations from input nodes passed through an activation function. The output values are simply the activations of the output nodes. The MRI images are divided into small 3x3 kernels. The weights of these kernels are updated with enhanced value during training time [5]. Other than the weights and biases there are no parameters in a node of its linear layer.

3) **Regularization**

Overfitting is reduced by using regularization. Dropout [15] is used in network layers. To get better learning performance it removes nodes in each training step.

4) **Loss Function**

The mean squared error and the binary cross entropy are used in our proposal. The loss function is usually minimized by some variant of gradient descent Stochastic Gradient Descent. For training mean squared error should also be minimized.

Fig. 5: Overview of proposed method
Training
The loss function discussed above must be minimized to train the patternnet. Bayesian learning method is used for the training. The optimization method, Stochastic Gradient Descent, which takes steps proportionally to the negative of the gradient in the direction of local minima[5]. In the regions of low curvature the training can be slow. So, to accelerate the algorithm in these regions we use Nesterov’s Accelerated Momentum [5].

C. Post-Processing
After segmenting the brain tumor the output image should contain some unwanted portion rather than tumor region, it must be eliminated for better accuracy. Morphological operations erosion is imposed to remove the erroneously classified tumor.

IV. Expected Outcome
The proposed architecture used to segment the BRATS 2015 Challenge data set. When comparing with the existing models, forexample, in tumor segmentation using fuzzy c-means method which improved computation time but fails to segment image corrupted by noise, outliers, and other imaging artifacts[4]. In another method, k-means clustering its accuracy is better than fuzzy c-means but its computation time is high.In the performance analysis, the efficiency of the proposed approach is compared with the existing method. By using Compositional Pattern-Producing Network the time required for the overall performance is lesser than other methods like clustering, CNN etc.

V. Conclusions
There are many research works are done on these area, but we have to go for an efficient method. So, Pattern net is like one which gives the better result in terms of some conditions. The pattern neural network described in this paper are capable of massively segmenting the tumor region and non-tumor region, and also the PNNs training will provide improved performance in the case of time consumption and accuracy compared to the segmentation methods discussed in the related works section.

References