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MRI Brain Tumour Detection using Feed-Forward Neural Network

D. Selvaraj and R. Dhanasekaran

***Abstract*---**This paper presents an effective brain tumour detection technique based on neural network and our previously designed brain tissue segmentation. This proposed method classifies the brain MRI volume into 3 classes: normal tissue (Gray matter, White matter), Pathological tissue (Tumour) and Fluid (Cerebrospinal fluid). Later, to extract the relevant features from each segmented tissue and classify the tumour images with neural network. The performance of the proposed technique is validated with the standard evaluation metrics such as sensitivity, specificity and accuracy values. The proposed method has been applied to a large number of MR images showing promising results for various image qualities.

***Keywords*---**Brain Segmentation, Magnetic Resonance Imaging, Feature Extraction, Neural Network, Tumour

I. INTRODUCTION

THE primary goal of MRI brain image segmentation is to partition a given brain image in to non- intersecting regions representing true anatomical structures such as grey matter, white matter, cerebrospinal fluid, skull, scalp and later, to detect the abnormalities of tissue in these structures. Identification and segmentation of brain tumor in magnetic resonance images is very crucial in medical diagnosis because it gives information related to anatomical structures as well as potential abnormal tissues necessary for treatment planning and patient follow-up. Precise segmentation of brain tumor is also useful for general modeling of pathological brains as well as the creation of pathological brain atlases [16, 17]. there is a significant inter-patient variation of signal intensities for the same tissues [3].

Although there are several approaches for MRI Brain image segmentation: discriminant analysis [5], neural networks [6,7], clustering [4], brain atlases [8], knowledge-based techniques [9], shape-based models [10,11], morphological operators [12], multivariate principal component analysis [13], pixel based models like Expectation Maximization Algorithm [14], Multi-resolution edge detection [6] and statistical pattern recognition [15], to name a few. Precise segmentation and classification of abnormalities are still a challenging and complicated task because of inherent noise, partial volume effect, different shapes, locations and image intensities of different types of tumors

Manual segmentation cannot be compared with the current high speed computing machines that allow us to visually observe the size and position of the superflous tissues. Supervised segmentation methods have exhibited problems with reproducibility, due to significant intra and inter-observer variance introduced over multiple trials of training Furthermore; they are time consuming and require domain experts. So these limitations suggest the need for a fully automatic method for segmentation.

In this paper, we have presented an efficient detection technique for the tumor region in the Brain MRI images. Here, we have utilized the brain tissue segmentation technique that we have proposed in our previous research paper [1, 2]. In addition with that, we have detected the tumor region with the aid of the regionprops algorithm [18]. Subsequently, the features vectors of all the segmented regions of the brain MRI image are calculated. Then, the abnormality classification is carried out by means of neural network.

The rest of this paper is organized as follows: Section 2 presents our proposed Brain tumor detection technique using neural network. The detailed experimental results and discussions are given in Section 3. Lastly section 4 concludes the paper

II. PROPOSED METHOD

The block diagram of the proposed technique is shown in Fig 1. The first processing step in the segmentation of brain tissues is skull stripping. The skull stripped images are further classified into white matter, Grey matter and cerebrospinal fluid. In the proposed method, the following are the steps involved for brain nuclei segmentation.

- Skull stripping
- CSF Segmentation and
- Grey matter segmentation
- white matter segmentation and
- Tumour detection

The obtained experimental results by our proposed technique in our previous research paper [1,2] are as shown in Fig 2 and Fig 3. Here, we have given all the outcomes of the input image with tumour and without tumour region.

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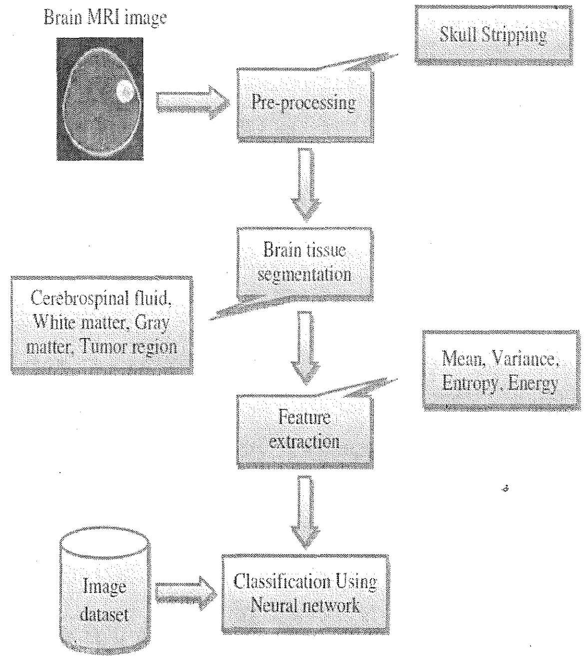
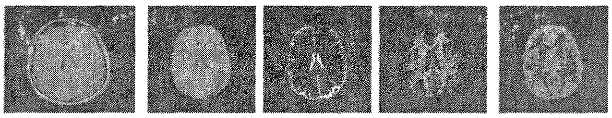
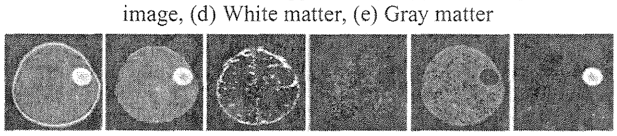


Fig-1: Block diagram of Proposed method



(a) (b) (c) (d) (e)

Fig-2: Segmented results of Brain MRI without tumor. (a) Input Brain MRI image, (b) Skull stripped image, (c) Cerebrospinal fluid image, (d) White matter, (e) Gray matter



(a) (b) (c) (d) (e) (f)

Fig-3: Segmented results of Brain MRI with tumor. (a) Input Brain MRI image, (b) Skull stripped image, (c) Cerebrospinal fluid image, (d) White matter, (e) Gray matter, (f) Tumor region

III. FEATURE EXTRACTION FROM THE SEGMENTATION

The analyzing methods have been done so far has used the values of pixels intensities, pixels coordinates and some other statistic features namely mean, variance or median, which have much error in determination process and low precision and efficiency in classification [19] . Here, the statistic features we have chosen are Mean M, Variance σ^2, Entropy E and Energy $E_{(E,V,D)}$ functions. The feature extraction process is carried out with some initial pre-processing. Each tissue segmented image is split into a limited number of blocks and the feature values are calculated for every block. The block diagram of the feature extraction process is given in Fig. 4. The initial steps are as follows:

- Find the neighbor blocks of the entire divided blocks.
- Find the distance between all the neighbor blocks.
- Find the feature values of the blocks with distinct distance measure.
- Find the average value of all the computed blocks' distance.
- Store all the features in a vector and fed as an input to the classifier.

The statistic feature's formula is depicted as below,

$$\textbf{Mean, } M = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{m} x(i,j)$$

$$\textbf{Variance, } \sigma^2 = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} (x(i,j)-M)^2$$

$$\textbf{Entropy, } E = -\sum_{i}\sum_{j} x(i,j)\log x(i,j)$$

$$\textbf{Energy, } E_{(H,V,D)} = \sum_{i}\sum_{j} x(i,j)^2$$

Selection of efficient features can reduce significantly the difficulty of the classifier design. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted features. The training feature vector F_V is defined by combining all the extracted features like mean M, variance σ^2, entropy E and the energy $E_{(H,V,D)}$. In order to obtain the three wavelet energies, the Haar wavelet transform is applied to each blocks of brain MRI image. After a one level wavelet transform, a 4×4 pixel block is decomposed into four frequency bands of 2×2 coefficients. For example, the coefficients in horizontal band of one block are H1, H2, H3, H4, in vertical band V1, V2, V3, V4 and in diagonal band D1, D2, D3 and D4. Then horizontal energy E_H, vertical energy E_V and diagonal energy E_D are combined to attain the feature value of the energy.

Feature Vector, $F_v = [f(M), f(\sigma^2), f(E), f(E_H), f(E_V), f(E_D)]$

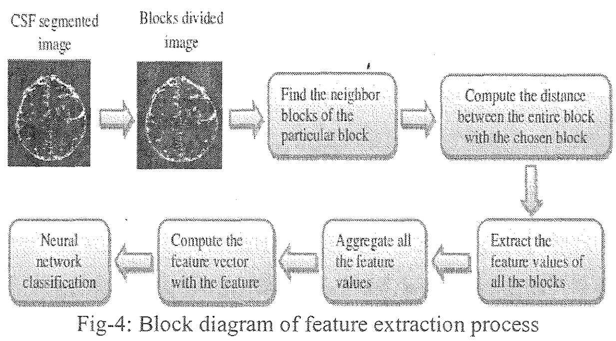


Fig-4: Block diagram of feature extraction process

IV. MRI IMAGE CLASSIFICATION USING NEURAL NETWORK

The classifiers we have used here is feed forward Neural network. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. Here, the network consisted of an input layer of 24 neurons, 1 hidden layer with 5 neurons, and an output layer with 1 output neuron, one for each channel. Using this neural network, the abnormality of the brain image is been detected. We have given all the computed features values as the input for training the neural network with normal and abnormal brain MRI images. A general structure of MLPNN comprising 3 layers is shown in Fig 5.

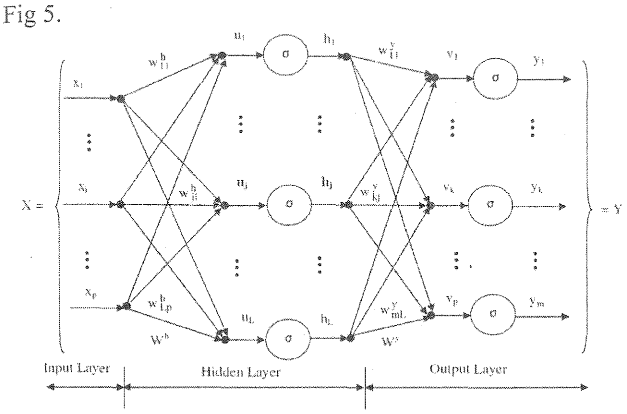


Fig-5: Structure of MLPNN

V. EXPERIMENTAL RESULTS

We have presented a technique for segmentation and detection of pathological tissues (Tumor), normal tissues (White Matter and Gray Matter) and fluid (Cerebrospinal Fluid) from magnetic resonance (MR) images of brain with the help of composite feature vectors comprising of wavelet and statistical parameters. The proposed technique can successfully segment the tumors as well as the brain tissues, provided that the parameters are set properly. The proposed technique is designed for supporting the tumor detection in brain images with tumor and without tumor. The obtained experimental results from the proposed technique are given in Fig. 2 and Fig. 3. The simulation result of neural network training dataset is as shown in Fig 6.

The segmentation result is evaluated with the help of quality rate given as follows,

$$\text{Quality rate, } q_r = area(A \cap B) / area(A \cup B)$$

The evaluation of brain tumor detection in different images is carried out using the following metrics [31],

$$\text{Sensitivity} = TP/(TP+FN)$$

$$\text{Specificity} = TN/(TN+FP)$$

$$\text{Accuracy} = (TN+TP)/(TN+TP+FN+FP)$$

Where, TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive. Table 1 defining the relevant terms of the evaluation metrics like TP, FP, FN, and TN.

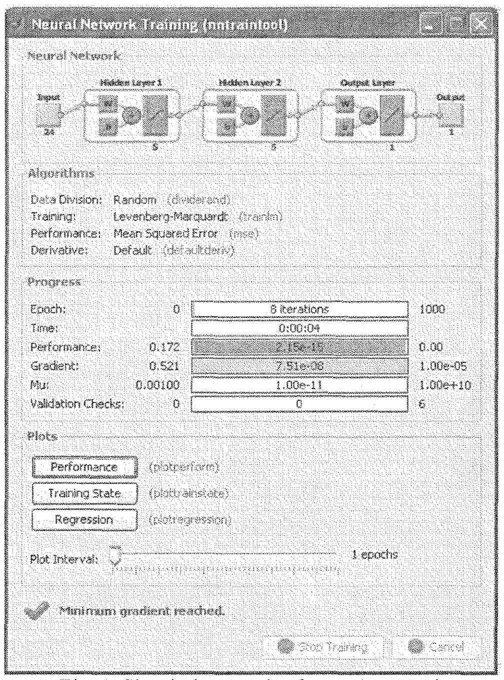


Fig-6: Simulation result of neural network

TABLE 1
TABLE DEFINING THE TERMS TP, FP, FN, TN

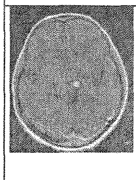
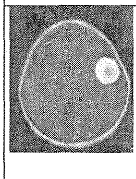
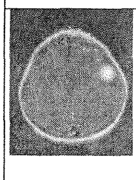
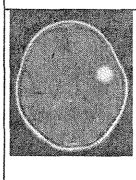
Experimental Outcome	Condition		Row Total
	Positive	*Negative*	
Positive	**TP**	**FP**	TP+FP
Negative	**FN**	**TN**	FN + TN
Column total	TP+FN	FP+TN	N=TP+TN+FP+FN

The performance analysis of our proposed techniques with the relevant segmented results by means of the quality rate is as shown in table III. With the aid of the input MRI image training and testing dataset, the values of TP, FP, FN, TN, Sensitivity, specificity and accuracy are given in table II. The results shows that the accuracy is almost 80%.

TABLE II.
DETECTION ACCURACY OF THE PROPOSED TECHNIQUE IN TRAINING AND TESTING DATASET

Evaluation Metrics	**Neural Network**
True Negative	3
False Positive	3
True Positive	2
False Negative	0
Specificity	075
Sensitivity	1
Accuracy	0.83

TABLE III
QUALITY RATE OF SEGMENTED BRAIN TISSUE

Images	*Cerebrospinal fluid*	*White matter*	*Gray matter*	*Tumor region*
	0.689614	0.9871	0.909301	0
	0.6102295	0.945	0.962626	0.9987
	0.696243	0.9987	0.942108	0.9821
	0.809706	0.9911	0.96046	0.998
	0.665306	0.963	0.949324	0.992

VI. CONCLUSION

In this paper, we have presented an effective neural network based brain tumor detection technique with MRI images. The efficiency is achieved with brain tissue and tumor segmentation, feature extraction of the segmented regions and the classification based on neural networks. The MRI image dataset contains 20 brain MRI images in which 10 images with tumor and the other 10 brain images without tumor is taken from the publicly available sources. The performance of the proposed technique is evaluated by means of the quality rate for all the segmented tissues. As well, the results for the tumor detection are validated through evaluation metrics namely, sensitivity, specificity and accuracy.

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