BRAIN TUMOR CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK ON MRI IMAGES

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Abstract

In this paper, an attempt has been made to summarize the multi-resolution transformation and the different classifiers useful to analyze the brain tumor using MRI. X-ray, MRI, Ultrasound etc. are different techniques used to scan brain tumor images. Radiologist prefers MRI to get detail information about tumor to help him diagnoses. In this paper we have used MRI of brain tumor for analysis. We have used Digital image processing tool for detection of the tumor. The identification, detection and classification of brain tumor have been done by extracting features from MRI with the help of wavelet transformation. The MRI of brain tumor is classified into two categories normal and abnormal brain. In this work Digital image processing has been used as a tool for getting clear and exact details about tumor in earlier stages. This helps the physicians and practitioners for diagnoses.

***Key word** – Brain tumor, Wavelet transform, segmentation.*

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1. INTRODUCTION

Brain tumor is the main cause of cancer deaths worldwide. Brain tumor can affect people at any age. Brain tumor increases mortality among children and adults. The brain is one of the complex organs in the human body. There are more than 100 billion nerves present in human brain that are in an overlapped form. Due to such a complex structure of the human brain, a diagnosis of the tumor area in the brain is a challenging task. The tumor is due to uncontrollable growth of cells in the brain. There are basically two types of primary brain tumors that are Benign tumor and Malignant tumor.

The tumor is small in size. The identification of the tumor is based on their growth pattern. Benign tumor grows slowly and it has well defined borders. It can be removed completely by surgery and it does not spread in the spinal cord, other parts of brain or other areas of the body. The malignant type of tumor is fast-growing and affects the healthy brain cells and may spread to other parts of the brain or spinal cord. It is more harmful and may remain untreated. So detection of such brain tumor location, identification and classification in earlier stage is a serious issue in medical science [1].

Imaging technology in Medicine helps doctors to observe the interior portions of the human body for easy diagnosis. Digital image processing is one of the tool by which it is easier to analyze medical images in a short span of times, by digital image processing it is possible to detect, identify and analyze the brain tumor easily. Digital image processing also has an advantage like reproducing original data without any change and enhancing an image which helps the Radiologist for diagnosis in earlier stage.

2. LITERATURE REVIEW

According to National Brain Tumor Society, people having primary tumor are about 688,000 and according to Central Nervous System (CNS) in the United States, 138,000 people with malignant tumor and 550,000 with nonmalignant tumors [2]. So classification of tumor is an important issue. Numbers of authors have worked on this issue, which described in this session. ShanShen *et al* proposed fuzzy c-means clustering (IFCM). The proposed algorithm is based on neighborhood attraction. It is considered that it exist between neighboring pixels. This neighborhood attraction depends on the pixel intensities , the spatial position of the neighbor pixels and on neighborhood pixel structure . The classification of tumor is done with the help of artificial neural network (ANN) based on the similarity between feature vectors [3]. Dina Aboul Dahab *et al* proposed a technique for the enhancement an image in a spatial domain based on direct manipulation of pixels in a neighborhood of pixels. The enhancement in frequency domain based on the concept of the convolution theorem and spatial filters. In this paper author used probabilistic neural networks (PNN) which is based on learning vector quantization (LVQ). LVQ is a supervised competitive learning technique; it defines object boundaries and the rules for pixels that are the nearest neighborhood [4]. Chandrakant Biradar *et al* proposed an algorithm to extract the tumor region from MRI images. They applied DWT to decompose an image. The author applied segmentation on DWT image to extract tumor region. They extracted the features like size; shape and texture to classify the type of tumor .they have used SVM classifier for classification [5]. Atiq Islam *et al* proposed an algorithm for segmentation of brain tumor MRI. Due to complex appearance of brain in MRI, author designed multiresolutionfractal technique to get multifractal features form tumor segmented images. The segmentation of proposed multiracial feature compared with Gabor features in this paper. The classification has been done by using multiracial features of tumor with the help of novel DiverseAdaBoost SVM classifier to improve tumor classification rate [6]. Meiyan Huang *et al* proposed the classification framework with the help of local independent projection into the classical classification model. The performance evaluation of proposed LIPC classifier had done by using two-spiral structure by authors. They also compared two classification techniques like SRC and Support Vector Machine (SVM) [7]. Dr. P.V. Ramaraju et *al* proposed an algorithm for classification of brain tumor. They have used MRI of brain to detect and classify a tumor. This algorithm is based on a wavelet transformation. The wavelet transformation is used to extract features from brain tumor MRI. Author has used feed forward probabilistic neural networks (PNN) to classify brain tumor based on these extracted features. They classified MRI of brain into benign, malignant or normal classes [8].

3. PROPOSED METHODOLOGY

The MRI of brain is represented here as a gray scale image. These gray scale images are having intensity levels ranging from 0-255, where 0 represents black color and 255 represents white color. Figure 1 shows a sample MRI of brain tumor from the data base used for this work. The database is of 72 brain MRI image.

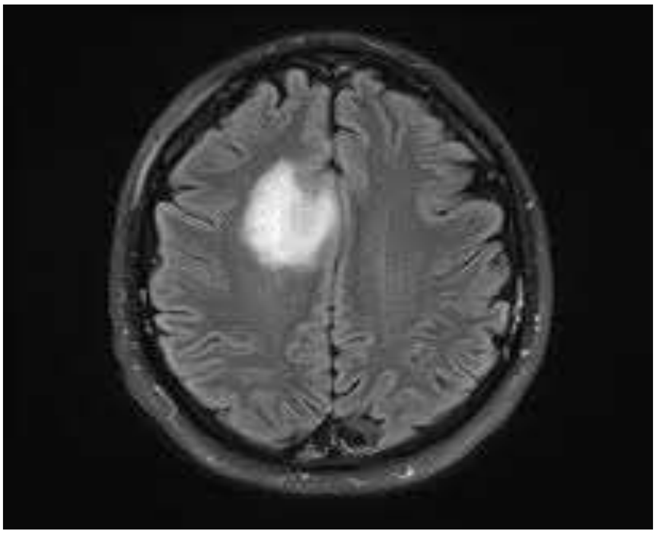

Figure.1. Brain Tumor MRI image

The blood cells in brain are represented by white color and remaining portion of brain is represented by different gray color shade, whose intensity is less than 255 in MRI. Using this basic idea we have designed our algorithm to find out first order textural features from MRI of brain tumor and selection of exact classifier technique from the study of different classifiers based on the features.

In this proposed algorithm MRI image of brain as are used as an input. These MRI images of brain are clearer than CT scan images. Figure 2 shows various stages that are followed for tumor declaration. The major blocks used are

I. Preprocessing.
II. Feature extraction
III. Classification

I. PREPROCESSING

Input for proposed algorithm is a brain tumor image obtained from MRI. These images are not that much clear for tumor declaration. So preprocessing is the first step to make an input image more visible to human eye. At this stage to remove the blurriness of MRI images we have used median filter .Median filter remove the noise from MRI of brain tumor. Median filter gives a smooth image. After getting a smooth image, the next step is enhancement. The image enhancement increases sharpness of this filtered image. Here the enhancement of this filtered image has been done using power law transform. Power log transform gives sharper image then the input image.

II. FEAURETURE EXTRAXTION

Feature extraction is a stage where we have extracted the features from the sharpened image, which required as an input for classifier. In this algorithm we have used discrete cosine transformation (DWT). It is one of the types of wavelet transformation.

In this algorithm, two level decomposition of 'Symlet' DWT is used. This transform is applied to enhanced image. The DWT divides enhanced image into four regions using low pass filter and high pass filter bank and gives four different coefficients like absolute coefficient, diagonal coefficient, horizontal coefficient and vertical coefficient. The major information of an image is present in absolute coefficients as compare to remaining three regions. So we have selected absolute coefficients for feature extraction. We extracted different features like Contrast, Homogeneity, Correlation, Energy etc. These features are used as an input to classifier for tumor declaration.

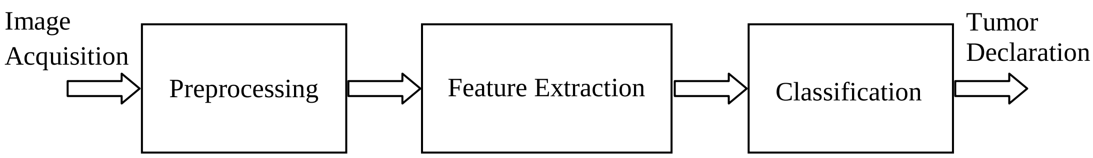

Figure.2. Block diagram of tumor declaration

III. CLASSIFICATION

Classification is the essential step, where the brain tumor MRI classified into cancerous and noncancerous classes. The selection of a particular classifier is based on number of inputs and number of outputs to the classifier, features extracted from patterns as well as the type of input images. There are number of classifiers can be used to classify an images into different classes. Some classifiers are as follows.

a. MULTILAYER PERCEPTRONS (MLP)

Multilayer perceptron's are layered feed forward networks. These networks are mostly used for classification of an image into different classes. Multilayer perceptron's are useful in number of applications, where statistical classification is required.

b. PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is useful to approximate the original information with the help of least number of component .PCA is useful for approximating data with lower dimensional vectors. The PCA approach is based on eigenvectors, which is based on covariance matrix of an original image. By using PCA the test image was first identified by projecting the original image onto the eigen space to extract the corresponding set of weights and then the comparison has done with the help of a set of weights of an image in the training set [9].

c. SUPPORT VECTOR MACHINE (SVM)

After feature extraction from an image, classification is the main task. The performance of classifier depends upon the number of features, samples. There are number of classifiers available for classification. SVM is one of the supervised classifier which gives good results in medical diagnosis. It gives better result in a high dimension feature space. SVM has also been applied on different real world problems such as face recognition, text categorization; cancer diagnosis .This SVM classifier gives better result for classification of binary MRI images [10].

d. PROBABLISTIC NEURAL NETWORK (PNN)

Probabilistic Neural Network is the classifier that is useful for medical application. In some algorithms feature extraction has done with the help of GLCM and classification of images has done by using PNN. This classifier gives fast and accurate classification [11].

In proposed methodology MLP classifier has used its advantage is that it is easy to use and it can easily approximate any gray scale input or output map. The MATLAB and Nerosolution tools have been used for the classification of brain tumor MRI.

4. RESULT AND DISCUSSION

In proposed algorithm classification of brain tumor has done using MLP. MLP verified these MRI input and classified it into Benign or Malignant tumor classes. Here MLP designed with number of hidden and output layers with different transfer functions and learning rules along with various percentages of training and testing data. Some sample results shown here are of three and five hidden layers and with different hidden layer transfer functions like TanhAxon, SigmoidAxon and LinearsigmoidAxon. The output layer transfer function is Sigmoid Axon. The learning rule at hidden layers and output layer is Levenbergmarqua. There are 29 different MLP combinations with their results shown here. This includes graph of mean square error (MSE) after three runs. The table which gives information regarding the minimum MSE, regression factor and percentage accuracy. By referring these results it's easy to verify a MLP network which gives accurate result by considering the conditions like true positive, false positive, true negative and false negative.

1. The results of MLP that designed with 50% database for training and 50%database for testing a network with three hidden layers has been shown in Figure 3 and Table 1. The TanhAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

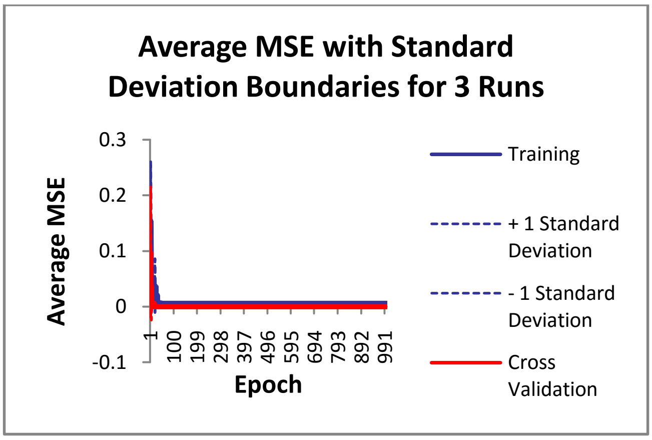

Figure.3. Average MSE with S.D.B. for three runs

Table.1. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	2
Epoch #	999	999
Minimum MSE	0.006136364	1.77468E-09
Final MSE	0.006136364	1.79021E-09

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	13	6
Col1(0)	5	14

Performance	*Col1(1)*	*Col1(0)*
MSE	0.290002106	0.289712851
NMSE	1.163230668	1.162070435
MAE	0.290280969	0.289828325
Min Abs Error	2.99852E-08	8.58814E-08
Max Abs Error	1.009131705	1.004234283
r	0.420533115	0.421132249
Percent Correct	72.22222222	70

2. The results of MLP that designed with 50% database for training and 50%database for testing a network with three hidden layers has been shown in Figure 4 and Table 2. The Sigmoid Axon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

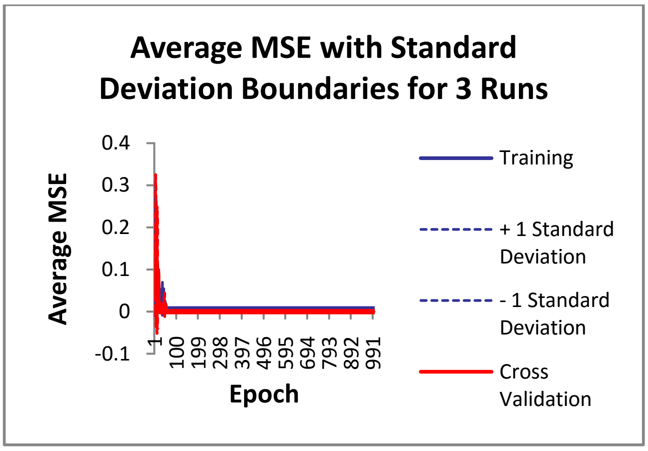

Figure.4. Average MSE with S.D.B. for three runs

Table.2. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	1
Epoch #	1000	1000
Minimum MSE	0.006136364	6.87844E-07
Final MSE	0.006136364	6.87844E-07

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	12	5
Col1(0)	6	15

Performance	*Col1(1)*	*Col1(0)*
MSE	0.284861912	0.284861912
NMSE	1.14261278	1.14261278
MAE	0.291762638	0.291762638
Min Abs Error	1.35502E-07	1.35502E-07
Max Abs Error	1.000821603	1.000821603
r	0.419999862	0.419999862
Percent Correct	66.66666667	75

3. The results of MLP that designed with 60% database for training and 40%database for testing a network with three hidden layers has been shown in Figure 5 and Table 3. The TanhAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design MLP classifier.

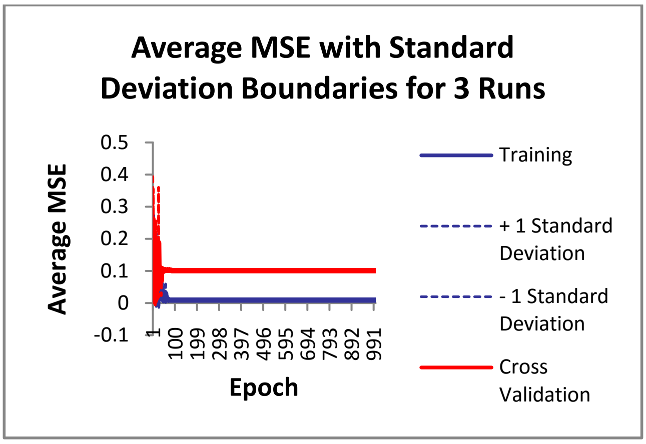

Figure.5. Average MSE with S.D.B. for three runs

Table.3. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	1
Epoch #	727	6
Minimum MSE	0.009878049	0.000508521
Final MSE	0.009878049	0.101250136

Output / Desired	*Col1(0)*	*Col1(1)*
Col1(0)	10	1
Col1(1)	5	14

Performance	*Col1(0)*	*Col1(1)*
MSE	0.171753813	0.176993994
NMSE	0.68701525	0.707975976
MAE	0.208805816	0.204471573
Min Abs Error	0.01867669	0.003248765
Max Abs Error	0.98049437	0.996037063
r	0.657378803	0.655903134
Percent Correct	66.66666667	93.33333333

4. The results of MLP that designed with 70% database for training and 30%database for testing a network with three hidden layers has been shown in Figure 6 and Table 4.The TanhAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

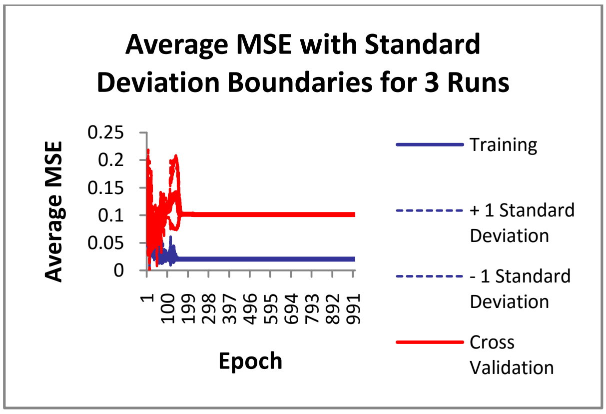

Figure.6. Average MSE with S.D.B.for three runs

Table.4. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	1
Epoch #	1000	50
Minimum MSE	0.020663265	0.000487995
Final MSE	0.020663265	0.101249976

Output / Desired	*Col1(0)*	*Col1(1)*
Col1(0)	8	1
Col1(1)	3	10

Performance	*Col1(0)*	*Col1(1)*
MSE	0.159034196	0.16115271
NMSE	0.636136782	0.644610842
MAE	0.178435182	0.179954692
Min Abs Error	0.000593434	3.47955E-05
Max Abs Error	0.997620132	1.000161918
r	0.678696463	0.673600142
Percent Correct	72.72727273	90.90909091

5. The results of MLP that designed with 80% database for training and 20% database for testing a network with three hidden layers has been shown in Figure 7 and Table 5.The Linear SigmoidAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

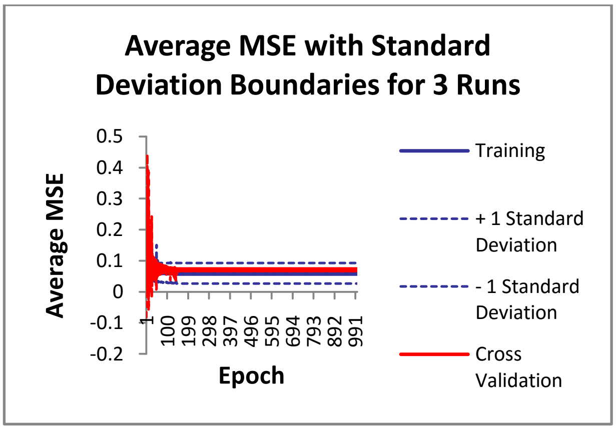

Figure.7. Average MSE with S.D.B.for three runs

Table.5. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	3
Epoch #	141	4
Minimum MSE	0.038974871	5.52201E-05
Final MSE	0.038974871	0.074255015

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	0	0
Col1(0)	9	6

Performance	*Col1(1)*	*Col1(0)*
MSE	0.585828947	0.586106719
NMSE	2.440953948	2.442111331
MAE	0.597553803	0.597578527
Min Abs Error	0.011661897	0.011327293
Max Abs Error	0.988214604	0.98850352
r	0.681737659	0.681731578
Percent Correct	0	100

6. The results of MLP that designed with 50% database for training and 50%database for testing a network with five hidden layers. The TanhAxon function at hidden layer has been shown in Figure 8 and Table 6, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

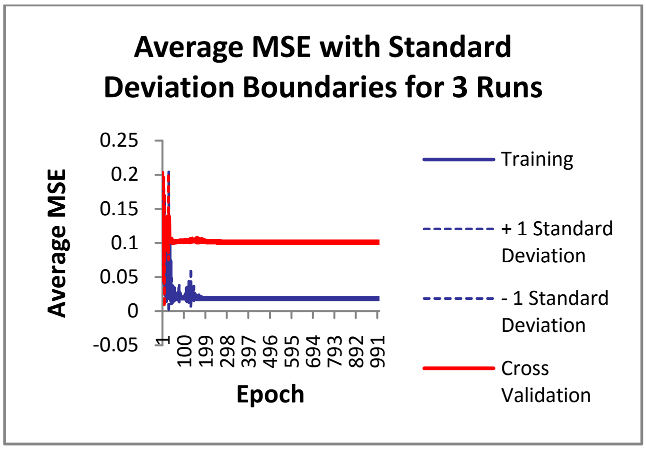

Figure.8. Average MSE with S.D.B. for three runs

Table.6. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	2
Epoch #	1000	10
Minimum MSE	0.018409091	0.004710426
Final MSE	0.018409091	0.101250078

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	10	0
Col1(0)	5	23

Performance	*Col1(1)*	*Col1(0)*
MSE	0.128431286	0.127960088
NMSE	0.537550078	0.535577877
MAE	0.209681988	0.206906826
Min Abs Error	0.02899802	0.026975136
Max Abs Error	0.934267124	0.936158062
r	0.721359045	0.722186609
Percent Correct	66.66666667	100

7. The results of MLP that designed with 60% database for training and 40%database for testing a network with five hidden layers has been shown in Figure 9 and Table 7. The SigmoidAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

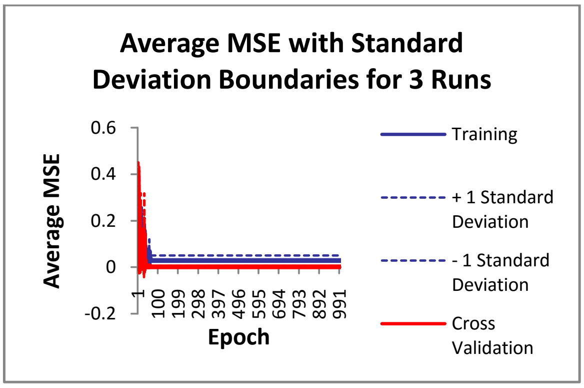

Figure.9. Average MSE with S.D.B. for three runs

Table.7. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	1
Epoch #	999	1000
Minimum MSE	0.004939024	3.08311E-13
Final MSE	0.004939024	3.08311E-13

Output / Desired	*Col1(0)*	*Col1(1)*
Col1(0)	15	6
Col1(1)	4	5

Performance	*Col1(0)*	*Col1(1)*
MSE	0.333292125	0.333295741
NMSE	1.435229248	1.43524482
MAE	0.333314401	0.333316308
Min Abs Error	8.81615E-08	4.62701E-08
Max Abs Error	1.00002567	1.000022725
r	0.256671268	0.256665338
Percent Correct	78.94736842	45.45454545

8.The results of MLP designed with 70% database for training and 30% database for testing a network with five hidden layers has been shown in Figure10 and Table 8. The TanhAxon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	5	3
Col1(0)	3	11

Performance	*Col1(1)*	*Col1(0)*
MSE	0.272784227	0.272809807
NMSE	1.178817554	1.178928093
MAE	0.272883818	0.272919695
Min Abs Error	2.91852E-06	1.71976E-06
Max Abs Error	1.000219309	1.000321875
r	0.410450333	0.410364346
Percent Correct	62.5	78.57142857

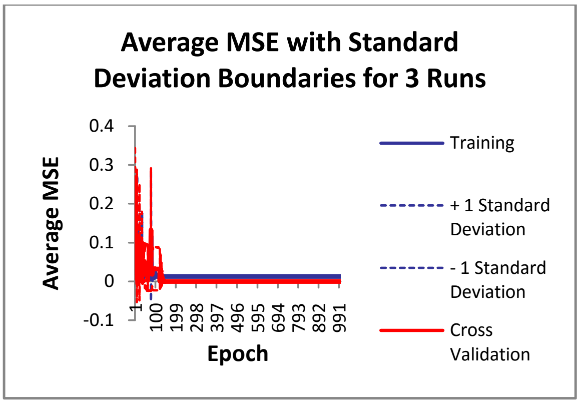

Figure.10. Average MSE with S.D.B. for three runs

Table.8. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	2
Epoch #	1000	347
Minimum MSE	0.012397959	1.01311E-09
Final MSE	0.012397959	1.08339E-06

9. The results of MLP that designed with 70% database for training and 30%database for testing a network with five hidden layers has been shown in Figure 11 and Table 9. The Sigmoid Axon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

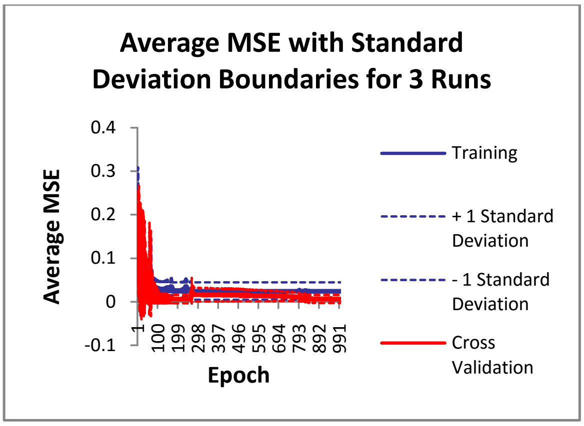

Figure.11. Average MSE with S.D.B. for three runs

Table.9. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	2	2
Epoch #	1000	1000
Minimum MSE	0.012397959	4.63139E-06
Final MSE	0.012397959	4.63139E-06

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	9	3
Col1(0)	1	9

Performance	*Col1(1)*	*Col1(0)*
MSE	0.187784297	0.187778004
NMSE	0.757396663	0.757371284
MAE	0.202055781	0.202035265
Min Abs Error	1.08352E-06	7.20899E-07
Max Abs Error	1.000000176	0.999999931
r	0.631840611	0.631864851
Percent Correct	90	75

10. The results of MLP that designed with 70% database for training and 30%database for testing a network with five hidden layers has been shown in Figure 12 and Table 10. The Linear Sigmoid Axon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

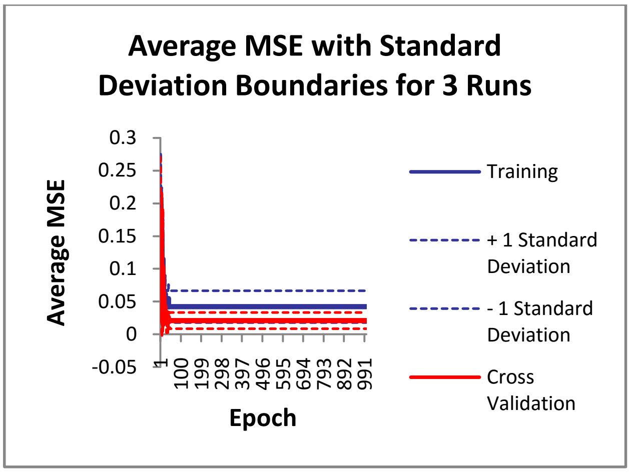

Figure.12. Average MSE with S.D.B. for three runs

Table.10. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	3	3
Epoch #	47	37
Minimum MSE	0.02637897	0.00013607
Final MSE	0.02637897	0.006843285

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	9	4
Col1(0)	1	8

Performance	*Col1(1)*	*Col1(0)*
MSE	0.120585703	0.12047363
NMSE	0.486362335	0.485910307
MAE	0.204653233	0.2023745
Min Abs Error	0.008063106	0.002503527
Max Abs Error	1.021844722	1.018708783
r	0.728278251	0.728898772
Percent Correct	90	66.66666667

11. The results of MLP that designed with 80% database for training and 20%database for testing a network with five hidden layers has been shown in Figure13 and Table 11. The Sigmoid Axon function at hidden layer, Linear Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

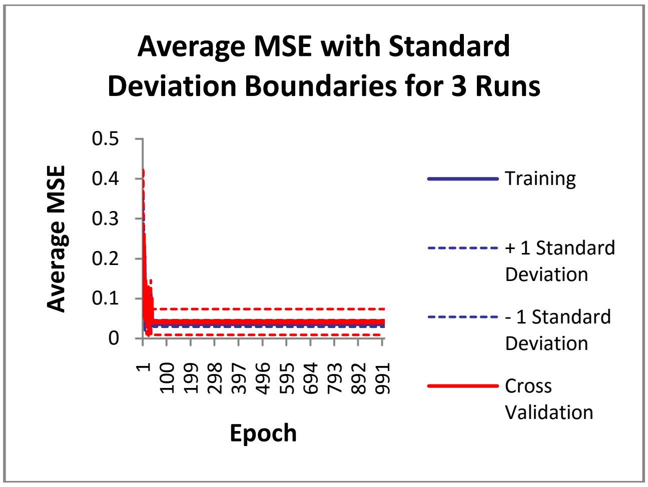

Figure.13. Average MSE with S.D.B. for three runs

Table.11. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	3	1
Epoch #	53	30
Minimum MSE	0.028464595	0.005342038
Final MSE	0.028464595	0.005342053

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	6	4
Col1(0)	2	3

Performance	*Col1(1)*	*Col1(0)*
MSE	0.318735299	0.31873529
NMSE	1.280632897	1.280632863
MAE	0.4240641	0.424064103
Min Abs Error	0.088236967	0.088237001
Max Abs Error	0.911763033	0.911762999
r	0.188982237	0.188982237
Percent Correct	75	42.85714286

12. The results of MLP that designed with 90% database for training and 10%database for testing a network with five hidden layers has been shown in Figure 14 and Table 12. The Sigmoid Axon function at hidden layer, TanhAxon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

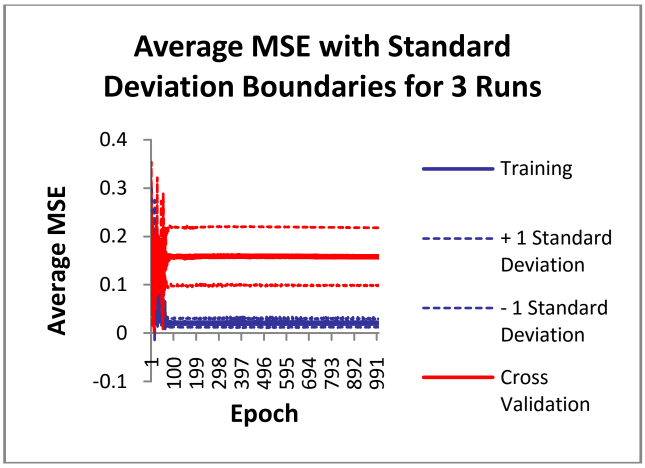

Figure.14. Average MSE with S.D.B. for three runs

Table.12. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	2	2
Epoch #	1000	14
Minimum MSE	0.016071429	0.001209166
Final MSE	0.01607143	0.20251269

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	5	1
Col1(0)	0	2

Performance	*Col1(1)*	*Col1(0)*
MSE	0.141924775	0.142004327
NMSE	0.605545707	0.605885129
MAE	0.180090077	0.180807332
Min Abs Error	0.051770794	0.054609445
Max Abs Error	1.055553126	1.0555548
r	0.745347813	0.745351192
Percent Correct	100	66.66666667

13. The results of MLP that designed with 90% database for training and 10%database for testing a network with five hidden layers has been shown in Figure 15 and Table13. The Sigmoid Axon function at hidden layer, Sigmoid Axon function at output layer and Levenberg learning rule has been used to design this MLP classifier.

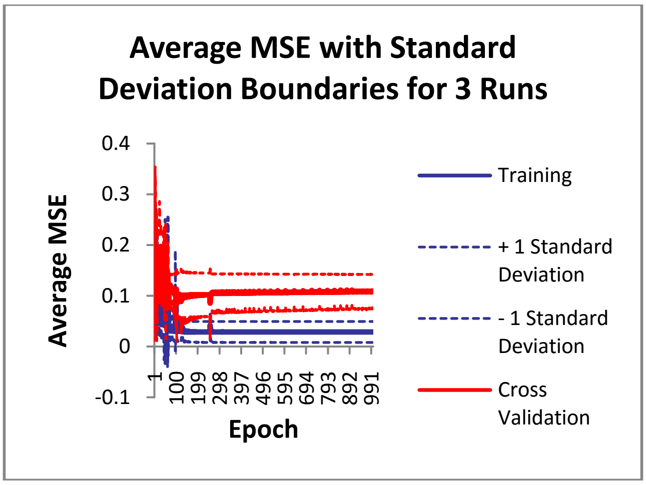

Figure.15. Average MSE with S.D.B. for three runs

Table.13. Performance of MLP

Best Networks	*Training*	*Cross Validation*
Run #	1	1
Epoch #	823	2
Minimum MSE	0.016071429	0.00125
Final MSE	0.016071429	0.101250941

Output / Desired	*Col1(1)*	*Col1(0)*
Col1(1)	4	0
Col1(0)	0	4

Performance	*Col1(1)*	*Col1(0)*
MSE	0.003086419	0.00308642
NMSE	0.012345676	0.012345679
MAE	0.05555555	0.055555555
Min Abs Error	0.055555544	0.055555555
Max Abs Error	0.055555556	0.055555555
r	1	1
Percent Correct	100	100

7. CONCLUSION

The proposed algorithm for classification of brain tumor MRI image classified MRI images database effectively into benign tumor and malignant tumor with the help of MLP classifier. The MLP classifier used here with three and five number of hidden layers by using different hidden layer functions and output layer functions. By observing the above results, it's seen that MLP classifier is the best classifier for brain tumor MRI database. MLP classifier classified the database accurately at 90% database for training and 10%database for testing a network with five hidden layers, Sigmoid Axon function at hidden layer, Sigmoid Axon function at output layer with Levenberg learning rule.

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