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RESEARCH ARTICLE

MRI BRAIN TUMOR DETECTION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Brain tumors are the most aggressive and devastating types of cancer and are one the most common or major reason for death among individuals. The chances of survival can be increased if the cancer is detected at its early stage. This paper present an artificial neural network technique, namely feed forward back propagation neural network to classify the magnetic resonance image (MRI) into normal and timorous MRI. Image processing technique helps in detection of tumor in MRI. Feature extraction from the gray level MRI achieves using gray level co-occurence matrix (GLCM). Neural network works in two modes first is training/learning mode and second is testing/recognition mode. The whole system is developed on a MATLAB version 7.5.0 platform

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INTRODUCTION

Brain tumor is one of the major causes for the increase in mortality among children and adults. A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth (Pal and Pal, 1993). The complex brain tumors can be separated into two general categories depending on the tumors origin, their growth pattern and malignancy. Primary brain tumors are tumors that arise from cells in the brain or from the covering of the brain. A secondary or metastatic brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Tumors may be embedded in regions of the brain that are critical to orchestrating the body's vital functions, while they shed cells to invade other parts of the brain, forming more tumors too small to detect using conventional imaging techniques.

Brain cancer's location and ability to spread quickly makes treatment with surgery or radiation like fighting an enemy hiding out among minefields and caves. Unfortunately, many of these tumors will be detected too late, after symptoms appear. It is much easier and safer to remove a small tumor than a large one. About 60 percent of glioblastomas start out as a lower-grade tumor. But small tumors become big tumors. Low-grade gliomas become high-grade gliomas. Once symptoms appear, it is generally too late to treat the tumor. Most Research in developed countries show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300 over past three decades. So it is necessary to develop a Computer-assisted surgical planning and advanced image-guided technology that will help in recovery of brain tumor. The proposed system is an efficient system for detection of tumor and classification for given MRI images in normal and timorous image. The method of detection and classification is presented during the process is explained. This method is developed in MATLAB environment in order to check for applicability of proposed technique.

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Proposed Methodology

The proposed work starts by reading the input brain MRI and follows four major steps. The first step is image preprocessing, second is feature extraction using GLCM method, third is image segmentation using expectation maximization clustering algorithm and forth is classification of MRI into normal and timorous using feed forward backpropagation neural network. Fig. 1 shows the steps included in proposed system.

Data Set

For the implementation of automated recognition system a data set collected from different source for various class of MRI image is considered. Fig. 2 shows the database considered for the implementation. The images shown in dataset are obtained using MRI scan and these scanned images are displayed in a two dimensional matrices having pixels as its elements.

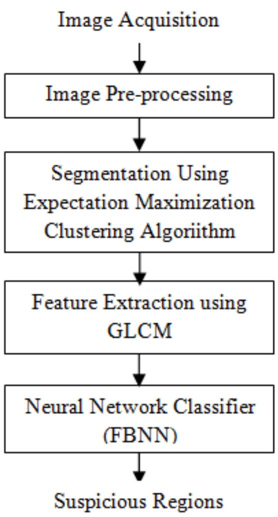

Figure 1. Steps for the MRI brain tumor detection using artificial neural network

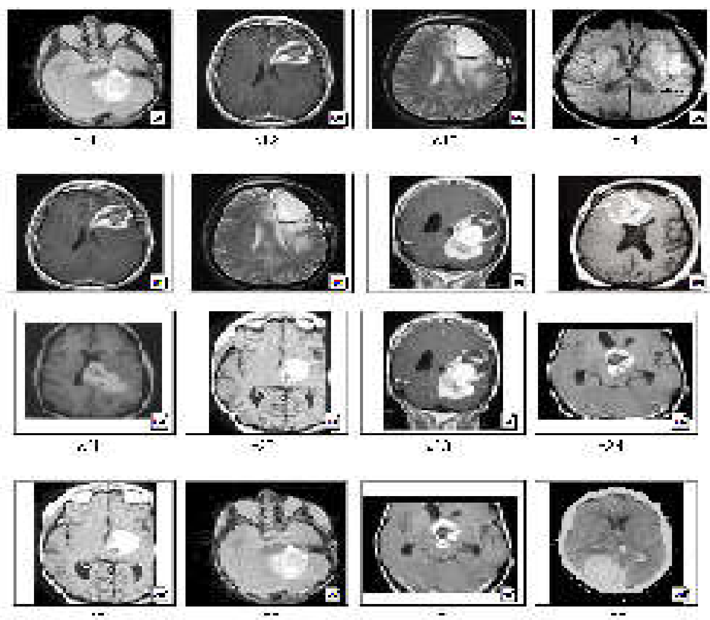

Figure 2. Database of MRI

Image Pre-processing

In this phase first RGB MRI is converted into gray level and then image enhancement is performed through histogram equalization and filtering. The superfluous information introduce in the image has removed by utilizing the preprocessing steps.

The major problem in the process of detection of edge of tumor is that the tumor appears very dark on the image which is very confusing. To solve this problem, Histogram Equalization was performed. To remove noise and smoothing an image in order to get the enhanced image for that purpose Gaussian filter is used. Gaussian filter is a thought of as a convolution filter

Image segmentation using expectation maximization clustering

In our project we have used expectation maximization clustering algorithm to differentiate the healthy and the timorous tissues. Expectation maximization (EM) is well-established clustering algorithm in the statistics community. EM is distance- based algorithm that assumes data set can be modeled as a linear combination of multivariates normal distribution and the algorithm finds the distribution parameter that maximize a model quality measure, called log likelihood.

EM steps are demonstrated in the following steps [8]:

Step1: Initialize mean and Covariance matrix using K-means.

Step2: Calculate membership probability of each training data.

Step3: Compute mean and variance of each gaussian component using membership function obtained in step 2.

The step 2 and 3 are repeated until convergence.

Feature Extraction

Texture features or more precisely, Gray Level Co-occurrence Matrix (GLCM) features are used to distinguish between normal and timorous brain tumors. Five co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal (0°, 45°, 90° and 135°.) A fifth matrix is constructed as the mean of the preceding four matrices, From the mean co-occurrence matrix obtained, we have extracted the 8 different statistical features. This features are as follow.

CONTRAST

Contrast is defined as the separation between the darkest and brightest area.

$$Contrast = \sum_{i,j=0}^{n-1} P_{i,j}\ (i-j)^2$$

CORRELATION

Correlation is computed into what is known as the correlation coefficient, which ranges between -1 and +1.

$$Correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i \quad \mu)(j \quad \mu)}{\sigma^2}$$

HOMOGENITY

Homogeneity is defined as the quality or state of being homogeneous.

$$Homogenity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2}$$

ENTROPY

Entropy is a measure of the uncertainty in a random variable.

$$Entropy = \sum_{i,j=0}^{N-1} -ln(P_{ij})P_{ij}$$

ENERGY

It provides the sum of squared elements in the GLCM .Also known as the uniformity or the angular second moment.

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

VARIANCE

The variance defines the variation of intensity around the mean.

$$Varience = \sum_{i,j=0}^{N-1} P_{i,j} \cdot (i - \mu)^2$$

Where,

$$\text{Mean, } \mu = \sum_{i=0}^{N_g-1} i.p(i)$$

MAXIMUM PROBABILITY

This is simply the largest entry in the matrix, and corresponds to the strongest response. This could be the maximum in any of the matrices or the maximum overall.

Maximum Probability = $\max_{i,j} p(i, j)$

DISSIMILARITY

$$Dissimilarity = \sum_{i,j=0}^{N-1} P_{i,j} * |i - j|$$

Neural network Classifier

Feed forward back propagation neural network classifier is used to detect candidate-circumscribed tumor. The two layer FBNN is used in the proposed system, it consists of one input node, 10 log-sigmoid (logsig) neurons in hidden layer and one log-sigmoid (logsig) neuron in output layer indicating whether the MRI is a candidate circumscribed tumor or not, resilent backpropagation (trainrp) training function is used for adjusting the weights and biases in order to minimize a cost function in training phase. The cost function always includes an error term a measure of how close the network's predictions are to the class labels for the examples in the training set. Fig. 3 shows backpropagation neural network used to classify the MRI into normal and timorous.

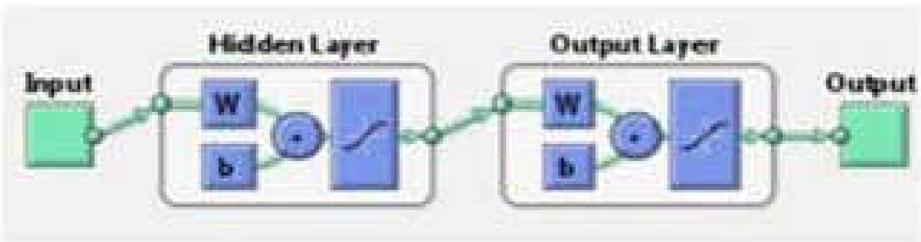

Figure 3. Feed forward backpropagation neural network

FBNN works in two mode, one is training/learning mode and another is testing/recognition mode. In training/learning mode the neural network is trained with the features of known MRI samples and in testing/recognition mode an unknown MRI samples features are applied to the input of FBNN to classify MRI into normal and timorousl.

Algorithm stages for BPN training/learning

- Initialization of weights
- Feed forward
- Back propagation of Error
- Updation of weights and biases

The activation function (logsig) used in hidden and output layer neuron is

$$f(x)=\frac{1}{1+e^{-x}}$$

Where, x is net input to a particular node (neuron). This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing.

EXPERIMENTAL RESULTS

In this paper, the pre-processing stage performs RGB to gray scale conversion of MRI. The Gaussian filter is used for image enhancement it is used to remove the Gaussian noise in an image. In image segmentation expectation maximization clustering method is used which gives more accurate, fast result and it is more robust to noisy data. In other words, the partitioned clustering is faster than the hierarchical clustering.

Fig. 4 shows the GUI for brain tumor segmentation when input is timorous image.

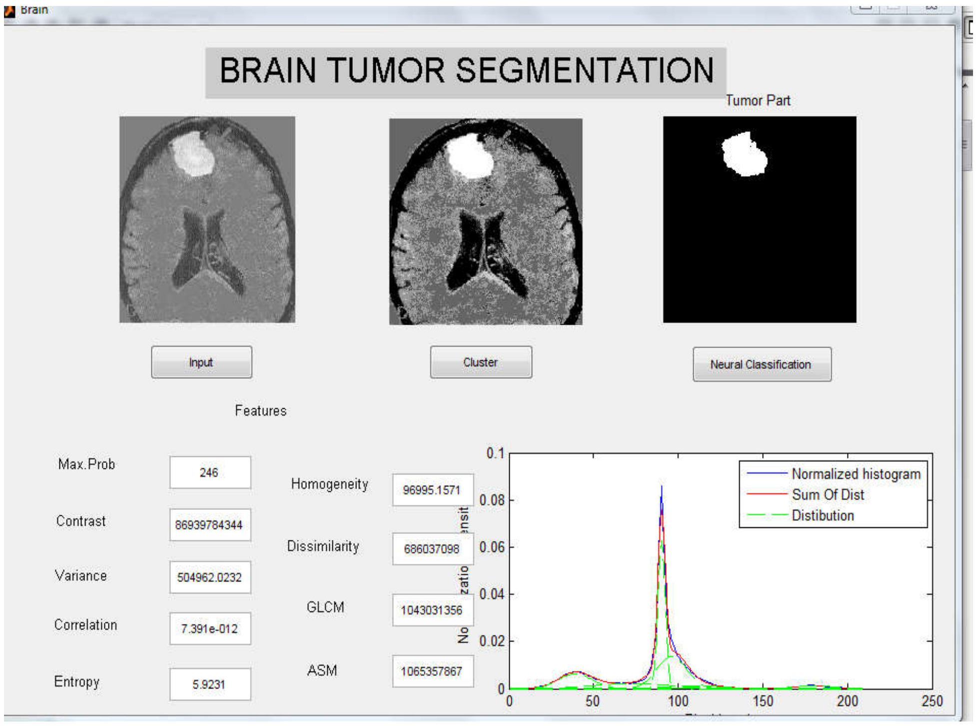

Figure 4. Screenshot showing Brain tumor segmentation when input is timorous MRI

Fig. 5 shows the screenshot showing decision taken by Feed forward back propagation neural network when input is timorous image

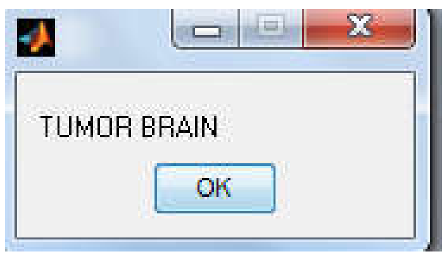

Figure 5. Screenshot showing Decision of FBNN Classifier

Fig. 6 shows the GUI for brain tumor segmentation when input is normal image.

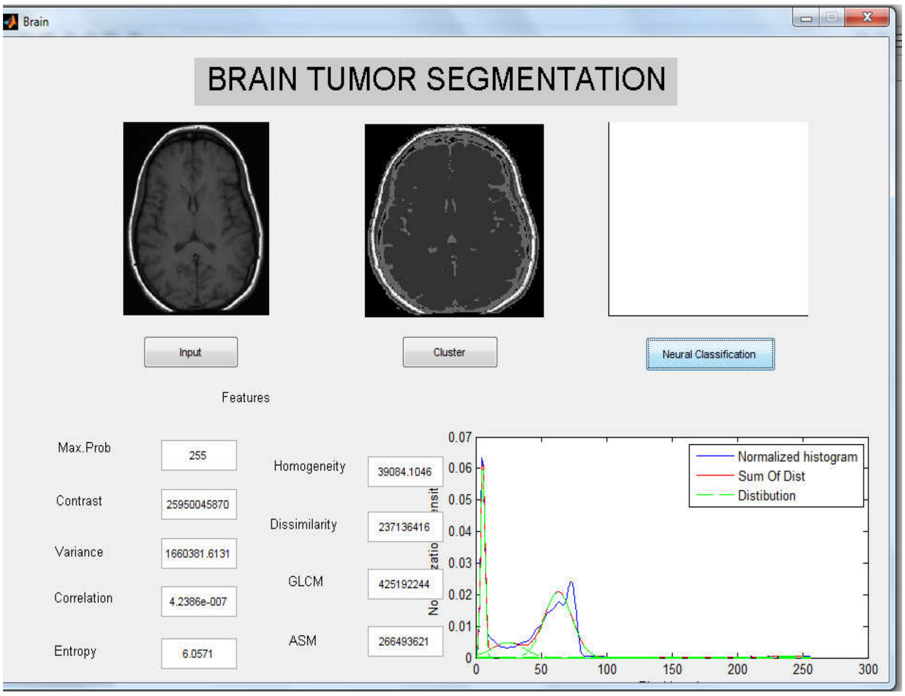

Figure 6. Brain tumor segmentation when input is normal MRI

Fig. 7 shows the screenshot showing decision taken by Feedforward backpropagation neural network when input is normal image.

Fig. 8 shows FBNN training phase and Fig. 9 shows FBNN performance when TRAINRP training function is used.

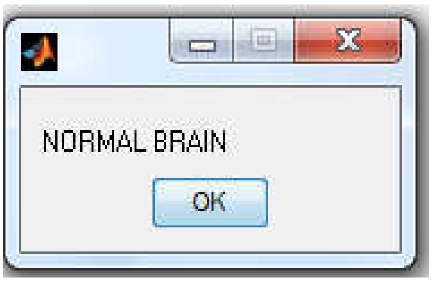

Figure 7. Screenshot showing Decision of FBNN Classifier

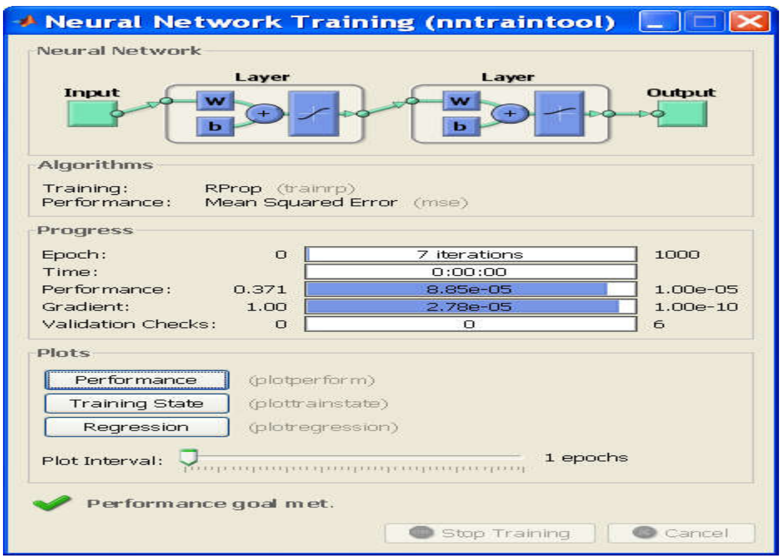

Figure 8. Screenshot showing FBNN training phase

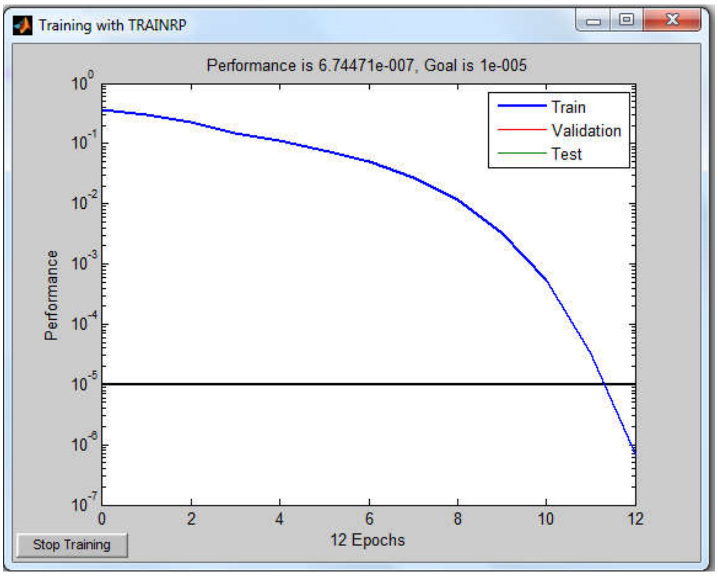

Figure 9. Screenshot showing FBNN performance with TRAINRP training function

Conclusion

This paper describes detection and Classification of Brain Cancer Using Artificial Neural Network approach namely, Back propagation network (BPNs). The proposed technique is developed for the diagnosing of tumor from MRI pictures of the brain. This technique performs diagnosing of Brain tumor through the pre-processing stage which performs histogram equalization and filtering on brain MRI, image segmentation that uses Expectation maximization clustering method. After that texture features are extracted from gray scale MRI using GLCM method, these extracted features are given as input to artificial neural network(FBNN) for classifying MRI into normal and abnormal (timorous) image. The system can be designed to classify types of cancer. The further scope of the system is to improved ANN architecture by using other approach.

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