Brain Tumor Segmentation Using Genetic Algorithm and Artificial Neural Network Fuzzy Inference System (ANFIS)

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Abstract. Medical image segmentation plays an important role in treatment planning, identifying tumors, tumor volume, patient follow up and computer guided surgery. There are various techniques for medical image segmentation. This paper presents a image segmentation technique for locating brain tumor (Astrocytoma-A type of brain tumor). Proposed work has been divided in two phases-In the first phase MRI image database (Astrocytoma grade I to IV) is collected and then preprocessing is done to improve quality of image. Second-phase includes three steps-Feature extraction, Feature selection and Image segmentation. For feature extraction proposed work uses GLCM (Grey Level co-occurrence matrix). To improve accuracy only a subset of feature is selected using Genetic algorithm and based on these features fuzzy rules and membership functions are defined for segmenting brain tumor from MRI images of .ANFIS is a adaptive network which combines benefits of both fuzzy and neural network. Finally, a comparative analysis is performed between ANFIS, neural network, Fuzzy, FCM, K-NN, DWT+SOM, DWT+PCA+KN, Texture combined +ANN, Texture Combined+ SVM in terms of sensitivity, specificity, accuracy.

Keywords: ANFIS, Brain tumor(Astrocytoma), sensitivity, specificity, accuracy, MR images, Neural network, Fuzzy, ANFIS, FCM, K-NN, GLCM, Genetic algorithm.

1 Introduction

Image segmentation plays an important role in medical field because it is important for treatment planning and identification of Brain Tumor, measures tissue volume to see tumor growth, patient follow up and computer guided surgery. Manual segmentation of magnetic resonance (MR) brain tumor images is a very challenging and time-consuming task [1,2,3,4]. Manual classification can cause human error, also result depends on human to human, time consuming process and results cannot be reproducible. So, an automatic or semi-automatic classification method is required because it reduces the load on the human observer, accuracy is not affected due to fatigue and large no. of images.

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For segmenting different body parts, different types of segmentation algorithm are present. But, proposed work focus literature related only to brain tumor segmentation. Monireh Sheikh Hosseini1 proposed a technique which presents a review of medical image segmentation using ANFIS[5]. He integrate the best features of fuzzy systems and neural network. A brief comparison with other classifiers, main advantages and drawbacks of this classifier are investigated. NOOR ELAIZA ABDUL KHALID [6] proposed a comparative study of Adaptive Network-Based Fuzzy Inference System (ANFIS), k-Nearest Neighbors (k-NN) and Fuzzy c-Means (FCM) in brain tumor segmentation. T. Logeswari [7] presents a brief comparison with other classifiers, main advantages and drawbacks of proposed classifier are analyzed. Rami J.Oweis[12] present the pixel classification of medical image using neuro fuzzy approach, which is based on spatial properties of the image features. N.Benamrane [13] has proposed an approach which combines Neural Networks, Fuzzy Logic and Genetic Algorithms as a hybrid system. For extracting image it uses region growing method.Ian Middleton[14] uses a neural network(a multi layer perceptron, MLP) and active contour model (‘snake’) to segment tumor in magnetic resonance (MR) images. Ramiro Castellanos [15] presents a image segmentation technique which uses adaptive fuzzy leader clustering (AFLC) algorithm.

Chin-Ming Hong [16] propose a novel neuro fuzzy network which use refined K-means clustering algorithm and a gradient-based learning rule to logically determine and adaptively tune the fuzzy membership functions for the employed neuro fuzzy network. S. Shen [17] presents a approach which is based on fuzzy c-means (FCM) clustering algorithm. In this algorithm, two factors of neighborhood attraction are the feature difference between neighboring pixels in the image, the other is the specification technique is applied on brain MR images before segmentation. The method enhances the contrast between different brain tissues.

1.1 Artificial Neural Networks

1.1.1 Learning

The proposed method shows high quality classification accuracy for images with simple components.

ANFIS is one of the widely used neuro-fuzzy systems. In this work, the neuro-fuzzy based approach namely adaptive neuro fuzzy inference system (ANFIS) is used for MR brain tumor classification.

2 Proposed Methodology

The methodology used for MR brain tumor images is Divided in to four steps and third step is further divided in to four parts as shown in fig. 1 and 2.

2.1 MR Image Database

MR image database consists astrocytoma type of brain tumor images of GRADE I to IV. These images are collected from web resource- **http://mouldy.bic.mni.mcgill.ca/brainweb/**

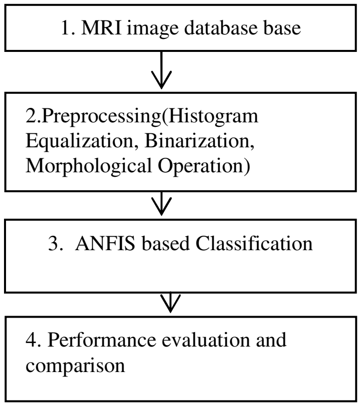

Fig. 1. Proposed Methodology for Classification of Brain Tumor

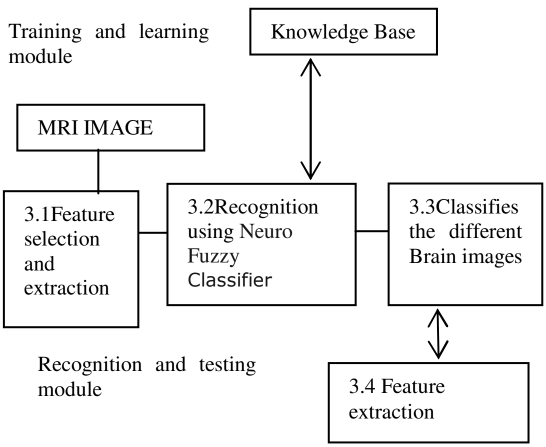

Fig. 2. Proposed Methodology for ANFIS based brain tumor classification

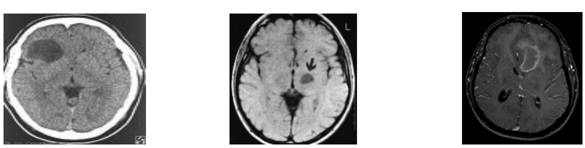

Fig. 3. Sample Data Set

2.2 Image Preprocessing

Image preprocessing involves different techniques to improve image quality before actual segmentation process. It removes irrelevant information like noise and enhances contrast to improve image quality. In the proposed work, three preprocessing techniques are used. They are-

a) Histogram Equalization

Image histogram is a graph which represents grey level frequencies of image. The histogram equalization is a technique that spreads out intensity values over the entire scale to obtain uniform histogram which in turn enhances the contrast of an image [11]. Histogram equalization used in this proposed work taken from MATLAB built-in function(histeq)[10].

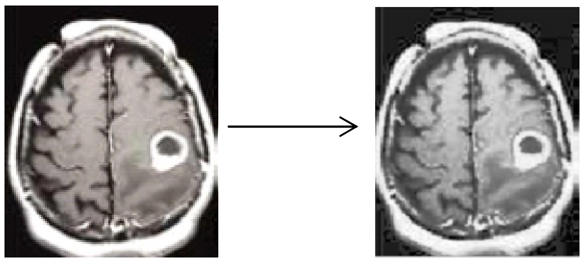

Fig. 4. Histogram Equalized Image

b) Binarization

Image binarization is used as preprocessor which converts grey scale image in to a binary image (either black or white) based on some threshold value. The pixel values above threshold value are classified as black and other are white[10].

$$G(x,y)=\begin{cases} 1 & f(x,y) \geq T \\ 0 & f(x,y) < T \end{cases} \quad (1)$$

In the proposed work only one threshold value is chosen for the entire image which is based on intensity histogram (mean of intensity values are taken)

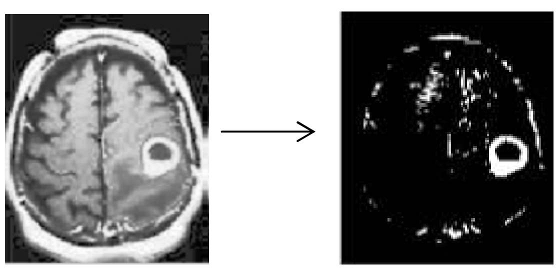

Fig. 5. Binarized image for the given grey scale image

c) Morphological Operations

This is used as a image preprocessing tools to sharpen regions and to fill gaps of binarized image. There are four basic morphological operations are defined like dilation, erosion, opening and closing. Here, proposed work uses only dilation and erosion. In erosion every pixel which touches background pixel is converted in to background pixel. Erosion turns object smaller. Mathematically erosion can be represented as,

$$(A\ominus B)(x)=\{x\text{€}\ X, x=a+b: a\ \text{€}A\ b\text{€}B\} \quad (2)$$

Where A represents matrix of binary image and B represents mask. Whereas, dilation change background pixel which touches object pixel is converted in to object pixel. Dilation combines multiple objects in one. Mathematically dilation can be represented as,

$$(A\ominus B)(x)=\{x€\ X,\ x=a+b:\ a\ €A\ b€B\} \quad (3)$$

The morphological algorithm used in this work is extracted from [11].

2.3 Feature Extraction

Features are the characteristics of the objects present in an image. Feature extraction is the procedure of extracting certain features from the pre-processed image. There are various techniques for measuring texture such as co-occurrence matrix, Fractals, Gabor filters, wavelet transform [9]. In this proposed work Gray Level Co-occurrence Matrix (GLCM) features are used to separate out normal and abnormal brain tumors. GLCM is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix)[8]. GLCM has following 20 features which are calculated using function available in MATLAB 7.0.4 for a given image:

GLCM2 = graycomatrix(image,'Offset',[2 0;0 2])

Where, image represents grey scale image. graycomatrix is the function available in MATLAB. It is used for calculating image feature values.

Table 1. Features Values of an given image

Feature No	**Feature Name**	**Feature Values**
1	**autocd**	**43.1530**
2	**contrd**	**1.8692**
3	**corrpd**	**0.1392**
4	**cpromd**	**34.6933**
5	**cshad1**	**5.2662**
6	**energd**	**0.1233**
7	**Dissid**	**0.6877**
8	**entrod**	**2.6980**
9	**homopd**	**0.65645**
10	**maxprd**	**0.6411**
11	**sosvhd**	**0.1973**
12	**savghd**	**44.9329**
13	**svarhd**	**13.2626**
14	**senthd**	**133.5676**
15	**dvarhd**	**1.8188**
16	**denthd**	**1.8927**
17	**inf1hd**	**1.2145**
18	**inf2hd**	**-0.0322**
19	**indncd**	**0.2863**
20	**idmncd**	**0.9107**

Table 1 shows feature values of an image which is calculated using above function.

3 Feature Selection

Feature selection helps to reduce the features extracted from GLCM which in turn improves the prediction accuracy, as well as computation time is also reduced. The main goal of feature selection is to select only relevant and informative features. Features are generally selected by search procedures. Popularly used feature selection algorithms are Sequential forward Selection, Sequential Backward selection, Genetic Algorithm and Particle Swarm Optimization. Here proposed work uses Genetic algorithm. Genetic algorithm is a heuristic search or optimization technique for obtaining the best possible solution in a vast solution space [21].

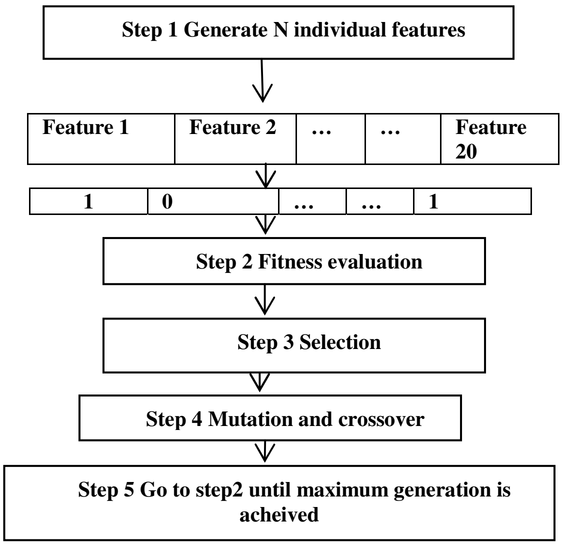

Fig. 6. GA Feature Selection Procedure

Following features are selected by Genetic algorithm:

1. Contrast: It calculates intensity contrast between a pixel and its neighbor pixel for the whole image. Contrast is 0 for a constant image.[8]

$$\text{Contrast}= \sum_{i,j} |i-j|^2 \, p(i,j) \tag{4}$$

Where, P(I,j) pixel at location (i,j)

2. Angular Second Moment (ASM): It is a measure of homogeneity.

$$\text{ASM}=\sum_{i,j} p^2\,(i,j) \tag{5}$$

3. Homogeneity (HOM): It measures the variation between elements in the neighbourhood [8].

$$\text{HOM}=\sum_{\text{i,j}} \frac{\text{p(i,j)}}{1+|i-j|} \tag{6}$$

4. Inverse Difference Moment (IDM): It is the measure of local homogeneity.[8]

$$\text{IDM}= \sum_i \sum_j \frac{1}{1+(i-j)^2}\, p(i,j) \tag{7}$$

5. Energy (E): Returns the sum of squared elements in the GLCM. Energy is 1 for a constant image [8].

$$\text{E}=\sum_{i,j} p(i,j)^2 \tag{8}$$

6. Entropy (EN): It is a measure of randomness [8].

$$\text{EN}=\sum_{b=0}^{L-1} p(i,j)\log_2\{p(i,j)\} \tag{9}$$

Where, L is no. of different values which pixels can adopt[8].

7. Variance (VAR): It calculates deviation of the gray level values from the mean [8].

$$\text{VAR}=\sum_i \sum_j p(i,j)p(i,j) - \mu^2 \tag{10}$$

In the proposed work, seven GLCM features are calculated per image in four directions 0,45,95 135 and hence the number of input linguistic variables are seven. The number of output linguistic value is 2. Table 2 show a sample of features value for image 1 and image 2.Based upon this value normal and abnormal brain can be differentiated.

Table 2. Seven features with range (low and High) of image1 and image2

	Features	**IMAGE1 Range(High-Low)**	**IMAGE2 Range(High-Low)**
1.	**Contrast**	7.08e+00-6.98e+00	3.60e+00-4.53e-001
2	**ASM**	8.76e-001-8.72e-001	6.05e-001-6.72e-001
3	**HOM**	8.87e-001-8.62e-001	8.72e-001-8.62e-001
4	**E**	2.93e-001-2.85e-001	2.28e-001-2.26e-001
5	**EN**	2.68e-001-3.44e-001	2.72e-001-3.01e-001
6	**VAR**	8.96e-001-8.54e-001	9.06e-001-8.81e-001
7	**IDM**	9.92e-001-9.90e-001	9.94e-001-9.93e-001

A sample of fuzzy if-then rules framed for the MR brain tumor classification is shown below:ï

Rule 1: If x is CON1 and y is HOM1 and z is E1and w is EN1 and a is IDM1 and b is VAR1, then o/p = 1

Rule2: If x is CON2 and y is HOM2 and z is E21and w is EN2 and a is IDM2 and b is VAR3, then output = 2

Rule3: If x is CON3 and y is HOM3 and z is E3and w is EN3 and a is IDM3 and b is VAR31, then output = 3

The number of membership functions used in this work is 2 (low and high) and hence there are 49 rules framed for this image classification system. These fuzzy if-then rules form the input for the ANFIS architecture.

3.1 ANFIS Architecture

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a very popular technique which includes benefits of both fuzzy and neural network (Jang,1993). According to [21], some advantages of ANFIS are:

- It refine fuzzy if-then rules for segmenting image
- It does not require human expertise all time.
- Provides more choices of membership function to use
- It provides fast convergence time

An ANFIS tune parameters and structure of FIS(fuzzy inference system) by applying neural learning rules The structure of ANFIS consists of 7 inputs and single output. The 7 inputs represent the different textural features calculated from each image. Each of the training sets forms a fuzzy inference system with 49 fuzzy rules. Each input was given two bell curve membership functions and the output was represented by two linear membership functions. The outputs of the 49 fuzzy rules comprised one single output, which represent output for that particular input image. The ANFIS architecture used in this work is extracted from [21].

The data set is divided into two categories: training data and testing data. The training data set consists of MRI brain images (Astrocytoma) from GRADE I to IV. These training samples are clustered in to four groups- white matter (WM), grey matter(GM), cerebrospinal fluid(CSF) and the abnormal tumor region using the fuzzy C-means (FCM) algorithm(Built-in function MATLAB).In the testing process, features are extracted and try to find best match. The algorithm used in this work is extracted from [21].

3.2 Performance Measures

Performance of different image segmentation algorithm can be analyzed in following terms:

True Positive (TP): Both Proposed Segmentation algorithm and radiologist results are positive

True Negative (TN): Both Proposed Segmentation algorithm and radiologist results are negative

False Positive (FP): Proposed Segmentation algorithm result is positive and radiologist results are negative.

False Negative (FN): Proposed Segmentation algorithm result is negative and radiologist results are positive.

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

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

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

Table 3. Comparison of classification performance for the proposed technique and recently other work

Algorithms	Sensitivity	Specificity	Accuracy
DWT+SOM[7]	95.13	92.2%	94.72
DWT+PCA+KNN]	96.2	95.3	97.2%
Second order+ANN	91.42	90.1	92.22
Texture Combined+ANN	95.4	96.1	97.22
Texture Combined+SVM	97.8	96.6	97.9
FCM	96%	93.3%	86.6
K-Mean	80%	93.12%	83.3
Proposed (ANFIS+Genetic)	96.6%	95.3%	98.67%

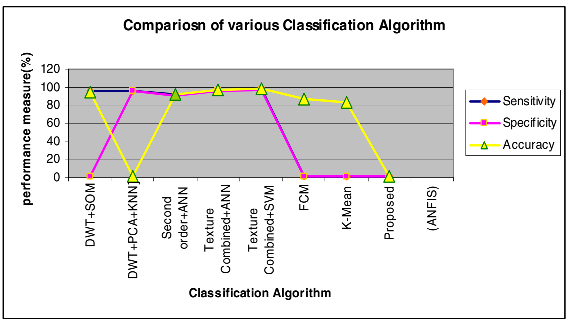

Fig. 7. Comparison of classification performance for the proposed technique and recently other work

4 Results

Proposed algorithm experimented on many images.Some of the results are shown in fig. 8.

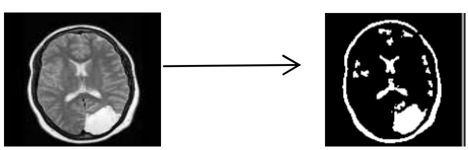

Fig. 8. Tumor Segmented from abnormal brain MRI image

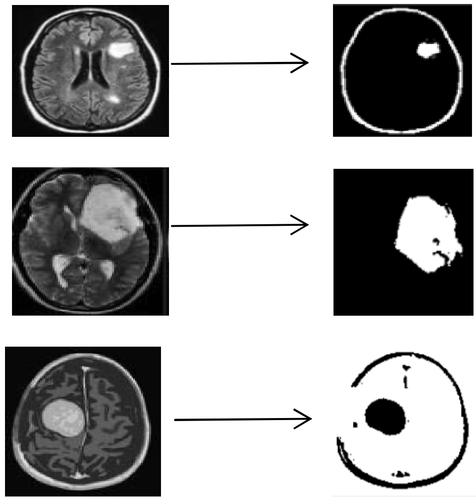

Fig. 8. (*continued*)

5 Conclusion

In this work, the application of ANFIS and genetic algorithm for MR brain tumor image classification is explored. Table 2 shows satisfactory results for proposed algorithm in terms of sensitivity, specificity, accuracy. The classification accuracy of proposed work as shown in fig.2.6. The future scope of this work is to enhance the ANFIS and genetic algorithm to achieve high classification accuracy, also measure thickness and volume of tumor.

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