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Performance Comparison of Adaptive Neural Networks and Adaptive Neuro-Fuzzy Inference System in Brain Cancer Classification

Bassam Al-Naami[a*] , Mohammed Abu Mallouh[b], Eman Abdel Hafez[c]

[a]Department of Biomedical Engineering, Hashemite University, P.O. Box 150459, Zarqa 13115, Jordan
[b]Department of Mechatronics Engineering, Hashemite University, P.O. Box 150459, Zarqa 13115, Jordan
[c]Department of Mechanical engineering, Al-Zaytoonah University of Jordan, P.O.Box 130, Amman 11733, Jordan

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Abstract

Brain tumors are amongst the top death-leading health conditions worldwide. Biopsy is the most accurate procedure that determines the brain tumor type whether it is malignant or benign. However, biopsy may not be applicable for some patients with brain cancer (BCa) and could be life-threatening. In this paper, an intelligent diagnosticimage-based systems are implemented to assist physicians in making diagnostic decisions about the BCa type without biopsy procedures. A combined method of artificial intelligent systems and MRI image segmentation is proposed as a tumor classification tool. This study employs image filtration and segmentation on a region of interest (ROI) of an MRI image. Then, extract accurate statistical features are fed into four artificial intelligent (AI) systems: Adaptive neuro-fuzzy inference system(ANFIS), Elamn Neural Network (Elman NN), Nonlinear AutoRegressive with exogenous neural networks (NARXNN), and feedforward NN. The four AI classifiers are investigated and tested on 107 patients with brain tumors. The data base of the brain tumor images used in this study contains both malignant and benign cancers. The performance of the four intelligent tumor classifiers is evaluated. It is found that the NARX NN shows best performance with a classification accuracy of 99.1%. The achieved accuracy level is superior and could be very helpful in clinical purposes.

Keywords: *: Adaptive Neuro-Fuzzy Inference Systems (ANFIS); Neural Networks; Brain Cancer; Image Segmentation; Nonlinear Auto Regressive; Region of Interest (ROI).*

1. Introduction

Brain tumors are the most complicated cancer diseases that are globally recognized by different organizations of cancer registry. It has been shown that brain tumors are fatal especially for children and they are listed among the highest causes of cancer among young adults [1]. In Jordan, 154 cases of malignant brain tumor were reported in 2008. The Age Specific Incidence Rates of brain tumors for males and females were reported in [2] as 8.1 and 4.8 per 100,000 populations for the age group (0-20 years), respectively, 5.1 and 10.3 per 100,000 populations for the age group (20-40years), and 33.9 and 19.1 per 100,000 populations for the age group (40-60 years).

There are varieties of cancer treatment techniques, such as: chemotherapy, radiotherapy, surgery, and amalgamation. However, the early determination the type of brain tumor is one of the most important factors for curing [1]. Therefore, tumor type and nature must be diagnosed before starting the treatment procedures. Advanced medical imaging modalities followed by a histological test known as biopsy are usually used in diagnosing. However, biopsy is still not applicable for some patients with brain cancer and could be life-threatening, and can cause a significant damage to the healthy brain tissues.

Thus, the objective of the proposed adaptive neural fuzzy system was to give primary information about the cancer existence in form of Classification Accuracy (CA) and the higher classification accuracy percentage, the greater the options for treatment. For under these circumstances, artificial intelligence, like fuzzy logic, neural networks and hybrid fuzzy logic and neural networks are implemented in image-based diagnostic systems. Such system serves to assist physicians in making diagnostic decisions based on database analysis and pattern recognition and without any risk. Also such system will be helpful in monitoring patients with low cancer risk without resorting to the frequent painful biopsy procedures. In [3], the fuzzy logic has been successfully implemented in breast cancer classification. Hybrid

* Corresponding author. e-mail: b.naami@hu.edu.jo.

particle swarm optimized fuzzy logic system was used in the modeling and design of a hypoglycemia monitor for patients with diabetes [4]. A complementary learning fuzzy neural network was proposed in [5] for Ovarian cancer diagnosis. In [6], a modified fuzzy cellular neural network was proposed to effectively segment CT liver images, which will help in early diagnosis of lever cancer. Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the intelligent systems that showed a promising performance in different aspects of our life, and more widely in medical applications. ANFIS has been implemented in many medical diagnoses such as: human action recognition [7] and epilepsy seizure [8-9]. Content-based image retrieval system, as a tool for discrimination between the normal and abnormal medical images, was developed in [10], heart valve diseases [11], rheumated arthritis [12], prostate cancer [13], and breast cancer [14]. ANFIS showed an overall accuracy in detecting glaucoma of 90.0% as reported in [15]. ANFIS illustrated a better performance in detecting four types of brain tumor when compared with the performance of probabilistic neural network classifiers [16].

Another promising intelligent cancer classification tool is based on Artificial Neural Networks (ANN). Karabatak in [17] presented an automatic diagnosis system for detecting breast cancer based on Association Rules (AR) and Neural Network (NN). The proposed AR with NN classifier showed an accuracy of 95.6%. In [18], a classification system was developed to detect tumor blocks or lesions, where the classification step was determined by ANN to discriminate between normal and abnormal MRIs for different patients with Astrocytoma type of brain tumors. An ANN automated diagnosis system was proposed for prostate cancer detection in [19]. Data taken by biopsy for 121 patients were used to train and tests the ANN classifier. The system showed an accuracy of 94.11%. In [19], An ANN discrete wavelet transformation hybrid technique was presented for brain cancer classification. A very adequate performance was obtained via a modified Probabilistic Neural Network (PNN) brain tumors classifier that was proposed in [20]. Their approach incorporated a non-linear Least Squares Features Transformation (LSFT) into the PNN classifier. The achieved classification accuracy was 95.24%.

In this study, a simple MRI tumor segmentation technique combined with artificial intelligent system to assist physicians in determining the brain tumor type is proposed. This proposed brain cancer classification approach will help in minimizing the examination time, cost and avoiding the unnecessary biopsy procedure. The key steps of the proposed method, technically, are illustrated in Figure (1). Step 1 of the approach is to obtain MRI investigated cases; step 2 is a preprocessing step, all images are filtered using the smoothing spatial low pass filter (averaging filter) and enhanced by the equalizing histogram. In step 3, the ROI is performed to segment the tumor part using threshold transformation function. Then the technique of feature extraction from each ROI is implemented to convert the original data set into minimum output features. This process is accomplished by measuring certain properties of the image, or features, that distinguish one input pattern from another pattern. In this Step, three textural features based on ROI of each gray level for each MRI tumor type are extracted; as: the mean, maximum, and standard deviation of pixel values for both. In Step 4, the extracted features are fed into ANFIS and three ANN systems that classify the tumor type into Malignant or Benign. Three types of ANN are investigated: Elman Network, NARX Network, and Feedforward Network.

This paper is organized as follows: In section 2, a detailed description of image preprocessing and extraction parameters from the ROI, and data collection are presented. Also, ANFIS theory and brief description about Elman NN, NARXNN, and Feedforward NN are reviewed. Section 3 addresses the obtained experimental results and discusses the performance of each classifier (ANFIS, Elman NN, NARXNN, and Feedforward NN) in BCa detection. Finally, section 4 is devoted for the conclusion of the presented work with relevance to BCa classification.

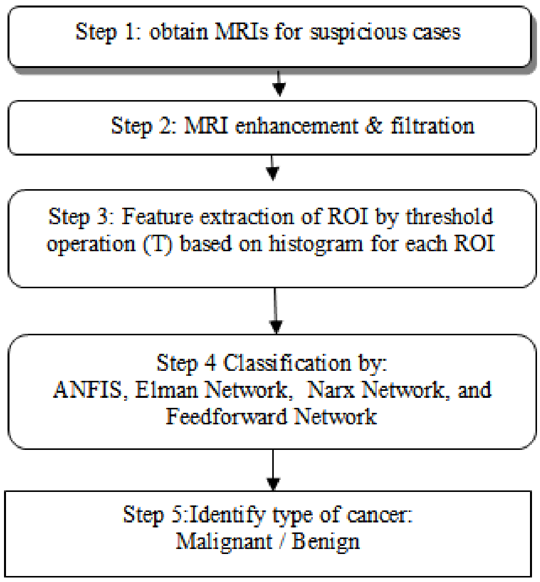

Figure 1. Flow chart of the proposed method

2. Materials and methods

2.1. Image Database

A total of 107 real brain MRIs that contain tumors were used in this study. The MRI data set contains (41) benign and (66) malignant MRIs that were collected from Jordanian hospitals. The MRIs were taken for different patients with several transverse slices. It is important to mention that all used MRIs were diagnosed and classified as benign or malignant by experts in the field. It was noticed that the tumors locations were in the middle, the right, and in the left half of the brain.

2.2. Enhancement and Segmentation

After converting all images to the gray scale, the histogram equalization was applied to improve the MRI quality. In this work, enhancement can be performed using the transformation function ($T(r)$), where $\boldsymbol{r}$ represents the gray levels of the MR image. This image was already normalized to the interval [0, 1], with r =0 representing black and r =1 representing white [21]. The transformations ($T(r)$) produces a level ***s*** for every pixel value ***r*** in the original MRI as shown Eq. 1:

$$s = T(r) \qquad 0 \le \mathrm{r} \le 1 \tag{1}$$

On the other hand, the probability of occurrence of gray level r_k in an image is calculated by Eq. 2:

$$P_r(r_k) = \frac{n_k}{n} \qquad k = 0, 1, 2, ..., \mathrm{L} - 1 \tag{2}$$

where n was the total number of pixels in the image, n_k was the number of pixels that have a gray level, and L is the total number of possible gray levels in the image [21]. Therefore, the histogram equalization was calculated by Eq. 3:

$$s_k = T(r_k) = \sum_{j=0}^{k} P_r(r_j) = \sum_{j=0}^{k} \frac{n_j}{n} \tag{3}$$

$$\mathrm{k} = 0, 1, 2, ..., \mathrm{L} - 1.$$

Thus, the processed tumor image was obtained by mapping each pixel with level r_k in the input image into a corresponding pixel with level s_k in the output image via Eq. 3.

The BCa MRI was filtered using the smoothing spatial low pass filter (averaging filter) as a preprocessing step to remove insignificant details from a brain image before the object of tumor was extracted by the ROI histogram for the segmented region. Averaging filter was chosen with 3×3 pixels containing equal weights of value "1" is applied to the original image (R_i), where $i \in 1 \text{ to } 3 \times 3$. In this case, the small objects with low intensity variations was blinded into the background, while leaving the objects of interest relatively (tumor) unchanged. The average filter is calculated by Eq. 4 [22] as follows:

$$X = \frac{1}{m \times n} \sum_{i=1}^{m \times n} R_i \tag{4}$$

Where *m*=3 and *n*=3. Resultant image *X* after applying the average filter in Eq. 4 is shown in Figures 2 and 3. As seen in both figures, each original image passes through an averaging filter (Figures 2(b) and 3(b)), where the majority of low intensity is eliminated by merging it within the background, while the last high intensity was appeared within tumor's region. In order to find ROI (region growing), threshold transformation function was applied to get the tumor segmented. To produce the ROI, it has to start with a set of "seed" points. Then from these points, the regions grow by appending to each seed those neighboring pixels that have properties similar to the seed [21]. A threshold value (T) is chosen by trial and error to produce a binary image which cut off the bright parts from the background [22]. Implementing the threshold results in two groups of pixels, $G_1(x,y)$ and $G_2(x,y)$ as illustrated in Eq. 5:

$$G(x,y) = \begin{cases} 1 & if \;\; G_1(x,y) \ge T \\ 0 & if \;\; G_1(x,y) < T \end{cases} \tag{5}$$

Figures 2(c) and 3(c) show the MRI after implementing the threshold. At the end of segmentation, the histogram for brain tumor was drawn as shown in Figures 2(d) and 3(d).

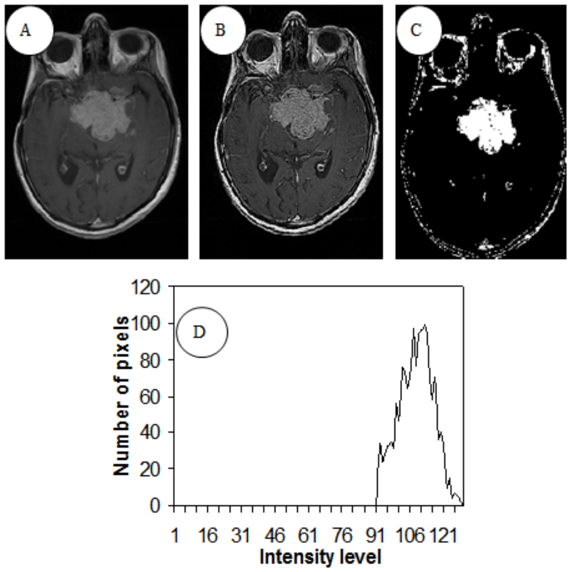

Figure 2. Original image of benign tumor (a), the result of averaging filter (b), segmented image by threshold operator (c), and the histogram for the tumor-ROI (d)

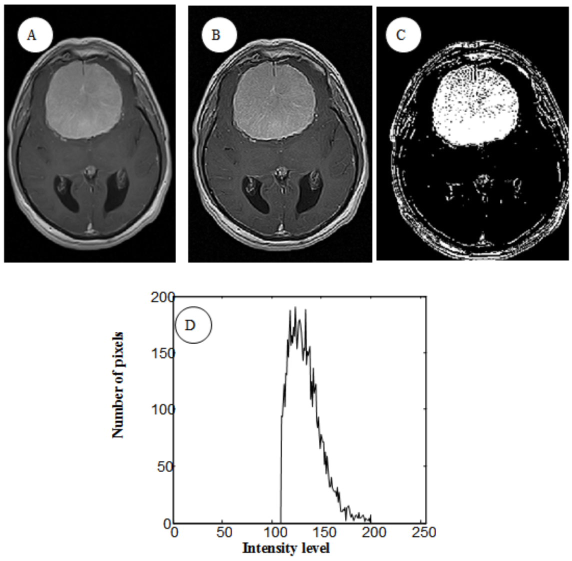

Figure 3. Original image of malignant tumor (a), the result of averaging filter (b), segmented image by threshold operator (c), and the histogram for the tumor-ROI (d)

2.3. Feature Extraction

To select an adequate set of features, we focused on the images characteristics of segmented ROI that physicians use to visually distinguish cancerous tumor from normal tissue. Hence, three features were extracted from the ROI for each of the 107 images, namely: (1) mean of the gray level values, (2) maximum gray level values, and (3) standard deviation of the gray level values. Table 1 shows the range of values for the three extracted features from the 107 MRI. The extracted features will be used as inputs to the intelligent systems tumor classifier as will be explained in next section.

Table 1.Range of extracted features values from all investigated MRI

Tumor Type	Extracted features from the segmented tumor by ROI in Pixels		
	Maximum value	Mean value	Standard deviation
Benign	163.11 ± 38.15	58.41 ± 28.12	22.12 ± 12.34
Malignant	214.96 ± 28.18	78.92 ± 30.36	31.26 ± 10.14

2.4. Adaptive Neuro Fuzzy Inference System

ANFIS is a novel architecture, initially proposed by Jang in 1993, in which a Sugeno fuzzy logic (FL) system is embedded in the framework of NN[23]. This combination of FL and NN produces an intelligent system that can learn and act similar to humans. Figure 4(a) shows a typical FL system. It is well known that constructing the rules and membership functions of a FL are the most difficult parts in designing and building a FL system. Rules and membership function are usually set by experts in the field. However, this drawback in FL design was solved in the ANFIS architecture shown in Figure 4(b). In addition, ANFIS does not need experts to set the rules and tune its membership functions, but it only needs pairs of input and output data similar to NN. Thus, ANFIS has the ability to tune the membership functions of inputs and outputs in simpler way. As shown in Figure 4(b), ANFIS has five layers Feedforward neural network in which each node performs a particular function on the inputs, for example a bell shape function with maximum equal to 1 and minimum equal to 0, represented as:

$$\sigma_i^1(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{o_i}} \tag{6}$$

where $\{a_i, o_i, c_i\}$ is the parameter set S_1. Parameters in this layer are referred to as premise parameters. This layer corresponds to the fuzzification step of the FL system, for more details on ANFIS structure refer to [23-25].A hybrid learning algorithm that combines a gradient descent and least squares are used to identify the adaptive network's premise parameters (S_1) and consequent parameters(S_2). A back propagation method is used in the backward pass and the least squares method is used in the forward pass.

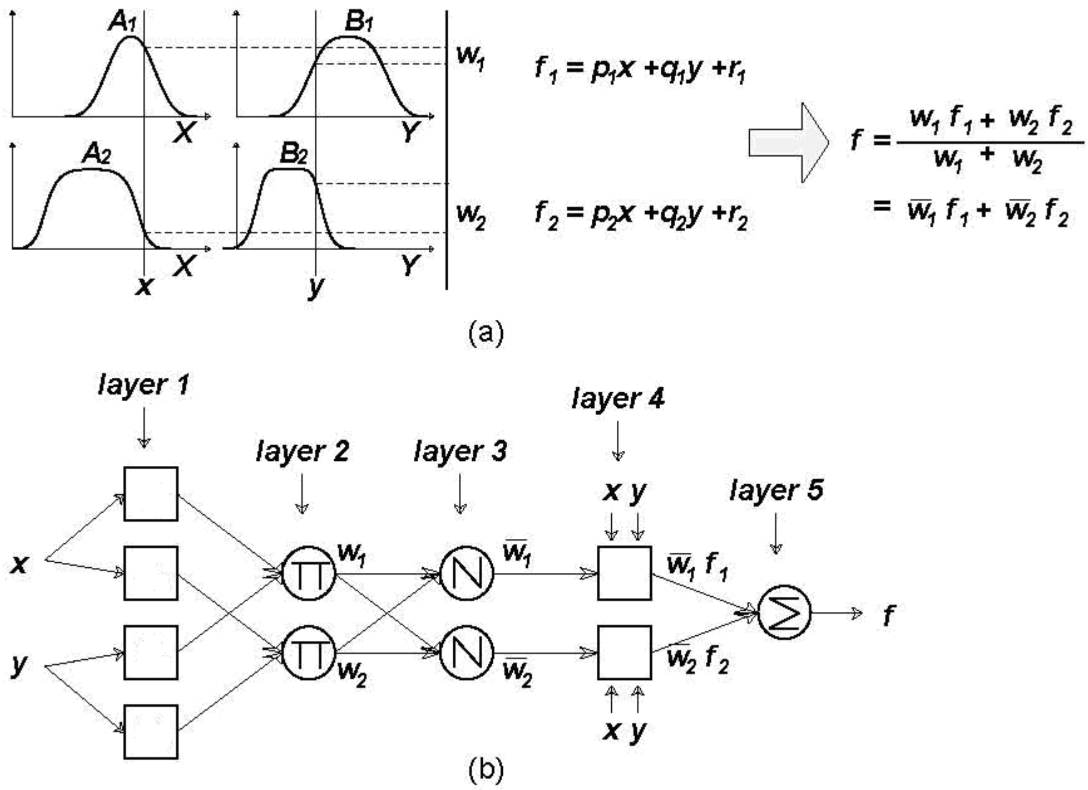

Figure 4. (a) Sugeno's FL system and (b) equivalent ANFIS [23]

2.5. Nueral Networks System

2.5.1. Elman Network

The Elman neural network, which was introduced in 1990, is a recurrent one [26]. As indicated in Figure 5, the main components of this network are input, hidden and output layers. In addition to these three layers, this NN also has an additional layer called context, which receives the output from the hidden layer without being weighted and then send them again to the hidden layer using trainable weighted connection. This enables the network to remember these values and used them as inputs to the network for the next run which helps in sequence prediction.

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2.5.2. NARX Network

The Nonlinear AutoRegressive with Exogenous (NARX) NN is shown Figure 6. It has exogenous input, which represents the feedback of the network output. This network usually used to model nonlinear system and time series [27, 28].

2.5.3. Feedforward Network

This network consists of an input layer of source neurons, at least one hidden layer of computational neurons, and an output layer of computational neurons. As shown in Figure 7, the input signals are propagated in a forward direction on a layer-by-layer basis

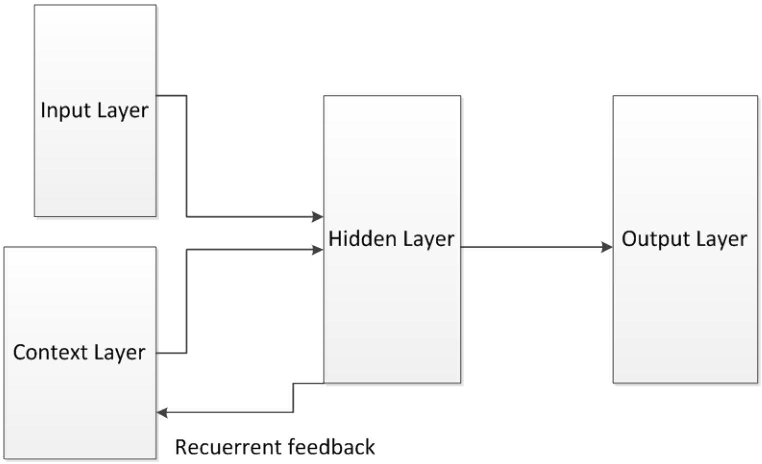

Figure 5. Elman Network

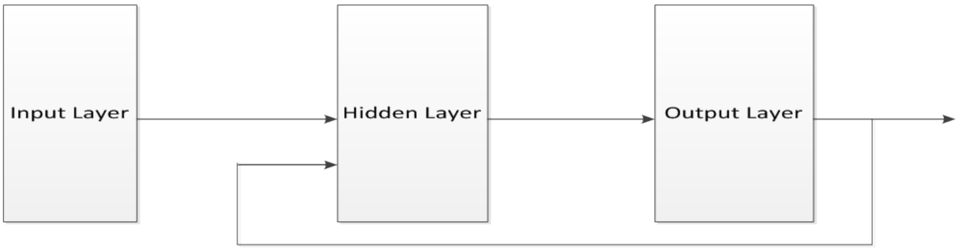

Figure 6. A typical neural network auto-regressive with exogenous inputs

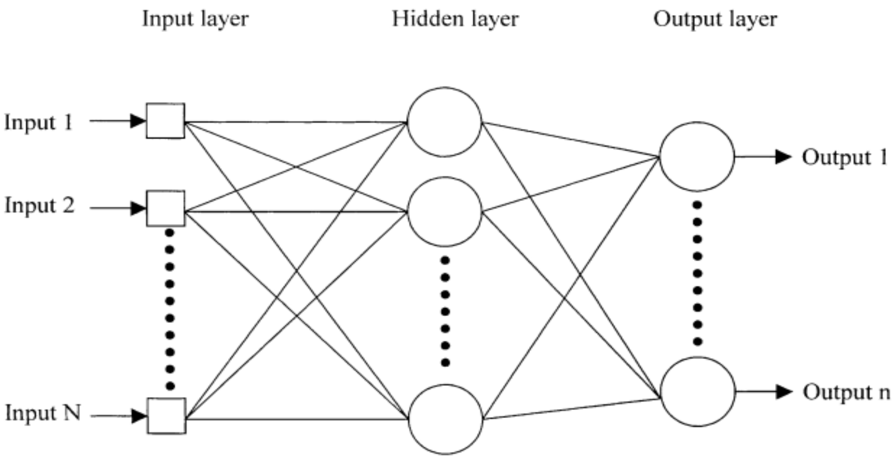

Figure 7. Multilayer feed forward network[29]

3. Results and Discussion

3.1. ANFIS Tumor classifier

An ANFIS brain tumor classifier is designed with the ANFIS library function available in the Matlab fuzzy logic toolbox. The tuning parameters of ANFIS are number and type of inputs, number and type of membership functions. As shown in Figure 8, the ANFIS tumor classifier has two inputs and one output. The two inputs to the ANFIS are the maximum and mean values and the output is the type of tumor (0 for benign and 1 for malignant).

These two inputs were found to be the most effective in determining the tumor type, where the third input (standard deviation) was excluded due to its similarity for the majority of MR images from statistical aspect. Different types of membership functions were tested, such as triangular, trapezoidal, Gaussian, sigmoidal and bell-shape function; the best results were obtained with bell shape function. In order to achieve good generalization capability of the ANFIS, it is important to have the number of training data set to be larger than the number of the modified parameters. Two bell shape node functions were selected for each input. As shown in Eq. 6, each node function has 3 parameters to be tuned. Thus, the total number premise parameters (S_1) is 12.

The ANFIS classifier has 4 rules and a total of 12 consequent parameters (S_2). Thus, the total tuning parameters are 24. The 107 data were divided randomly into three sets: 70% (75 data points) of the data were used for training, 15% of the data (16 data points) used for checking, and 15% of the data (16 data points) used for testing. The training data are actually used to update the ANFIS parameters, the checking and testing data were not used in updating the ANFIS parameters. The checking data are used to determine when to stop the training process while the testing data are used to test the performance of the ANFIS on data that have not been used in training.

The ratio of number of data to number of ANFIS modifiable parameters is 75/24. The training, checking and testing data consist of both benign and malignant tumor data, where zero output is assigned for benign and one for malignant. The training method used is a combination of traditional back propagation and a least squares technique. The training is done offline, usually once and before delivering the classifier to real clinic for application. After the training stage the ANFIS classifier was tested using the testing data, which were not used in the training stage.

3.2. NN Tumor Classifiers

The neural network library function available in the Matlab neural network toolbox is used to design the three NN *Tumor classifiers* (Elman, NARX and feedforward). The NN tumor classifiers have two inputs and one output. Ten neurons in the hidden layer are used. The selection of number of hidden neurons is made based on a trial-and-error procedure. Similar to the ANFIS, the two inputs to the NN are the maximum and mean values and the output is the type of tumor (0 for benign and 1 for malignant). The same data used in building the ANFIS are used in building the three NN. The 107 data were divided randomly into three sets. 70% (75 data points) of the data were used for training, 15% of the data (16 data points) used for checking and 15% of the data (16 data points) used for testing. Figures 9, 10 and 11 show the after-training performance responses for Elman, NARX and Feedforward networks, respectively.

Table 2 lists the performance of the ANFIS, Elman, NARX and Feedforward tumor classifiers in terms of sensitivity, specificity and classification accuracy. Sensitivity (Se), Specificity (Sp), and Classification accuracy (Ca) are important measures to validate the performance of the proposed method and calculated using Eqs. 7, 8 and 9, respectively [30].

$$\text{Sensitivity}\,(\%) = \frac{TP}{TP+FN} \times 100 \tag{7}$$

$$\text{Specificity}(\%) = \frac{TN}{FP+TN} \times 100 \tag{8}$$

$$\text{Classification accuracy}\,(\%) = \frac{TP+TN}{TP+FP+FN+TN} \times 100 \tag{9}$$

where TP, TN, FP, and FN denotes true positives, true negatives, false positives, and false negatives, respectively.

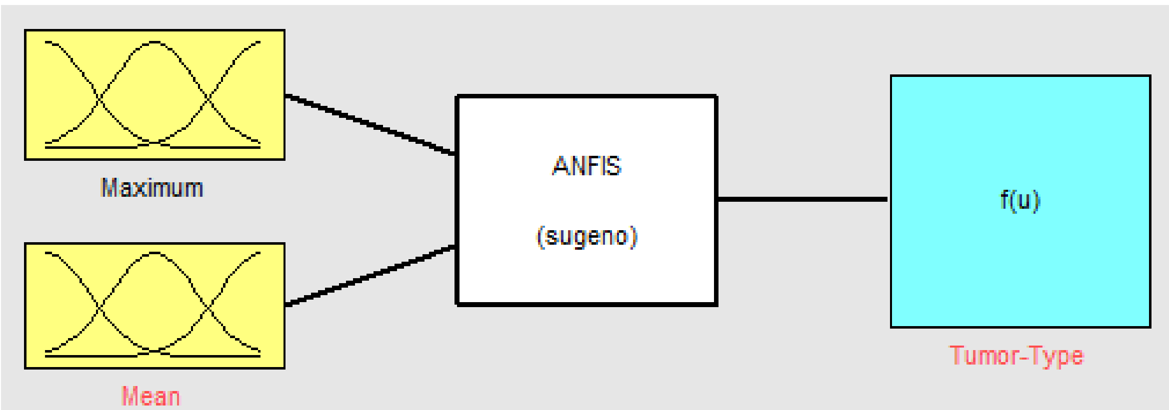

Figure 8. The designed ANFIS tumor classifier

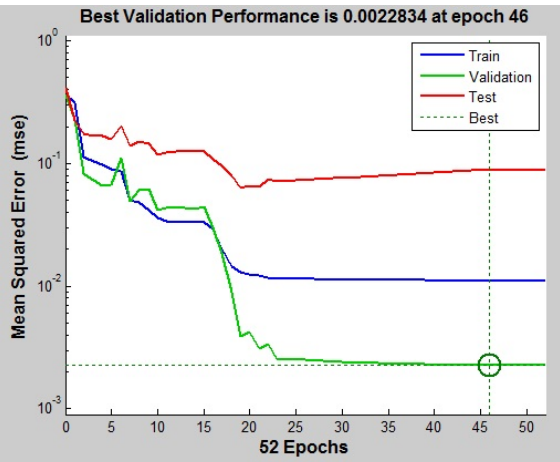

Figure 9. Performance responses for Elman NN

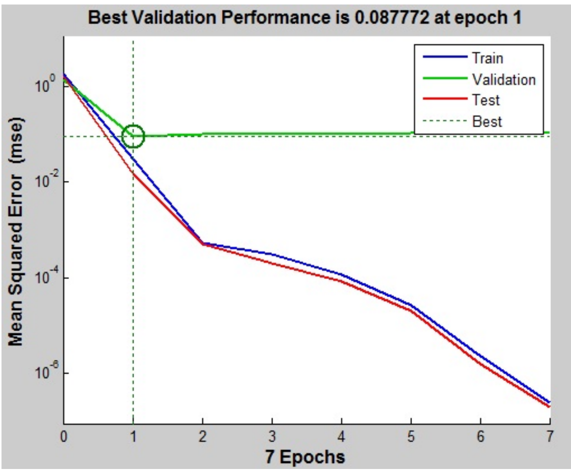

Figure 10. Performance responses for NARX NN

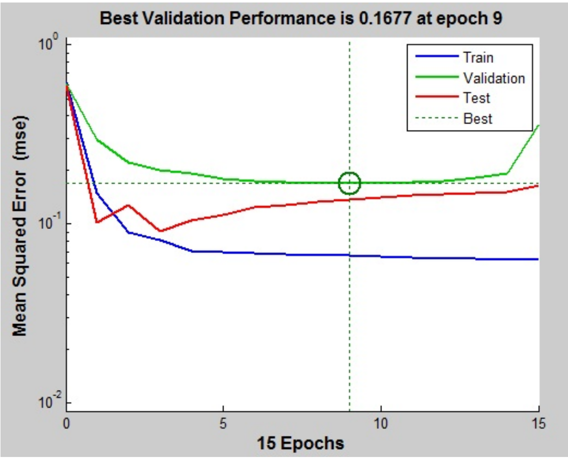

Figure 11. Performance responses for Feedforward NN

Table 2. Performance results of ANFIS with other neural networks.

Model	TP	FN	TN	FP	Se %	Sp %	Ca %
ANFIS	65	3	31	8	95.6	79.5	89.7
Elman	66	0	38	2	100	95	98.1
NARX	67	0	38	1	100	97.4	99.1
FeedForward	60	6	33	8	90.9	80.5	86.9

ANFIS classifier performance in terms of sensitivity, specificity and accuracy are 95.6%, 79.5% and 89.7%, respectively. The performance of Elman classifier shows better results than those of the ANFIS, where sensitivity, specificity and accuracy values are100%, 95% and 98.1%, respectively. The best performance is achieved by NARX classifier with values of 100%, 97.4% and 99.1% for sensitivity, specificity and accuracy, respectively. Feedforward classifier has the worst performance in terms of sensitivity and accuracy with values of 90.9% and 86.9%, respectively, while the specificity is 80.5%.

4. Conclusion

In this study, four artificial intelligent MRI image-based systems were developed for brain tumor classification. The developed systems consist of three stages. The first stage includes image filtration and enhancement. In the second stage, the ROI is employed for features extraction and the histogram is constructed for each case. In the third stage, the extracted features (mean and maximum values of ROI pixels) are fed into an artificial intelligent brain tumor classifier. Four artificial intelligent systems are investigated: ANFIS, Elman NN, NARX NN and feedforward NN. The best performance, in terms of classification accuracy, was obtained with the NARX NN with a value of 99.1% that is better than ANFIS, Elman and feedforward classifiers by 89.7%, 98.1%, and 86.9%, respectively.

The classification results show that the proposed method is effective in detecting BCa and it could be considered as an alternative approach for the previous approach in [31]. Moreover, development of this diagnostic approach will provide assistance to physicians in determining the tumor type without the need of performing biopsy or any other invasive procedures.

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