Level Set Based Feature to Segment Brain Tumor Segmentation for Human Head Scans

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ABSTRACT—The research proposes a method to segment brain tumor from magnetic resonance images (MRI). The method uses artificial neural network (ANN) with novel level set and wavelet based features. Automatic brain tumor segmentation methods are very essential in many diagnostic and therapeutic applications. Existing works used more number of features but the proposed method uses only minimal number of strategic features and compared against support vector classifier (SVM). Quantitative and qualitative results of both methods compared and proved the outstanding result of the proposed method.

Keywords: MRI, brain tumor, ANN, SVM, segmentation

1. INTRODUCTION

Uncontrolled growth of cancerous cells will cause brain tumor which is life threading. MRI is the most commonly used technique for lesion detection, definition of extent, detection of spread and in evaluation of either residual or recurrent disease. MRI machine produces numerous images per patient. Based on time MRI machine produces multi modality of images called T1-weighted, T2-weighted, T1-contrast and Fluid attenuated inversion recovery (FLAIR) images. In recent times, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient [1]. It addresses the need computer based of brain tumor segmentation method.

The tumor segmentation methods are broadly classifies as knowledge based (generative) and feature based (discriminative). Generally, feature based methods make use of classifiers such as neural network [2]. ANN, Deep convolution neural network [3][4], Random forest [5], and decision tree [6]. The classifiers are formulated by mathematical functions which carried out the task in two steps such as training and implementation. In training state, many image features are given as input to obtain some optimal parameters. The training carried out with estimated result is called supervised learning and others are called unsupervised learning. They are investigated and reported in [7].

Recently, kernel class severability based features have been selected and implemented in support vector machine (SVM) to segment brain tumor tissue [8]. This kind of classifier is unsupervised but requires nearly forty four features [9]. The ANN is a simple supervised classifier and requires less number of features. The proposed method uses minimum number of strategic features.

The all methodologies require preprocessing task before segmentation. The proposed work chosen a simple and morphological based concept called Modified Weber's law to enhance the contrast of the given image [10]. The ANN is a layered architecture and it uses two phases of processes such as training and testing.

The remaining part of this paper is organized as three sections. The section 2 describes the proposed method, the section 3 discusses the results of the proposed work and compared against SVM and the section 4 concludes the results.

II. REVIEW OF RELATED WORKS

Brain tumor segmentation and classification has attracted a lot of research effort over the last few years. Researchers have used both image processing and machine learning to solve the problem. In this section, we briefly describe some of the representative techniques.

Minakshi S et al. [2] presented a discriminatively trained conditional model based on logistic regression and showed that this model achieves better segmentation results as compared to the traditional generative models.

Havaei M et al. [3] segmented brain tumor using undecorated wavelet transform, Gabor wavelets and the K-means clustering algorithm. They used T1 and T2 modalities of MRI for their experiments.

Urbon G et al. [4] used feature selection techniques to select best features from amongst the texture, shape and intensity features. Results were achieved by using Kullback-Leibler divergence for the ranking and selection of features and then by using expectation maximization algorithm for the fusion of selected features along with segmentation of tumor. T1, T2 and Flair modalities were used.

Festa J et al. [5] presented a technique using a hybrid classifier of RDF and hierarchal random field regularization. Preprocessing involved de-noising, bias field correction, rescaling and histogram matching. They achieved better results by RDF as compared to SVM. For their experiments, they used T1, T1c, T2 and Flair sequences.

Gladis Pushpa Rathi VP et al. [8] extracted intensity, neighborhood, context and texture features from T1, T1c, T2 and Flair sequences of MRI and then classified voxels by using RDF classifier. A total of 324 features were extracted for each voxel.

Meier et al. [9] presented a technique using density forest. The sequences used in their work were T1, T1c, T2 and Flair.

Reza and Iftekharuddin [10] segmented brain tumor using texture features. They used RDF to classify different tumor grades using the dataset that included T1, T2, T1c and Flair.

Tustison et al. [11] implemented an algorithm using novel features and then classified brain tumor grades using a parallelized RDF classifier. They used T1, T2, T1c and Flair sequences for their experiments

III. PROPOSED METHODOLOGY

The proposed method consists of four stages as given in Fig. 1. The first stage enhances the image contrast, features of the required image is extracted in the second stage, the extracted features and the experts annotated result are given as input to train the network in third stage and unknown images are given to get segmented tumor portion in the fourth stage.The proposed algorithm make use of Modified Weber's law for contrast enhancement [10] wavelet packet based feature set [11], energy level [12] and neighborhood based features.

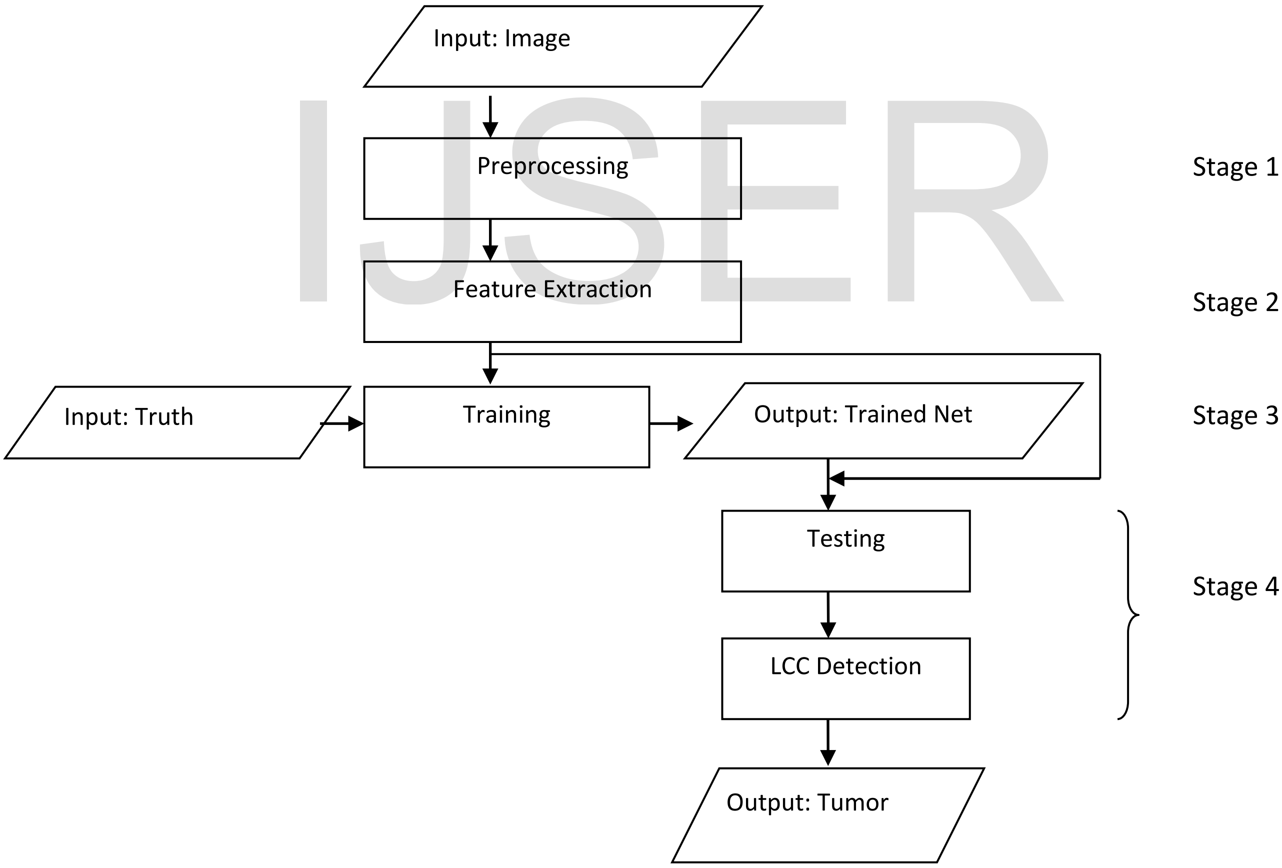

Figure 1: Flowchart of the proposed method

3.1. *Preprocessing*

Modified Weber's law is used to enhance the images. The method is a two stage process and uses morphological

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operations such as erosion and dilation to identify the background image pixels. Further, modified Weber's law given in Eqn.(1) is used to enhance the brightness and contrast of the image.

$$T(f_{i,j}) = \begin{cases} k\tau_{i,j} log(f_{i,j}+1) + M_{i,j}\ ,\ f_{i,j} \geq \tau_{i,j} \\ k\tau_{i,j} log(f_{i,j}+1) + m_{i},_{j}\ , otherwise \end{cases} \quad (1)$$

where f represents image, M and m represent eroded and dilated images, the threshold value is defined as

$$\tau_i = \frac{m_i + M_i}{2} \quad (2)$$

and the scaling parameter is defined as follows,

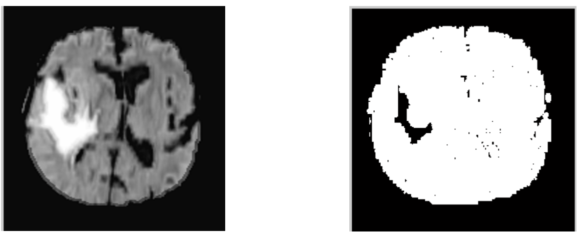
$$K = \frac{255 - \tau_i}{log256} \quad (3)$$

3.2. Feature Extraction

Features are relevant image information for solving the computational task related to a certain application. Features may be specific structures in the image such as points, edges or objects. The proposed method make use of eight kinds of features such as tumor location, energy level of each pixel based on the location, intensity of the pixel and pixel neighborhood based features.

Tumor location:

Wavelet packet transform is applied to detect the high frequency components in the images, and then modulus maxima are applied to detect singular points. Further Otsu thresholding is applied to locate the tumor portions in the image. The obtained feature image is given in Fig.2.



(a) (b)

Figure 2: Tumor location.

(a) Original contrast enhanced image and (b) tumor location

Energy level of each pixel:

The border of located tumor portion is taken to obtain level sets. The distance of each pixel from the border is obtained to get the energy level of possible tumor pixels. Then Heaviside function which separates the image into two regions foreground and background is applied to get the level sets. The Heaviside function is as follows,

$$H(x,y) = \begin{cases} \Omega^{+}, & \mathrm{d(x,y)} > 0 \\ \Omega^{-}, & \mathrm{d(x,y)} < 0 \end{cases} \quad (4)$$

where d(x,y) is the Euclidean distance, Ω^{+} is the level set of foreground and Ω^{-} is the level set of background (tumor). The feature image is given in Fig. 3.

Neighborhood based features:

A 5×5 window is chosen to get the neighborhood features. Mean, variance, standard deviation and number of pixel redundancy of the window are chosen as the neighborhood features. Additionally, mean square error of each pixel window is chosen as another feature.

Figure 3: Level sets. Bright pixels represent foreground and dark pixels represent background of the image

3.3. Artificial Neural Network

The proposed method uses Feed forward neural network. It is a directed acyclic graph which means there are no feedback connections or loops in the network. It has an input layer, an output layer and hidden layers as shown in Fig.4. Each node in the layer is a neuron, which can be thought of as the basic processing unit of a neural network. Each neuron calculates the weighted sum of its inputs and then applies an activation function to normalize the sum. The activation function is used as decision making body at the output of a neuron.

Training: Network structure number of layers, number of neurons per layer, connections between the layer and training function are chosen to set a net. Further, both inputs and the outputs are provided. Each pixel features are given as input and experts result regarding each pixel is given as output vectors. The network then processes the inputs and compares its resulting outputs against the desired outputs.

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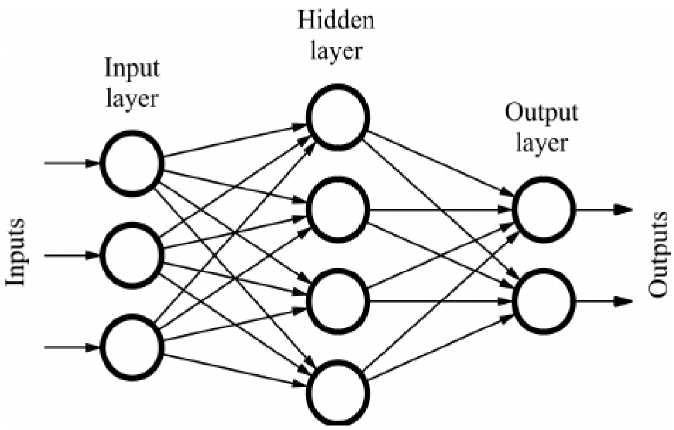

Figure 4: Feed forward neural network structure

3.4. Testing

Unknown image features are given during testing features. The trained net automatically extracts tumor from the given unknown input image. It contains some number of regions along with the tumor region. The tumor region is exactly identified by its area. The largest connected component (LCC) that is the largest region is finally outputted as the tumor.

3.5. Evaluation Parameter

Dice is a best similarity measure to indicate the performance of the proposed work. The Dice coefficient is a measure of the similarity ranging between 0 and 1, where "0" indicates the sets are disjoint and "1" indicates the sets are identical. The equations is defined as follows,

$$Dice = 2 * \frac{|A \cap B|}{|A| + |B|} \tag{5}$$

where A and B are the ground truth and the segmented image respectively. In these images, $|A \cap B|$ represents the number of required pixels, $|A|$ is the number of expected pixels in the ground truth image and $|B|$ is the number of segmented pixels in the output of segmented image.

IV. RESULT AND DISCUSSION

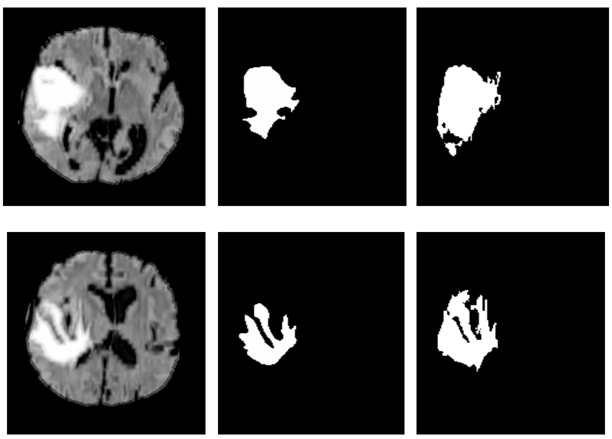

Figure 5: Results of the proposed method. Column1 shows the original image, column 2 and column 3 show the ground truth and segmented results respectively.

The proposed work applied over some MRI images. The images were collected from web resources. Some images are lack in brain anatomy description. That is no better delineation between the white matter, gray matter and border of all the regions. The original and segmented images are given Fig. 5. In Fig.5, column 1 shows the given image, column 2 shows the ground truth and column 3 shows the output of the segmented result. Initially, experiments conducted with five layer network further the experiments conducted over ten layer network. The ten layer network gives better result than five layer network. The final results are compared with the results of Support vector machine (SVM). The same features were given to the SVM classifier the results are given in Fig.6.

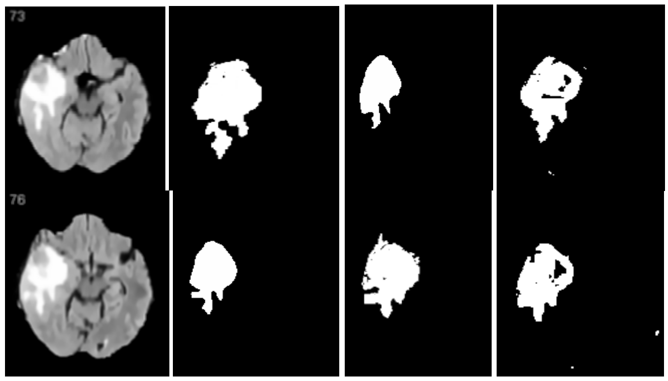

Figure 6: Result comparisons with SVM classifier. Column 1 shows the original image, column 2 shows the ground truth, column 3 and 4 show the output of the proposed method and SVM classifier

Fig.6 explains the comparative result. Column 1 and column 2 show the original and ground truth. Column 3 and column 4 show the output of the proposed ANN and SVM classifier. The SVM classifier misses some tumor pixels but the proposed ANN clearly picked the tumor pixels. The performances of the both classifiers are analyzed using evaluation parameter Dice value. The values are listed in Table 1. In Table 1, column 1 shows the slice number; column 2 shows the dice value of the proposed method and column 3 shows the dice value of SVM classifier.

For all images, the proposed method gives better result than the SVM. The both visual and quantitative results proved that the proposed method gives good results.

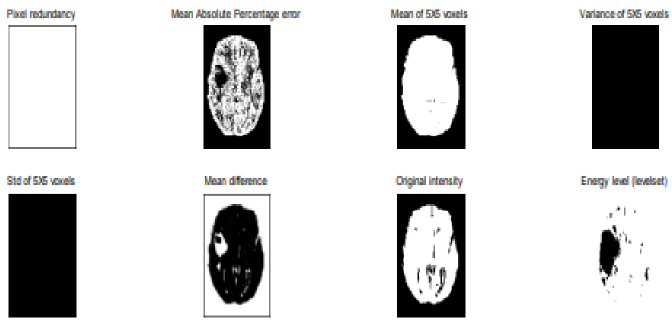

Figure 7: The both visual and quantitative results proved that the proposed method gives good results.

Table 1. Dice value of the proposed ANN and SVM classifier

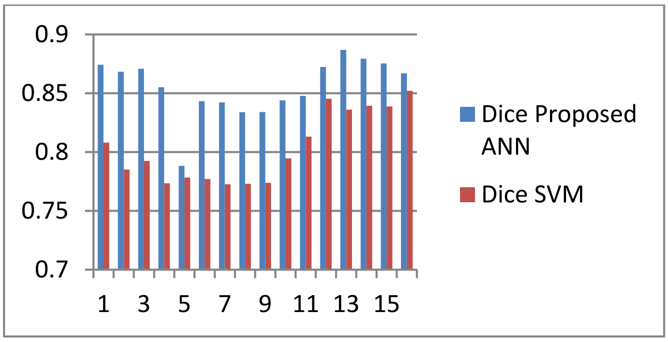

Figure 8: Sensitivity, Specificity and Accuracy of the Result sample images.

Slice no	Dice	
	Proposed ANN	**SVM**
65	0.8742	0.8081
66	0.8682	0.7851
67	0.8709	0.7925
68	0.8551	0.7734
69	0.7882	0.7783
70	0.8433	0.7771
71	0.8422	0.7726
72	0.8339	0.7730
73	0.8340	0.7739
74	0.8440	0.7947
75	0.8477	0.8131
76	0.8723	0.8453
77	0.8869	0.8361
78	0.8794	0.8393
79	0.8753	0.8388
80	0.8669	0.8521

V. CONCLUSION

The research proposed ANN based tumor segmentation algorithm. It uses very less number of features and compared against SVM classifier. This work provides an effective result that helps to locate exact tumor in brain MR images. The principal advantage of this proposed method is that, it is very easy for complex unknown images and the end user does not need to prior knowledge about brain anatomy. Because the proposed method is purely based on feature based method and it is applicable to Flair images only. In future, new features will be added to obtain better result.

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