Classification of Brain Tumor Using Artificial Neural Network

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Abstract— In our work we try to exploit the capability of Back propagation neural network (BPN) and Radial Basis Function Neural network (RBFN) to classify brain MRI images either cancerous or Non- cancerous tumour automatically. Classification is with respect to symmetry of brain images exhibited in the axial and coronal images. The initial objective of our work is to study which algorithm is superior in classification tasks, and to examine the advantages and downfalls of each algorithm under varying conditions. We use BPN and RBF classifiers to classify and segment the tumour portion in abnormal images using optimal texture feature extracted from normal and tumour region of MRI by using statistical features. Since testing and training phase gives the percentage of accuracy on each parameter in neural networks, which gives the idea to choose the best one to be used in further works. Later feasible modifications will be incorporated in the BPN and RBF classification to obtain the promising results.

Key words: brain tumor disease, image segmentation, image processing, BPN, RBFN

I. INTRODUCTION

Classification is one of the most frequently encountered decision making tasks of human activity. A classification problem occurs when an object needs to be assigned into a predefined group or class based on a number of observed attributes related to that object. The application of machine learning techniques to biomedical image analysis and pattern recognition problems has gained a widespread acceptance. Involving classification of tumors is that it could be the case the system does not correctly detect a tumor with a rare shape which is distinct from all members of the training set. On the other hand, a novelty detector would still potentially highlight the object as abnormal. Novelty detection has potential applications in many problem domains such as condition monitoring or medical diagnosis.

Among the techniques developed for classification, popular ones include Bayesian classification, Neural Networks, Generic Algorithms and Decision Trees. Many researchers have used different classification techniques for MRI data analysis, such as Bayes classifier , k-Nearest Neighbors classifier, Artificial Neural Networks , Back Propagation Network , Support Vector Machines and Expectation

Maximization as a statistical classification scheme. Inspired by biological neural networks, Artificial Neural Networks are developed to mimic the characteristics such as robustness and fault tolerance. To perform classification task of medical data, the neural network is trained. Neural networks have emerged as an important tool for classification. Neural networks receive extensive application in biomedical systems and have wide application in cardiology, gastroenterology, pulmonologist, oncology, neurology, brain function, ophthalmology and radiology.

The increased importance of automated computer diagnosis for anatomical brain mapping from MR images and quantitative brain image analysis methods leads to an increased need for validation and evaluation of the effect of image. The categorization of brain tumor process had led the radiologists to seek better accuracy from soft tissue delineation of MRI findings. Diagnostic imaging with suspected intracranial neoplasia is fourfold: lesion detection, localization, characterization, and determination of tumor extension. In contrast to CT, MR imaging allows more precise determination of lesion location and demonstrates better subtle mass effects, particularly along the cerebral convexities. MR imaging is superior to CT for differentiating between tumor and perifocal edema, for defining extent of tumor, and also does not cause harmful ionizing radiation, though it does not provide a precise histologic diagnosis.

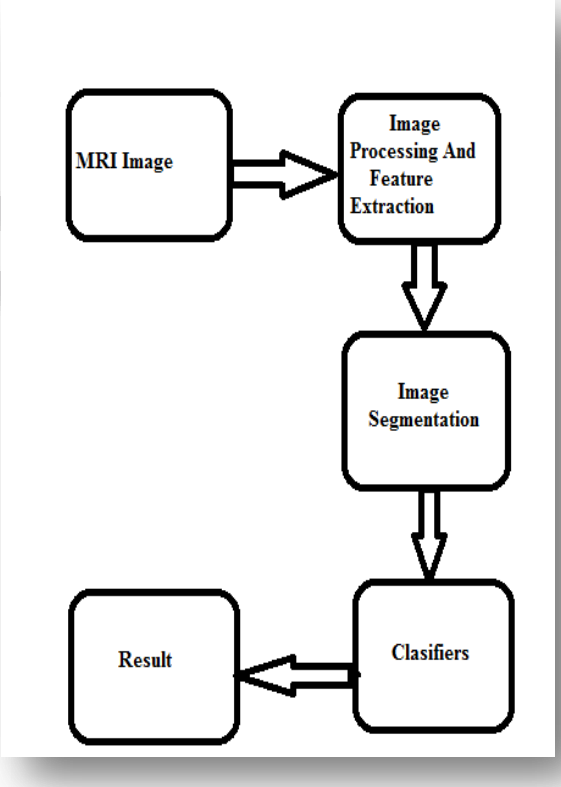

Fig. 1: Block Diagram of step wise procedure used in our work

The step by step procedure adopted in our work as fallow:

- Pre-processing The Image
- Using GLCM matrix we are calculating the features of image
- Segmentation Of Image Using FCM Clustering

- Extract the images
- Extracted images feature are given to neural network for classification
- Classifier Classifies the image condition

The simulations are carried out in MATLAB software using brain MR Images and the better results are obtained in detection and classification of normal or abnormal of brain.

II. DETAILS OF THE PROPOSED WORK

A. Input Image:

The first step in the proposed approach is to taking the sample from the scanned images and extract the features. The sample is taken from the scanned images and the features are then stored in the database.

B. Image Database:

The next point in the project is creation of the image database with all the images that would be used for training and testing. The construction of an image database is clearly dependent on the application. The image database in the proposed approach consists of 140 image samples. The image database itself is responsible for the better efficiency of the classifier as it is that which decides the robustness of the algorithm.

1) Pre-processing:

Feature selection reduces the dimensionality of feature space, removes redundant, irrelevant, or noisy data. The sequence of steps to image classification performed are histogram equalization, region isolation and feature extraction.

2) Segmentation:

Image segmentation is process i.e. used to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. As the premise of feature extraction and pattern recognition, image segmentation is one of the fundamental approaches of digital image processing. From the above steps, the infected portion of the leaf is extracted. The infected region is then segmented into a number of patches of equal size. The size of the patch is chosen in such a way that the significant information is not lost. In this approach patch size of 32x32 is taken. The next step is to extract the useful segments. Not all segments contain significant amount of information. So the patches which are having more than fifty percent of the information are taken into account for the further analysis.

3) Extraction of texture feature:

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Texture contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. The three fundamental pattern elements used in human interpretation of images are spectral, textural and contextual features. Spectral features describe the average tonal variations in various bands of the visible and/or infrared portion of an electromagnetic spectrum. Textural features contain information about the spatial distribution of tonal variations within a band. The fourteen textural features proposed by Haralick et all contain information about image texture characteristics such as homogeneity, gray-tone linear dependencies, contrast, number and nature of boundaries present and the complexity of the image. Contextual features contain information derived from blocks of pictorial data surrounding the area being analyzed.

GLCM has been used extensively in the field of image processing. It has been applied from a range of applications like texture analysis to synthesis including gray scale as well as color texture recognition. The use of co-occurrence probabilities using GLCM for extracting various texture features. GLCM is also called as Gray level Dependency Matrix. It is defined as "A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship."

Few of the common statistics applied to co-occurrence probabilities are discussed ahead.

a) Energy:

$$\text{Energy (ene)} = \sum_i \sum_j g_{ij}^{\,2}$$

This statistic is also called Uniformity or Angular second moment. It measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normalized range. The GLCM of less homogeneous image will have large number of small entries.

b) Entropy:

$$\text{Entropy (ent)} = -\sum_i \sum_j g_{ij} \log_2 g_{ij}$$

This statistic measures the disorder or complexity of an image. The entropy is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy.

c) Contrast:

$$\text{Contrast (con)} = \sum_i \sum_j (i-j)^2 g_{ij}$$

This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

d) Correlation:

The correlation feature is a measure of gray tone

$$\text{Correlation (cor)} = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$$

linear dependencies in the image

e) Variance:

$$\text{Variance (var)} = \sum_i \sum_j (i-\mu)^2 g_{ij}$$

where μ is the mean of g_{ij}

This statistic is a measure of heterogeneity and is strongly correlated to first order statistical variable such as standard deviation. Variance increases when the gray level values differ from their mean.

This statistic is also called as Inverse Difference Moment. It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant.

III. NEURAL NETWORKS FOR BRAIN TUMOR CLASSIFATION

A. BPN

BP neural network is a multi-level error feedback network proposed by Rumelhart and Mc Clelladn in 1985. BP neural network architecture with one hidden layer operating on log sigmoid transfer function has been employed for the classification of normal and abnormal tumour. There is a full connectivity between the upper and lower layers and no connections between neurons in each layer.The weights on these connections encode the knowledge of a network. The data enters at the input and passes through the network, layer by layer, until it arrives at the output . The parameters of a network were adjusted by training the network on a set of reference data, called training set. The training of the network was performed under back propagation of the error. The trained networks were then be used to predict labels of the new data.

Algorithm stages for BPN

(1) Initialization of weights
(2) Feed forward
(3) Back propagation of Error
(4) Updation of weights and biases

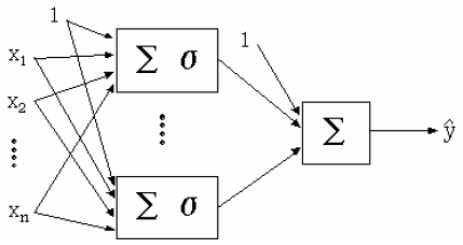

Fig. 2: Neural network Feed forward architecture

During the first stage' which is the initialization of weights, some small random values are assigned. During feed forward stage each output unit (Xi) receives an input signal and transmits this signal to each of the hidden units z1, z2.....zp. Each hidden unit then calculates the activation function and sends its signal to each output unit. The output unit calculates the activation function to form the response of the net for the given input pattern. During back propagation of errors, each output unit compares its activation yk with its target value tk to determine the associated error for that pattern with that unit. Based on the error, factor _k (k=1, ...m) is computed and is used to distribute the error at output unit back to all units in the previous layer. Similarly _j (j=1, ...p) is computed for each hidden unit zj. During final stage, the weights and biases are updated using the _ factor and he activation.

B. RBFN

Radial basis function (RBF) neural network are also based on supervised learning. RBF networks are good at modelling nonlinear transformation with no adjustable parameters in the hidden layer neurons. The architecture of the entire RBF network consists of two stage layers as modelled in figure 1. The first layer is a hidden layer of radial basis neurons and the second layer is a linear layer- the output which implements a weighted sum of hidden units. When this network is presented with the *X* vector of input values derived from the input layer, a hidden neuron computes the Euclidean distance from the test case to the central point of the neurons and then applies the RBF kernel function to this distance, using the spread. The resultant value is transferred to the output layer. The activation function of hidden units is symmetric in the input space, and the output of each hidden unit depends only on the radial distance between the input vector X and the centre for the hidden unit.

vector and is the spread (width)of the Gaussian function and ‖ *X* −μj‖^ 2 is the squared Euclidean distance between the input vector and the prototype vector. The center and width are associated with each hidden unit in the network. The weights connecting the hidden and output units are estimated using least mean square method. Finally, the response of each hidden unit is scaled by its connecting weights to the output units and then summed to produce the overall network output.

The Training of Radial Basis Function Networks which involves the estimation of the parameters is often

Separated into two stages:

(1) Determine the centers μj and the relative spreadsj
(2) Estimate the output weights based on the previously determined centers and spreads.

IV. GRAPHICAL USER INTERFACE

A graphical user interface (GUI) is a graphical display in one or more windows containing controls, called components that enable a user to perform interactive tasks. The user of the GUI does not have to create a script or type commands at the command line to accomplish the tasks. Unlike coding programs to accomplish tasks, the user of a GUI need not understand the details of how the tasks are performed. GUI components can include menus, toolbars, push buttons, radio buttons, list boxes, and sliders—just to name a few. GUIs created using MATLAB® tools can also perform any type of computation, read and write data files, communicate with other GUIs, and display data as tables or as plots.

GUIDE automatically generates a program file containing MATLAB functions that controls how the GUI operates. This code file provides code to initialize the GUI and contains a framework for the GUI callbacks—the routines that execute when a user interacts with a GUI component.

Use the MATLAB Editor to add code to the callbacks to perform the actions you want the GUI to perform.

V. RESULTS & OBSERVATIONS

The results of the neural algorithms presented here, compared to the most popular and fast algebraic one, arevery encouraging. It is found that RBFN performs better with high convergence when the data is preprocessed and given as input. The previous BPN method inevitably involves more classifiers, greater system complexities and computational burden, and a longer training time.

The brain images are divided into training and testing set, where 5% of the brain images from each group are used to train the system and the remaining images serves as the testing set. The number of images used for training, testing and classification gain for brain image. the detected brain diseases are then classified into various categories. Training and the testing sets for each type of brain disease along with their detection accuracy is shown in Tables

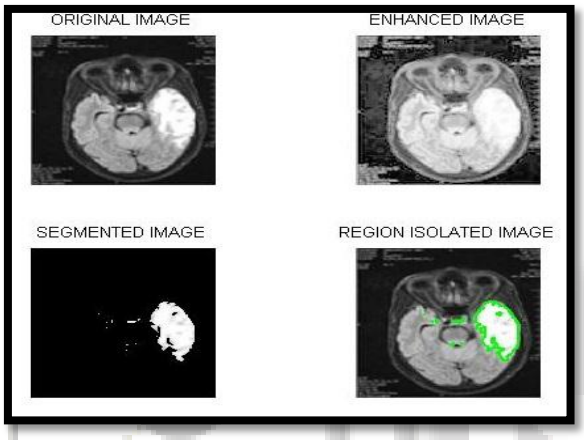

Fig. 3: Detected diseased region of brain

BPN	Actual Value		
	Normal	Abnormal	Total
Prediction	TP =14	FP =7	21
False Negative	FN=3	TN=18	21
Total	17	27	42

Table 1: Performance of BPN

RBFN	Actual Value		
	Normal	Abnormal	Total
Prediction	TP =15	FP =4	19
False Negative	FN=2	TN=21	23
Total	17	25	42

Table 2: Performance of RBFN

Indices	BPN	RBFN
Accuracy	76.19 %	85.71%
Sensitivity	82.3%	72%
Specificity	88.23%	84%

Table 3: Comparison of BPN and RBFN

Graphical User Interface:

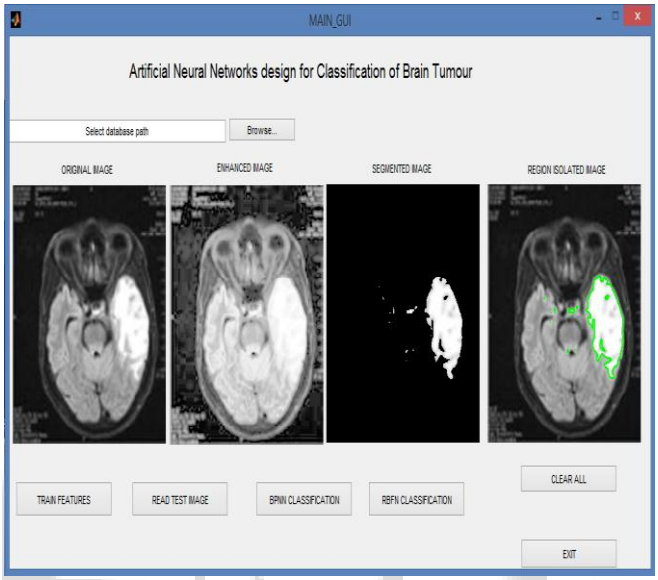

Fig 4.: Detected diseased region of brain with GUI component

VI. CONCLUSION:

Applied to the task of solving classification problem of brain tumor, the features extracted based on statistical properties, the accuracy is in higher end for RBFN. Further geometrical properties like moments, can be implemented to further classify the grades of tumor along with cystic component and solid component with white matter and grey matter.

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