Classification of MRI Brain images using GLCM, Neural Network, Fuzzy Logic & Genetic Algorithm

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Abstract— Detection of Brain abnormality could be a vital and crucial task in medical field. Resonance Imaging Brain image detection method offers the knowledge of the various abnormalities in Brain. This helps the doctors in treatment coming up with. Within the previous work, within the field of medical image process several scientist and soft computing techniques have totally different strategies like totally automatic and semiautomatic. During this projected technique, 2 totally different classification strategies are used along for the classification of magnetic resonance imaging Brain pictures. Those classification strategies square measure Neural Network and fuzzy logic. With this projected hybrid technique Genetic algorithmic program is employed for the optimization. Projected technique consists of various stages. Knowledge assortment through numerous hospitals or repository sites and convert original data pictures into gray scale image. Gray Level Co-occurrence Matrix technique is employed for the extraction of the options from the gray scale image. Optimization technique Genetic algorithmic program is especially used for reducing the options that square measure extracted by GLCM for simple classification and reducing the convergence time or computation time. there\'s a hybrid classifier is employed for classification of magnetic resonance imaging brain pictures specifically Neural and Fuzzy classifier.

Keywords- *Specificity, classification accuracy, sensitivity, GLCM, Genetic algorithm, Neuro-Fuzzzy classifier, Convergence time.*

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I. INTRODUCTION

In the medical field, since it is very critical for treatment planning and diagnosing brain abnormality such as study anatomical structure, tumour etc. Hence the classification of Magnetic Resonance images is becoming an important and difficult task. Classification of MRI brain images can be classified manually but this is a challenging task and time-consuming. Manual classification has a higher error rate because of human error and inters observer variability. Therefore, as a result of this the manual classification becomes highly poorer. Therefore, to reduce the load on the medical practitioners and human observer, an automatic classification method is highly desirable for detecting brain abnormalities. There are different number of methods are presented in literature survey. But they are having limited performance.

Artificial Neural network is method for automatic classification of MRI Brain images. Neural Network consist of supervised & unsupervised both the techniques. But in this paper supervised feed-forward back-propagation neural network technique is used for the classification of normal and abnormal brain images. Artificial neural networks working for brain image classification are being computationally heavy. And it also do not guarantee high accuracy.

Feed Forward Back Propagation Neural Network Algorithm having supervised learning that means it has target value which is used for adjusting the weights and minimizes the errors and gives the true or approximate results. Property of Back Propagation Algorithm is to train a network with a set of input vectors and get the true result. Back Propagation network and Radial Basis Function (RBF) network having similar properties and performs similar function mapping. Feed Forward Back Propagation network is the global network where Radial Basis Function network is the local network. This network is also trained by a supervised manner. In Learning Vector Quantization (LVQ) method, there are two different layers are used, input neurons layers and output neurons layers, and the network is given by prototype called as vectors of weights. This data can be changes the weights of the network for data correction.

In this paper, Feed Forward Back propagation Neural Network technique is used for supervised classification of Magnetic Resonance Imaging brain images. This is the automatic method for detection of brain abnormalities from MRI brain images. There are different unsupervised & supervised neural network has been used for the classification of MRI brain images. And different statistical techniques have been also used for the segmentation and classification of brain abnormalities. Different supervised techniques such as Artificial Neural Network (ANN), Back Propagation (BP), Learning Vector Quantization (LVQ), Radial Basis Function (RBF) and Support Vector Machine (SVM) are used for detection of brain tissues or abnormalities. Unsupervised techniques are self organizing map is used for the classification of MRI brain images.

Artificial neural networks employed for image classification problems do not guarantee high accuracy besides being heavy computation. There is necessity for a large training set to achieve high accuracy is also drawback of artificial neural network. On the other side, fuzzy logic which promises better accuracy depends heavily on expert knowledge, which cannot always available. And also it requires less convergence time, it depends on trial and error method in selecting either the fuzzy membership functions or the fuzzy rules. All these problems are overcome by the approach hybrid model namely, neuro-fuzzy model. This system removes the stringent requirements since it enjoys the benefits of both ANN and the fuzzy logic systems. In this thesis, the application of neuro-fuzzy system for MR brain abnormalities classification has been demonstrated.

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II. PROPOSED METHODOLOGY

The proposed method consists of four different steps, including the data collection through various hospitals or MRI scan laboratory, feature extraction through gray level co-occurrence matrix, optimization with the help of Genetic Algorithm and classification through Neuro-Fuzzy model. For the automated classification system the MRI Brain Images are collected from hospitals and various repository sites. The database contains both normal brain and abnormal brain images. First of all, original brain images are converted to gray scale image. Then features of the MRI brain images are extracted through (GLCM) gray level co-occurrence matrix. There are various features are extracted from the image such as Auto-correlation, Contrast, Entropy, Correlation etc. After that Genetic Algorithm optimization technique is used to reducing the features which helps for the classification purpose. Combined Neuro-Fuzzy classifier is used for the classification of normal and abnormal MRI brain images. Figure 2.1 shows the flow diagram of the proposed work.

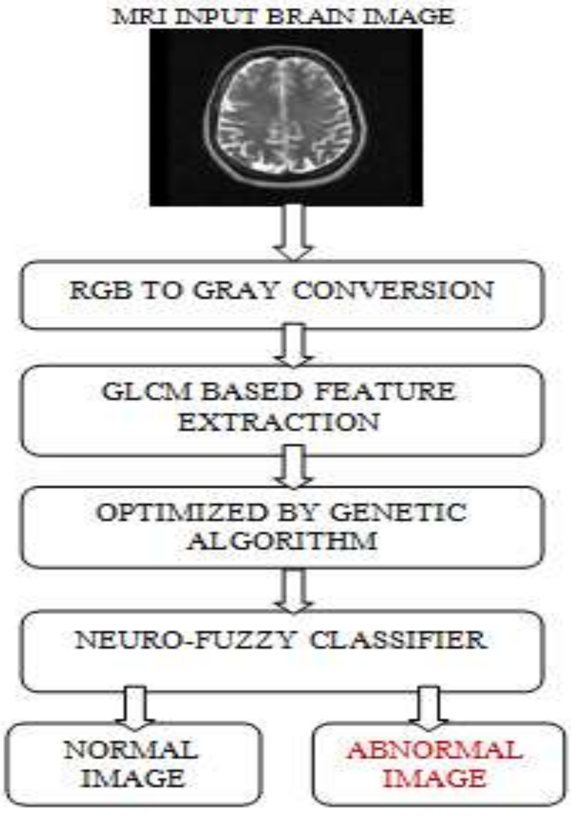

Figure 2.1 Process flow of proposed system

A. Mri image data set

For the classification normal and abnormal MRI brain images database is collected from City Life Care Durg Hospital, Chhattisgarh. Figure 2.2 shows the set of database considered for the classification of normal and abnormal brain images.

B. RGB to gray conversion

RGB to grey conversion process is used to convert a true color image in to a grayscale image. Figure 2.3 shows RGB to grey conversion of MRI brain image.[12]

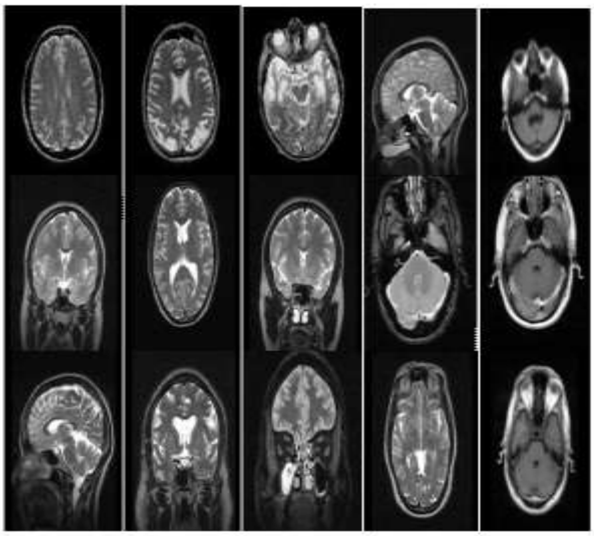

Figure 2.2 Examples of MRI Brain images

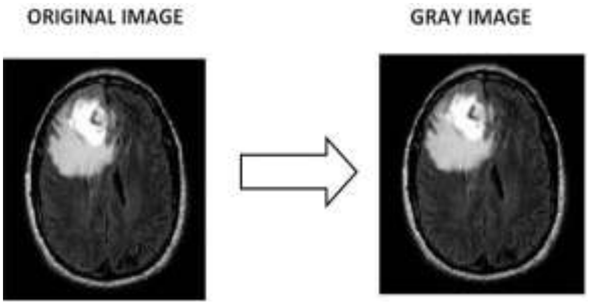

Figure 2.3: RGB to Gray conversion

C. GLCM based feature extraction

Feature extraction is the process in which, all the features are extracted for accurate classification of MRI brain images. After extracting the features, it gives the properties of the image characters, which can be used for training of MRI brain image database. That obtained trained features are compared with the test sample feature and classified as extracted characters. In this paper, feature extraction process is done using the Gray Level co-occurrence Matrix (GLCM). There are 22 features are extracted in GLCM feature extraction method for MRI brain images. The main purpose of the feature extraction process is to reduce the original dataset image by measuring assured features. The extracted features acts as input to Neural classifier by considering the description of appropriate properties of brain image into feature space.

In GLCM feature extraction method, G represents the number of gray levels used and mean value of P is represented by μ & means and standard deviations respectively P_x and P_y is represented by μ_x, μ_y, σ_x and σ_y. $P_x(i)$ shows the ith entry that is obtained by taking sum of rows of $P(i,j)$:

- ✓ Px(i) = $\sum_{j=0}^{G-1} P(i,j)$
- ✓ Py(j) = $\sum_{i=0}^{G-1} P(i,j)$
- ✓ μx = $\sum_{i=0}^{G-1} P(i,j)$
- ✓ μy = $\sum_{j=0}^{G-1} P(i,j)$
- ✓ $\sigma x^2 = \sum_{i=0}^{G-1}(Px(i) - \mu x(i))^2$
- ✓ $\sigma y^2 = \sum_{j=0}^{G-1}(Py(i) - \mu y(i))^2$

Following equations are used to compute the different textural features that can be used to train the three classifiers separately.

- ✓ Entropy = − $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times \log(P(i,j))$ (1)
- ✓ Contrast = $\sum_{n=0}^{G-1} n2\{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j)\}, |i,j| = n$ (2)
- ✓ Correlation = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i\times j\}\times P(i,j)-\{\mu x\times \mu y\}}{\sigma x\times \sigma y}$ (3)
- ✓ Variance = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} x(i-\mu)^2 P(i,j)$ (4)
- ✓ Inertia = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} x(i-j)^2 P(i,j)$ (5)
- ✓ Cluster Shade = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i+j-\mu x-\mu y)^3 P(i,j)$ (6)
- ✓ Cluster Prominence = $\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i+j-\mu x-\mu y)^4 P(i,j)$ (7)
- ✓ Maximum Probability = max(max(co_matrix)) (8)
- ✓ Autocorrelation => $r_k = \frac{C_k}{C_0}$,

  $$C_k = \frac{1}{N}\sum_{i=1}^{N-k}(z_i - z)(z_{(i+k)} - z) \quad (9)$$

  where, k= 0,1,2,3…….K, N= no. of samples
- ✓ Sum Average = $\sum_{i=0}^{2G-2} i\, P_{x+y}(i)$ (10)
- ✓ Sum Entropy = $\sum_{i=0}^{2G-2} i\, P_{x+y}(i) \log P_{x+y}(i)$ (11)
- ✓ Difference Entropy = − $\sum_{i=0}^{G-1} i\, P_{x+y}(i) \log P_{x+y}(i)$ (12)
- ✓ Information Measure of Correlation (1) = $\frac{HXY-HXY1}{\max\{HX,HY\}}$ (13)
- ✓ Information Measure of Correlation (1) = $(1-\exp[-2(HXY2-HXY)])^{0.5}$ (14)

  Where,

  HXY = $-\sum_i\sum_j P(i,j)\log(P(i,j))$,

  HX and HY are the entropies of Px and Py,

  HXY1 = $-\sum_i\sum_j P(i,j)\log\{(Px(i)Py(j)\}$,

  HXY2 = $-\sum_i\sum_j Px(i)Py(j)\log\{(Px(i)Py(j)\}$,
- ✓ Maximal Correlation Coefficient = Sqare root of the second largest eigenvalue of Q (15)

  where $Q(i,j) = \sum_k \frac{P(i,k)P(j,k)}{P_x(i)P_y(k)}$

Where x and y are the coordinates(column and row) of an enrty in the co-occurrence matrix, and P_{x+y} (i)is the probability of co-occurrence matrix coordinates summng to x+y.

D. Genetic algorithm

A Genetic Algorithm (GA) is a searching technique which is used in computing to find the true or approximate solutions to search problems. This is an Artificial Neural Network Technique. Genetic algorithms are categorized as globally search heuristics technique. This algorithm is a particular class of evolutionary algorithms that use different techniques such as crossover, selection process, mutation process and inheritance. GAs is implemented as a computer simulation, which optimizes the problem and gives toward better solutions.

The Genetic Algorithm creates new generations of chromosome-population by applying specially designed technique called crossover and mutation techniques. These methods are steady-state type of selection methods. In Genetic Algorithm, first step is to generate randomly initial populations to enable the Genetic Algorithm technique. Chromosomes in Genetic Algorithms are encoded in the form of binary. The result of encoding the chromosomes is very long binary strings. To avoid this difficulty and achieve the required precision values, two different steps are used that are cross over and mutation. There are two types of cross over is used in this paper. First is one point and another is two point cross over. In cross over, any point is selected in any population and then exchange those values by another population. And then in mutation method any selected value change by any random value. And lastly evaluate all fitness values and compare all and choose the best fitness value and apply this value as an input to the Neural classifier. Fig:2.4 show the steps of Genetic Algorithm presenting Generation Cycle.

E. Neuro-fuzzy classifier

The proposed in this paper is the combination of neural classifier and fuzzy logic classifier. It gives the advantages of both neural and Fuzzy classifier and gives the more accurate result as compare to individual neural and fuzzy logic classifier. The classification of accuracy of fuzzy logic

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classifier is better to neural classifier. And it is also inferior to Neuro-fuzzy classifier. The neural network classifier gives less accuracy because it requires large amount of training data set for high accuracy which is practically not feasible. In this paper, neuro-fuzzy classifier is used for detection or classification of the abnormalities or tissues in the MRI brain images. The neural network classifier system is work with learning capabilities. Feed Forward Back Propagation method is used in the neural classifier. This is a supervised learning based method in which desired output is available. In this proposed method comparing the result by adjusting the weight and get the good result. In this proposed methodology, rule based fuzzy logic classifier system is used. Both systems can improve the performance of the system and this neuro-fuzzy classifier system can also provide a mechanism to overcome the drawback of both the individual neural & fuzzy classifier. This hybrid classifier gives the advantages of both the classifier system& fuzzy classifier. Neural network required large training sets for achieving the high accuracy. However, using a neuro-fuzzy technique this problem can be overcome. But, Neuro-Fuzzy classifier is more complex and time consuming. Fig 2.5 shows the Neuro-Fuzzy classifier.

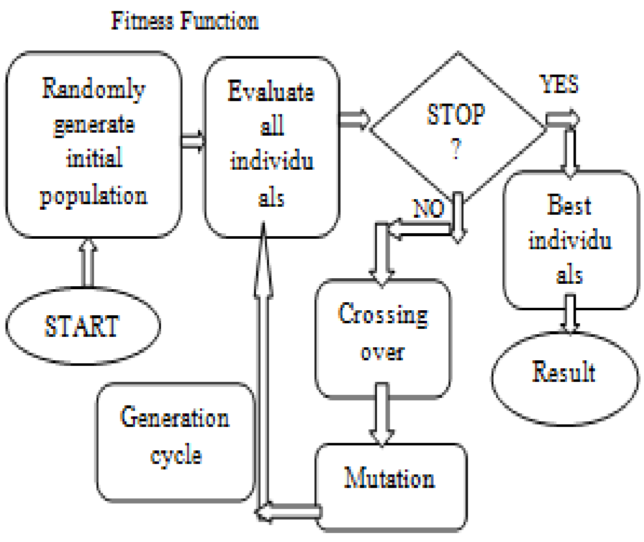


Figure 2.4: Genetic Algorithm presenting Generation Cycle

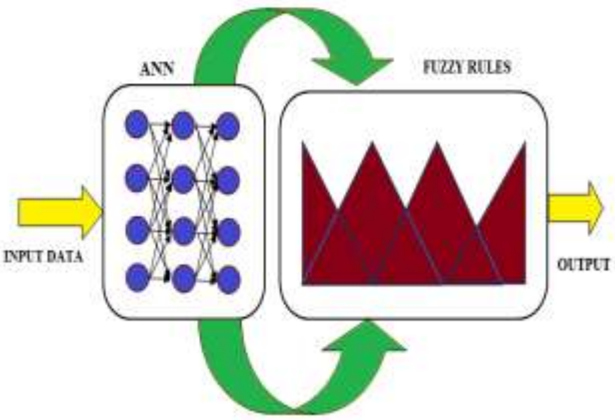


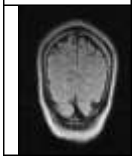
Figure 2.5: Neuro-Fuzzy Classifier

Neural-fuzzy hybrid model is performing successfully where other individual methods do not. The classification performance parameters such as accuracy, specificity, sensitivity are comparatively higher in hybrid neuro-fuzzy model than the individual fuzzy and neural classifiers. But the convergence time period of neuro-fuzzy logic classifier is more. To improve the convergence time, for Optimization Genetic Algorithm technique is used for optimization process. This reduces the processing time.

III. RESULT AND CONCLUSION

The proposed model is tested over a large no. of database of MRI brain images. In this proposed work many features have been extracted from these images. In below table.1, shows the some important extracted features and their values of these images.

Table 1: extracted features for various images

Input Image	Entropy	Contrast	Correlation	Autocorrelation	Cluster Shade
	0.4336	0.9294	25.0948	0.1841	2.315
	0.4814	0.9203	27.9746	0.1735	2.3720
	0.2377	0.9602	53.1841	0.3781	1.6720
	0.2153	0.9651	59.0189	0.3968	1.6662
	0.1632	0.9721	58.6357	0.4182	1.6107
	0.1422	0.9731	65.5944	0.4819	1.4497
	0.4606	0.9331	41.2505	0.3825	1.8191

After extracting the features by GLCM feature extraction method, we get the different feature values for the abnormal and normal MRI brain images. Below some graph shows the Entropy and Contrast values for the MRI brain normal and abnormal images.

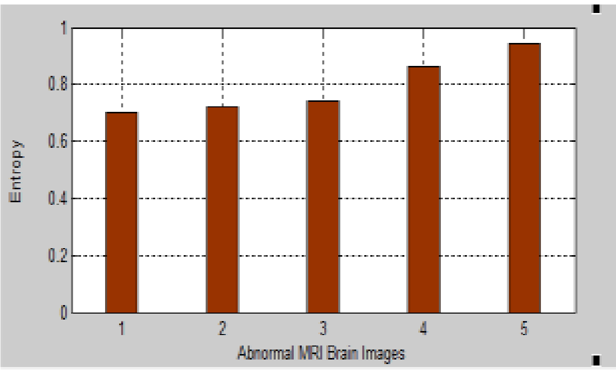


Figure 3.1: Entropy graph for abnormal MRI brain images

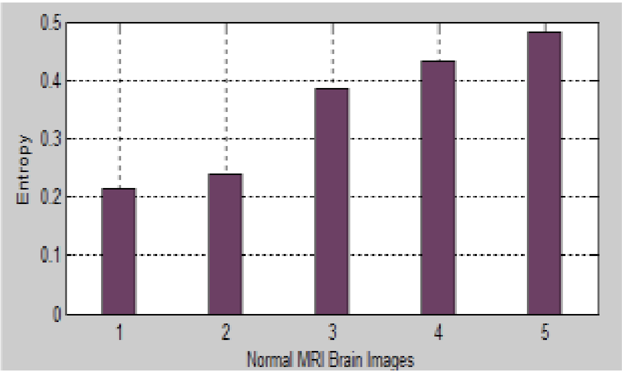


Figure 3.2: Entropy graph for normal MRI brain images

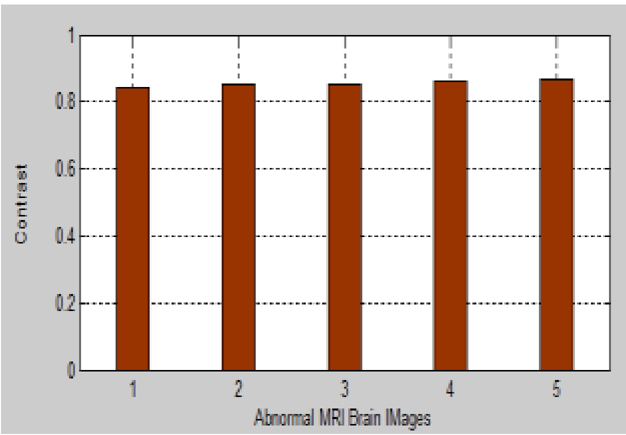


Figure 3.3: Contrast graph for abnormal MRI brain images

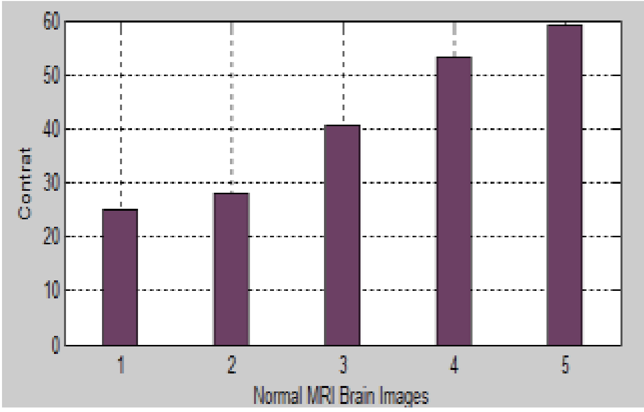


Figure 3.4: Contrast graph for normal MRI brain images

The below figure 3.5 shows the graph for the convergence time of a MRI brain image.

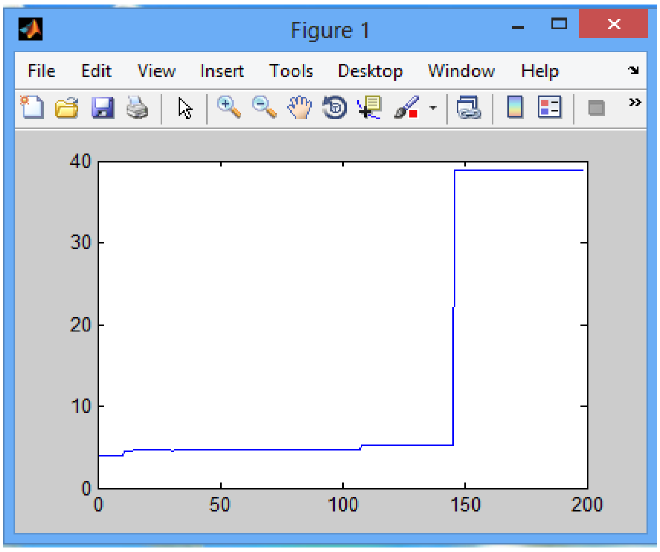


Figure 3.5: Convergence time of an Input brain image

Convergence time for the applied input MRI brain image is 0.235 seconds, which is calculated with the help of proposed methodology.

Graph between performance of the Training, validation and Testing & 23 Epochs shown in the below fig: 3.6.

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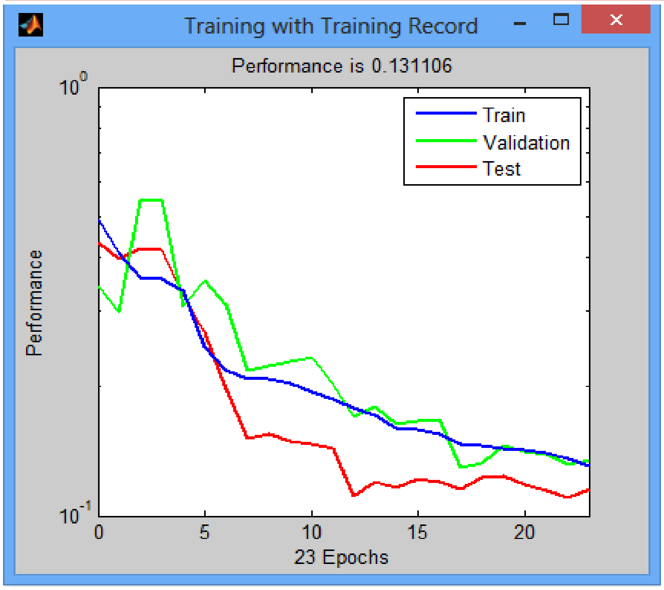

Fig 3.6: Performance graph between Train, Validation & Test

Confusion matrix is the graph between the Target class and Output class. In this matrix green color box shows the true positive values and red box shows the true negative valve. The below fig: 3.7 shows the confusion matrix for the proposed training set.

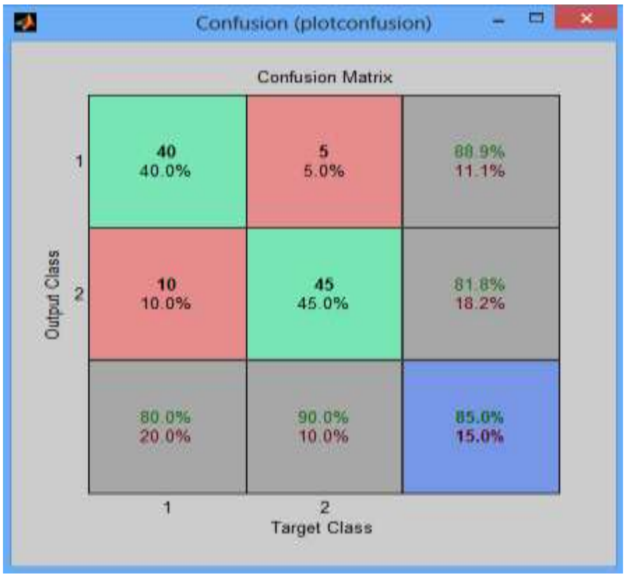

Figure 3.7: Confusion matrix between Target class & Output class

To evaluate the performance parameters of the proposed classification approach such as classification of accuracy, specificity of proposed method and sensitivity are calculated. The performance measures are as follows:-

Accuracy = (TP+TN)/ (TP+TN+FP+FN)*100 %,

Specificity = TN/ (TN+FP) *100%,

Sensitivity = TP/ (TP+FN) *100% where

True Positive (TP): Correctly classified positive cases.

True Negative (TN): Correctly classified negative cases.

False Positive (FP): Incorrectly classified negative cases.

False Negative (FN): Incorrectly classified positive cases.

Here in this practical work, we have used database of 100 images in which 50 images are Abnormal MRI brain images and 50 images are Normal MRI brain images. Here all the parameters are calculated and they are as follows:
Accuracy = 98%,
Specificity = 97.50% and
Sensitivity = 98.80%.

All those values are achieved through proposed method. The graph of performance measure is shown in the below figure 3.8:-

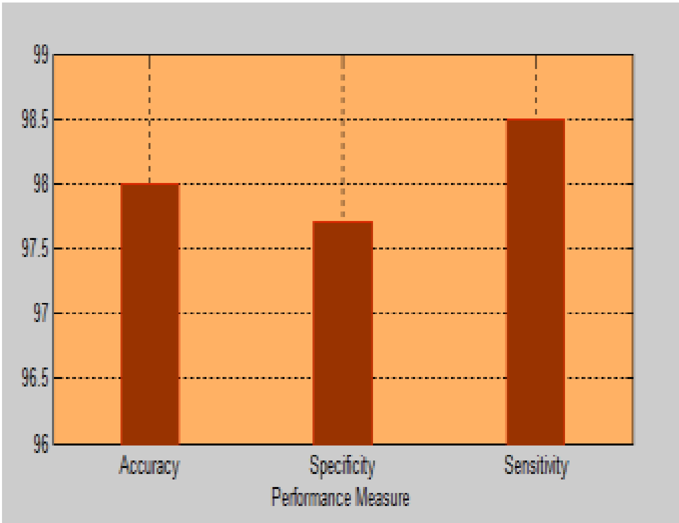

Figure 3.8: Performance Measure of Proposed Classifier

IV. COCLUSION

In this proposed work, we have tried to give a solution for the problems associated with the automatically detection of MRI brain abnormalities. The experimental results show that the propose work gives the less convergence, good accuracy, sensitivity & specificity for the classification of MRI brain abnormalities. This proposed methodology Neuro-Fuzzy classifier with Genetic algorithm can overcome the drawback of the convergence time of the hybrid neuro-fuzzy classifier. It also overcomes the drawbacks of individual artificial neural network classifier and fuzzy logic classifier by integrating the both techniques.

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