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Classification of Brain Tumor Grades by MRI Images using Artificial Neural Network

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Abstract

In recent years, the use of MRI images has been very much considered due to their high clarity and quality in diagnosing along with determining brain tumors and their features. In this study, to improve tumor detection performance, we investigated the comparative approach of the different classifiers to select the most appropriate classifier for identifying and extracting abnormal tissue and selected the best one by comparing their detection accuracy rate. In this research, GLCM and GLRM methods are used to extract discriminating features, and their results lead to reduced computational complexity. The fuzzy entropy measurement method is used to determine the optimal properties. Then, we compared the four FFNN, MLP, BPNN, ANFIS neural networks to perform the decision making and classification process. The purpose of these four neural networks is to develop tools for discriminating the malignant tumors from benign ones assisting in deciding clinical diagnosis. Based on the results, we achieved high results among all classifiers. The proposed methods result in accurate and speedy detection of tumors in the brain and identifies the precise location of the tumor. In our opinion, the use of these classifiers can be very useful in the diagnosis of brain tumors in MRI images. Our other goal is to prove the suitability of the ANN method as a valuable method for statistical methods. The research novelty lies in implementing the proposed method for discriminating malignant tumors from benign, which results in accurate and speedy detection of tumors in the brain along with identifying the precise location of the tumor. The efficiency of the method is proved through plenty of simulations and comparisons.

Keywords: Brain tumor, MRI images, GLCM, GLRM, Artificial neural network

1.Introduction

Any abnormality in the brain hinders the normal functioning of it. This abnormality can be due to tumor, hemorrhage, ischemia, trauma, etc. Image processing has played a vital role in today's technological world. It can be applied in numerous application areas such as medical, remote sensing, computer vision, etc. The brain tumor is caused due to formation of abnormal tissues within the human brain. Therefore, it is necessary to remove the affected tumor part from the brain securely. The tumor can be diagnosed using techniques such as:

- X-Ray
- Computed Tomography (CT Scan)
- Positron Emission Tomography (PET)

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- Magneto Encephalography (MEG)
- Biopsy
- Magnetic Resonance Imaging (MRI)

Among various medical imaging techniques, Magnetic Resonance Imaging (MRI) employs a vital role in generating images of internal parts of the human body. Brain Tumor results due to the uncontrolled and abnormal division of the cells present in the brain, which is divided into more than 120 categories. Brain tumors are one of the most important causes of death among people. Due to brain tumors, the high human casualties, the need for early diagnosis and timely treatment of patients, the inadequacy of the usual and old methods, etc. were factors that made the automated systems in this direction more advanced.

The primary tumors are further categorized as benign and malignant tumors. Benign tumors have well-defined boundaries which are not deeply rooted inside the brain tissues, so it can be easily removed by surgery, whereas malignant tumors spread faster and it is difficult to remove them in comparison to benign tumors. As a complex tissue of human organs, the brain causes manual diagnosis of its tissues and brain tumors very time consuming and dependent on the operator's conditions. The high human casualties due to brain tumors, the need for early diagnosis and timely treatment of patients, the inadequacy of the usual and old methods, the need for knowledgeable people to carry out these old methods was one of the factors that made the automated systems in this direction more advanced. Depending on the degree for tumor, the treatment time and type of treatment will vary for patients. In the field of tumor detection, much work has been carried out and different results have been achieved. Kurani et al. [1] investigated a new approach to the co-occurrence matrix currently for volumetric data used to extract textural features. The co-occurrence matrices for volumetric texture that are introducing in this paper are 2D dependence matrices that are able to capture the spatial dependence of gray-level values in a set of 3D data i.e. a set of CT scans for a given patient is given as a single three-dimensional input. they examined the five organs of the Backbone, heart, liver, kidney (L and R), and spleen. The results of their experiments that 86% of the volumetric feature values fall within the corresponding 2D feature ranges across all organs. Of the five organs, the Heart and Kidney hade the least consistency between the volumetric data and the 2D data. This inconsistency can be explained by the varying textures within these organs as moving from one slice to the next.

Chaplot et al. [2] proposed a novel method using wavelets as input to SOM[1] and SVM [2]classifiers for classify normal and abnormal axial T2-weighted MR images of the human brain. The performances of both these classifiers are evaluated and based on this neural network is found to be the efficient classifier.

Arthi and Tamilarasi [3] presented a valuable alternate predictive method in diagnosing ADHD for the pediatricians and special educators. The approach proposed in this paper uses a hybrid neural network system consisting of Kohonen's self-organizing maps followed by a radial basis function which uses fuzzy membership values as input. then results were compared with the backpropagation algorithm. The hybrid model of SOM and RBF networks had better accuracy when compared to backpropagation neural networks. Even they were less vulnerable to problems with nonstationary inputs due to the behavior of the radial basis function hidden units.

S. N. Deepa and B. Aruna Devi [4] exploited the capability of BPN[3] and RBFN[4] to classify brain MRI images to either cancerous or noncancerous tumor automatically. The accuracy was in higher end for RBFN. N. Varuna Shree and T. N. R. Kumar [5] have used brain MR images, segmented into normal brain tissue and abnormal tumor tissue. Discrete wavelet transform based decomposes the images and textural features were extracted from GLCM followed by morphological operation. Then PNN[5] classifier used for the classification. Results expressed the detection of brain tumor was fast and accurate when compared to the manual detection carried out by clinical experts.

Bahadure et al. [6] segmented brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid (background), and tumor-infected tissues. To get the best possible segmentation results, they developed the comparative approach for comparing four segmentation techniques based on watershed, FCM, DCT, and BWT and selected the

[1]Self-Organizing Maps
[2] Support Vector Machine
[3] Back propagation neural network
[4] Radial Basis Function Neural network
[5] Probabilistic neural network

best by comparing their segmentation score. Further, to improve the classification accuracy, the genetic algorithm was employed for the automatic classification of tumor stage. The experimental results also obtained an average of 93.79% dice similarity index coefficient, which indicates better overlap between the automated extracted tumor regions.

Pandiselvi and Maheswaran [7] used fourty one slices of brain tumor parts of the real patients. The process of Feature Extraction was performed by using GLCM algorithm. The SVM involved Gaussian kernel functions in classifying the MRI image as either Normal or Abnormal by using the ACRC[1] algorithm. Next, the segmented tumor part was converted from 2D into the 3D format by applying RMIM[2] algorithm and cubic interpolation technique. Then the volume of the tumor was estimated by using a bounding cube. The accuracy rate of this proposed system for the slices used varied from 89 to 99.7.

This paper is structured as follows: After a general introduction and a review of the work done in the field of MRI image classification in the first section, the second phase describes the proposed system. Then, in the third section, experimental and empirical results of the system and comparison are discussed. The final part of the paper is the section of the conclusion and future work.

2. Proposed System

The proposed system for brain tumor classification can be done by first extracting its features, and the flow diagram is shown in fig.1.

2.1. Data Collection

This study used fifty randomly selected MRI images from 5000 data sets, including normal and abnormal human brain images. The brain images used for the experiments, which include both normal and abnormal, are shown in fig.2.

2.2. Feature Extraction

Feature extraction is a process in which its prominent features are determined by performing operations on the data. An image can be described with features that it has. In identifying tumors in the images, many factors, such as tumor color, tumor size, movement, homogeneity, shape, etc., are involved. By defining the filter for each of these features, factors and objects other than the tumor can be identified and deleted in the image. In order to determine the identity of the image from the patterns of an image, a certain general or specific profile of the image should be drawn out of the image. General features include pixel-level features, local and global features. Application-specific features vary depending on the type of application for which the feature is to be extracted. For example, color information is represented using the color models and based on the similarity of color models. The color feature is used as the visual features in image retrieval.

In the field of extracting features, we can use different methods such as Wavelet transform [8, 9, 10, 11, 12], histogram [13], use of the law of symmetry of the brain and Statistic features [12, 13, 14, 15], Statistical features [2, 9, 12, 16], PCA[3] method [11, 17] and etc.

To extract the feature, we extract the optimal and desired features from the GLCM and GLRM matrices, which we will explain below.

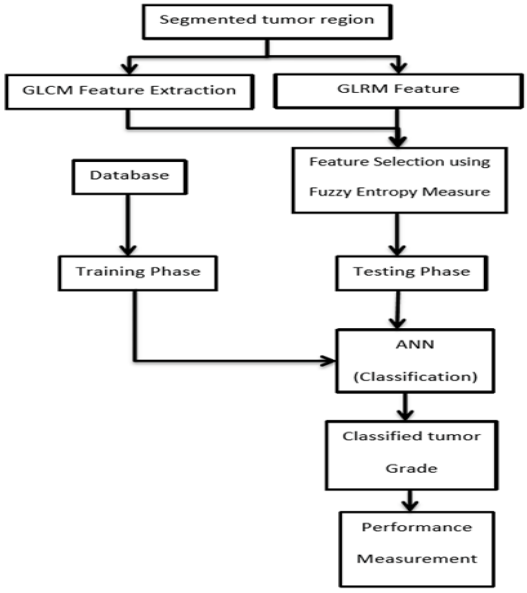

Fig.1. Flow Diagram For The Proposed System

[1] Adaptive Convex Region Contour
[2] rapid mode image matching
[3] Principal component analysis

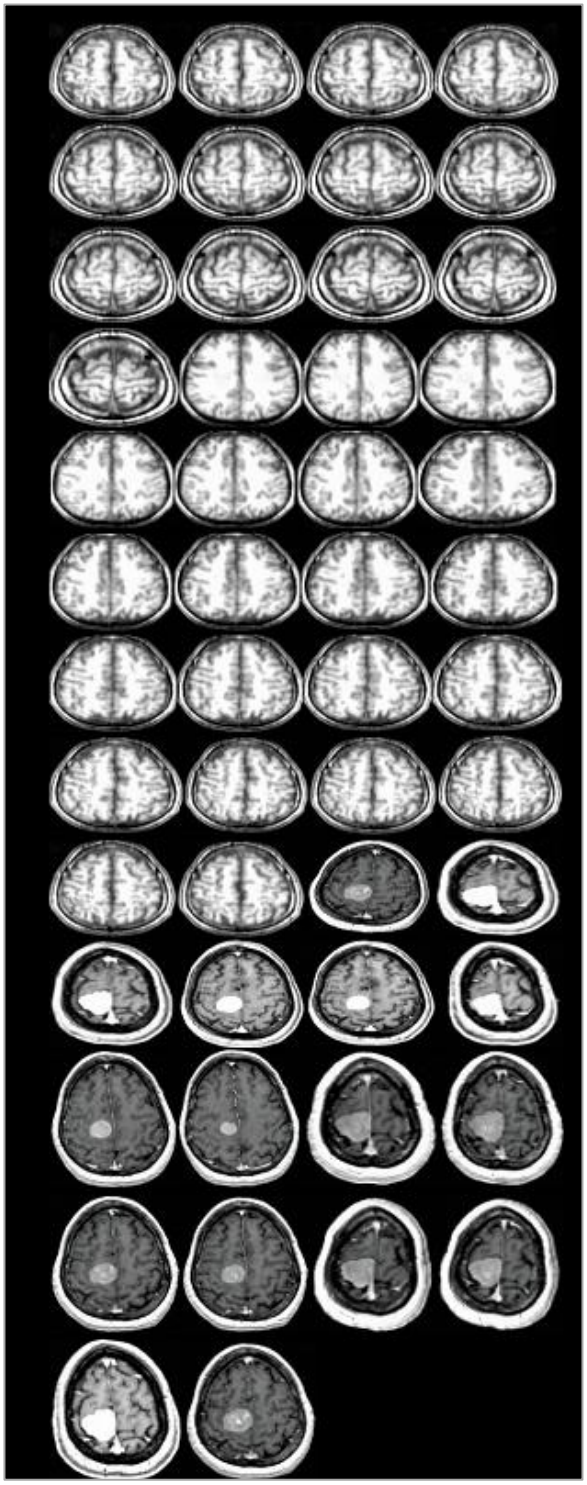

Fig. 2. Dataset Of MRI Brain Images. Our Dataset Contains 42 Normal MRI Images And 16 Abnormal Brain Images.

2.2.1. GLCM Based Feature Extraction

Gray Level Co-occurrence Matrix (GLCM) is a matrix that can extract statistical properties from a texture. initially, from the neighborhood window of each pixel of the image, a matrix P(i,j) is generated. The GLCM algorithm was proposed by Haralick. This matrix indicates that there are points with a given brightness level at a given distance and angle from each other in the image. So the GLCM function depends on the number of gray levels used. In our approach, we use GLCM to extract the features of the image.

we have extracted statistical characteristics of the GLCM matrix that are correlation, contrast, energy, homogeneity. The definitions and formulas for some of the features are given below:

Correlation: Intensity of relationship and type of relationship (direct or inverse). Returns a measure of how correlated a pixel is to its neighbor over the whole image.

$$\text{Correlation}=\frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{i*j\}*P(i,j)-\{\mu_x*\mu_y\}}{\sigma_x*\sigma_y} \qquad (1)$$

Where μ_x and μ_y are the mean values obtained from P_x and P_y. σ_x and σ_y are the standard deviation values of P_x and P_y. G is the number of gray levels.

Energy: The energy of an image is actually the measurement of image homogeneity. So, it's a good measure for estimating the distortion of the image. As the image is less homogeneity, image energy decreases. The sum of the squares of inputs is in GLCM.

Energy=∑_(i=0)^(G-1∑_(j=0)^(G-1) Pij (2)

Contrast: A criterion for the variety and local difference of an image, and its formula is as follows:

$$Contrast = \sum_{n=0}^{G-1} n^2\{ \sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\} \qquad (3)$$

Homogenity: The degree of uniformity in the ima
ge (such as color, shape, size, texture, etc.) is expressed. In fact, it measures the difference and similarities in the image. Or, in other words, returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogenity=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{P(i,j)}{1+|i-j|} \quad (4)$$

2.2.2. GLRM Based Feature Extraction

Gray Level Run Matrix (GLRM) is defined as the consecutive pixels that have the same gray level intensity along specific orientation. Fine textures contain short run with similar gray level intensities whereas coarse textures contain long run with different intensities. The elements in the run length matrix P (i,j) is defined in which the number of runs with pixels of gray level intensity equal to i and length of run equals to j which is the specific orientation. The element (i,j) of GLRM corresponds to the number of homogeneous runs of j voxels with intensity i in an image and is called GLRM (i,j). The features extracted from the GLRM matrix are as follows:

SRE= Short-Run Emphasis is the distribution of the short homogeneous runs in an image and it is meant for fine textures. Short Run Emphasis is given as

$$SRE=1/H\sum\_(i=1)^M\sum\_(j=1)^N (P(i,j))/j^2 \quad (5)$$

Where H corresponds to the number of homogeneous runs in the volume of interest.

LRE= Long-Run Emphasis is the distribution of the long homogeneous runs in an image and it is mainly for coarse textures. It is defined as

$$LRE=1/H\sum\_(i=1)^M\sum\_(j=1)^Nj2 * P(i,j) \quad (6)$$

LGRE=Low Gray-level Run Emphasis is the distribution of the low grey-level runs and it is given as

$$LRGE= 1/H \sum\_(i=1)^M\sum\_(j=1)^N P(i,j)/i^2 \quad (7)$$

HGRE = High Gray-level Run Emphasis is the distribution of the high grey-level runs and denoted as

$$HGRE=\frac{1}{H}\sum_{i=1}^{M}\sum_{j=1}^{N} P(i,j) * i^2 \quad (8)$$

GLNU = Gray-Level Non-Uniformity for run is the non-uniformity of the grey-levels of the homogeneous runs and it is given as

$$GLNU = \frac{1}{H}\sum_{i=1}^{M}\left(\sum_{j=1}^{N} P(i,j)\right)^2 \quad (9)$$

RLNU = Run Length Non Uniformity is the non-uniformity of the length of the homogeneous runs. It is defined as

$$RLNU=\frac{1}{H}\sum_{j=1}^{N}\left(\sum_{i=1}^{M} P(i,j)\right)^2 \quad (10)$$

RP=Run Percentage, measures the homogeneity of the homogeneous runs and denoted as

$$RP=H/(\sum\_(i=1)^M\sum\_(j=1)^N (j*P(i,j))) \quad (11)$$

2.3. Feature Selection

With feature selection can simplify the model and this way computational cost can be reduced and also when the model is taken for practical use fewer inputs are needed which means in practice that fewer measurements from new samples are needed. also by removing insignificant features from the data set one can also make the model more transparent and more comprehensible. There are several ways to choose the optimal features such as the fuzzy entropy measurement, DWT [2, 8], K-means [18], Topsis and methods, etc.

In this article, optimal features selection method based on fuzzy entropy measures is selected for our dataset. The feature selection task can be formulated as follows: given a feature set Y = (y_1, y_2, …, y_n) and a subset Z = (y_1, y_2, …, y_k) of Y with k<n, which optimizes an objective function W(Y). The fuzzy

entropy measures will be used in feature selection process to evaluate the relevance of different features in the feature set, this is done by discarding those features with highest fuzzy entropy value in our training set: if the entropy value is high we assume that the feature is not contributing much for the deviation between classes, then it will be removed in our feature set. This process will be repeated for all features in the training set. The higher the similarity values are, the lower the entropy values are. The need for feature selection is that it will increase the classifier accuracy.

2.4. Classification

After extracting useful information, these data are given to the classifiers for separation and obtaining the desired results. We use neural network classifiers due to their successful application in pattern recognition. Neural networks consist of a set of interconnected neurons which operates together to perform a particular task. Each neuron is associated with its weight. In training phase, network uses training set to update weights of its neuron in order to reduce network error. After the training phase, trained network is used for classification.

In this study, we used 50 Brain MR Image as data, which divides 50 data into two categories of trained data and test data. Trained data is data, in which the neural network creates and develops a model and then examines it through test data from the network. Of these 50 data, we select 42 images as a training image, which includes 30 normal images and 12 abnormal images (containing a tumor). And is used eight images for network testing, which are divided into four normal and four abnormal images. Generally, we have used 34 normal images and 16 abnormal images in this collection. Below is an example of a normal and an abnormal image:

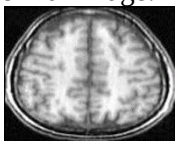

Fig.3. Normal Brain MR Image

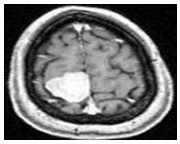

Fig.4. Abnormal Brain MR Image

Four neural networks have been selected for our research that are FFNN, MLP, BPN and ANFIS classifiers. Data containing useful information is given to each of these classifiers and we obtain their output to achieve the purpose of the article. The description of each classifier is given below.

2.4.1. Feed Forward Neural Network

Feeding neural networks are often one or more hidden layers of sigmoid neurons and use a linear output layer. The response path in such networks is always processed forward, not returning to the neurons of the previous layers. The signals only cross the one-way path, from input to output, so there is no feedback meaning that the output of each layer does not affect the same layer.Multilayer networks with a nonlinear transfer function allow the network to learn the linear and nonlinear relationship between inputs and outputs. The linear output layer allows the network to have outputs outside the +1 and -1 range.

2.4.2. Multi-layer perceptron (MLP)

Multi-layer networking is one of the most important structures of artificial neural networks. Typically, these networks include a set of sensory units (base neurons) that comprise an input layer, one or more hidden layers, and an output layer (MLP contains at least 3 layers). The input signal is transmitted through the network and in the forward direction in a layer-to-layer manner. It includes a summer and a nonlinear activation function.

2.4.3. Back Propagation Neural Network (BPN)

BP neural network architecture with one hidden layer operating on log sigmoid transfer function has been employed for the classification of normal and abnormal tumor. There is a full connectivity between the upper and lower layers and no connections between neurons in each layer. The weights on these connections encode the knowledge of a network. The data enters at the input and passes through the network, layer by layer, until it arrives at the output. The parameters of a network were adjusted through training the network on training set. The training of the network was performed under back propagation of the error. The trained networks were used to predict labels of the new data.

2.4.4. Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS system is a multi-layer network, consisting of the main elements and functions of fuzzy logic systems that is a powerful problem-solving method with different applications, as well as in the processing of images and diagnosis of brain tumors. The ANFIS system consists of a 5-layer structure with a number of input variables, each input of two or more membership functions. This network consists of two inputs, one output and two rules. Three hidden layers are used in this grid. The method of training this network is a back propagation technique that combines with the least squares of errors, the hybrid method is obtained. In each training round, when moving forward, nodal outputs are calculated as normal to the fourth layer, and then the result parameters are calculated by the least sum of squares of the error.

3. Experimental Results and Analysis:

Each algorithm was trained and tested for each dataset, under the same model in order to achieve the same accuracy. In order to evaluate the classification efficiency, two metrics have been computed: (a) the training performance (i.e. the proportion of cases which are correctly classified in the training process) and (b) the testing performance (i.e. the proportion of cases which are correctly classified in the testing process). Basically, the testing performance provides the final check of the NN classification efficiency, and thus is interpreted as the diagnosis accuracy using the neural networks support.

Various indices are mainly used to evaluate the performance of computer diagnostic systems. In various studies, the performance of these systems is not measured on a fixed basis. we have considered the normal images, the images without a tumor, to be positive, and abnormal images containing the tumor as negative and we have considered several parameters for evaluate outputs as follows:

TP= Normal images are correctly detected.

FP= Normal images that are not recognized correctly.

TN=Detection of abnormal images (Tumoral) that is done correctly.

FN=Detection of abnormal images (Tumoral) not performed properly.

In general, using the above concepts for functional analysis, important criteria are used which are called sensitivity, specificity, accuracy, detection rate (DR) and False Positive Rate (FPR) that if the FPR lower is obtained better results.

Table 1 shows the properties of MR brain images extracted using GLCM, and this is a sample data set. The properties of the extracted GLRM for the same dataset are shown in Table 2. In both tables, the first five images are normal and the nest five images are the images containing the tumor. From all these features, only the features containing useful data are selected using the fuzzy entropy measure. then classifier is trained Based these features. The performance of the classifier can be estimated using the following equations:

$$\text{Sensitivity}=\frac{\text{TP}}{\text{TP+FN}}\times 100\% \quad (12)$$

$$\text{Specificity}=\frac{\text{TN}}{\text{TN+FP}}\times 100\% \quad (13)$$

$$\text{Accuracy}=(\text{TP+TN})/(\text{TP+TN+FP+FN})\times 100\% \quad (14)$$

$$\text{DR}=\frac{\text{TN}}{\text{TP+TN+FP+FN}}\times 100\% \quad (15)$$

$$\text{FPR}=\frac{\text{FP}}{\text{TP+FP}}\times 100\% \quad (16)$$

Table1
Features extracted using GLCM

Images	Contrast	Correlation	Energy	Homogenity
Brainim1	0.6999	0.9392	0.0811	0.8277
Brainim2	0.6073	0.9497	0.0899	0.8528
Brainim3	0.5999	0.9505	0.0925	0.8577
Brainim4	0.6103	0.9496	0.0955	0.8557
Brainim5	0.6018	0.9517	0.0988	0.8574
Brainim6	0.7941	0.9231	0.1366	0.8164
Brainim7	0.9645	0.9227	0.0943	0.7810
Brainim8	0.8963	0.9315	0.1328	0.7970
Brainim9	0.0596	0.8955	0.1004	0.7823
Brainim10	0.0251	0.8993	0.0978	0.7831

We used the TP, FP, TN, and FN parameters described above to evaluate the performance of the four systems we used for classification. We then used them to evaluate the final performance of our proposed system according to five properties (Equations 12 to 16) that We also evaluate and compare each classifier on the basis of features 12 to 16 and give their accuracy rates in Tables 7, 8, 9 and 10.

can be seen in Tables 3 to 10.
Tables 3, 4, 5 and 6 also show the results of the classifiers FFNN, MLP, BPN and ANFIS, respectively, based on TP FP TN and FN parameters.

Table 2.
Features Extracted Using Glrm

Images	SRE	LRE	GLN	RP	RLN	LGRE	HGRE
Brainim1	0.7555	5.6234	4.9811	0.6097	3.2226	0.0727	107.0466
Brainim2	1.1305	9.2748	1.8115	1.7950	1.4019	0.1120	162.6124
Brainim3	1.5024	12.5005	4.7833	3.5414	3.6476	0.1506	218.8101
Brainim4	1.8711	14.5868	9.8776	5.8423	7.4538	0.1879	275.3641
Brainim5	2.2380	17.9348	1.7619	8.6957	1.3221	0.2252	331.4970
Brainim6	13.7190	103.5555	4.5033	381.5260	3.7006	1.2452	1.7338
Brainim7	14.0821	105.5508	4.8844	403.3669	4.0157	1.2839	1.7798
Brainim8	14.4615	107.9925	5.2908	425.8179	4.3529	1.3257	1.8273
Brainim9	14.8258	110.5887	5.7132	448.9052	4.7039	1.3673	1.8722

Brainim10	15.1952	94.5602	6.1596	471.7683	5.0749	1.4104	1.9174

Table 3

MLP	Train-data	Test-data
Sensitivity	93.548%	85.714%
Specificity	100%	100%
Accuracy	95.238%	87.5%
DR	26.1905%	12.5%
FPR	0%	0%

Performance of both training and testing sets on FFNN classifier based on TP, FP, TN and FN parameters. In the training set 42 data and in the test set used 8 data. In each set, the value of each parameter is measured

FFNN	TP	FP	TN	FN	Total
Train-data	29	0	12	1	42
Test-data	6	0	2	0	8

Table 4

Performance of both training and testing sets on MLP classifier based on TP, FP, TN and FN parameters. In the training set 42 data and in the test set used 8 data. In each set, the value of each parameter is measured.

MLP	TP	FP	TN	FN	Total
Train-data	29	0	11	2	42
Test-data	6	0	1	1	8

Table 5

Performance of both training and testing sets on MLP classifier based on TP, FP, TN and FN parameters. In the training set 42 data and in the test set used 8 data. In each set, the value of each parameter is measured.

BPN	TP	FP	TN	FN	Total
Train-data	29	0	12	1	42
Test-data	6	0	2	0	8

Table 6

Performance of both training and testing sets on MLP classifier based on TP, FP, TN and FN parameters. In the training set 42 data and in the test set used 8 data. In each set, the value of each parameter is measured.

ANFIS	TP	FP	TN	FN	Total
Train-data	25	4	11	2	42
Test-data	5	1	2	0	8

Table 7

Performance evaluation of the proposed system for both training and testing sets for the FFNN classifier. The performance of the system in each set is expressed as % based on each criterion.

FFNN	Train-data	Test-data
Sensitivity	96.667%	100%
Specificity	100%	100%
Accuracy	97.619%	100%
DR	28.5714%	25%
FPR	0%	0%

Table 8

Performance evaluation of the proposed system for both training and testing sets for the MLP classifier. The performance of the system in each set is expressed as % based on each criterion.

Table 9

Performance evaluation of the proposed system for both training and testing sets for the BPN classifier. The performance of the system in each set is expressed as % based on each criterion.

BPN	Train-data	Test-data
Sensitivity	96.667%	100%
Specificity	100%	100%
Accuracy	97.619%	100%
DR	28.5714%	25%
FPR	0%	0%

Table 10

Performance evaluation of the proposed system for both training and testing sets for the ANFIS classifier. The performance of the system in each set is expressed as % based on each criterion.

ANFIS	Train-data	Test-data
Sensitivity	92.593%	100%
Specificity	73.333%	100%
Accuracy	85.714%	100%
DR	26.1905%	25%
FPR	13.7931%	0%

Figures 5, 6, 7 and 8 shows the neural network diagram of four classifiers. The line on the figure is the best value, which is the same as the MSE (mean squared error) value. The horizontal axis represents the network's repetitions before the network training is stopped, where network training stops by reaching the optimal MSE. The vertical axis represents the value of MSE.

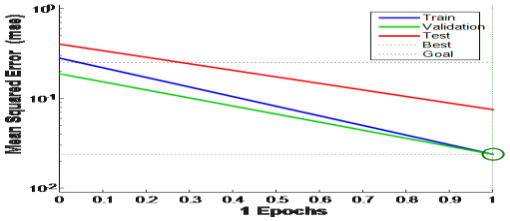

Fig.5. Ffnn Network Diagram

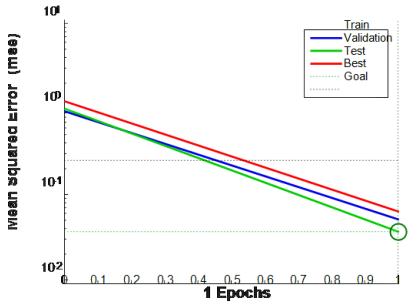

Fig.6. Mlp Network Diagram

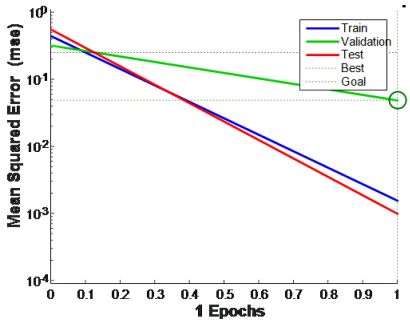

Fig.7. Bpn Network Diagram

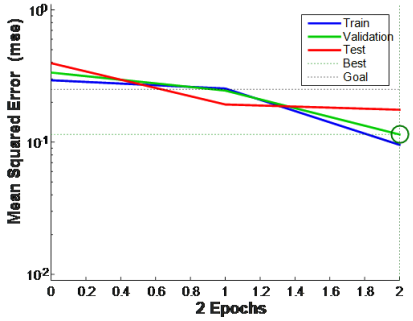

Fig.8. Anfis Network Diagram

4. Conclusion And Future Work

In this paper, various image processing methods improve the MRI images and prepare these images for extracting the feature on them. For these studies, from the 5000 data that contains MRI images from a healthy person and tumoral images, we selected 50 data at random to use as test and train data. Using the fuzzy entropy method, the data dimension of data was reduced, and data containing useful information was selected. This paper has used the four classifiers of FFNN, BPN, MLP, and ANFIS to classify the data. The purpose of these four networks is to develop tools for discriminating malignant tumors from benign ones assisting in deciding clinical diagnosis. The performance of these four classifiers is measured on the collected data using specificity, accuracy, sensitivity, DR, FPR.

Based on the results, we can say that all four classifiers are highly accurate in both the test and the train set. In the train set, the two classifiers of FFNN and BPN achieved the highest accuracy of 97.61%. Also in the test set, FFNN, BPN, and ANFIS classifiers have been able to achieve accuracy of 100%. It can be concluded that the FFNN classifier had the best performance in both sets. Using neural networks, we obtained high and accurate results to separate and detect brain tumors from MRI images. The results of our experiments have high accuracy among researchers in this field and particularly using neural networks. Based on the results, it can be proved that ANN is a valuable method for the classification and diagnosis of brain tumors.

In future work, more experiments with normal and abnormal images can be done. Ensemble neural systems can also be used instead of single neural networks or a more distinctive approach to feature extraction, optimum feature selection, and dimension reduction. We hope these solutions will improve the accuracy of the diagnosis of brain tumors and help people suffering from brain tumors, Alzheimer's, and other brain diseases, and improve these patients' quality of life.

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