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Improved Artificial Neural Network Fuzzy Inference System (ANFIS) Technique for Classification of MRI Brain Image

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ABSTRACT - Detection and segmentation of Brain tumor is very important because it provides anatomical information of normal and abnormal tissues which helps in treatment planning and patient follow-up. In the proposed methodology, features are extracted from MRI images which are fed to ANFIS (Artificial neural fuzzy inference system).ANFIS being neuro-fuzzy system harness power of both hence it proves to be a sophisticated framework for multi object classification. A extensive feature set and fuzzy rules are selected to classify an abnormal image to the corresponding tumor type. This proposed technique is swiftly in execution, efficient in classification and easy in implementation.

Keywords: MRI, FCM, GLCM, ANFIS.

I. INTRODUCTION

The classification of MR images is becoming increasingly important in the medical field since it is crucial for treatment planning and diagnosing abnormality (For e.g Brain Tumor),measure tissue volume to see tumor growth, study anatomical structure and patient follow up. Classification of magnetic resonance (MR) brain tumor images is a challenging and time-consuming task [1].Manual classification is highly prone to error due to inter observer variability and human error. As a result, the classification results are highly quality which leads to deadly results. Thus, an automatic or semi-automatic classification method is highly desirable as it reduces the load on the human observer , large number of events can be handled with same accuracy, also, results are not affected due to fatigue, data overload, faster communication .There are no universal algorithm for segmentation of every medical MR images. Different body parts MRI image needs different type of segmentation. Various methods proposed in the literature have only limited success [3,4] due to overlapping intensity distributions of healthy tissue, tumor, and surrounding edema. The most common event of methods is statistical classification using multi parameter images [5]. These methods are highly power based and hence the accuracy is very low. Warfield et al. [6] united elastic atlas registration with statistical classification. Marcel Prastawa [7] used a modified spatial atlas for classification which includes former probabilities for tumor and edema. Another group of researchers highly depend on computational intelligence for MR brain tumor classification which assured high accuracy. Zumray et.al [8] elaborates the inferior results of multi layer perception for the biomedical image classification problem. The Self Organizing Feature Map (SOFM) ANN based algorithms [9] shows excellent outputs in the classification of brain tumor images. Other studies based on learning vector quantization (LVQ) ANN show the potential of these architectures in the case of supervised classification. Hop field neural networks (HNN) [10] achieved to be efficient for unsupervised pattern classification of medical images, particularly in the detection of abnormal tissues. The use of ART2 network for pattern acknowledged has been studied by Solis and Perez [11]. Several modifications on the existing neural networks are implemented successfully and superior outputs have been achieved. One such work is reported by William Melson [12]. In addition to robust, they require large training dataset to prove high accuracy. This increases the dimensionality problem which accounts for the complexity of the model. On the other hand, several researches based on fuzzy logic techniques are also described in the literature. Marcin Denkowski [13] used the rule based fuzzy logic inference for MR brain image classification. Experiments based on fuzzy C-means algorithms are proposed in the literature [14].Yang and Zheng [15] implemented a modified fuzzy C-means algorithm for image classification. The fuzzy set theoretic models try to mimic human causes and the capability of handling uncertainty, whereas the neural network models attempt to emulate the architecture and information representation schemes of the human brain. Integration of the merits of the fuzzy set theory and neural network theory

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promises to provide, to a great extent, more intelligent systems to handle real life problems. A neuro-fuzzy approach as a joining of neural networks and fuzzy logic has been introduced to overcome the individual weaknesses and to offer more appealing features. The final goal of applying such a system is to get rid of imprecise information present in an image such as pixel greyness ambiguity, geometrical segmentation of the image and the uncertain interpretation of a scene. This exploits, respectively, the learning capabilities and the portraying power of systems, thus providing results characterized by a high interpretability and good degree of accuracy [16]. Partitioning of images using neuro fuzzy model has been studied by Rami J. Oweis and Muna J. Sunna [17] .Image partition using neuro fuzzy tools are also implemented by Mausumi Acharyya [18]. ANFIS is one of the most widely used neuro-fuzzy systems.In this work, the neuro-fuzzy based approach namely artificial neuro fuzzy inference system (ANFIS) is used for MR brain tumor classification.

II. PROPOSED METHODOLOGY

In the proposed method, Brain Tumor Detection is involved the steps are preprocessing using Wiener filter, segmentation using Fuzzy C-means clustering, feature extraction using GLCM and classification using ANFIS Neuro-fuzzy classifier. Tumor Region identification is done using pre-processing and segmentation process. In pre-processing, Wiener filtering is used to remove the unwanted noise. In segmentation step, the tumor region is identified using Fuzzy C-means clustering. Consequently, GLCM technique is used for feature extraction process. Finally, in the classification, neuro-fuzzy classifier is used to detect tumor.

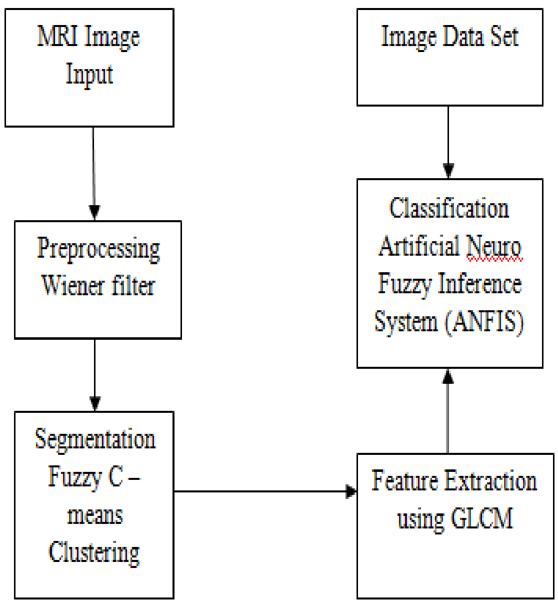

Fig1: Block diagram of proposed method

MRI IMAGES

MRI stands for Magnetic Resonance Imaging. It is one of the significant techniques for examining human body. Brain MRI images are useful in distinguishing and clarifying the neural architecture of human brain. It scans and captures the internal soft tissue structure of human body. It can be very useful in detection of diseases in brain. It takes the images of the brain in the presence of magnetic field and strong radio waves. Image segmentation is the first step and also one of the most critical tasks of MRI image analysis. Its objective is that of extracting information (represented by data) from an image via image segmentation, object describe, and feature measurement. Effect of segmentation; obviously have considerable influence over the accuracy of feature measurement. The computerization of medical image segmentation plays an vital role in medical imaging applications. It has establish expansive application in different areas such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, and computer-integrated surgery. However, the variability and the complexity of the anatomical structures in the human body have effected in medical image segmentation remaining a hard problem.

DATASET

For different Brain tumor MR images are used for this experimental work in which total 50 samples are collected .Every image is having the exact size of 256x256 in axial view.

PRE-PROCESSING

The input MRI image might be influenced by different noises during image generation. In order to obtain a more exact segmentation outcome, noise removal is a critical task. To enhance the image quality pre-processing is a basic step in image processing and computer vision, next morphological operations is applied to detect the tumor in an image. In this work, the unwanted noise present in the MR brain image has been eliminated by using the Wiener filter. The quality of denoised image is measured by PSNR

$$=10 log_{10}\,[MAX_j^2\,/\,MSE] \qquad (1)$$

Where MAX_j^2 is maximum value of pixel present in an image and MSE is the mean square error between original and denoised image with M*N size.

$$\text{MSE} = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}[x(i,j) - y(i,j)]^2 \qquad (2)$$

Where, x (i , j) is original image and y (i , j) is denoised image.

TUMOR IMAGE SEGMENTATION

Image segmentation is the most basic and important part of image processing which segments an image into meaningful areas according to some characteristics such as

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gray level, spectrum, texture, color, and so on. The aim of image segmentation is to divide an image into a group of disjoint regions with uniform and homogeneous attributes such as intensity, color, tone or texture etc.

Fuzzy C-Means algorithm

In Fuzzy C-Mean, the data has to be processed by giving the partial membership value to each pixel in the image. The membership value of the fuzzy set is in the range of 0 to 1. In fuzzy clustering basically, a member of one fuzzy set can also be a member of other fuzzy sets in the same image. There are three basic features involved in characterization by a member function. The core is the full member of the fuzzy set, Support is the non-membership value of the set and Boundary is the partial membership with the value between 0 and 1. Generally, it is hard to determine whether a pixel belongs to a region or not. This is due to unsharp transitions at region boundaries. Fuzzy partition is carried out by an iterative optimization of object function, with the update of the membership function and cluster centre. Nearer the data point to the cluster centre the more possible its membership towards the particular centre. FCM provides better results for overlapped region and data point which belongs to one or more cluster.

Fuzzy c-mean Algorithm steps:

Step (1): Compute the cluster prototypes (means):

$$V_i^{(j)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m}, \quad 1 \le i \le c \tag{3}$$

Step (2): Compute the distances:

$$D_{ikA}^2 = (Z_k - V_i^{(j)})^T A (Z_k - V_i^{(j)}), \quad 1 \le i \le c,\ 1 \le k \le N \tag{4}$$

Step (3): Update the partition matrix:

If $D_{ikA} > 0$ for $1 \le i \le c, 1 \le k \le N$

$$\mu_{ik}^{(j)} = \frac{1}{\sum_{n=1}^{c} (D_{ikA}/D_{nkA})^{2/(m-1)}} \tag{5}$$

Otherwise

$$\mu_{ik}^{(j)} = 0 \text{ if } D_{ikA} > 0, \text{ and } \mu_{ik}^{(j)} \in [0,1] \quad \text{with } \sum_{i=1}^{c} \mu_{ik}^{(j)} = 1 \tag{6}$$

Until,

$$\| U^{(j)} - U^{(j-1)} \| < \varepsilon. \tag{7}$$

Stop; else so return to step 2.

FCM is a popular clustering method. For example, it creates noise points when the method is applied to partition two clusters with an object having equidistance from two cluster's centers. FCM uses standard Euclidean distance norm.

FEATURES EXTRACTION

The input brain MRI is initially preprocessed using wiener filter and is skull stripped to make it more suitable for further processing. Then for the skull stripped MRI, GLCM is formulated and all the above mentioned Second order statistical features are extracted. Gray-level co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial connection of the pixels. The GLCM functions distinguishing the texture of an image by counting how often pairs of pixel with specific values and in a specified spatial connection occur in an image, creating a GLCM, and then extracting statistical find the size from this matrix. The gray co matrix function in MATLAB creates a gray-level co occurrence matrix (GLCM) by counting how often a pixel with the intensity (gray-level) value i occurs in a specific spatial connection to a pixel with the value j. By default, the spatial connection is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial connections between the two pixels. Each element (i, j) in the effects GLCM is not complicated the sum of the number of times that the pixel with value I occurred in the specified spatial connection to a pixel with value j in the input image. A GLCM is a matrix where the number of rows and columns is quality to the number of gray levels, G, in the image. The matrix element P(i, j | Δx,Δy) is the relative frequency separated by a pixel distance (Δx,Δy).Matrix element also represented as P(i, j | d,ɵ)which contains the second order probability values for alteration between gray level I and j at distance d a particular angle ɵ . Various features are extracted from GLCM.

- **Entropy:** Entropy refers to the quantity of energy that is having no change lost to heat every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term can be understood as amount of irremediable chaos or disorder. The Entropy is expressed by

$$Entropy = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} p(i,j)\log p(i,j) \tag{8}$$

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- **Inverse Difference Moment (IDM):** IDM is usually called Homogeneity that measures the local homogeneity of an image. IDM feature obtains the measures of the closeness of the distribution of the GLCM elements to the GLCM diagonal written as

$$IDM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} p(i,j) \tag{9}$$

- **Mean (M):** The mean of an image is calculated by adding all the pixel values of an image partitioned by the total number of pixels in an image.

$$M = \frac{1}{m\,x\,n} \sum_{x=0}^{m-1} . \sum_{y=0}^{n=1} f(x,y) \tag{10}$$

- **Variance:** Variance is a measure of the scatter of the values around the mean. The variance can also be defined as find the size of how far the gray values are spread out in the input image.

$$V = \sum\sum(i-\mu)^2 \, p\,(i,j) \tag{11}$$

- **Standard Deviation (SD)**: The standard deviation is the second central moment portraying probability distribution of an observed population and can serve as a measure of in homogeneity.

$$SD(\sigma) = \frac{1}{m\,x\,n} \sum_{x=0}^{m-1} . \sum_{y=0}^{n=1} (f(x,y)-M)^2 \tag{12}$$

- **Energy (En)**: Energy can be defined as the quantifiable amount of the extent of pixels of pair repetitions. It is a parameter to measure the similarity of an image. It is the sum of squared elements in GLCM. If energy is designed by Haralicks GLCM feature, then it is also referred to as angular momentum, and is defined as

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2 \tag{13}$$

- **Skewness:** The measure of equal is given by this textural feature. Which value can be either positive or negative. The value is usually zero if the image is exactly equal.

$$S(X) = \frac{1}{m\,x\,n} \frac{\sum(f(x,y)-M)^3}{SD^3} \tag{14}$$

- **Kurtosis:** Kurtosis is a find the size of whether the datas are peaked or flat relative to the normal distribution

$$K = \frac{1}{m\,x\,n} \frac{\sum(f(x,y)-M)^4}{SD^4} \tag{15}$$

- **Angular Second Moment (ASM):** The ASM is known as Uniformity or Energy. It measures the Homogeneity of an image. When pixels are very similar, the ASM value will be large and is given by

$$ASM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{p(i,j)\}^2 \tag{16}$$

- **Contrast:** The local contrast of an image is measure this feature. It is expected to be low if the intensity values of the pixel are equal.

$$Contrast = \sum_{i,j=0}^{n-1} P_{i,j}\ (i-j)^2 \tag{17}$$

- **Correlation:** The linear dependency of grey levels on the nearing pixels is represented by the correlation feature. The statistical relationship between the two variables is denoted by this feature.

$$Correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{18}$$

- **Homogeneity:** Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to GLCM diagonal**.**

$$Homogenity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \tag{19}$$

CLASSIFICATION USING ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a Fuzzy Inference System (FIS) implemented in the framework of an adaptive fuzzy neural network. It unites the explicit knowledge representation of an FIS with the learning power of artificial neural networks. The aim of ANFIS is to integrate the best features of fuzzy systems and neural networks. The ANFIS approach learns the direction and membership functions from data. ANFIS is an adaptive network. An adaptive network is the network of nodes and directional links. It is called adaptive because certain or all of the nodes have parameters which affect the output of the

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node. These networks are learning the relationship between inputs and outputs.

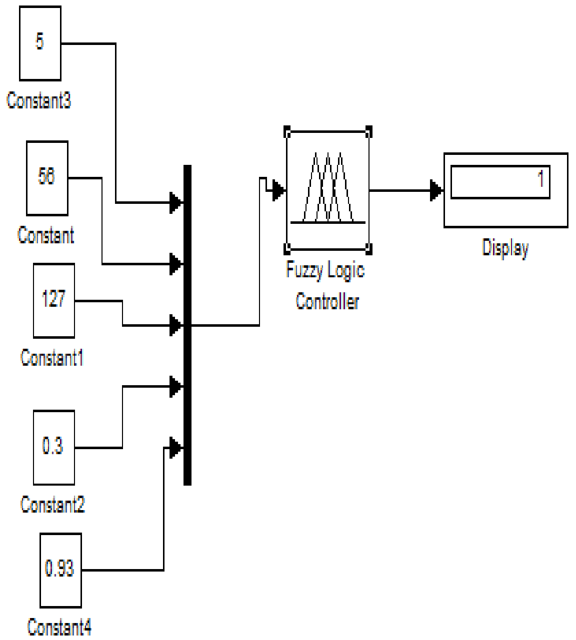


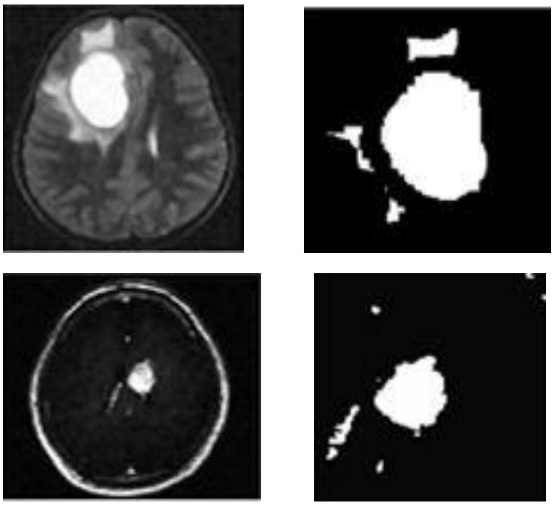
Fig 2: Simulation Model

ADVANTAGES of ANFIS:

- Pure fuzzy if–then rules to describe the behavior of a complex system
- Not requiring prior human expertise that is often needed in fuzzy systems, and it may not always be available
- Fast convergence time.

III. EXPERIMENTAL RESULTS

The experimental results from real MR brain images using segmentation and classification are presented. In the proposed method, MR image is initially segmented by fuzzy c-means algorithm. Then successfully the tumor and non-tumor images are segmented by setting the parameters correctly. The proposed technique is designed for supporting the tumor extraction in brain images. The obtained experimental results of the MRI images with tumor from the proposed technique are shown in Figure 2. The result shows the filtered and the segmented images with tumor.



(a) Filtered image **(b)Segmented output**

Fig 3: MRI image with tumor filtered image and corresponding segmented image

Feature Extraction

The extracted feature values for normal and abnormal images given in Table 1 and Table 2 respectively. Features are extracted from the tumor regions of MRI images which involves in reducing the quantity of data required to describe a large set of data accurately. The achieved features are used as inputs to classifiers which assign them to the class which they represent.

Table 1: Observed GLCM texture features for Normal Data set

Features	Image 1	Image 2	Image 3	Image 4
f1 Entropy	5.6904	4.9859	4.6112	4.5765
f2 Mean	52.6408	56.0379	54.9342	54.3712
f3 Std Deviation	49.0969	59.0093	73.8841	73.4563
f4 Variance	2.4105e+003	3.4821e+003	5.4589e+003	5.3958e+003
f5 Energy	184.5594	154.3041	111.7499	112.4259
f6 Skewness	0.0463	0.0396	0.0185	0.0189
f7 Kurtosis	1.9371e-005	1.1495e-005	3.3938e-006	3.5116e-006
f8 Contrast	0.1261	0.1584	0.1318	0.1315
f9 Correlation	0.9710	0.9703	0.9843	0.9843
f10 Glcm Energy	0.2760	0.3546	0.3668	0.3636
f11 Homogeneity	0.9386	0.9457	0.9491	0.9498
f12 Angular Second Moment(ASM)	1.7116e+005	2.1833e+005	2.2668e+005	2.2468e+005

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Table 2: Observed GLCM texture features for Abnormal Data set

Features	Image 1	Image 2	Image 3	Image 4
f1 Entropy	0.6255	1.5302	0.3992	0.6805
f2 Mean	6.8922	26.5400	2.7639	7.0188
f3 Std Deviation	38.8325	60.6712	23.7639	38.8075
f4 Variance	1.5080e+003	3.6810e+003	571.9915	1.5060e+003
f5 Energy	9.3625	84.7974	4.3855	10.2080
f6 Skewness	0.0061	0.0068	0.0078	0.0067
f7 Kurtosis	4.0754e-006	1.8595e-006	1.3941e-005	4.4820e-006
f8 Contrast	0.0294	0.0702	0.0178	0.0304
f9 Correlation	0.9873	0.9884	0.9799	0.9868
f10 Glcm Energy	0.9277	0.7923	0.9662	0.9227
f11 Homogenity	0.9911	0.9753	0.9946	0.9907
f12 Angular Second Moment(ASM)	1.6696e+005	1.5646e+005	1.3784e+005	1.5043e+005

Table 3 Performance Indices

INPUTS	ACCURACY OF ANFIS
Sample Input Images	95%

IV. CONCLUSION

In this work, the application of ANFIS for MRI brain tumor image classification is examine. Experimental results yield promising outputs for ANFIS as an image classifier. ANFIS could be a good classifier for medical image classification and assist physicians for earlier diagnosis of different diseases. In general, the performance of classifier depends on several factors such as size and quality of training set, the rigor of the training imported and also parameters chosen to feed to ANFIS as inputs can be influence the classifier performance.

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