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A HYBRID FRAMEWORK FOR BRAIN TUMOR DETECTION AND CLASSIFICATION USING NEURAL NETWORK

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ABSTRACT

Magnetic Resonance Imaging (MRI) has been a robust tool for the diagnosis of brain tumors. MRI is an imaging technique that provides detailed information about brain anatomy. This paper announces a novel method for efficient and accurate MRI analysis. The images are pre-processed to increase the contrast and to remove the skull region. A novel algorithm is used to check whether the given image is normal or not. This algorithm reduces the computational complexity and increase the speed of proposed classification system by selecting abnormal images alone for further processing. Segmentation is performed on abnormal images to find the tumor region. Segmentation is based on a hybrid algorithm using K-means clustering and Texture Pattern Matrix. Texture Features and shape features are separately extracted from the segmented binary image using Gray Level Co-occurrence Matrix (GLCM) and connected regions. The features thus obtained are used to train the neural network using Back Propagation Algorithm defined by Levenberg-Marquardt (LM) algorithm. Feed Forward Neural Network (FFNN) is used for the classification of MR images. While using the proposed method, accuracy is 98.06%, specificity is 97.77% and sensitivity is 98.34%. Speed, Robustness and computational complexity are the major advantages of the proposed system.

Keywords: MRI classification, hybrid segmentation algorithm, texture pattern matrix, gray level co-occurrence matrix, feed forward neural network, back propagation algorithm.

INTRODUCTION

Earlier detection of brain tumor and its classification is essential for effective treatment planning. Researchers have developed versatile techniques for brain MRI classification using various features. Neural networks categorize brain MR images into three different categories such as normal, malignant and benign. The difference between brain soft tissues and the tumors are determined apparently. Euclidean distance [5] is used to measure the similarity between different shapes of brain tumor. The neural network is trained using ground truth images. Classification of tumors is a tedious and complicated task due to the complexity and discrepancy of brain MRI [2]. An automated brain tumor classification system consist of image preprocessing, image segmentation, feature extraction and classification algorithms. Malignant tumors are cancerous and harmful, while benign tumors are non-cancerous and less harmful [4]. In pre-processing, the image quality is enhanced and unwanted regions are clipped off. Segmentation is a binary process in which image is divided into regular cells and tumorous cells. Classification is the process of categorizing the input images to corresponding class [6]. For effective classification to occur different features has to be extracted from the segmented image [10].

A hybrid method based on PCA and SVM has been proposed by Chun *et al* [13]. PCA is used for dimensionality reduction and SVM was used for classification. Deepa *et al* developed a system using Radial function neural network [16] for the classification of brain MRI. Major flaw in this classification scheme is the poor feature selection process. Ibrahim *et al* [17] proposed a neural network technique for better classification of brain MRI. Contrast enhancement was performed in the pre-processing stage. PCA was used for dimensionality reduction. Back propagation neural network was used for classification and an accuracy of 96% was obtained. Joshi et al [19] developed a computer based system using neuro-fuzzy classifier and GLCM was used for feature extraction. Nandapuru *et al* [15] used SVM along with linear kernels for the identification of abnormal brain MR images. Feature reduction was done using Principal Component Analysis (PCA). SVM was applied to obtain classified output. Using quadratic kernel, maximum accuracy of classification was obtained. Shivapriya *et al* [18] implemented least square support vector machine (LS-SVM) training along with chaotic Particle Swarm Optimization (PSO). The classification results were accurate and efficiency obtained was very high. Goswami *et al* [14] presented a classification technique for brain MRI based on unsupervised learning in artificial neural network. Kauss *et al* [20] used KNN classifier for detection of low grade gliomas. The performance was validated against manually segmented results. Zhang *et al* [21] developed single class Support Vector Machine (SVM) for the classification of tumors. The method was found superior over multi class SVM techniques. Kumar *et al* [22] developed a frame work based on PCA and ANN based classification for categorizing tumorous and normal MR images.

From this extensive literature review it is noticed that the computational complexity is high and classification accuracy is low. The main purpose of our work is to implement a novel computer aided diagnosis (CAD) system for brain MRI analysis. Contrast enhanced T1 and FLAIR images are used for the analysis of tumors.

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The selection of slice entirely depends on the choice of radiologist. The rest of this paper is arranged as follows. Proposed methodology for the classification of MR images is explained in section 2. Experimental results are shown in section 3 and conclusion is provided in section 4.

METHODOLOGY

In this research work we implement a novel method for the classification of human brain MRI. The method is less complex compared to the state of the art classification methods based on neural network. In this method the normality of the MR Image is checked before doing segmentation. This will reduce the complexity of computation. The segmentation is done only if the image is abnormal. Initially the input image is pre-processed and the area of interest is calculated. While pre-processing, the image is enhanced and skull stripping is performed to calculate the area of interest. In the next step abnormality of the image is checked using a separate algorithm. If the image is normal, the output is displayed as normal. If the given MRI is abnormal, segmentation is performed using novel hybrid segmentation method. The method is based on K-means clustering and Texture Pattern Matrix. Then the features are extracted using Gray Level Co-occurrence Matrix (GLCM) and connected regions.

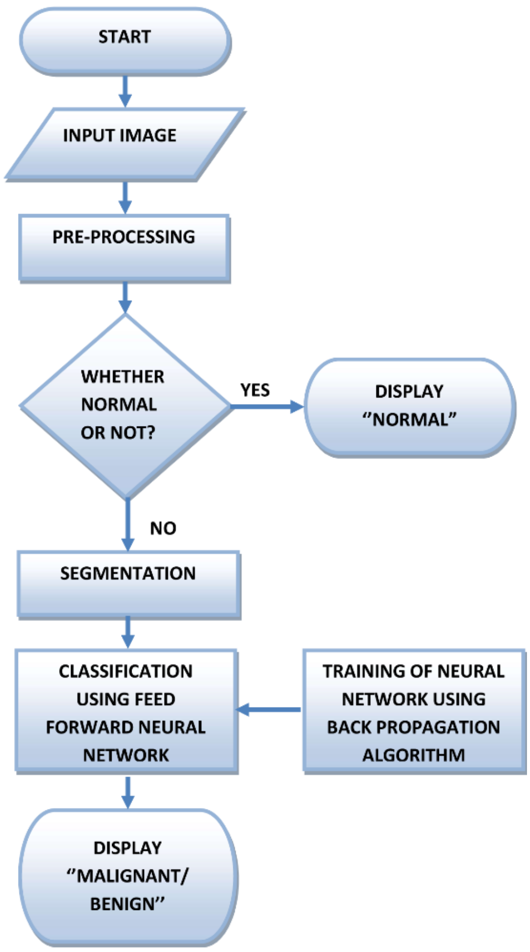

Figure-1. Process flow of proposed methodology.

The extracted features are given as input to the neural network. The neural network used is feed forward neural network and training is done using back propagation algorithm. Test images are classified into normal, malignant and benign tumors. The process flow of the proposed methodology is illustrated in Figure-1.

A. Brain MRI database

Brains MRI with various types of tumors are obtained from publicly available dataset verified by major doctors across the globe. The dataset consist of MR Images with various types of tumors such as benign and malignant [11]. 700 images are obtained from publicly available dataset and 300 images are obtained from various scan centers in Kerala, India. This increased dataset can enhance the accuracy and efficiency of classification algorithm. FLAIR and T1 weighted contrast induced images are considered for experiment.

B. Pre-processing

Pre-processing is a major step in image processing, which plays an inevitable role in human brain MRI analysis. The major goal of this process is to improve the quality of input image and to remove unwanted regions from the image. The quality of the image is increased using image enhancement techniques. Contrast Limited Adaptive Histogram Enhancement (CLAHE) is used for image enhancement. This will help to distinguish between tumorous and non-tumorous tissues. In the next step the skull region is removed from the MR image. Tumor is absent in skull region and skull stripping will help to avoid misclassification. The method used for skull stripping is based on connected regions and morphological operations. The skull stripping algorithm makes use of the dilation property of the morphological operation to remove unwanted skull region in the MR image [3].

C. Algorithm to check abnormality of MR image

Computational complexity is the major drawback of all classification methods. Each image has to go through all processes while performing classification. This will increase computational complexity and computational time. While dealing with large amount of clinical data, this is a major disadvantage. In order to reduce computational complexity, a novel algorithm is proposed to check whether the given image is normal or abnormal. If the image is normal there is no need for further processing. Segmentation, feature extraction and classification are performed only if the image is abnormal.

The output of pre-processing is the enhanced skull stripped image contains brain region alone (Region of Interest). Initially the region of interest is read. The lower intensity regions are removed based on a threshold value. The maximum intensity (Max) and minimum intensity (Min) are calculated. Average of the intensities from (Min) to (Min+25) is calculated. Similarly average of the intensities from (Max-25) to (Max) is calculated. The difference between these two averages (D) is calculated. The number of pixels (n) with intensities ranging from (Max-25) to (Max) is calculated. If n is greater than 80%, the value of N is stored as 0 and if n is less than 80%, the value of N is stored as 1. If the value of D is greater than 40 and N=1 the image is normal, else the image is abnormal.

Algorithm 1: To check abnormality of MRI
Step 1: Read the Region of Interest.
Step 2: Remove lower intensity regions.
Step 3: Find maximum and minimum intensity values in the remaining region..
Step 4: Take avg [(Max-25) to Max] and avg [Min to (Min+25)] forming two groups.
Step 5: Find the difference (D) between them.
Step 6: Find the number of pixels (n) with intensities ranging from (Max-25 to Max).
Step 7: If n>80% of the pixels in the region of interest, then put N=0; else N=1.
Step 8: If D>40 & N=1, then the given image is not normal; else, the given image is normal.

D. Brain MRI segmentation

Segmentation is an important process used to identify the tumor regions in an image. The skull stripped image is used for segmentation. The segmentation process divides the MR image into different regions based on the properties of the regions. Tumor regions have a particular set of properties. Segmentation reduces the processing time for further operations involved in image analysis. The segmented image contains tumor regions separated from the background image. A novel method to segment brain MRI has been developed using K-means clustering algorithm and Texture Pattern Matrix [9]. The method exhibits reduced complexity and higher efficiency. The accuracy of segmentation obtained using this method is 99.91%.

K-means clustering algorithm is well known technique for segmentation of MR Images into different regions. Primarily the number of clusters and centroids are initialized. The clusters are calculated in such a way that no clusters contain similar intensities of pixels, i.e. the final clusters are unique. The clusters thus obtained are saved separately. Next step is to calculate Local Pattern Histogram (LPH). A 5x5 moving window is used to calculate LPH. The image thus obtained is quantized into 3 values such as, +1, 0 and -1. The matrix thus obtained is called Texture Pattern Matrix (TPM) and the values represent the texture properties [9]. The Texture Pattern Matrix (TPM) is then split into Positive matrix, Negative Matrix and Equal Matrix (EM).

$$\mathrm{EM} = \begin{cases} 1, & \mathrm{Q_j} = 0 \\ 0, & \text{others} \end{cases}, \mathrm{j} \in [1,2, \ldots, \mathrm{N}] \tag{1}$$

Equal Matrix (EM) refers to the tumor structure and this matrix is AND operated with the K-means clustering output. The resultant image is the segmented output. The performance parameters of the proposed hybrid segmentation method are higher compared to the existing K-means clustering method.

E. Feature extraction

Feature extraction reduces the image data by taking necessary information from the image. Texture features and shape features are the two types of features considered in this work [12]. We used different method for the calculation of these features. Texture features provide specific information about the distribution of various gray levels in an image. The texture features calculated are standard deviation, variance, mean, homogeneity, entropy, energy, dissimilarity, correlation and contrast. Gray Level Co-occurrence Matrix (GLCM) is used to extract texture features from the segmented image. It is the easiest and most efficient way to extract texture features from an image. Secondly shape features such as circularity, area and perimeter were calculated using connected regions. From these extracted features it is possible to distinguish malignant and benign tumors. The proposed feature extraction methods are efficient, fast and simple. The quality of extracted features determines the efficiency and accuracy of classification algorithm.

F. Brain MRI classification

Classification is the process of categorizing the given MR images into various groups. In our case the given images are classified into malignant tumor and benign tumor. Two phases in the classification process are training and testing. The classifier used in this method is Feed Forward Neural Network (FFNN). For training this neural network Back propagation algorithm is used.

In a Feed Forward Neural Network, information travels in a single direction; i.e. from input nodes to the hidden layers and from hidden layers to the output node. Loops, cycles and feedback paths are absent in this neural network. In the proposed method input layer consist of 18 nodes and one bias value. There are 3 hidden layers with 18 nodes each. The output layer has a single node. Initially the extracted features are given as input through the input layer. These inputs are given to the first hidden layer. The weighted sum is calculated in the all hidden layers. An activation function is applied in the hidden layers and the function used in our method is sigmoid. The final result is obtained through the output layer.

Training is the process involving the modification of weights and biases of a neural network in order to reduce error function. Sigmoid function used as activation function limits the output of nodes between 0 and 1. The training of neural network is done to reduce the value of mean square error (MSE). Levenberg-Marquardt (LM) algorithm is used to decrease MSE of the neural network. This method is higher order adaptive back propagation

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approach. LM algorithm is applied after implementing the neural network. Initially the Jacobian Matrix (J) is calculated with (i,j)th element.

$$J_{(i,j)} = \frac{\delta_p\,(y_i, \alpha)}{\delta\alpha_i} \qquad (2)$$

where i= 1,2,3,…,m and j=1,2,3,…..,n. α is a vector quantity containing n parameters.

Then the error gradient is calculated. Cross product of Jacobian Matrix is used to calculate the approximate value of Hessian function. From this function the search direction (p) is calculated by solving following equation.

$$[J(\alpha)^T J(\alpha) + \tau I]p = -J(\alpha)^T F(\alpha) \qquad (3)$$

Then the network weights (w) are updated using the direction (p). The sum of squares is recalculated using the updated weights. If MSE is not decreased, weight is increased and the process is repeated. The iteration process ceases when the value of MSE stops decreasing.

EXPERIMENTAL RESULT

500 images from the MRI database are used for the experiment. Out of these images 200 images are malignant, 200 images are benign and 100 images are normal. The classifier and GUI were implemented using MATLAB. Initially the images are pre-processed and skull stripped image is obtained. The normality of the image is checked using a novel algorithm. If the output of the algorithm is normal, the output is displayed as “NORMAL MRI”. If the output of the algorithm is abnormal, the image is segmented and the features are extracted. Features are given as inputs to the classifier. The output of the classifier will be either “MALIGNANT” or “BENIGN”. GUI showing segmentation, feature extraction and classification of brain MRI is shown in Figure-2.

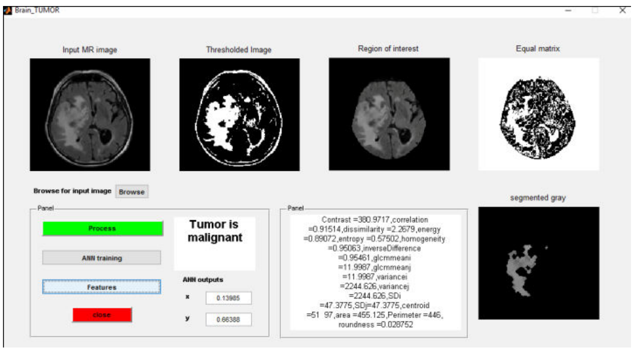

Figure-2. GUI of proposed framework for classification of brain MRI.

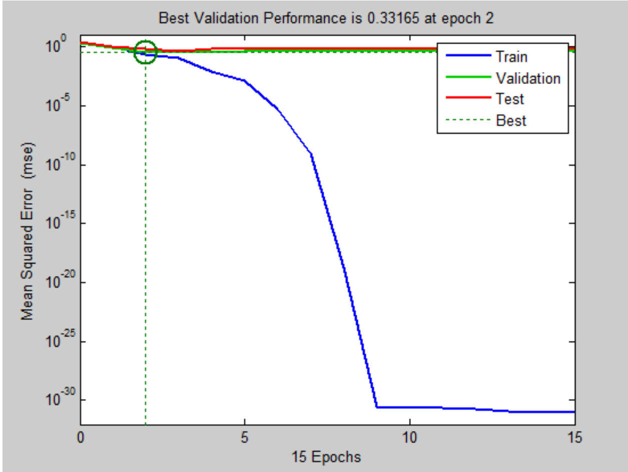

Figure-3. Performance plot.

A. Performance evaluation

The performance of hybrid segmentation based FFNN classifier is illustrated in Figure-3. The regression rate obtained is 0.53872 and the best evaluation performance is 0.33165 obtained at 2nd epoch. Training performance, testing phase, validation and regression rate are illustrated in Figure.4. The regression graph specifies the relationship between actual output and target of classification.

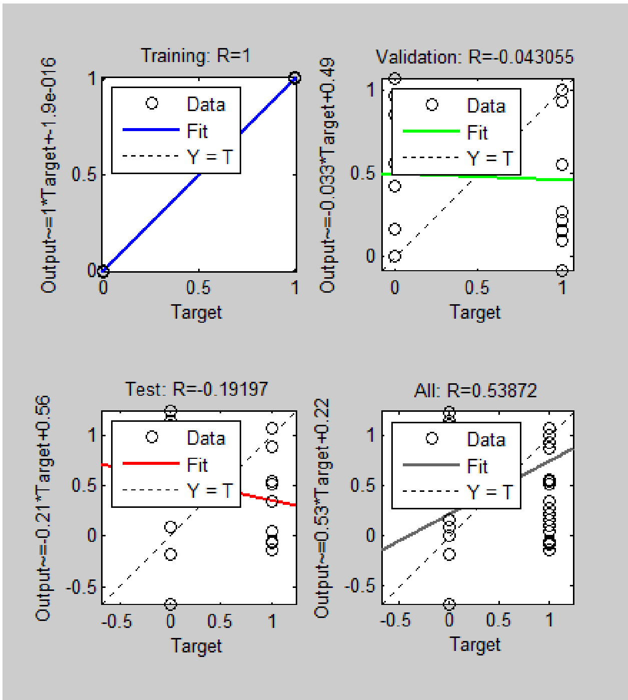

Figure-4. Regression graph.

The classification performance of our system is evaluated using three parameters. Accuracy, Specificity and Sensitivity are calculated from the experimental results. True Positive (TP) represents an instance of positive classification or correct classification. True Negative (TN) represents an instance in which an image is correctly classified as negative. False positive (FP) represents a negative instance misclassified as positive. False Negative (FN) represents a positive instance misclassified as negative. These values are required for the calculation of performance parameters. Accuracy is the measure of correctly classified MR images. It is the ratio of number of correctly classified images to the total number of images. Specificity is the ratio of number of True Negative cases to the total number of negative cases. It is also known as True Negative Rate. Specificity represents the positive cases that are identified correctly. It is the ratio of number of True Positive cases to the total images classified as positive.

Table-1. Performance of proposed method.

Performance parameters	Normal	Benign	Malignant
True Positive	79	78	79
True Negative	15	14	15
False Positive	0	1	0
False Negative	1	2	1
Accuracy (%)	98.4	96.84	98.94
Specificity (%)	100	93.33	100
Sensitivity (%)	98.75	97.53	98.75

Accuracy, Specificity and Sensitivity are calculated separately for normal, malignant and benign image. For training the neural network 90 benign MR images, 90 malignant MR images and 80 normal MR images were used. For testing and calculation of performance parameters, 80 benign MR images, 80 malignant MR images and 80 normal MR images were used. The values obtained for performance parameters while using proposed method is given in Table-1.

A. Performance comparison

Average values of performance parameters are calculated to compare the performance of the proposed system with existing systems [8]. Average accuracy of the proposed system is 98.06%, which is higher compared to accuracy of existing classification methods. The accuracy obtained using the combination of Principal component Analysis (PCA) and Artificial Neural Network (ANN) is 97%, which is little bit lower than the accuracy of proposed method. Average specificity of the proposed system is 97.77% and all other methods exhibits lower specificity during classification. The specificity obtained using Support Vector Machine (SVM) and Active Contour Method (ACM) is 94.74%, which is very much less than the specificity of proposed method. Average sensitivity of proposed method is 98.34%, which is higher than the sensitivity of PCA+ANN method.

Table-2. Comparison of performance.

Method	Accuracy (%)	Specificity (%)	Sensitivity (%)
SVM	78.96	74.87	74.87
KNN	80.91	79.94	79.98
ANNLM	83.55	85.89	87.59
SVM+ACM	86.50	94.74	89.47
KNN+ACM	91.14	89.68	86.84
FFNN	86	62	87.5
PCA+ ANN	97	90	98.3
IPSONN	86	93.3	96
Proposed Method	98.06	97.77	98.34

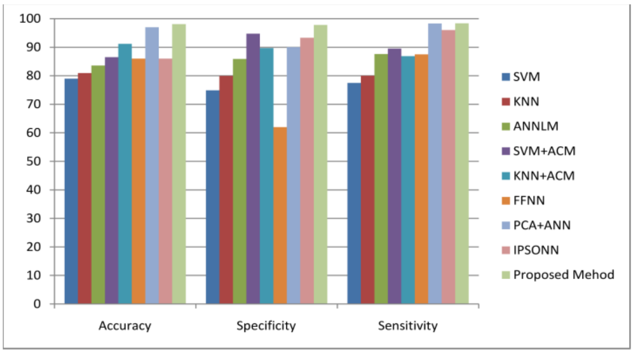

Figure-5. Performance comparison.

Table-2 shows a detailed comparison of performance parameters while using various methods for classification and it is graphically represented in Figure-5.

CONCLUSIONS

In this work a novel approach for the diagnosis of tumor using MR images is proposed. The proposed method is robust and more accurate compared with existing classification methods. The proposed system was implemented using hybrid segmentation algorithm and FFNN. Experimental results show that proposed method provides high specificity and sensitivity and accuracy during segmentation and classification. For easily accessing input images and to display output, a graphical user interface (GUI) has been designed and implemented. So, we suggest that hybrid segmentation and FFNN classification based system reduces complexity and provides better decision making in categorizing brain tumors. It also increases the efficiency of neural network classifier by providing a novel algorithm for checking normality. Our future work is to further increase the performance parameters by training the neural network using more number of images and modifying the algorithm.

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