

Back Propagation Neural Network Based Detection and Classification of Brain Tumors Using Matlab

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Abstract— The conventional method for medical resonance brain image classification and tumor detection is by the inspection of an expert. Operator-assisted classification methods are impractical for large amounts of data and are also non-reproducible as well as time consuming. Here introducing Neural Network techniques for the classification of human brain MRIs. The efficacy of the model is demonstrated in patient-independent brain tumor texture feature extraction and tumor segmentation in MRIs. Varying intensity of tumors in MR images make the automatic segmentation of such tumors extremely challenging. The proposed Neural Network technique consists of the following stages namely, feature extraction, dimensionality reduction, and classification. The features extracted from the magnetic resonance images (MRI) have been reduced using principal component analysis (PCA) to the more essential features such as mean, median, variance and correlation, values of maximum and minimum intensity. In the classification stage, classifier based on Back-Propagation Neural Network has been developed. This classifier has been used to classify subjects as normal, benign and malignant brain tumor images. The results show that BPN classifier gives fast and accurate classification than the other neural networks and can be effectively used for classifying brain tumor with high level of accuracy. It is workable with an accuracy ranged from 70% to 98%. The accuracy depends on the number of training images. If more number of training images is used, better will be the accuracy.

Index Terms—Back propagation neural network, PCA, magnetic resonance image (MRI)

I. INTRODUCTION

In clinical practice, the early detection of brain tumors and its classification is very important for effective treatment. A number of techniques were proposed for the automatic classification of brain tumors. In this paper we propose a technique for brain tumor classification of the Magnetic Resonance Images (MRI) collected with normal brain, benign and malignant tumors. Our goal is to achieve a classifying system to discriminate the three types of brain MRIs, namely normal, benign and malignant with high accuracy. It can be possible through the combination of several processing steps such as image pre-processing, feature extraction and classification. The proposed technique has the potential to support clinical diagnosis without the aid of an expert medical practitioner.

In Biomedical engineering, image processing techniques have an important role in analyzing anatomical structures of human body. In-order to capture digital images of human body, image acquisition techniques like Magnetic Resonance Imaging (MRI), X-Ray, ultrasound, CT- scan, mammography, etc. are widely used. As soon as generating digital images, image processing techniques can be further applied for analyzing region of interest (ROI).

A tumor is a mass of unwanted tissues that is absolutely useless and often exists at the expense of normal tissues. Brain tumors can be broadly classified into two categories, namely malignant and benign. Malignant brain tumors lack clear and distinct borders. They are growing rapidly and tend to increase the pressure within the brain. It can spread in the brain or spinal cord beyond their point of origin. They grow faster than benign tumors and are more likely to cause health problems or sometimes it may create lethal effects. Most of the brain MRIs of malignant tumors shows a finger like projection which indicates its spreading nature of the tumor [1].

Benign brain tumors are composed of harmless cells and have well defined borders. Usually they are completely removable and are unlikely to recur. A benign tumor doesn't spread to other parts of the body and it tends to grow more slowly than malignant tumors. They are less likely to cause health problems and lethal effects. In brain MRIs, classification into normal, malignant and benign is a difficult task due to complexity and variations in tumor tissue characteristics like its shape, size, gray level intensities and location.

Feature extraction is an important issue for any pattern recognition application. This paper presents a hybrid approach to classify malignant and benign tumors using some prior knowledge like pixel intensity and some anatomical features are proposed. MATLAB® 2012, its image processing toolbox is used for feature extraction and ANN toolbox has been used for classification. The overall organization of the paper is as described below. The steps used for feature extraction and dimensionality reduction into principal features using Principal component analysis are explained in Section II. Section III describes the proposed methodology that is used here and in each subsection it has been explained in details. Section IV demonstrates some simulation results and their performance evaluation. Some other future scopes and modification in this field has been proposed in section V. Finally conclusions are presented in section VI which also narrates the advantages of this classification technique.

II. FEATURE EXTRACTION AND DIMENSIONALITY REDUCTION USING PCA

A. Feature Extraction

Feature extraction is the process of extracting useful information for solving application based problems. It is possible to extract a number of features such as mean, median, variance, correlation, values of minimum and maximum intensity, Eigen values, etc. The features that are going to be extracted are application dependent. In this paper features like mean, variance and Eigen values are extracted from the given set of MR images. But it is necessary to create separate binary image for each MRI before proceeding to feature extraction. The binary image of dimension $N \times M$ will produce $N \times M$ Eigen values and Eigen vectors. In order to reduce this huge dimensionality by ignoring components of lesser significance, principal component analysis (PCA) is used as a feature extraction algorithm[2].

B. Principal Component Analysis (PCA)

Principal component analysis is one of the most successful and widely used techniques that have been used in image recognition and compression. The purpose of using PCA is to reduce the large dimensionality of the extracted features. Instead of incorporating all of the features, a feature selection is performed using PCA as a preprocessing step to ignore the redundant features. The feature selection is based on the statistical information, hence only the most informative features extracted from the MR images are utilized in this process. These selected features are called principal components (PC). PC retains the greatest amount of variation in the samples. The variance of reconstructed data is preserved. This principal components lead to efficient classification algorithm utilizing supervisory learning.

The steps followed to obtain the principal components using PCA are as described below

1. Convert the 2D images into one dimensional image into one dimensional image using reshape function for both training images and test images.
2. For each one dimensional image find the mean value using Matlab function.
3. Find the difference matrix for each image by $[MRI] = (\text{original pixel intensity of 1D image}) - (\text{mean value})$
4. Find the covariance matrix by, Covariance of MRI = $(1/N-1) * MRI * MRI^T$.
5. Find the Eigen vector for 1D image by, $[V \ D] = \text{eig}(\text{covariance})$
6. Sort the Eigen vector in descending order and select the principal components. Finding the Eigen face of 1D image by, Eigen face = Eigen vector * MRI.

In dimensionality reduction using principal components analysis, for a given a set of data, PCA finds the linear lower-dimensional representation of the data in such a way that the variance of the reconstructed data is preserved. The PCA retains the greatest amount of variation in the sample. Using a system of feature reduction based on a principle component analysis on the feature leads to an efficient classification algorithm utilizing supervised learning approach. So, the main intention of using PCA in this approach is dimensionality reduction which leads to more efficient and accurate classifier. PCA can be defined as a mathematical procedure that uses an orthogonal transformation to

convert a set of values of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This orthogonal transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it be uncorrelated with (i.e., orthogonal to) the preceding components. The term variance means it accounts for as much of the variability in a given set of values as possible. Principal components are assured to be independent only if the given data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, the orthogonal transformation used here is also named as the discrete Karhunen-Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD). It is mostly used as a powerful tool in exploratory data analysis and for making predictive models[4].

The first principal component is the combination of variables that have the greatest amount of variation. The second principal component defines the next largest amount of variation and is independent to the first principal component. That is PCA chooses totally uncorrelated data values. There can be as many possible principal components as there are variables. It can be viewed as a rotation of the existing axes to new positions in them space defined by the original variables. In this new rotation, there will be no correlation between the new variables defined by the rotation. The first new variable contains the maximum amount of variation; the second new variable contains the maximum amount of variation unexplained by the first and orthogonal to the first, etc.

PCA can be performed by Eigen value decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data matrix for each image. The results of a PCA are usually discussed in terms of component scores, otherwise known as factor scores. Component score or factor score is the transformed variable values corresponding to a particular data point and loadings. Loading refers to the weight by which each standardized original variable should be multiplied to get the component score.

III. PROPOSED METHODOLOGY

There are four major steps in the proposed approach for brain tumor classification using back propagation neural network. They are (a) Database preparation: collecting MRIs from various sources and creating a database; (b) Feature vector calculation: getting meaningful features of the ROI identified by segmentation; (c) Classification: learning the back propagation neural network classifier using the extracted features; (d) Methodology: various steps and operations performed for implementing this technique.

A. Database preparation

The brain MRI images consisting of normal brain, malignant and benign tumors were collected from open sources like internet and some hospitals to create a database for further processes like training and testing of neural network. Some sample images from the database

are shown in Fig 1. A set of sample images are used for training and another set is used for validation and testing.

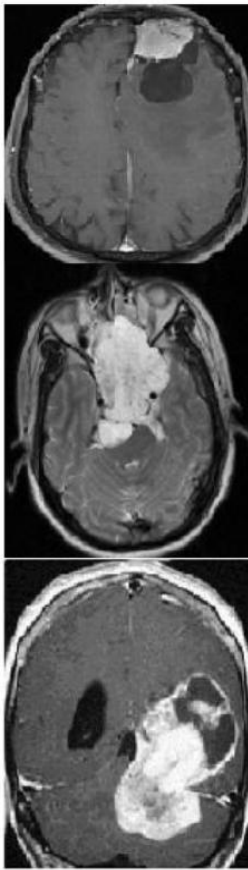


Fig. 1 Sample images from database

B. Feature vector Calculation

Feature extraction is the major aspect of any data classification system. Feature extraction is performed for each image in the database and its feature vector is calculated. These feature vectors for the database images are stored as .mat file. The main features extracted in this technique are mean, variance and Eigen vectors.

In the training phase of neural network, the feature vectors of each training set image are extracted. A preprocessing step which includes the processes like image resizing, RGB to grey conversion and normalization should be performed prior to feature extraction. Eigen value decomposition is performed in this paper. Let Ω_i be a training image which has a pixel resolution of $M \times N$, that is it contain M rows and N columns. But it must be ensure that all images used in this technique, including both training and testing image sets should have same dimensionality. In order to extract feature vectors of Ω_i , the image is first convert into a pixel vector Φ_i by concatenating each of the M rows into a single vector. The length (dimensionality) of the vector Φ_i will be $M*N$. It is not practical to use such a huge dimension vector. Due to this inconvenience a dimensionality reduction technique is performed. In this paper, the Principal Component Analysis (PCA) algorithm is used as a dimensionality reduction technique which transforms the vector Φ_i to a vector ω_i which has a reduced dimensionality d where $d \ll M * N$. For each

training image Ω_i , these feature vectors ω_i are calculated and stored. These selected feature vectors are known as Principal Components (PC).

In the testing phase, the feature vector ω_j of the test image Ω_j is computed and reduced using PCA. In order to identify the test image Ω_j , the similarities between ω_j and all of the feature vectors ω_i 's in the training set are computed. The similarity between feature vectors is computed using Euclidean distance. The identity of the most similar ω_i is the output of the image recognizer. If $i = j$, it means that the MR image j has correctly identified, otherwise, that is $i \neq j$, it means that the MR image j has misclassified[3]. Schematic diagram of the MR image recognition system is shown in Fig 2.

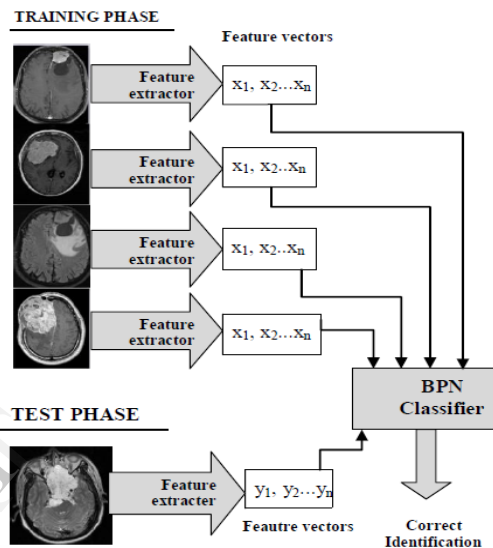


Fig.2 Schematic diagram of MRI recognizer

C. Classification

The back-propagation algorithm is finally used for classifying the MRI of normal, malignant and benign tumor. It is an adaptive network since it is able to change its weight. A neural network has 3 layers, namely input layers, hidden layers and output layer. Here a three layer feed forward back propagation neural network was created with 15 nodes in the input layer, 1 to 15 nodes in the hidden layer, and 1 node in the output layer. The number of nodes in the hidden layer in a simulation can be varied in order to determine the optimal number of hidden nodes. The back-propagation learning rule is used for adjusting the weights and biases of networks to minimize the mean square error of the network or called cost function. The activation function considered for each node in the network is the binary sigmoidal function or otherwise known as tan-sigmoid, defined (with $s = 1$) as $\text{output} = 1 / (1 + e^{-x})$, where x is the sum of the weighted inputs to that particular node. This is a common function used in many BPN. This function limits the output of all nodes in the network to be between 0 and 1. Neural networks are basically trained until the mean square error for each training iteration stops decreasing. A feature vector of each image in the database was generated and saved as in .mat file in MATLAB environment. 70% of the data has been used for training and from remaining 30%, 25% was used for validation and 5% for testing.

This ratio can adjusted according to our wish and it should be specified while creating the neural network.

D. Methodology

Back propagation neural network has been used for data classification problems. It performs supervisory learning. An important issue concerning supervisory learning is the problem of error convergence. That is minimization of error between desired and computed values. The aim is to determine a set of weights which minimizes the error. The BPN classifier presented good accuracy, very small training time and robustness to weight changes.

There are 6 stages involved in the proposed model which are starting from the data input to output. The first stage should be the image pre-processing system. Basically in image pre-processing system, image acquisition and image enhancement are the steps that have to be done. In this paper, these two steps are skipped and all the images are collected from available resources like internet, hospital records, etc. As an initial step the RGB MR image is converted into grey level image and normalizes it. Then the proposed model requires converting the image into a format capable of being manipulated by the computer. So the MR images are converted into matrices form by using MATLAB commands. But it must be ensure that the matrix elements should have values with double precision. These matrix forms of input MR images have undergone certain operations in-order to obtain the principal components. Then, the BPN is used to classify the MR images. Lastly, performance based on the result will be analyzed at the end of the development phase. It is known as acceptance ratio. It depends on the rate of training. If we are using more MRIs for training, then the acceptance ratio will be higher. The proposed brain MR image classification method is shown in Fig 3.

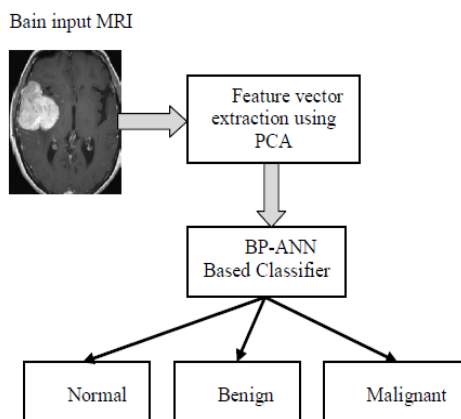


Fig. 3 Proposed Model

IV SIMULATION AND OUTPUT

Various experiments were performed on this technique. The MR image set in the database was grouped into two separate data sets – the training data set and the testing data set. The training data set was used to train the neural network, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained network for the classification of brain tumors. Based on the testing data set outcome the acceptance ratio is calculated and expressed in percentage form. If the acceptance ratio is higher, the system will be more

efficient. The proposed technique is implemented in the working platform MATLAB ® 2012 and it is evaluated using 15 medical brain MRI images as testing set, which are collected from open source resources and some hospitals. Among the 15 MRI images, 5 images are normal, 5 images contain benign tumor and the remaining 5 have malignant tumor. The Fig 1 shows some sample input MRI brain images in the database used for the MRI image classification process. A back propagation neural network was used to classify the input brain MRI images. Input values used for training the neural network are features extracted using principal component analysis such as mean, median, variance, correlation, Eigen values and Eigen vectors, etc. These networks are trained using back propagation algorithm, which is an efficient tool for data classification applications. A set of database images are used for training purpose. The output of neural network training is shown in Fig 4. The result of BPN network is evaluated by giving unknown testing images. The classification accuracy of testing data set brain images ranged from 60% to 85%. A neural network cannot achieve 100% efficiency, which is the main drawback of neural network based applications. Maximum performance can be obtained through intensive training. Further work is to check the performance of the system by increasing the database.

The classification results of BPN networks are shown in figures 5 to 7. All classification result could have an error rate and in some occasion it may either fail to identify an abnormality, or identify an abnormality which is not present. It is common to describe this error rate by the terms true and false positive and true and false negative. The performance of the network is derived from the MSE value.

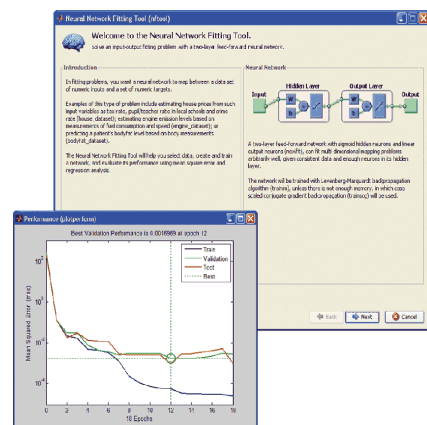


Fig. 4 Neural network training

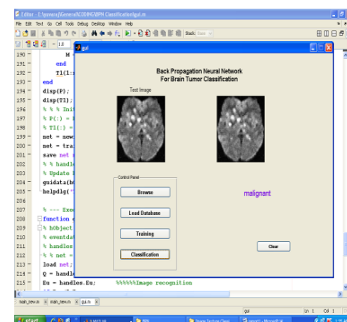


Fig. 5 Classification result of Malignant Tumor

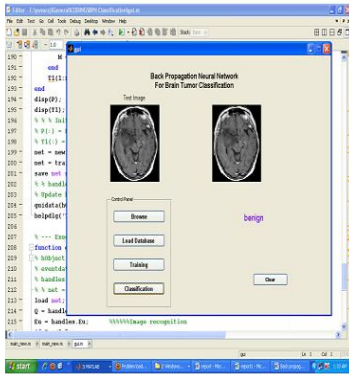


Fig. 6 Classification result of benign tumors

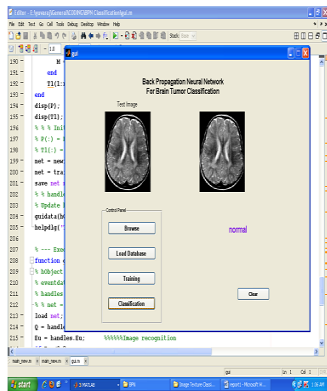


Fig. 7 Classification result of normal brain

V MODIFICATION AND FUTURE WORKS

The brain tumor classification through Eigen value decomposition method has suffered by a low accuracy problem. It can be overcome by extracting feature vectors and principal components using wavelet decomposition. The proposed system uses the Discrete Wavelet Transform (DWT) coefficients as feature vector and PCA is used for dimensionality reduction. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from MR images. Wavelets are localized basis functions, which are scaled and shifted versions of some fixed mother wavelets. The main advantage of wavelets is that they provide localized frequency information about a function of a signal, which is particularly beneficial for data classification.

The wavelet $\Psi_{a,b}$ is computed from the mother Ψ wavelet by translation and dilation of the wavelet; 'a' the dilation factor and 'b' the translation parameter. Both are real and positive numbers. Under some assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean. The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale.

In DWT method, the original image is process along the x and y direction by $h(n)$ and $g(n)$ filters which, is the row representation of the original image. As a result of

this transform there are 4 subband (LL, LH, HH, HL) images at each scale. Subband image LL is used only for DWT calculation at the next scale. To compute the wavelet features in the first stage, the wavelet coefficients are calculated for the LL subband using Harr wavelet function.

These LL coefficients are used as feature vectors and its dimensionality is reduced through principal component analysis to obtain principal components for training and testing the neural network. This data classification technique achieves an extended efficiency of 80% to 98% which depends on training.

VI CONCLUSION

In this paper, an automatic method for classification of brain tumors in to normal, malignant or benign are proposed. Here, we propose two approaches for Brain Tumor Detection based on artificial neural networks. Feature extraction through Eigen value decomposition and wavelet decomposition. Back propagation neural Network is used as an efficient data classifier. Back propagation algorithm was used for training, testing and classification of the tumor. BPN is adopted for it has fast speed on training and simple structure Results show that the features extracted can give satisfactory result in analysis and classification of brain tumors. The purpose is to develop tools for discriminating normal brain MRI, malignant tumors and benign ones for assisting decision making in clinical diagnosis. The proposed approach utilizes a comparison of these two feature extraction techniques and is composed of several steps including segmentation, feature vector extraction and model learning. This method can then be used to filter out non-suspecting brain scans as well as to point out suspicious regions that have similar property as the tumor regions. The Eigen value decomposition feature vectors give an accuracy of 70% to 85% whereas the wavelet decomposition shows an efficiency of 80% to 98%

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