Brain MR Image Segmentation for Tumor Detection using Artificial Neural Networks

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***Abstract*— Detection, diagnosis and evaluation of Brain tumour is an important task in recent days. MRI is the current technology which enables the detection, diagnosis and evaluation. The medical problems are severe if tumour is detected at the later stage. Hence diagnosis is necessary at the earliest. In this work, pulse coupled neural network is applied for enhancing the MR Images. The enhanced images are segmented and classified using back propagation networks. The Classification involves labelling the images into normal and abnormal (tumor detected). If the input MRI brain images are more in number, the physician could seek the help of this model and the network would help the physician to save time for further analysis. PCNN and BPN are less complex in nature and hence the processing of MRI brain images is very simple. The term 'abnormal' indicates the presence of tumour. The tumour may be benign or malignant and it needs medical support for further classification.**

Keywords - Brain MR Images, Image Enhancement, Image Segmentation, PCNN and BPN.

I. INTRODUCTION

A tumour is formed by an abnormal growth of cells which looks like a swelling. For over a decade, Pulse Coupled Neural Network (PCNN) based algorithms have been used successfully in image interpretation applications including image segmentation [6]. The Pulse coupled neuron (PCN) model used in PCNN is a modification of Eckhorn's cortical neuron model. Pulse coupled neural networks are capable of image smoothing, image segmentation and feature extraction.

Current technology involves in the detection, diagnosis and evaluation of many common and not so common ailments through non-invasive imaging. One of these imaging techniques is magnetic resonance imaging (MRI). Through this procedure, physicians obtain images, or 'slices', of various parts of the human body. They then analyse these slices to gather information to perform a variety of tasks especially brain extraction [2]. One anatomical region of particular interest is the human brain. MRI permits researchers and physicians to study the delicate brain's functional and physical characteristics with less risk to the patient.

MR image segmentation is an important step for a number of applications that include the identification of anatomical ROIs for diagnosis, treatment and tumour volume measurement. A new neuronal model was developed based on the primate visual system for the detection and diagnosis of tumor and the network found on this model is the pulse coupled neural network.

This model is promising because it may model the neuron's behaviour more closely than other popular neural networks. Many researchers are working on image segmentation techniques using pulse coupled neural networks since the network (PCNN) is suitable for image pre-processing [3]. Image Segmentation finds its best usage in medical applications. The segmentation results play a major role in detecting diseases or deficiencies. Brain MR Images and ultrasound images are mostly supportive in diagnostics. Mankind would be benefited with this type of trained networks (PCNN) which help in segmenting images.

II. METHODOLOGY

Implement and test pulse coupled neural network (PCNN) and back propagation network (BPN) model for enhancing and segmenting the two-dimensional MR brain images:

The medical data used is magnetic resonance head data. The data is obtained from a lab and consists of normal and abnormal MR images of human volunteers. The scope of this work is to investigate the application of a pulse coupled neural network (PCNN) and back propagation network (BPN) model for the enhancement and segmentation of MR brain images. This section presents pre-processing and segmentation methods that have been applied to MR brain images. Fig.1 illustrates the basic components of a generic image processing system. Image segmentation is usually preceded by image pre-processing and feature extraction and can be followed by a classification step which assigns labels to the segmented regions.

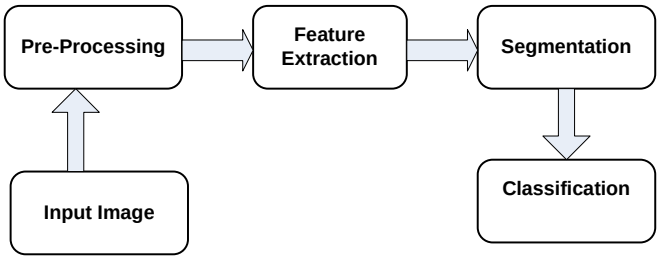

Fig.1. Components of an Image Analysis System

A. Image Pre-Processing

Image pre-processing can be the first step in image understanding. Generally pre-processing techniques try to reduce the artifacts introduced by the imaging modality. Two pre-processing techniques applicable to image segmentation in general are noise removal and contrast enhancement. In this work, the converted gray scale MR images are median filtered to reduce noise and artifacts. The image obtained is enhanced using pulse coupled neural network (PCNN).

B. Feature Extraction

MR Image segmentation is based on a set of measurable features which are extracted or computed from the images. Features themselves can be classified as pixel intensity-based features, calculated pixel intensity-based features and edge and texture-based features. Intensity values can be from a single image, a volume data set, a multispectral data set, or a multimodal image set. In this process of tumor detection, pixel intensity-based features are extracted.

C. Segmentation

Image segmentation groups pixels into regions, and hence defines object regions. Segmentation uses the features extracted from the image(s); therefore, good feature selection greatly influences segmentation results. MRI segmentation methods use either a single 2D or 3D image or a series of multispectral or multimodal images. Common segmentation approaches to MR images are thresholding [4], edge detecting, clustering, genetic algorithms, neural networks, and probabilistic techniques.

In this work, thresholding and neural networks have been used for segmentation. The Complete process of the tumour detection is given as a flow chart in Fig.2

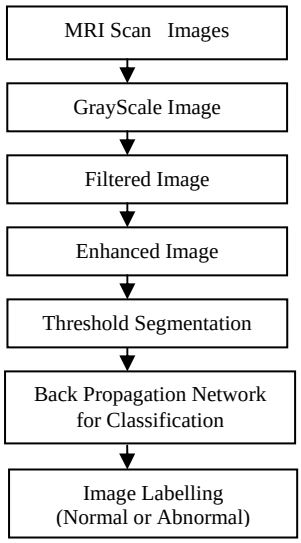

Fig.2. The Complete process of Brain Tumour detection

D. Classification

Classification is the last step in the process of Figure 1. During segmentation, a pixel, based on features, is assigned to a particular class. However, some methods make no connection between the segmentation classes and the tissue classes. They simply group like pixels or regions together. Strictly speaking, this is truly segmentation.

III. IMPLEMENTATION

The model is developed and implemented using pulse coupled neural network and back propagation network. The theoretical concepts supporting the networks are discussed below in sub section A and B

A. Pulse coupled Neural Network (PCNN)

A PCNN neuron contains two main compartments: the Feeding and Linking compartments which are shown in Figure 3: Schematic Representation of a PCNN Processing Element. References [1], [5] give a detailed structure and functioning of the PCNN model. Each of these communicates with neighbouring neurons through the synaptic weights M and W respectively. Each retains its previous state but with a decay factor. Only the Feeding compartment receives the input stimulus, S. The values of these two compartments are determined by,

$$F_{ij}[n] = e^{\alpha_F \delta_n} F_{ij}[n-1] + S_{ij} + V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1] \quad (1)$$

$$L_{ij}[n] = e^{\alpha_L \delta_n} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1] \quad (2)$$

Where F_{ij} is the Feeding compartment of the (*i*, *j*) neuron embedded in a 2D array of neurons, and L_{ij} is the

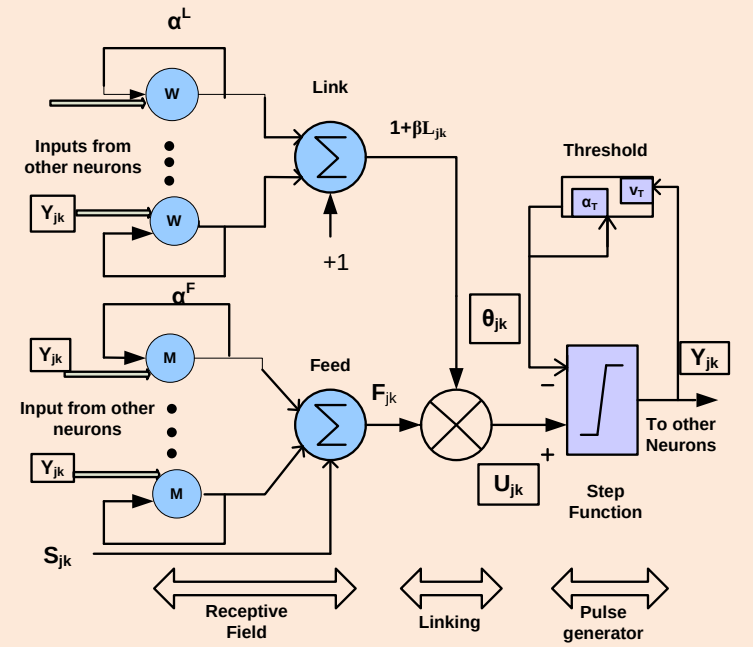

Fig.3. Schematic Representation of a PCNN Processing Element

corresponding Linking compartment. Y_{kl} 's the outputs of neurons from a previous iteration [$n-1$]. Both compartments have a memory of the previous state, which decays in time by the exponent term. V_F and V_L are normalising constants. If the receptive fields of *M* and *W* change then these constants are used to scale the resultant correlation to prevent saturation.

The states of these two compartments are combined in a second order fashion to create the internal state of the neuron, *U*. The combination is controlled by the linking strength, *β*. The internal activity is calculated by,

$$U_{ij}[n] = F_{ij}[n]\left[1 + \beta L_{ij}[n]\right] \quad (3)$$

The internal state of the neuron is compared to a dynamic threshold, θ , to produce the output, Y, by,

$$Y = \begin{cases} 1, & if\ U_{ij}[n] > \theta_{ij}[n] \\ 0, & otherwise \end{cases} \quad (4)$$

The threshold is dynamic in that when the neuron fires (Y > θ) the threshold then significantly increases its value. This value then decays until the neuron fire again. The process is described by,

$$\theta_{ij}[n] = e^{\alpha_\theta \delta_n} \theta_{ij}[n-1] + V_\theta Y_{ij}[n] \quad (5)$$

Where V_θ is a large constant that is generally more than an order of magnitude greater than the average value of U. The pulse coupled neural network is a feedback or recurrent network which includes feedback loops and the networks are powerful in medical image analysis [9]. Based on the scholarly work, PCNN is suggested for contrast improvement and image enhancement in automatic medical image segmentation [7] , [8] and [10].

The MATLAB code for the PCNN algorithm is as follows :

```
for n=1:np
    K=conv2(Y,W,'same');
    L=exp(-alpha_L)*L+vL*K;
    Theta=exp(-alpha_Theta)*Theta+vTheta*Y;
    U=F.*(1+beta*L);
    Y=im2double(U>Theta);
    Y0=Y0+Y;
```

B. Back Propagation Network

Back propagation is a common method of training artificial neural networks so as to minimize the objective function. It is a multi-stage dynamic system optimization method. It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks.

IV. Experimental Results

A set of MRI images both normal and tumorous are acquired for the project. Each original image contained a header with information regarding the patient, scanning facility and scanning parameters. This header is removed prior to filtering and segmenting. Only pixel information is given to the neural networks for processing.

A. Image Resizing

The images acquired after removing the header are of various sizes. In order to be able to perform matrix arithmetics on the images it is necessary for the images to be square matrix. Therefore all the images procured after removing the header are resized to a standard dimension of 512x512 pixels. The resizing of the images is done in MATLAB. Fig.4 represents the normal MR image , Fig. 4(a) and Fig.4(b) are the original and resized images. Similarly Fig.5 represents tumerous MR image .The original and resized image are shown in Fig.5(a) and 5(b). The images are resized using inbuilt MATLAB function ‘imresize’. The is read using ‘imread’ and then converted to datatype double. Then the image is resized from its original size to 512x512.

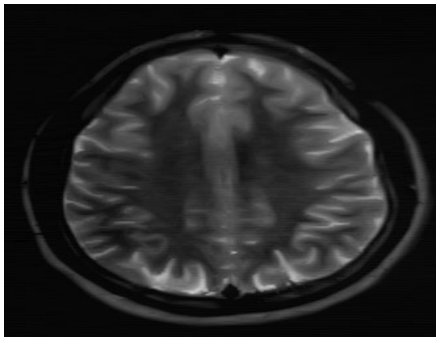

Fig. 4(a). Original Image

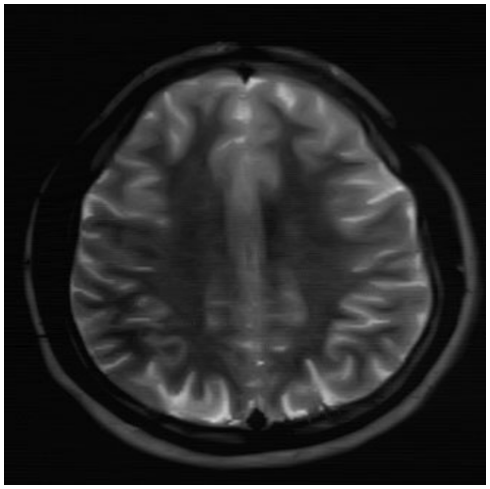

Fig. 4(b). Resized Image
Fig .4. Normal MR Image

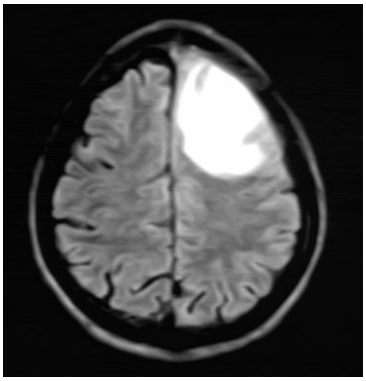

Fig. 5(a). Original Image

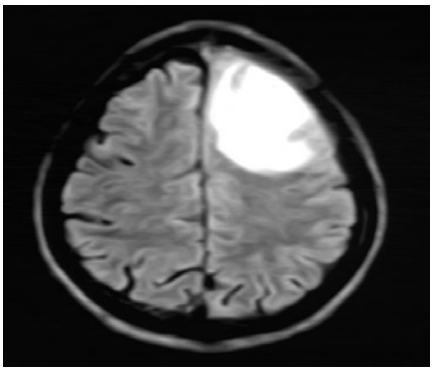

Fig. 5(b) Resized Image
Fig.5. MR Image with Tumour

The resized images are then input to a pulse coupled neural network. This stage therefore performs steps to enable the image to be PCNN compatible.

B. Image Enhancement Using PCNN

The images produced from the resizing stage are then input one by one to a PCNN algorithm. Fig. 6(a) is the resized normal input image and Fig. 6(b) is the output image after enhancement.

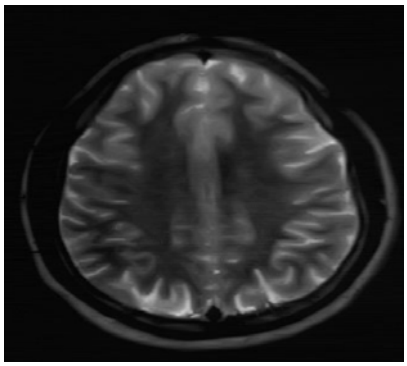

Fig.6(a). Resized Input Image

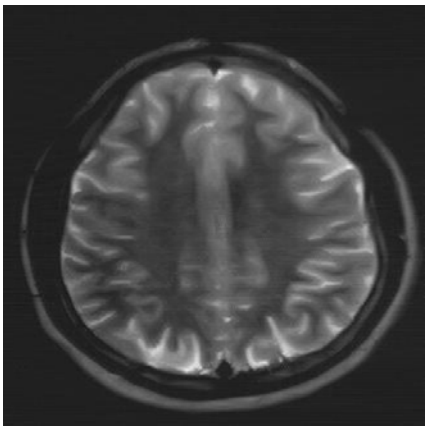

Fig.6(b). Enhanced Image
Fig.6. Image Enhancement of Normal MR Image Using PCNN

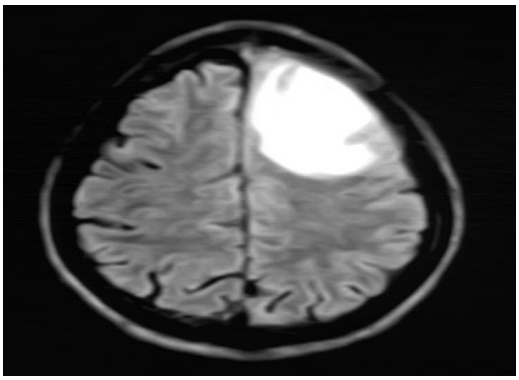

Fig.7.(a). Resized Input Image

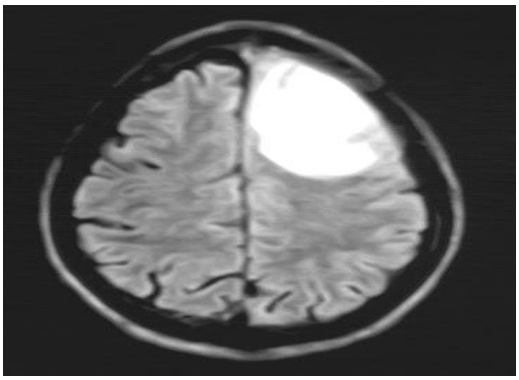

Fig.7(b). Enhanced Image
Fig. 7. Image Enhancement Of MR Image With Tumor Using PCNN

Fig. 7(a) and 7(b) are tumerous input image and tumerous output image from the pulse coupled neural network. The network reads the images in the form of a matrix. The matrix elements are between 0 and 1 since the image is in grayscale. The constants α_L ,α_F ,α_θ ,β ,V_F , V_L and V_θ are initialized to appropriate values. The proper values of these constants are found by running the program and changing the values manually to produce better results. The matrix of the parameters F, L, Theta, Y and U are all initialized to zero as per the PCNN algorithm.

In Fig. 7(b), it can be seen that the tumour part of the MR image in Fig. 7(a) has been substantially increased in brightness. Thus the tumour in the MR image is easier to recognize which makes the segmentation process smoother.

C. Feature Extraction

Various texture and shape based parameters of these MR images are extracted [11], [12] and used for further analysis. These extracted parameters are used as an input for the training of the BPN. The parameters are calculated for the images which are enhanced MR images with tumour and without tumour using inbuilt MATLAB functions. The parameters used for this purpose and their importance are as follows,

(1) Area (A): Calculating the area of a black and white image gives the number of on pixels in the image. An on pixel means a bright pixel which corresponds to a value of 1 in the image. If a MR image shows the presence of a tumour it shows it as a white mass.

(2) Mean (M): The mean of a region gives the average intensity of the pixels in that region. A higher mean can indicate the possibility of small regions with concentrated bright pixels.

(3) Third Moment (μ3): Skewness is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the perfectly symmetric or normal distribution is zero. Skewness is measured from the histogram plot of the image

(4) Entropy (e): Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Thus it helps to measure the degree of randomness of the image intensities [5].

(5) Standard Deviation (σ): It is a measure of average contrast of the image.

The MATLAB code followed for calculating the parameters is given below:

```
function [I1,I2,I3,I4,I5]= paras(f)

I1=mean2(f);
I2=std2(f);
g=im2bw(f,0.8);
I3=bwarea(g);
p=imhist(f);
I4=skewness(p);
I5=entropy(f);
```

The Parameters extracted from the normal MRI and MRI with tumour is tabulated in Table I. Comparison of Parameters. The results from the table give us the hope to identify the MR image with tumour. Each of the parameters is important in their own way. Since, each human has different characteristics; a standard cannot be maintained for the parameters.

TABLE I
Comparison of Parameters

Parameters	Normal MRI	MRI with Tumour
Area	261.75	17618.75
Mean	62.6022	88.8865
Third Moment	7.7750	9.7856
Entropy	6.0709	5.8393
Standard Deviation	34.9337	69.9474

Therefore a decision cannot be made based on any one of the parameters alone. The calculated values of all the parameters are processed together to decide whether a MRI is normal or tumour containing.

D. MRI Classification Using BPN

The MATLAB functions have been used to calculate the values of various parameters of the images. These values are to be used to differentiate whether a given MR image is normal or tumour containing. Sixteen different images are used as training and testing set. Eight of these images are normal MR images whereas the rest eight are images bearing tumours. The parameters of the sixteen images are arranged into a matrix form and fed to a back propagation network.

The first fourteen images are used for training the network. The parameters and the target output for each of the images are entered into the network. A target output of 0 means the MR image is normal whereas a target output of 1 indicates the presence of a tumour. The network is then run to train it. The weights are updated such that the error produced is minimized. The next two images are then used to test the network.

The output of the fifteenth and sixteenth images are checked. The fifteenth image has a tumour present and the sixteenth image is a normal one. A value very close to zero means that the image is normal. A value infinitesimally smaller to and approaching 1 indicates a tumour. This evaluation is done based on the threshold fixed for the presence of tumour and without tumour. The output is generally not exactly equal to either 0 or 1 because of a relatively small training set. With the increase in the size of the training set the error is vastly reduced and more accurate outputs are delivered.

E. BPN Outputs

Table II shows the output values of the training and testing set. The output is saved in a variable of 1x16 dimension matrix form. It can be seen that some of the values are not exactly 0 but can be approximated to 0. The fifteenth and sixteenth images are the test images. The results produced in the display shows a tumour detected in the fifteenth image (1.00) and also displays a normal MR image for the sixteenth (0.00) which is concurrent with the information in hand.

Table II
Actual BPN Outputs

Columns 1 through 9								
1.00	0.00	1.00	-0.00	1.00	0.00	1.00	0.00	1.00
Columns 10 through 16								
-0.00	1.00	0.00	1.00	0.00	1.00	0.00		

V. CONCLUSION AND FUTURE WORK

An enhancement and segmentation method based on a model of pulse coupled neural network and back propagation network has been implemented and tested on MR brain images. This new application of PCNN and BPN results in better segmentation of images. The segmentation helps in detection of tumour in brain MR images. This is primarily due to the additional spatial information that the PCNN is capable of incorporating.

A mapping of each segmented region's new pixel intensities to original image intensities demonstrates that the method developed by this research performs more than just simple thresholding. This research clearly demonstrates that PCNN and BPN can be used as an effective image analysis tool.

ACKNOWLEDGMENT

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