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Brain Tumor Detection Using Artificial Neural Network Fuzzy Inference System (ANFIS)

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Abstract: Manual classification of brain tumor is time devastating and bestows ambiguous results. Automatic image classification is emergent thriving research area in medical field. In the proposed methodology, features are extracted from raw images which are then fed to ANFIS (Artificial neural fuzzy inference system).ANFIS being neuro-fuzzy system harness power of both hence it proves to be a sophisticated framework for multiobject classification. A comprehensive feature set and fuzzy rules are selected to classify an abnormal image to the corresponding tumor type. This proposed technique is fast in execution, efficient in classification and easy in implementation.

Keywords: EEG; GLCM; ANFIS; FIS;BPN

1. INTRODUCTION

Manual brain tumor detection is time consuming and bestows ambiguous classification. Hence, there is need for automated classification of brain tumor. Normally, this turnover takes place in an orderly and controlled manner. The cells of tumor continue to separate, developing into a lump, which is called a tumor. brain tumor is divided in two types, primary and secondary brain tumor. The recognition of primary brain tumor is possible by observing the EEG (Electroencephalography) signals. EEG has been used to render a clearer overall view of the brain functioning at initial diagnosis stages. Being a non-invasive low cost procedure, the EEG is an attractive tumor diagnosis method on its own. It is a reliable tool for the glioma tumor series. The EEG in vascular lesions shows abnormality on first instance where as a CT scan shows abnormal on the third or fourth day .Medical Resonance images include a noise which is created due to operator's method of detection which can lead to serious inaccuracies in classification of brain tumor [1]. With increasing problems of brain, it is vital to develop a system with novel algorithms to detect brain tumor efficiently .The present method detects tumor area by darkening the tumor portion and enhances the image for detection of other brain diseases in human being. A comprehensive feature set and fuzzy rules are selected to classify an abnormal image to the corresponding tumor. Section I explores introduction of previous implemented techniques, Section II presents research work, Section III proposes the methodology used Section IV shows the simulation results, and Section V gives the conclusion.

The author in [2] employed the Hidden Markov Random Field (HMRF) for segmentation of Brain MRI by using Expectation-Maximization algorithm. The study shows that HMRF can be merged with other techniques with ease. The proposed technique acts as a general method that can be applied to a range of image segmentation problems with improved results.

Ahmed [3] explored an customized algorithm used for estimation of intensity of homogeneity using fuzzy logic that supports fuzzy segmentation of MRI data. The proposed algorithm is articulated by altering the objective function used in the standard FCM algorithm.

Habl, M. and Bauer, Ch. and Ziegaus, Ch., Lang, Elmar and Schulmeyer, F [4] presented a technique to detect and characterize brain tumors. They removed location arifactual signals, applied a flexible ICA algorithm which does not rely on a priori assumptions about unknown source distribution. Author have shown that tumor related EEG signals can be isolated into single independent ICA components. Such signals where not observed in EEG trace of normal patients.

2. PROPOSED METHODOLOGY

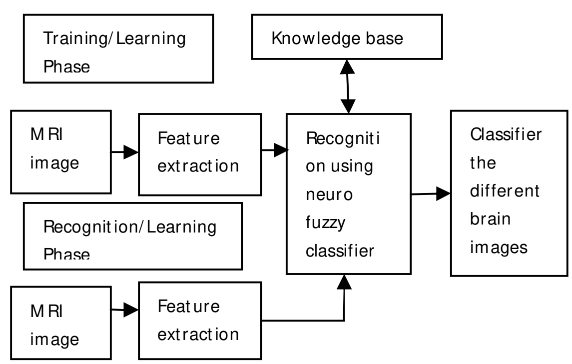

Figure.1 Block diagram of proposed system

Neuro-fuzzy systems use the combined power of two methods: fuzzy logic and artificial neural network (ANN). This type of hybrid system called as ANFIS ensures detection of the tumor in the input MRI image . The work carried out involves processing of MRI images of brain cancer affected patients for detection and Classification on different types of brain tumors. A suitable Nero Fuzzy classifier is developed to recognize the different types of brain tumors. Steps which are carried out for detection of tumor is enlisted below.

Step 1: Consider MRI scan image of brain of patients.
Step 3: Train the neural network with database images.
Step 2: Test MRI scan with the knowledge base.
Step 3: Two cases will come forward.
i. Tumor detected

ii. Tumor not detected.

A. Database Preparation:

The brain MRI images consisting of malignant and benign tumors were collected from open source database and some hospitals.

B. Image Segmentation:
The main objective of segmentation is to detach the tumor from its background.

C. Histogram Equalization:

The histogram of an image represents the relative frequency of occurrences of the various gray levels in the image.. Histogram equalization employs a monotonic, non-linear mapping which re-assign the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities.

D. Sharpening Filter

Sharpening filters work by increasing contrast at edges to highlight fine detail or enhance detail that has been blurred.

E. Feature Extraction:
The feature extraction extracts the features of importance for image recognition. The feature extracted gives the property of the text character, which can be used for training in the database. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted character.

2.1 Feed Forward Neural Network

Figure 3 demonstrates the strategy of the Feed Forward for detecting the existence of the tumor in the input MRI. image, which is accomplished in the final categorization step. Here we use the Feed Forward neural network classifier to classify the image.

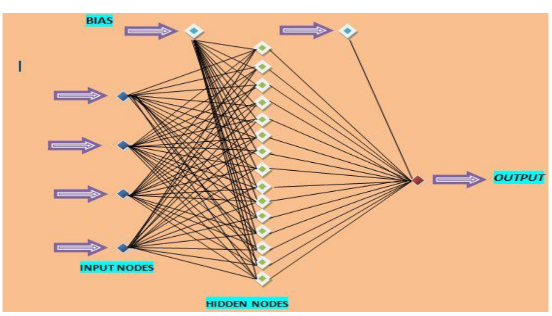

Figure. 2 Feed forward neural networks

Figure.3.Depicting back-propagation learning rule which can be used to adjust the weights and biases of networks to minimize the sum squared error of the network [8].

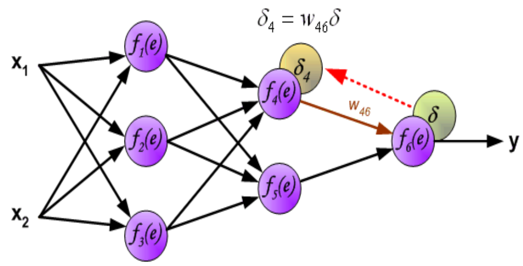

Figure. 3.Depicts the flow of information from output node back to hidden layer to reduce error.

The activation function considered for each node in the network is the binary sigmoid function defined (sgn = 1) as 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 error for each training iteration stops decreasing. The features which are extracted from image are listed below.

Angular second moment:

$$f_1 = \sum_i \sum_j P(i,j)^2 \tag{1}$$

Contrast:

$$f_2 = \sum_{n=0}^{N_g-1} n^2 P_{x-y}(n) \tag{2}$$

Correlation:

$$f_3 = \frac{\sum_i \sum_j (i,j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

Sum of Square: Variance:

$$f_4 = \sum_i \sum_j (i-\mu)^2 \tag{4}$$

Inverse difference moment:

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} P(i-j) \tag{5}$$

Sum Average:

$$f_6 = \sum_{i=2}^{2N_g} i P_{x+y}(i) \tag{6}$$

Sum Variance:

$$f_7 = \sum_{i=2}^{2N_g} (i-f_6)^2 P_{x+y}(i) \tag{7}$$

Sum entropy:

$$f_8 = -\sum_{i}^{2N_g} P_{x+y}(i) \log P_{x+y}(i) \tag{8}$$

Entropy:

$$f_9 = -\sum_i \sum_j P(i,j) \log P(i,j) \qquad (9)$$

Difference variance:

$$f_{10} = -\sum_{i=0}^{N_g-1} (i - \mu_x - y)^2 P_{x-y}(i) \qquad (10)$$

Difference entropy:

$$f_{11} = -\sum_{i=0}^{N_g-1} P_{x-y}(i) \log (P_{x-y}(i)) \qquad (11)$$

Standard deviation

$$f_{12} = \frac{\sum_{i=1}^{n}(xi-\bar{x})^2}{(n-1)} \qquad (12)$$

Where P(i,j) is $(i,j)^{th}$ entry in a normalized gray-tone spatial-dependence matrix.
$P_x(i)$ is i^{th} entry in the marginal-probability matrix obtained by summing the rows of P(i,j),$= \sum_j^N g, P(i,j)$.
N_g Number of distinct gray levels in the quantized image.
μ_x, μ_y, σ_x, and σ_y are the measured standard deviations of P_x, P_y.

3. GUI OF PROPOSED SYSTEM

Figure. 5 shows the GUI of proposed system for brain tumor detection. Figure. 6 showing the database of images containing tumor.Fig7 showing histogram equalization of input image in which intensity of image are equalized. Figure 8 showing segmentation of image in which tumor part is isolated from background. Figure 9 showing feature extraction of input image containing tumor.Figure.11showing detection of tumor

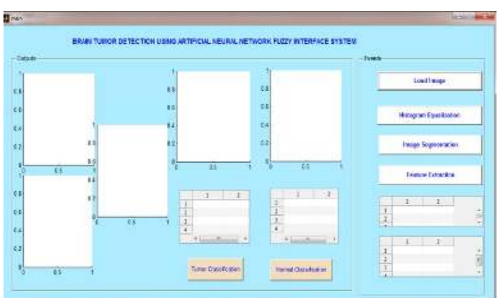

Figure. 5 Screenshot of GUI

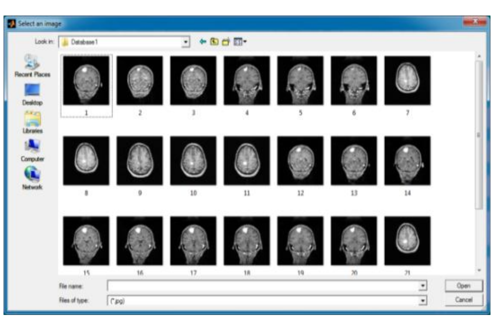

Figure.6 Screenshot images of brain tumor

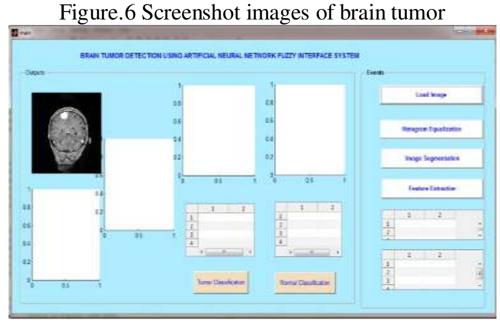

Figure.7 Screenshot showing loading of MRI image

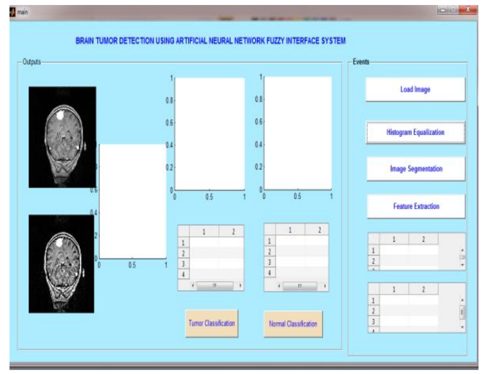

Figure.8 Screenshot showing histogram equalization

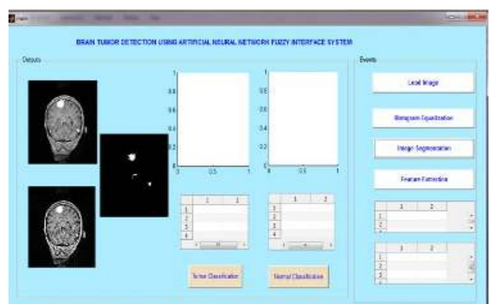

Figure.9 Screenshot showing image segmentation

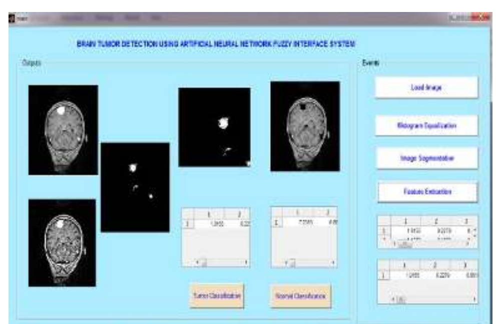

Figure.10 Screenshot showing feature extraction.

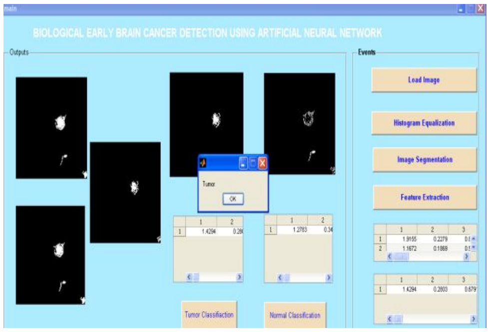

Figure. 11 Screenshot showing detection of tumor

4. NEURO-FUZZY CLASSIFIER

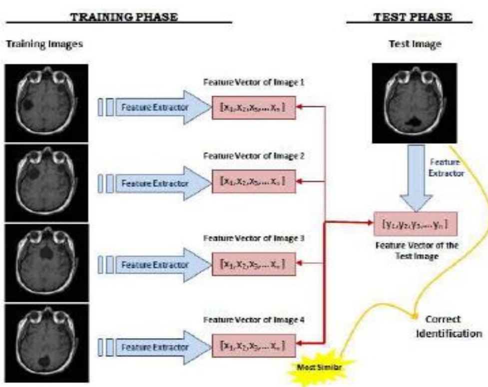

Figure.12 Testing and training phase of ANFIS

The features extracted from image are further given to Neuro-fuzzy classifier which is used to detect candidate circumscribed tumor. Generally, the input layer consists of seven neurons corresponding to the seven features. The output layer consists of one neuron indicating whether the MRI is a candidate circumscribed tumor or not, and the hidden layer changes according to the number of rules that give best recognition rate for each group of features.

5. SIMULATION RESULTS

Fig 11 shows the GUI neural network toolbox.

Fig 12 shows Performance Plot mean square error dynamics for all your datasets in logarithmic scale. Training MSE is always decreasing with increasing in number of epochs.

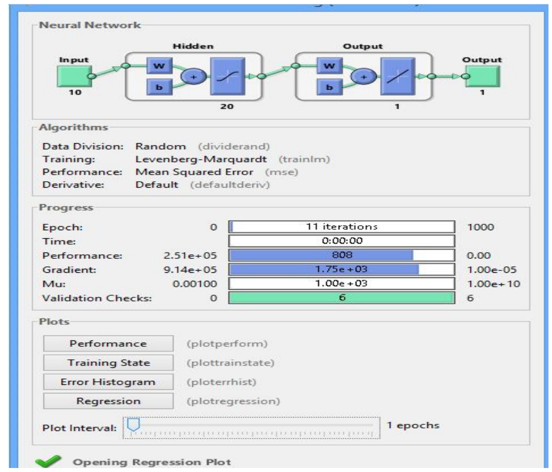

Figure. 13 Screenshot of GUI neural network training phase.

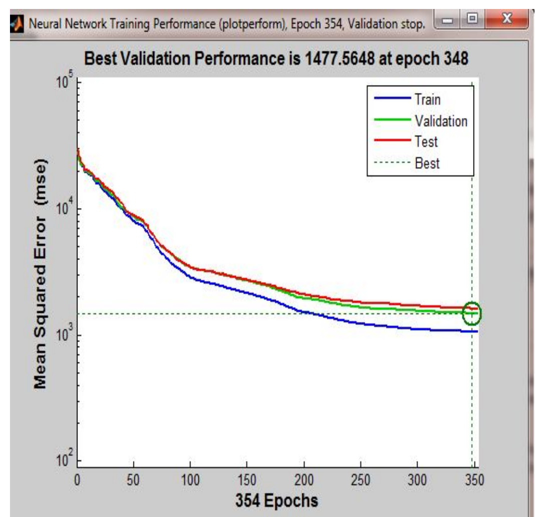

Figure.14 Screenshot of validation phase of neural network

6. CONCLUSION

This paper presents a automated recognition system for the MRI image using the neuro fuzzy logic. It is observed that the system result in better classification during the recognition process. The considerable iteration time and the accuracy level is found to be about 50-60% improved in recognition compared to the existing neuro classifier.

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