Alzheimer's Disease Image Segmentation with Self-Organizing Map Network

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Abstract: Detection and segmentation of Alzheimer's disease (AD) is very important because it provides structural information of abnormal and normal tissues. Functional Magnetic Resonance Imaging (FMRI) is a promising tool for detecting brain image. Alzheimer's disease (AD) FMRI image segmentation is treated as texture classification problem. In this paper proposed a novel method for AD image segmentation using Self-Organizing Map Network (SOMN). Four different types of features are extracted from the FMRI AD images such as the first order gray level parameters, multi-scale features, textural measures and moment invariant features. These features are used for image segmentation. Application of Adaptive Neuro-Fuzzy Inference System (ANFIS) model utilized for classification of Alzheimer's disease segmentation image. The proposed Segmentation and classification results are promising.

Key word: Alzheimer's disease (AD), self-organizing map network (SOMN), ANFIS (artificial neural network fuzzy inference system), segmentation.

1. Introduction

Functional Magnetic Resonance Imaging (FMRI) imaging is progressed medicinal imaging approaches are giving rich data about the human delicate tissue anatomy. It has a few favorable circumstances over other imaging procedures [1], [2]. FMRI can give three-dimensional (3d) information with high complexity between delicate tissues. Since, the measure of information is used as an extreme degree excessively for manual analysis and interpretation, this has been one of the most concerning issues in the successful utilization of FMRI. In the particular instance of brain FMRI, the problem of segmentation is especially discriminating for both treatment and diagnosis purposes. In these cases, the exact area of an image is specifically identified with an early recognition of a potential pathology. The brain FMRI offers an efficient technique to perform post and pre surgical evaluation, which are keys to characterize systems and to confirm their effects. Therefore, Self-Organizing Map Network (SOMN) algorithms to achieve robust image segmentation such that the subsequent may be perceived such as first order gray level parameter, Multi scale feature, textual measure, movement invariant feature.

Most of the image segmentation methods can be broadly grouped into edge-based techniques or boundary-based, hybrid method and region based techniques. They are all depending on two basic pixel neighborhood properties: similarity and discontinuity [3]. Boundary based method is based on pixel discontinuity, whereas the region based method is based on pixel similarity. Thus the clustering viewpoint of these approaches is divided into unsupervised and supervised texture segmentation. The above segmentation methods are combined and can be overlapped.

In this paper proposed a novel method for AD image segmentation using Self-Organizing Map Network (SOMN). It is a continuous valued unsupervised pattern recognition method. Four different types of features are extracted from the FMRI AD images such as the first order gray level parameters, multi-scale features, textural measures and moment invariant features. These features are used for image segmentation. Numerous brain MRI segmentation methods using neural networks are reviewed in literature. This paper presents adaptive fuzzy inference System (ANFIS) for AD MRI image classification. The proposed method provides the promising results for the AD Patient structural information of abnormal and normal tissues, which make use of earlier deduction of Alzheimer's disease.

The paper is structured as follows: Related work is presents in Section 2. Particulars of the proposed technique are described in Section 3. Section 4 contains details of Self-Organizing Map Network (SOMN), Section 5 contains the details of ANFIS (Artificial Neural Network Fuzzy Inference System), Experimentation and results are presents in section 6. Conclusion is presented in Section 7.

2. Related Work

In medical field emerging recent research work is nuclear image processing. The image processing meets the different challenge in the research field. Thus, Positron Emission Tomography (PET) may help to assist localize disease for right treatment. Author proposes a novel method of Spatial Fuzzy C-Means (PET-SFCM) clustering algorithm which makes use of PET scan image datasets [4]. This algorithm is tested and implemented on huge data collection of AD patient. The traditional FCM with spatial neighborhood information which make use of updating the objective function of each and every cluster. This method focused on the Alzeimer's disease such as the brain neuro degenerative disorder.

An Atrophy Differential Diagnosis Approach for early detection of Alzheimer disease (AD), where the atrophy is located on the brain and it offers hippocampus, a regional atrophy analysis for differential diagnosis of different neurodegenerative diseases, which is a computer aided system [5]. The shrinkage happening in the whole brain is determined by the atrophy based calculation.

A novel approach Spatial Fuzzy C-Means (PET-SFCM) clustering algorithm for the Positron Emission Tomography (PET) scan images is proposed [6]. By using this approach, the objective function of each cluster is updated and the spatial neighborhood information is incorporate with traditional FCM. The data of the patients with the brain neuro degenerative disorder such as Alzheimer's disease has been collected and the implemented algorithm has been tested on the data collection. The results are compared with K-Means clustering algorithm and FCM.

A segmentation method for ultrasound images is proposed in [7], which is a region based using local statistics. A look up table consist of local statistics of every pixel is used for initial region growing procedure in this method. The homogeneous region is produced by grouping the pixels and it should be satisfy the specified homogeneity criteria. The similar intensity values in the neighboring regions are merged and it suppresses the high frequency artifacts. The segmented image is formed by the updated merged regions. The method is less sensitive to the pixel location.

Automatic segmentation using binarization process based on the threshold value of the fMRI images. The solution has been obtained by following the three steps: Preprocessing the raw fMRI images, Otsu's algorithm is used for threshold estimation and Based on the calculated threshold value, the binarization of the images is performed for segmentation [8]. The diagnosis of white matter related disease and the study of brain will be benefit from the segments results.

The technique Echostate Neural Network (ESN) is used for segmentation in functional Magnetic Resonance Imaging (fMRI). The ESN is a valuation technique with energy minimization. The complicated profile of the fMRI is segmented better by using the estimation property [9]. The performance is compared with the back propagation algorithm (BPA) and the results shows that ESN achieve better PSNR value compared to BPA.

Wavelet Fuzzy C- Means (WFCM) algorithm is used for image segmentation in noisy medical image. The feature extraction is done by wavelet Decomposition and the feature vector is fed as input to FCM. The segmented image using this approach found to be robust against various noise levels in the image [10]. The result is compared with Fuzzy C- Means (FCM) and Kernelized Fuzzy C- Means (KFCM) and it shows the satisfactory performance compared with the other two algorithms.

3. SOMP Based MRI Brain Image Segmentation

The medical images are normally contain in-homogeneity, unknown noise and complicated structure. Thus, the medical image segmentation processes is a complex and challenging task for required denoising and deblurring. There is not any common algorithm for the medical image segmentation, some kind of segmentation algorithms consider homogeneous regions, intensity of image or identifying object segmentation for recognizing items [15]. In this proposed approach utilizing the first order gray level parameters, multi-scale features, textural measures and moment invariant features for segmentation process. Self-Organizing Map Network (SOMN) method is used for image segmentation process.

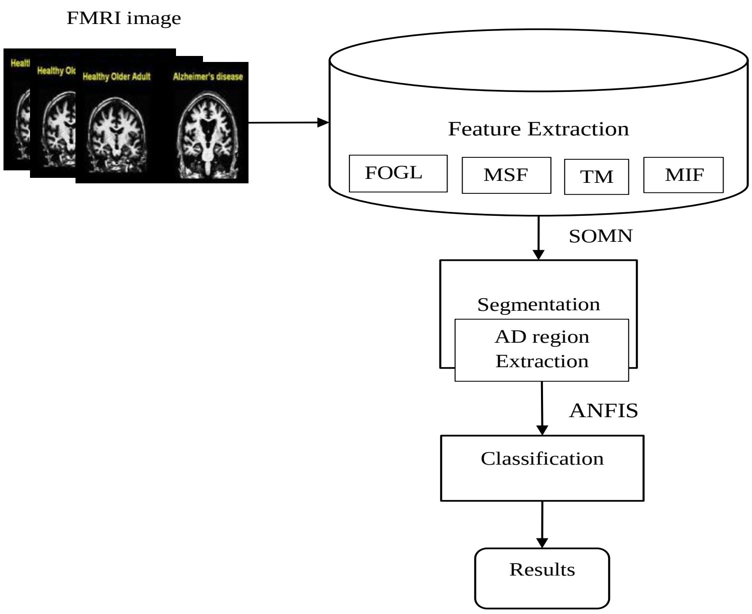

Fig. 1. Proposed AD image segmentation method.

3.1. Feature Extraction

Alzheimer Disease (AD) is a condition where the brain slowly goes down, as well as a serious loss of thinking ability in a person and cognitive impairment. Four types of feature extraction method are used for image segmentation process. The First method is based on first order gray level parameters, this method works on statistical information about the image order texture feature. The Second method is based on multi-scale features represented by the invariant rotation, scaling and translation. Third one is textural measures; it is based on pathological changes of hippocampus early Alzheimer Disease patient and mild cognitive impairment. Fourth one is moment invariant features; it involves in shape discrimination based on some unique features of brain images.

3.2. First Order Gray Level Parameters (FOGL)

First Order Gray Level Parameters (FOGL) is based on first order histogram which is local in nature of the feature extraction process. A Histogram of the image provides particulars of the statistical information about the image. The statistical information of the image can be acquired utilizing histogram of the image. The total number of pixel image is represented by Equation (1).

$$P(i) = h(i)NM \qquad i = 0, 1, G-1 \tag{1}$$

where N is the number of resolution cells in horizontal domain and M is the number of resolution cells in vertical cell and G represents the total gray level image.

For quantitatively labeling the first order statistical features of the image, valuable features of the image can be obtained from the histogram. Mean is the average value of the intensity of the image. Variance tells the intensity variation around the mean. Skewness is the measure which tells the symmetry of the histogram around the mean. Kurtosis is the flatness of the histogram. Uniformity of the histogram is characterized by the entropy. Following is the list of features obtained utilizing histogram of the image

The image quantitative represents the statistical features of the image, the feature of the image acquired from the histogram. Variance represents the variation around the mean. Mean is nothing but the average value of the image. Skewness represents the symmetry of the histogram mean value. Uniformity denotes entropy, kurtosis is the histogram flatness. The Histogram image feature are acquired by using following Table 1.

Table 1. First Order Gray Level Parameters

Metric	Formula
Variance:	$\sigma^2 = \sum_{I=0}^{G-1} (i-\mu)^2 P(i)$
Mean:	$\sigma^2 = \sum_{I=0}^{G-1} ip(i)$
Kurtosis:	$\mu_3 = \sigma^{-4} \sum_{I=0}^{G-1} (i = \mu)^4 p(i) - 3$
Skewness:	$\mu_3 = \sigma^{-3} \sum_{I=0}^{G-1} (i = \mu)^3 p(i)$
Entropy:	$H = -\sum_{I=0}^{G-1} p(i) log_2[p(i)]$

3.3. Multi-Scale Features

Multi-scale features are selected using squared gradient that uses the First Order Gray Level Parameters. Multi-scale features represented by Spatial Feature, Textual Feature, Descriptor Feature, Super-Pixel Feature, Final High-Dimensional Feature [11], [12].

Spatial Feature $F(v_i, s)$comprises of the spatial position of each and every voxel v_i with the distance d_{v_p, v_i} where v_p denotes the center of the image which is used to estimate the minimal average input landmark around the central points. The angle vector $\beta(Vv_p \rightarrow v_i)$which denotes the direction x, y, z.

Textual Feature $F(v_i, T)$, it is utilized to the find the intensity variance using pixel neighborhood. These features contain the variance between the intensity standard deviation and means.

Descriptor Feature $F(v_i, H)$ is related to Histograms of Oriented Gradient (HOG) features is robust to be responsible for useful information of object segmentation and intensity variation. Each voxel, crop a patch in its multi-scale HOG descriptors are created. The parameters of HOG as shown as Table 2.

Table 2. Parameters for HOG

Patch Size	Cell Size	Block Size	Patch Size	Cell Size	Block Size	Patch Size	Cell Size	Block Size	Patch Size	Cell Size	Block Size
8 × 8	4	2	16 × 16	4	3	24 × 24	6	3	32 × 32	8	3
8 × 8	8	1	16 × 16	8	2	24 × 24	12	2	32 × 32	16	2
			16 × 16	16	1	24 × 24	24	1	32 × 32	32	1

Super-Pixel Feature $F_s(vi, H)$ is established on the histogram intensity of the super-pixel standardized with esteem to the neighboring super-pixels. Then, a histogram is calculated for each and every super-pixel utilizing the intensity values of each and every pixel within the super-pixel. To compute the final feature $F_s(vi, H)$ for histogram of super-pixel neighborhood is utilized k nearest super pixel.

$$H_i = h_i + \sum_{K=1}^{K} h_{i,j} \tag{2}$$

$$F_s(v_i, H) = \frac{H_i}{\|H_i\|_i} \tag{3}$$

where h_i represents the histogram super-pixel, K denotes the nearest neighborhood and F_s denotes the super pixel features.

Final High-Dimensional Feature $F(vi)$ is calculated by using above discussed features $F(vi) = [F(v_i, s), F(v_i, T)]F(v_i, H)\ F_s(vi, H)]$ the voxel probabilities is defined as $P_f = \frac{1}{N}\sum_{i=1}^{N} P_{fi}$ where P_f denotes prediction label.

Texture analysis process is a significant task in computer applications of image analysis for segmentation or classification process of image processing based on local spatial patterns of intensity. The texture segmentation is a main process of texture analysis. Which means, the images are segmented by the set of sun regions, each region have a homogeneously textured. However the AD image processing a challenging task due to the complexity of tumor characteristics in images, such as shapes, sizes, intensities and locations and large variance. However, the AD image processing utilizing the above texture analysis method.

3.4. Moment Invariant Features

The movement invariant is computed from the each pixel, it will make use of creating feature vectors. The movement invariants process is based on ration and scaling [13]. First, the center of segmented image is computed using Equation (4)

$$\bar{x} = \frac{1}{N}\sum(xy) \in T \sum x \tag{4}$$

$$\bar{y} = \frac{1}{N}\sum(xy) \in T \sum y \tag{5}$$

where T head region of pixel I and x and y are the coordinates of the image. Moments of the order (p,q) as following equation.

$$m_{p,q} = \sum(x,y) \in T \sum(x-\bar{x})^p.(y-\bar{y})^q \tag{7}$$

where $m_{p,q}$ denotes the $(p+q)$ order of central moments for$p,q = 0,1,2,\dots,m$.

Moments for $(p,q) = 0$ and Equation (7) is denotes the left and right side tissues of segmented image. Then the weighted area $WA_{L,i}$ of the segmented image is denoted as

$$M_{R,i,00} = \sum(x,y) \in Ri \sum(x-\bar{x})^u.(y-\bar{y})^u \tag{8}$$

$$M_{L,i,00} = \sum(x,y) \in Li \sum(x-\bar{x})^u.(y-\bar{y})^u \tag{9}$$

$$M_{T,i,00} = M_{R,i,00} + M_{L,i,00} \tag{10}$$

$$WA_{L,i} = \frac{M_{L,i,00}}{M_{T,i,00}} \tag{11}$$

$$WA_{R,i} = \frac{M_{R,i,00}}{M_{T,i,00}} \tag{12}$$

$$WA_i = \left|WA_{L,i} - WA_{R,i}\right| \tag{13}$$

where $M_{L,i,00}$ and $M_{R,i,00}$ denotes the number of pixels and $WA_{L,i} - WA_{R,i}$ represents the tissues with AD.

4. Self-Organizing Map Network (SOMN)

FMRI AD images are contains significant number of complex relationship and independent variables. They normally demonstrate a nonlinear character that makes use of statistical approach for particular analysis. Thus the neural networks are good techniques to analyses the FMRI data. It will classify the different tissues of intensity or contrast and texture. Before classification, segmentation is important tasks in image processing. Segmentation process is very efficient utilized in the classification process. In this proposed approach the segmentation process using a very efficient approach such as SOMF.

In Self–Organizing Map Network (SOMN) every input is connected comprehensively to every output node via adjustable weights. The proposed approach SOMN inputs are using above mentioned different types of features. Let p $X = [x_1, x_2, x_3, \dots x_{N-1}]^T$denotes the set of input in R^N where N denotes the number of features or dimensions. $W_j = \left[w_{0j}, w_{1j} \dots, w_{(N-1)j}\right]^T$ represents the reference vector or weight. Let P denotes the number of outputs. W_j is the all the vector weights from N which means the output node of j to N input. w_{ij} denotes weights from input node i form output node j. Updating weights for any particular inputs in SOFM structure is carried out just for yield units in a localized neighborhood. The neighborhood is centered on the output node whose distance d_{ij} is minimum. The dimension of $d_{ij}$is a Euclidean distance, defined as

$$d_{ij} = min_j \left\|x_i - w_{ij}\right\|^2 \tag{14}$$

A single node contains its bounds means the size with time of the neighborhood is decreased. A learning rate, $\alpha_{ij}(t)$ is also essential which decreases uniformly in time. The updating weight rule is as follows

$$w_{ij}\,(t+1) = w_{ij}(t) + \alpha_{ij}(t)\left(x_i - w_{ij}(t)\right) \tag{15}$$

However, SOFM algorithms are highly in need of the training data respectively and the connection weight initialization. In SOFM calculating the white and black similarity map, the distance of the high similarity map is get from using more neighbors.

SOFM contain the modules are called neurons. The training process the feature sets are selected form the feature section process. The FMRI AD image segmentation process is as follows.

FMRI AD image segmentation

Initialization stage: Assign the initial weight to all the nodes

Competition: the input nodes are contest for input pattern ownership, Then the Euclidean distance is measured as the Best Matching Unit (BMU) utilizing $U_w(t) = argm\, in_i\{\|x(t) - w_i(t)\|\}$. Where, the input vector time t and $w_i(t)$ denotes the prototype vector related to unit i

Cooperation: In this stage the neighboring nodes change their weight using BMU neuron.
Learning Process: The BMU neuron and neighboring neuron are adjusted with the below rule, $w_i(t) = w_i(t) + \alpha(t)h_{ul}(t)(x(t) - w_i(t))$. Where $\alpha(t)$ denotes the learning factor and $h_{ul}(t)$ denotes the neighborhood function.

SOMF quality measurement considers the two criteria such as topological error and Quantization error. The distance between BMU and every data vector refers to quantization error and the first and second BMUs ratio is denote the topological error. The final output of SOFM is promising the minimum topological and quantization error.

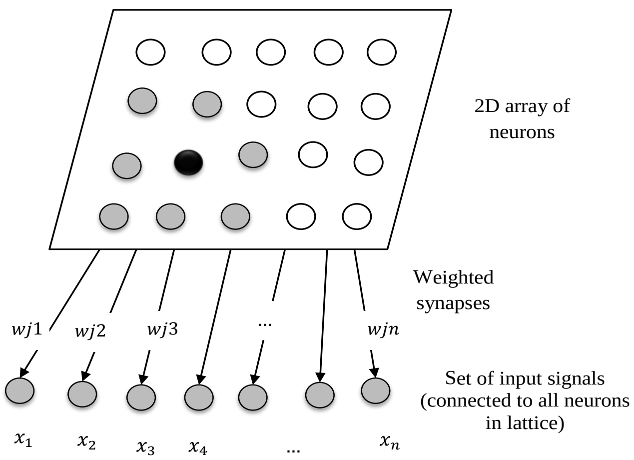

Fig. 2. The self-organizing map network.

5. ANFIS (Adaptive Neuro Fuzzy Inference System)

The ANFIS is a fuzzy Sugeno structure of adaptive process to make easy adaptation and learning [14]. ANFIS structural design, based on two fuzzy if–then rules measured as follows

Rule 1: if x is $p1$ and y is $q1$ then $f_1 = a_1x + b_1x + c_1$

Rule 2: if x is $p2$ and y is $q2$ then $f_{12} = a_2x + b_2x + c_2$

where x and y are the inputs to the system and $(ai, bi\ and\ ci)$ are the adaptable parameters. The output of the ANFIS is given as

$$f = (\bar{W}_1 x)p_1 + (\bar{W}_1 y)q_1 + (\bar{W}_1)r_1 + (\bar{W}_2)p_2 + (\bar{W}_2 y)q_2 + (\bar{W}_2)r_2 \quad (16)$$

It is linear combination of the different resultant parameters which is $p_1, q_1, r_1, p_2, q_2, r_2$. The least squares approach is utilized to classify these parameters effortlessly. Then find the maximum repeated pixel intensity in the AD of a brain. Then the histogram values are compared to whole AD image. The classifier results are detecting the AD segmentation using all the features.

6. Results and discussion

6.1. Materials

The data applying in this study were acquired from ADNI (Alzheimer's disease Neuroimaging Initiative) database. Feature index as shown as Table 3.

True Positive (TP): Proposed Segmentation and previous results are positive.

True Negative (TN): Proposed Segmentation and previous results are negative.

False Positive (FP): Proposed Segmentation is positive and previous results are negative.

False Negative (FN): Proposed Segmentation is negative and previous results are positive.

$$Sensitivity = {}^{TP}/_{(TP + FN)} \times 100 \quad (17)$$

$$Specificity = {}^{TN}/_{(TN + FP)} \times 100 \quad (18)$$

$$Accuracy = {}^{(TP + TN)}/_{(TP + TN + FP + FN)} \times 100 \quad (19)$$

Table 3. Feature Index

Feature index	Feature	Feature type
1	Variance	First order Feature
2	Mean	
3	Kurtosis	
4	Skewness	
5	Entropy	
6	Homogeneity	Textural Feature
7	Sum average	
8	Autocorrelation	
9	moment	
10	Cluster prominence	
11	Max probability	
12	Dissimilarity	
13	variance	
14	Moment(1)	Moment Invariants
15	Moment(2)	
16	Moment(3)	
17	Moment(4)	
18	Moment(5)	
19	Moment(6)	
20	Moment(7)	

6.2. Results

Evaluation of the proposed approach by using 184 AD patients and 220 healthy patients, where the proposed method used an ANFIS classifier based on SOFM segmentation of the AD FMRI image. Table 4 shows the segmentation feature values utilizing AD FMRI brain data. The results illustrate that the proposed segmentation approach is superior segmentation to compare other segmentation approaches.

Table 4. Segmentation Feature Values

Feature	Value
Variance	0.8636
Mean	0.7351
Kurtosis	0.8075
Skewness	0.8555
Entropy	0.8155
Homogeneity	0.7543
Sum average	0.7502
Autocorrelation	0.7630
moment	0.8299
Cluster prominence	0.8431
Max probability	0.7410
Dissimilarity	0.7722
variance	0.6592
Moment(1)	0.8207
Moment(2)	0.7359
Moment(3)	0.7807
Moment(4)	0.6621
Moment(5)	0.8026
Moment(6)	0.7427
Moment(7)	0.7639

Different types of comparison table as shown as Table 5. The sensitivity, specificity and accuracy results are shown that the proposed SOFM and ANFIS get the promising results compared to other previous implemented algorithms.

Table 5. Comparison of Different Type of Algorithm

Algorithm	Sensitivity	Specificity	Accuracy
First order with ANN	91.42%	90.1%	92.22%
Texture combined with ANN	95.4%	96.1%	97.22%
K-mean	80%	93.12%	83.3%
ANFIS with Genetic Algorithm	95.6%	94.36%	96.52%
SOFM with ANFIS	96.9%	95.56%	98%

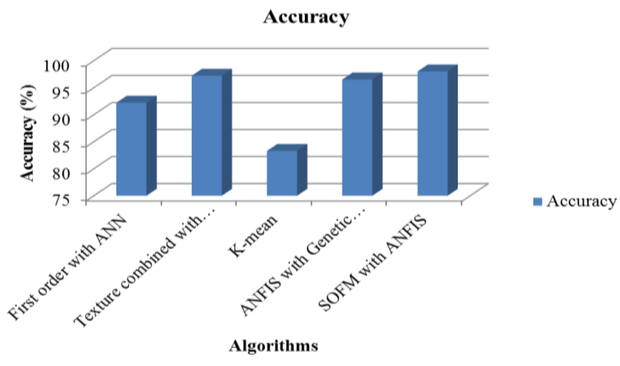

Fig. 3. Accuracy.

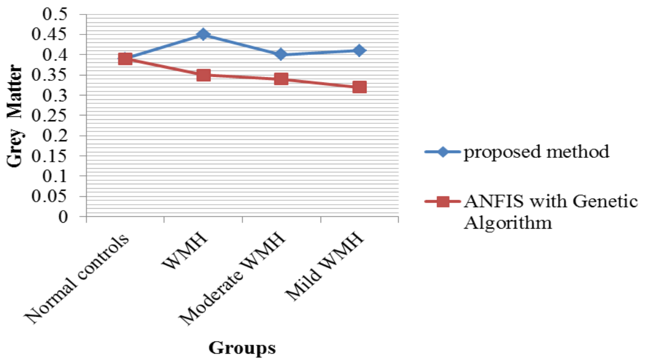

Fig. 4. Grey Matter of segmented image.

Fig. 3 show the accuracy results of different types of segmentation and classification algorithms.

Mean Grey Matter (GM) volumes of AD patients with and without White Matter Hyperintensities (WMH) segmentation as compared to ANFIS with genetic algorithm in the middle frontal region as shown in Fig. 4 and segmented image are shown in Fig. 5.

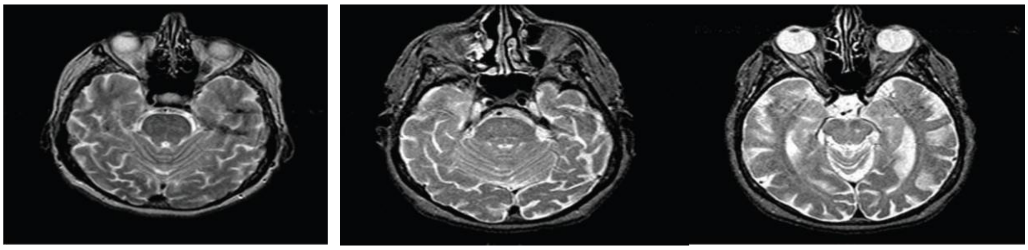

Fig. 5. (a). Healthy image. (b). AD image

7. Conclusion

In this paper, the proposed system is technologically advanced for diagnosing the Alzheimer's disease from brain FMRI images. This proposed system achieves this diagnosis in multiple phases. First order gray level parameters, multi-scale features, textural measures and moment invariant features for feature extraction. These extracted ADFMRI image features are utilized for classification. In classification phase proposed system is utilized for ANFIS (Adaptive Neuro Fuzzy Inference System) classifier for classifying FMRI images as malignant and benign. Once the images are resolute as malignant these are additional deal with the segmented part extraction from them. Alzheimer's disease extraction is performed in the segmentation phase. Segmentation phase stands a multistep phase. All experiments expresses that the proposed system provides better results as compared to the previously proposed segmentation and classification techniques. The system achieved accuracy of classification 98% and also attained very accurate results of segmentation which efficiently extract the Alzheimer's disease region from brain FMRI images.

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