*i*Journals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 8 Issue 12 December 2020

A MODIFIED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR BRAIN TUMOR CLASSIFICATION

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DOI< 10.26821/IJSHRE.8.12.2020.81203 >

ABSTRACT

In recent years, researchers from both medical and computer sciences have combined their knowledge and efforts to diagnose brain tumor diseases using intelligent algorithms. However, existing brain tumor classification techniques produce high levels of misclassification which in turn cause inaccurate diagnosis of brain tumor. In this paper, we classified brain tumor into meningioma, glioma and pituitary tumor with different shapes, sizes and locations using a Modified Adaptive Neuro- Fuzzy Inference System (M-ANFIS) where self-organizing maps are used to carry out dimensionality reduction.

Results obtained showed that M-ANFIS classifier has accuracy, specificity, sensitivity, precision and F-score of 99, 98, 99, 96 and 98%, respectively while the traditional ANFIS classifier gave accuracy of 95%, specificity of 96%, sensitivity of 92%, precision of 92% and F-score of 92 %, respectively.

Key Words: M-ANFIS, Classification, Diagnosis, Tumor

I. 2INTRODUCTION

Artificial neural network is one of the main tools used in machine learning and a brain-inspired system which is premeditated to repeat the way humans learn. Artificial Neural Networks (ANN) consists of input and output layers in most cases an obscure layer consisting of units that transform the input into something that the output layer can use. They are excellent tools for finding patterns which are too complex for a human programmer to extract and teach the machine to recognize [1]. Artificial neural networks have been used on variety of tasks such as medical diagnosis, speech recognition, computer vision, machine translation, social network filtering and playing video games.

Neuro fuzzy system is a fusion of neural network and fuzzy systems in such a way that neural network or neural network algorithms are used to find the parameters of the fuzzy system. This means that the primary intention of neuro fuzzy technique is to strengthen or improve a fuzzy system automatically by means of neural network methods. The important aspect is that the approach should always be interpretable in terms of fuzzy if-then rules, because it is based on a fuzzy system reflecting vague knowledge. The idea of a neuro fuzzy system is to find the parameters of a fuzzy system by aid of learning process obtained from neural network [2].

Brain tumor is one of the most deadly and intractable diseases which has affected and devastated many lives. According to International Agency for Research on Cancer (IARC), it is estimated that more than 126,000 people diagnosed for brain tumor per year all over the world with more than 97,000 mortality. The statistics shows low survival rate of brain tumor patients, even though brain tumor disease has been the center of researchers for many decades around the world [3].

Magnetic Resonance Imaging (MRI) is a medical imaging approach used in radiology to visualize the internal structure of the body. MRI provides information about human soft tissues anatomy and the physiological strategy of the body in both health and diseases. Images obtained by the MRI are used for examining and studying the behavior of the diseases. Image intensity in MRI depends upon four parameters; one is Proton Density (PD) which is determined by the relative concentration of water molecules. Other three parameters are T1 which is spin – lattice that is magnetization in the same direction as the static magnetic field, T2 which is spin –spin that transverse to the static magnetic field and T2* relaxation which refers to decay of transverse magnetization caused by a combination of spin – spin relaxation and magnetic field inhomogenity [4].

The aim of this paper is to develop a modified adaptive neuro-fuzzy inference system for brain tumor classification.

The objectives of this paper include:

i. Creation of a dataset
ii. Development of an improved brain tumor classification approach
iii. Evaluation of the proposed approach

II. Related Review of Brain Tumor Classification

Sami, Mays and Talib (2018) developed a brain tumor classification using probabilistic neural networks. Gaussian filter and fuzzy c means was used to segment the preprocessed images. Curvelet transform was used to achieve the features extraction and classification is done using probabilistic neural networks and the recognition rate of this system is 98%.

Anjali and Priya (2017) developed an efficient classifier for brain tumor classification. Brain MRI dataset were used for training and testing. The MRI images were preprocessed using median filter and canny edge detection was used for segmentation. Feature extractions is done using first and second order texture feature; particle swamp optimization was used for feature selection. Classification Regression Tree (CART) and support vector machine were used to classified the brain tumor. The accuracy of the system is 92%, sensitivity of 97% and specificity of 78%.

Bhavana and Mahajan (2016) presented a system for detection and classification of normal or abnormal brain tumor using support vector machine. The system had five main stages, images was acquired using MRI, the acquired images were filtered using median filter for enhancing the images, opening operation was used for skull masking. Gray level occurrence matrix was used to extract feature from gray image and support vector machine classified the brain tumor into normal or abnormal. The overall accuracy was 83.33%, sensitivity of 91.52% and specificity of 67.74%.

III. Methodology

Creation of a dataset

The dataset was downloaded from figshare.com and contained 900 T1-weighted contrast-enhanced images from 233 patients with three kinds of brain tumor: meningioma (300 slices), glioma (300 slices), and pituitary tumor (300 slices). 83.33% of the dataset was used for training and 16.67% was used for testing.

Date Pre-processing and feature extraction

Image Intensity

Image intensity technique is used to improve the overall visual representation of brain images. Image intensity is computed using the equation (3.1) as follows:

$G = (g(x,y):(x,y)) \in R$ is the difference in visual properties (3.1)

$$G = \frac{gmax - gmin}{gmax + gmin} \text{ or } \frac{g(x,y) - gb}{gb}$$

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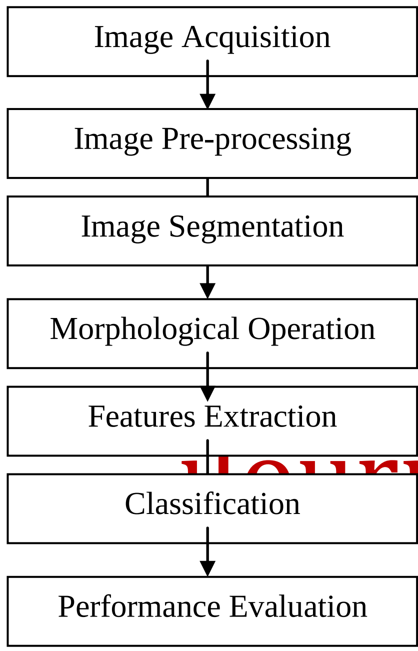


Figure 1: Generic diagram of the developed system

Where g_{max} and g_{min} is the maximum and minimum image brightness respectively and g_b is the background pixel value.

Adjustment by adding a constant offset or bias b to pixel values of an image g to form the new image f.

$$F(x,y) = g(x,y) + b \quad (3.3)$$

The brightness increases if $b > 0$ and decreases if $b < 0$ (Wilhem and Mark, 2008).

Image Segmentation

We used thresholding image segmentation technique because thresholding is a way of partitioning an image into a foreground and background. The algorithm of this technique is shown below and the flowchart is shown in Figure 3.2.

Step 1: start;

Step 2: Select an initial estimate for T (threshold) value;

Step 3: Segment the image using T. this will produce two groups of pixels: G1 consist of all

pixels with gray level values > T and G2 consisting of pixels with values ≤ T;

Step 4: Compute the average values μ_1 and μ_2 for the pixels in regions G1 and G2;

Step 5: Compute a new threshold value;

$$T = \frac{1}{2}(\mu_1 + \mu_2) \quad (3.4)$$

Step 6: Repeat steps 2 through 4 until the difference in T in successive iterations is smaller than a predefined parameter T_o;

Step 7: stop.

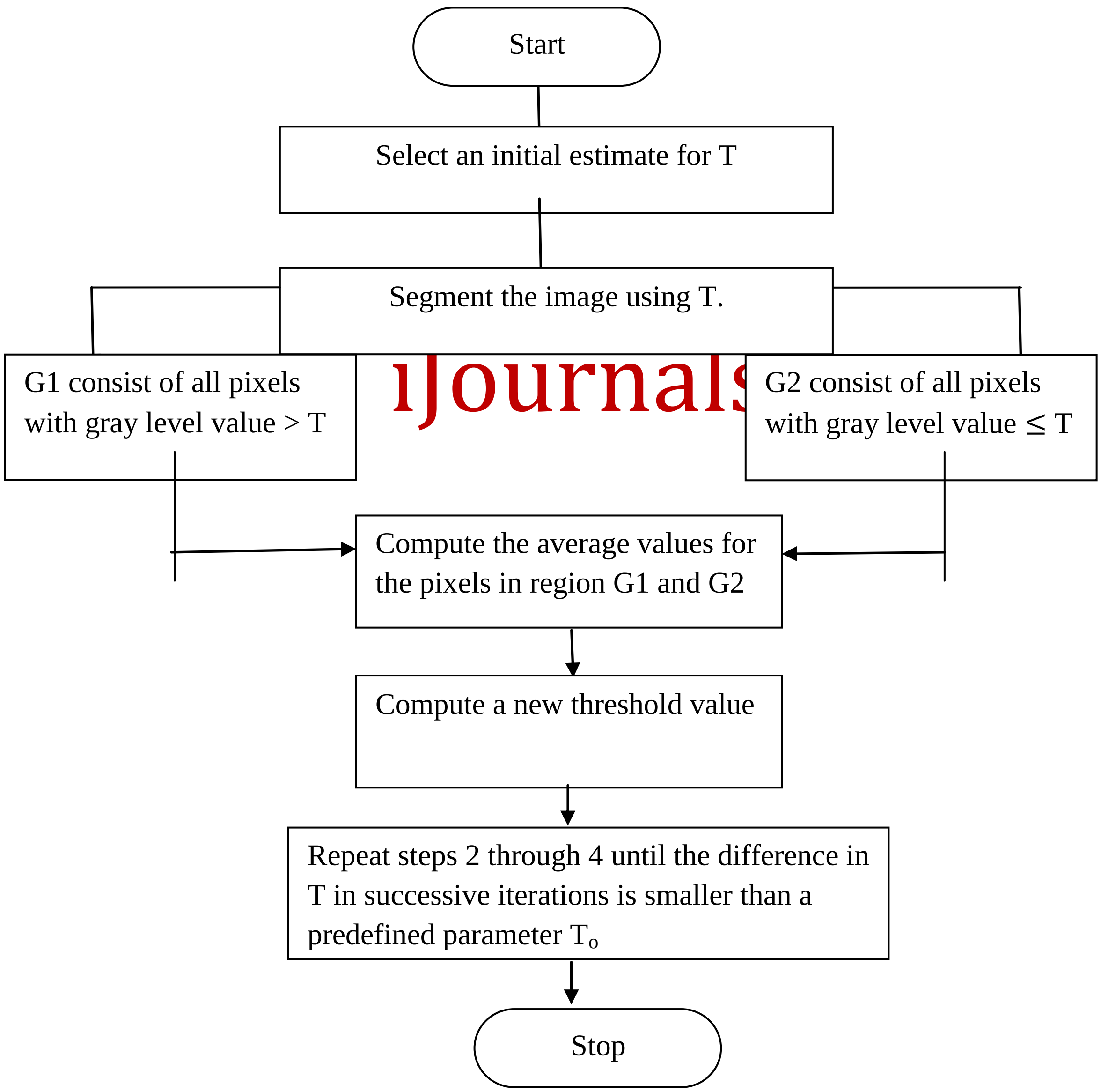


Figure 2: Flowchart illustrating steps of thresholding technique.

Morphological Operations

The morphological operation that we used are erosion and dilation. These operations are fundamental of morphological processing. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. The equations for dilation and erosion are stated as:

(i) For set A and B in Z^2 the dilation of A by B is denoted by A B and is defined as $\oplus$

$$A \quad B = \{Z/(\hat{B})_z \cap A \oplus\} \qquad (3.5)$$

(ii) For set A and B in Z^2 the erosion of A and B is denoted by $A \ominus B$ and is defined as

$$A \ominus B = \{Z/(B)_z \subseteq A\}$$ (Rafael and Richard, 2002) (3.6)

Feature Extraction

We used four textural features namely contrast, energy, correlation and homogeneity based on the gray level co-occurrence matrices (GLCM) or Spatial Gray Level Dependency matrix (SGLD). Gray Level Co occurrence Matrix (GLCM) features are used to distinguish between meningioma, glioma and pituitary tumor.

(i) Contrast: contrast is also called inertial is a measure of image intensity contrast or the local variations present in an image to show the texture fineness. This parameter is specified by the following equation:

$$\text{Contrast} = -\sum_i^{Ng}\sum_j^{Ng}(i,j)^2 p(i,j) \qquad (3.7)$$

(ii) Energy (EG):The Energy feature (EG) returns the sum of squared elements in the SGLD matrix as expressed by the following equation:

$$EG = \sum_i^{Ng}\sum_j^{Ng}\{p(i,j)\}^2 \qquad (3.8)$$

(iii) Correlation: The descriptor Correlation (CO) measures the linear dependence of gray

Level values in the co-occurrence matrix or describes the correlations between the rows and columns of the co-occurrence matrix. This parameter is specified by the following equation:

$$CO = \frac{\sum_i^{Ng}\sum_j^{Ng}(i-\mu x)(j-\mu y)p(i,j)}{\sigma x \sigma y} \qquad (3.9)$$

(iv)Inverse Difference Moment (IDM): Inverse Difference Moment is also called the "Homogeneity" Mathematically, it can be written as:

$$IDM = \sum_i^{Ng}\sum_j^{Ng}\frac{1}{1+(i-j)}p(i,j)$$ (Haralicks and Lee, 1990) (3.10)

Algorithm of modified ANFIS

The modified ANFIS is developed by using self-organizing map algorithm to carry out dimensionality reductionbefore classification is performed by the Adaptive Neuro-fuzzy Inference System (ANFIS). The sequences of steps for modified ANFIS are shown below:

Step 1: Start

Step 2: Each nodes weight are initialized;

Step 3: Vector is chosen at random from the set of training data;

Step 4: Vector is chosen at random from the set of training data;

Step 5: Each node is examined to calculate which weight are most likely the vector.

The winning node is commonly known as the Best Matching Unit (BMU);

Step 6: The neighborhood of the best matching unit is calculated and the amount of

Neighbors decreases over time;

Step 7: The winning weight is rewarded with becoming more likely the sample vector.

The closer a node is to the BMU, the more its weight gets altered and the farther

Away the neighbor is from the BMU and the less it learns;

Step 8: Repeat (ii) for N iterations;

Step 9: output;

Step 10: Stop.

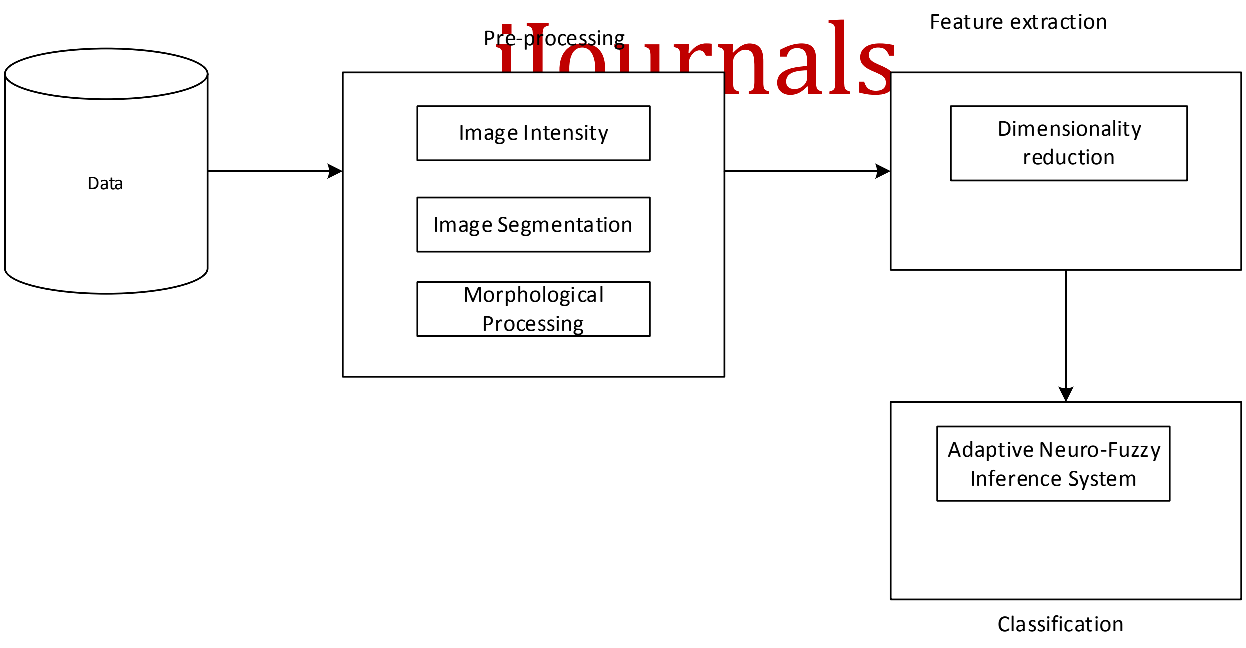


Figure 3 High level system overview of modified ANFIS system

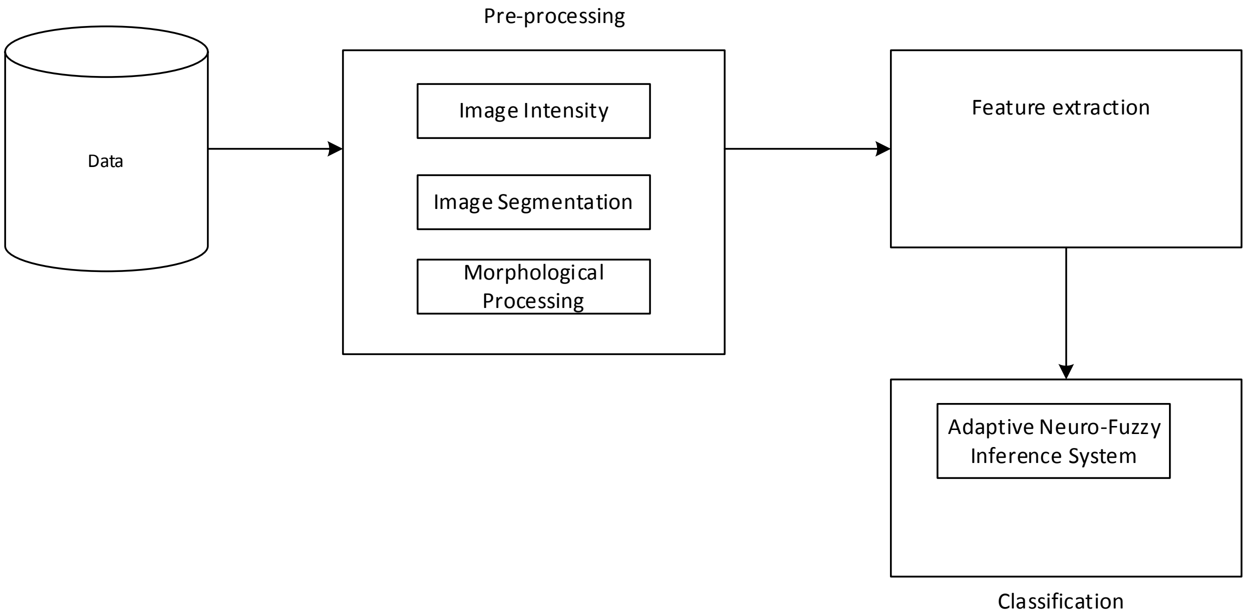
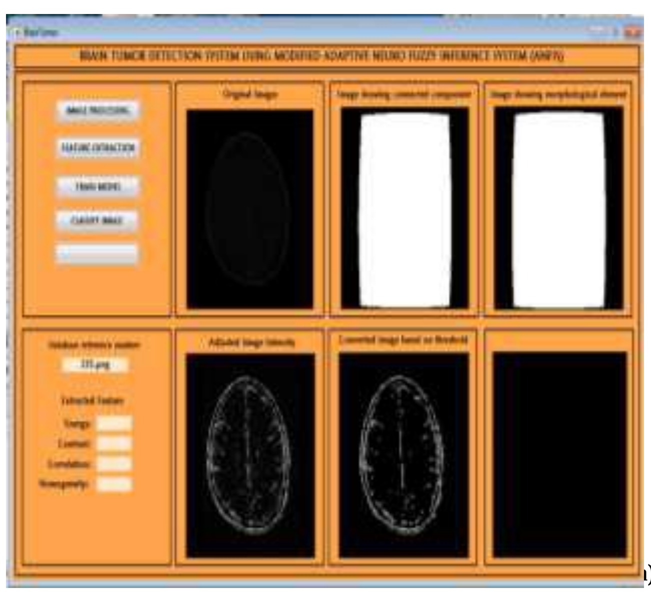


Figure 4 High level system overview of traditional ANFIS system

IV. Results and Discussion

The acquired brain tumor images were loaded into software graphical user interface in matlab software package (R2016a). The features were calculated from the region of interest characteristics such as the size, shape, density and smoothness of the borders; Figure 4.2 shown the region of interest and features of the tumor. The four textural features namely contrast, energy, correlation and homogeneity based on gray level co-occurrence matrix are used to distinguished between classes of brain tumor; class1 represent meningioma, class2 represent glioma and class3 represent pituitary tumor. Table 1 shown a unique record of some features extracted from the three classes of brain tumor.



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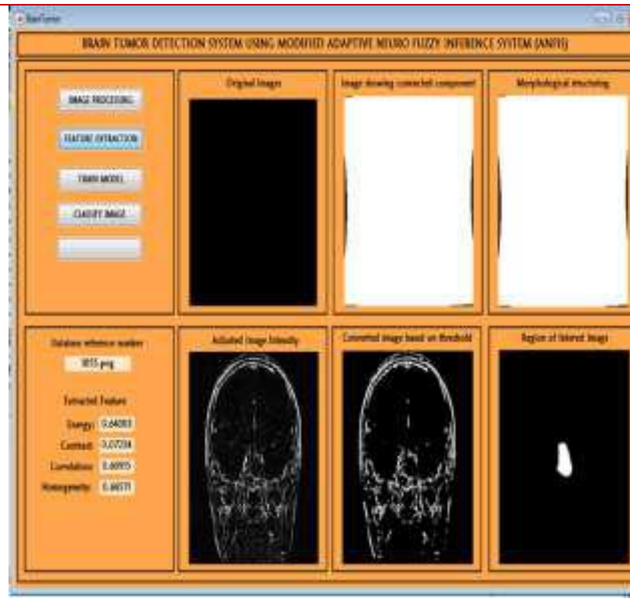
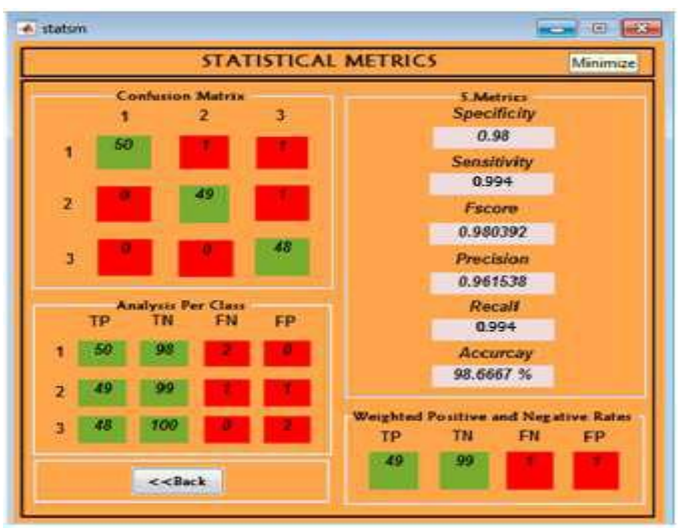


b)

Figure a) Pre-processed data b) Extracted features and regions of interest

V. Evaluation

The confusion matrix reveals the predicted and target output of the system that misclassified as another. The confusion matrix for the M-ANFIS classifier revealed 50 samples out of 52 were classified correctly for class 1 and 2 were classified incorrectly, 49 samples out of 50 were classified correctly for class 2 and 1 was classified incorrectly and 48 samples were classified correctly for class 3 and non was classified incorrectly.



The confusion matrix for the traditional ANFIS classifier reveals 46 samples out of 50 were classified correctly for class 1 and 4 were classified incorrectly, 46 samples out of 50 were classified correctly for class 2 and 4 were classified incorrectly and 46 samples out of 50 were classified correctly for class 3 and 4 were classified incorrectly. Analysis per class indicate the True positive (TP), False positive (FP), True Negative (TN) and False Negative (FN). For each class the TP, FP, TN and FN are shown in Figure 4.8 (b); the weighted positive rate and negative rate for the three classes are TP is 46, TN is 96, FN is 4 and FP is 4.

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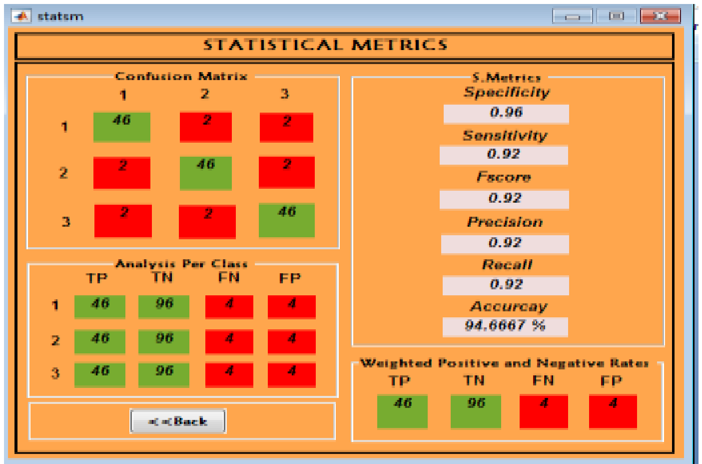

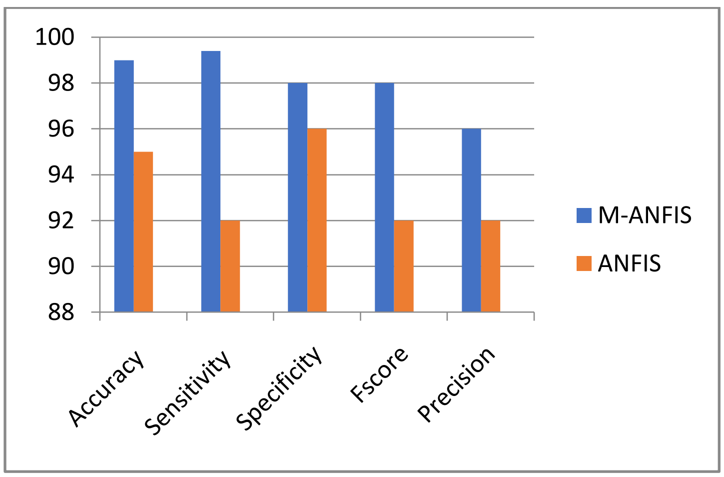

Table 1: Comparison of M-ANFIS and traditional ANFIS

Statistical Parameter	Modified ANFIS (%)	ANFIS (%)
Accuracy	99	95
Specificity	98	96
Sensitivity	99	92
Precision	96	92
Fscore	98	86

CONCLUSION AND FUTURE WORK

Modified adaptive neuro-fuzzy inference system and ANFIS was used to classify the datasets to meningioma, glioma and pituitary tumor and the performance metrics was evaluated and compared.

Results showed that modified ANFIS classifier has been successfully tested and achieved the best results with accuracy of 99%, sensitivity of 100%, specificity of 98%, recall of 100%, precision of 96% and fscore of 98% compared with ANFIS with accuracy of 95%, sensitivity of 92%, specificity of 96%, recall of 92%, precision of 92% and fscore of 92%. These results indicate that the technique has some great potentials in the reduction of high rate of false diagnosis of brain tumor in patients. In the future, more harallick's features could be added to the system such as difference average, difference variance, difference entropy, sum variance, sum entropy and information measures of correlation 1 as well as classification of brain tumors according to tumor grading.

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