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Detection of Brain Tumors using Learning Machine Approach and Spatial Fuzzy Segmentation

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***Abstract*— Detection of tumors such as normal, benign and malignant stage tumors are detected. This method includes MRI brain image classification and segmentation approach. It is an learning machine approach where the network is trained with PNN-RBF and it is used to detect the tumor regions along with the spatial fuzzy clustering method. The classifier includes wavelet transform followed by feature extraction called GLCM and the training network called PNN-RBF. Finding benign stage tumors improves the chances saving the human life. The proposed segmentation process includes Spatial fuzzy clustering where the process is carried out by calculating centroid, distance and membership. The neural network is trained with images in each benign, malignant and normal stage. The system also uses to segment the tumor cells along with this morphological filtering which is used to remove background noises for smoothening up of region. The result includes segmented tumors with parameter evaluation. The segmentation prcess also results with the number of cells defected and the measurement of tumor area detected.**

***Index Terms*—DT-CWT, GLCM, PNN-RBF, Spatial fuzzy clustering.**

I. INTRODUCTION

Finding the tumors in benign stage increases the chances of saving the human lives. This paper not only finds the benign stage but also increases the percentage of accuracy. In order to reduce the false negative commands from human beings, computerized results are preferred and it is also proven. It is also preferred in terms of reduction of cost i.e., consulting too many doctors may include charges whereas once the report generated by the computer is done, no other work is needed. Since there are many patients to be taken care in the intensive care unit at the same time, the computerized automated diagnostic system is in relying.

In brain disease diagnosis system, texture discrimination and clustering inefficiency are some of the limitations in existence. In order to overcome this DT-CWT Multiscale decomposition is used for texture analysis and spatial clustering for classification and segmentation of an image. In this paper image acquisition and image enhancement are the two steps skipped as the images are collected from the available resources. These images are converted by using MATLAB i.e., from an image into a number of matrices. Dt-cwt is applied to the image which results both high frequency and low frequency images. The resulted high frequency images are given as input to the feature extraction called glcm. This results co-occurrence matrices for each pixel. Depending on these matrix values the network is trained. With the help of different combinations involved the neural network is trained as benign, malignant and normal. The segmentation process is applied to the resulted benign and malignant images.

In this paper, the image is taken as pixel and grouping is done in terms of matrices. The classifier used here is the radial bias in neural network. It consumes time, human concentration and large amount of data to be referred by the doctors etc., for segmentation we use spatial fuzzy because it has the capability of finding the intermediate values.

IN [1], Clustered image is produced when the Fuzzy C-means (FCM) algorithm proposed has variation. This proposed algorithm would add in the local spatial information along with information that are in gray level in a frizzy or fluffy frayed texture. This algorithm could be abbreviated as FLICM i.e., Fuzzy Local Information C-Means. This FLICM helps to overcome two important factors . One is enhancement of images clustered and the known FCM's disadvantage. The vital role found in FLICM is usage of spatial and gray level measures that are similar that are aimed to produce noise free and detailed preservation of image.

Moreover, this proposed algorithm would be free from the analytically adjusted parameters that include complete FCM algorithms that are suggested in literature. FLICM algorithm is found to be potent and competent that is vigorous to noisy images when experiment is carried out on artificial images.

In [7], both the methods "powerful run length" and "concurrence texture features" are discovered for the tumor region approximately. The major disadvantage is found that, this method could be applied only to the image of brain computerized tomography.

In [8], hybrid segmentation method is suggested that the image information on both the region and edge would segment the tumor. They compare fuzzy classification method and symmetry analysis method to detect the tumors and it uses a model that is deformable in natures which are controlled by spatial arrangement of segmentation refinement. But this paper failed in detecting symmetrical tumor across the mid-sagittal plane.

In [9], they contributed to three technical concepts, A mathematical formulation used for bridging graph based affinities and generative model based techniques. They extend SWA algorithm to integrate model based terms into the affinities during the coarsening. The mathematical formulation for learning the parameters of the model specific affinity functions directly for the training data. But in this method the accuracy of segmentation was near 70%.

II. PROPOSED SYSTEM

A. Identification of tumor

1) Dual-Tree Complex Wavelet Transforms(DT-CWT)

Detection of tumor using Dual-tree complex wavelet transforms (DT-CWT) is nearly a shift invariant property and 2d DWT is an selective directionality and the multi-dimensional DT-CWT is inseparable. But this includes the computational effects based on the “separable filter bank (FB)”.

The complex wavelets in dual-tree transform works well with good properties in both signal and image processing. This is proved in theoretical part of DT-CWT.

2) The Wavelet Transformation

With huge success among the gamut of signal processing, the wavelet transform has been oppressed. The DWT replaces the oscillating sinusoidal general functions infinitely in a nutshell which are called wavelets. A very potent algorithm is existed to compute all the coefficients c(n) and d(j,n) based on octave bands, up and down sampling ,high pass filter h1(n) and low pass filter operation h0(n). These would facilitate parameterization of wavelets and other scaling functions.

Here by using the Dual Tree Complex Wavelet Transform multi scale decomposition, the image is divided into 16 sub bands which include 4 low frequency images and 12 high frequency images. The low frequency images are based on color, brightness and contrast whereas the high frequency images are based on features such as texture and edges.

This process includes two filters namely farras filters and dual filters. Here the vertical decomposition is done first which followed by the horizontal decomposition.

In complex wavelets, the magnitude of the Fourier transform will not deal with the oscillation of positive and negatives but rather they provide a positive envelope with smoothening effect in the Fourier domain. Also, the magnitude of the Fourier transform has a perfect shifting invariant property which deals with a linear phase offset which encodes the shift.

For the signal to be reconstructed, the Fourier coefficients will not either aliase or they do not rely on a complicated aliasing cancellation property.

The sinusoids of the M-D Fourier basis are highly directional plane waves. The DWT, which is based on real-valued oscillating wavelets, the Fourier transform is based on complex-valued oscillating sinusoids

$$e^{j\Omega t}=\cos(\Omega t)+\mathrm{j}\sin(\Omega t) \qquad (1)$$

3) Feature Extraction-glcm

The texture could be described by three principle approaches which are as follows, Statistical Approach, spectral Approach and structural Approach

For optimal classification, we use the popular statistical representation of texture called Co-occurrence Matrix.

Here for texture analysis we use the gray level co-occurrence matrix as the tool for feature extraction

B. Network with rbf as classifier

The Neural network using MAT Lab which has about 2000 inputs where 11 nodes and T ANSING transfer function are hidden in first layer where as in second hidden layer there are 7 nodes and T ANSING transfer function .

One among the two outputs was used for the detection of tumor and the other is for localization.

To limit the signal between -1 and 1, TANSING function was selected. PURELIN transfer function was chosen for output layer, which would help in bringing out complete probable cases for the position of tumor. The figure that follows is the suggested network used in our project.

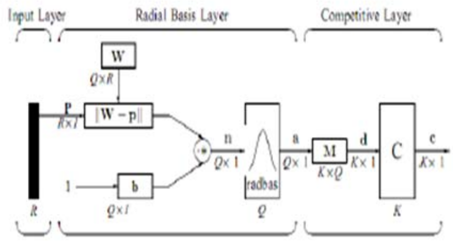

Fig. 1. Proposed Network

1) Input Layer

The input vector is represented by the symbol **p.** The black vertical bar is the input vector whose dimension is *R × 1 where* R *= 3 in this paper*.

2) Radial Basis Layer

In this Layer, the vector distances for each row of weighted matrix W are calculated between input vector p and the weight vector. The dimension of **W** is denoted as Q×*R*. The dot product between **p** and the *i*-th row of **W** produces the *i*-th element of the distance vector i.e., ||**W-p**||, whose dimension is *Q×1*. Here minus, “-”, indicates the distance between vectors. Then, an element-by-element multiplication takes place between the bias vector **b and** ||**W- p**|| .The result is stored in n **i.e., n**= ||**W- p**||.**p**. The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, the transfer function in PNN is defined as radbas *(n)* = 2ne. For each substitution of **n** it produces its corresponding element **a**, called the output vector of Radial Basis Layer. If ai is the *i*-th element of **a** then ai can be represented as radbas of the products bi and (Wi-p).

3) Competitive Layer

In Competitive Layer, there is no bias in it. In this Layer, vector **a** is multiplied with a layer weight matrix **M**, which yields an output vector **d**. For a competitive function, the output vector is denoted as **C**, which produces 1 if the value d is higher and 0’s elsewhere. The value 1 in **c** represents the presence of tumor. The output vector has 5 as its dimension.

The important disadvantage of PNN model when compared to the multilayer perceptron networks model is large and this is due to the presence of one neuron in every training row. This would cause the model to run slower than the multilayer. Two layer networks are created by NEWPINN. First layer would hold to RADBAS neurons, which would help in calculating the weighed inputs along with its DIST, and net input with NETPROD. Second layer holds COMPET neurons and it calculates its weighed input along with DOTPROD and its net inputs along with NETSUM.

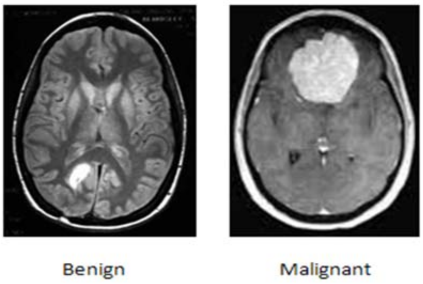

Fig. 2. Benign and malignant stage tumor.

C. Local Fuzzy clustering

Based on the distance criteria, fuzzy clustering methods are suggested. FCM is the widely used algorithm which uses reciprocal distance to figure out fuzzy weights. FCFM algorithm is the most potent one that computes the cluster center with Gaussian Weights.

FLICM can easily overcome the disadvantages of the well-known fuzzy c-means algorithms and at the same time it also enhances the clustering performance. Fuzzy local includes both spatial and gray level. It also has the characteristics such as analogy measures, designed for the assurance of noise ferocity.

The Experiments performed on synthetic and real-world images show that FLICM algorithm is effective and efficient, providing robustness to noisy images.

1) Initialize the Fuzzy Weights

In comparison between FCM and FCFM, the selection of weights can be done in either by using feature vector or can be made as random, this is left to the user's choice. For the initialization of weights through feature vector it first assigns K_{init} (user-given) feature vectors to the prototypes then it continues with the take account of weights.

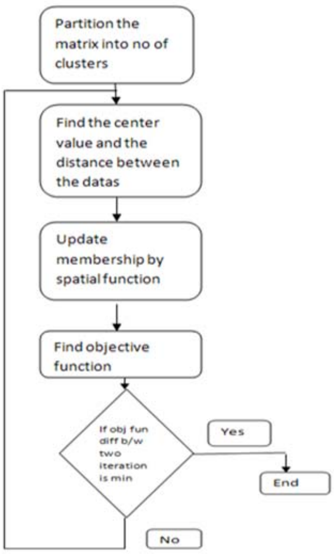

Fig. 3. Algorithm Flow

2) Standardize the Weights over Q

During the iteration of FCM, the clusters of centers get closer. In order to avoid the convergence, we use

$$w[q,k] = (w[q,k] - w_{min})/(w_{max} - w_{min}) \qquad (2)$$

Where w_{max} is the maximum weight, w_{min} are the minimum weights in common class prototype for all feature vectors.

3) Eliminating Empty Clusters

When the fuzzy clustering loop gets terminate it eliminates the clusters that are empty. If this is skipped then the minimum distance is also assumed to be empty clusters. In order to avoid this method is called by passing 0 as the parameter to the process. Following is the Modified Xie-Beni validity κ

$$\kappa = D_{min}^2 / \{\sum_{(k=1,K)} \sigma_k^2\} \qquad (3)$$

The variance of cluster is calculated by adding all the nodes of each cluster, which contrasts with the original Xie-Beni validity measure as

$$\sigma_k^2 = \sum_{\{q:\, q \text{ is in cluster } k\}} w_{qk} \, \| \mathbf{x}^{(q)} - \mathbf{c}^{(k)} \|^2 \qquad (4)$$

D. Morphological Process

Morphological process is a group of operations that are nonlinear and is related to morphological features of an image. These operations rely on relative pixel values and not on numerical values and hence these are preferred for processing binary images. Hence morphological techniques review an image along with template called "structuring element". This structuring element is placed at all possible locations of the image. In some test the element "fits" and in some tests it "hits" the neighbourhood.

1) Erosion and dilation

The erosion is denoted as f in binary image and structuring element is denoted as s. Both one by one produces a new binary image $g = f \ominus s$. If s fits f then it ensures the presence of ones in all locations of *x and y* . i.e., $g(x,y) = 1$ and 0 elsewhere. This process is repeated for all pixel coordinates (x,y).

If two structuring elements say s1 and s2 are identical but s2 may be twice as that of s1 in its pair, then

$$f \ominus s_2 \approx (f \ominus s_1) \ominus s_1 \qquad (5)$$

Erosion not only removes the conjecture content but it also reduces the size of the region. If we replace the original image with the eroded image, we can easily extract the boundary: $b = f - (f \ominus s)$ where f is the regional image, s is a structuring element with 3x3 as dimensions.

The **dilation** of element f by element s is denoted as $f \oplus s$ called new binary image g. If a structuring element s hits f, then $g(x,y) = 1$ and 0 elsewhere, this process is repeated for every pixel coordinates (x,y). Dilation and erosion are opposite to each other, it can be represented as follows

$$f \oplus s = f^c \ominus s_{\mathrm{rot}} \quad (6)$$

Where s_{rot} denotes the structuring element s pivoted by 180 degree. If both s and pivoted elements are same then s_{rot} and s are same. In binary images actual image is set to 1 and a background pixel is set to 0, then erosion is related to the fitting of actual element and dilation is related to fitting of an element s into the background. The simulated result for segmentation is as follows

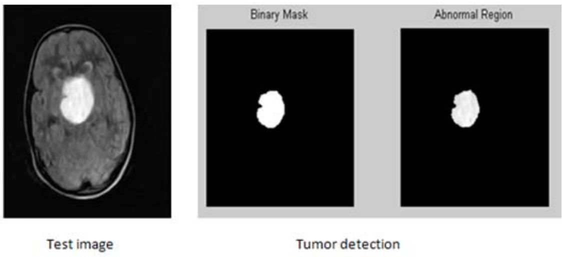

Fig. 4. Segmentation process for benign stage tumor.

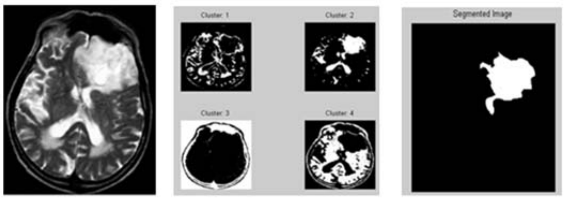

Fig. 5. Segmentation process for malignant stage tumor.

III. CONCLUSION

The implementation of proposed system gives effective results in finding benign stage tumor called initial stage of brain tumor. The classifiers performance can be evaluated by using number of training samples. In this paper, for each stage (i.e., normal, benign and malignant) five different corresponding samples are given as training input. This increases the identification of tumors in nature with better accuracy. For the removal of background noises and the smoothening up off the region we use morphological filtering. The segmented tissues the project results will be presented as segmented tissues with parameter evaluation to show algorithm efficiency. The performance analysis of test samples such as the percentage of sensitivity, specificity and accuracy are shown below.

TABLE I. performance analysis.

parameter	sensitivity	specificity	Accuracy
Test Samples	85.7143%	100%	90.9091%

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