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A Hybrid Approach for Alzheimer's Disease Classification using 2D Gabor Wavelet Transform and Extreme Machine Learning Classifier

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Alzheimer's disease (AD) is the most common type of dementia which is a significant public health problem. Therefore, several different automatic techniques have been established to support the clinicians in their diagnosis of AD and its stages. In this paper, a new novel combination of efficient and well-known techniques is introduced to effectively diagnosis of Alzheimer's disease (AD) with its prodromal stages including Mild Cognitive Impairment (MCI). The 2D Gabor Wavelet approach is implemented on the images to extract the possible features from the images. The features are minimized by using the feature selection process and it is done using the genetic algorithm. The optimal minimized features are fed into the extreme machine learning classifier which classifies the prodromal stages of AD patients. Structural MRI (SMRI) is a promising tool for diagnosing AD image for measuring the brain atrophy. The input data images are taken from the Alzheimer's disease Neuroimaging Initiative (ADNI) database. The input sample images are given. The proposed 2D Gabor Wavelet feature extraction technique is compared with the Gray-Level Co-occurrence Matrix method and the Extreme Machine Learning classifier is compared with existing techniques such as Support Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System and the Hybrid Neuro Fuzzy Runge Kutta. The results of this comparison show that the proposed techniques outperform all other techniques. The proposed system as a whole is evaluated in the final.

Key words: Alzheimer's disease (AD), Structural MRI, 2D Gabor Wavelet (GW), Genetic Algorithm(GA), Extreme Machine Learning Classifier (EMLC).

Present multi-site clinical studies give an effective approach to understand the diseases and their analysis. Recently, neuroimaging results have progressively been consolidated into such studies[1]. In contrast, the data is often lacking about the variability and robustness of these results in a multi-site setting. The quantitative assessment of cerebral tissue was viewed as unreliable for the Alzheimer's disease detection. But the observations was directed to biomarkers of global atrophy, while late research has proposed that the estimation of regional atrophy (hippocampus, perihippocampal structures, and hippocampal formation) is a challenging approach to separate AD patients from healthy control patients.

For computer-based measurement of brain atrophy, the semi-automated and recently automated methods have been proposed, for example manual delineation and watershed segmentation are utilized to recognize eight dissimilar sulci regions, brain surface grey matter thickness/volume area, local gyrification index, geodesic sulcal depth, and curvature are used for atrophy measurement. Atrophy analysis from longitudinal MR images is used by fuzzy logic

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approach for segmentation. Like the automatic approach, ruction based on the implicit surface evolution is perceived and same as the geodesic sulcal curvature and depth and the grey matter thickness are all measured from the MR images of the AD patients.

In this proposed approach, the well-known 2D Gabor Wavelet (GW) approach for AD feature extraction from SMRI image[2]. The extracted features are sub-selected using Genetic algorithm, where selected features are fed into Extreme Machine Learning Classifier (EMLC)[3]. The 2D Gabor wavelet (GW) approach has been commonly employed in face recognition and detection due to the robustness of GW features against variance of illumination, local distortions and so on. Considering these advantages and results, the GW approach is utilized in the proposed system. Recent work in the field of medical image recognition and classification explores the utilization of evolutionary algorithms for feature selection, and genetic algorithm (GA)[4] is one sort of evolutionary algorithms used in the proposed approach for effectively solving the features sub-selection problem. Finally the feature classification is based on EMLC approach. EMLC is one sort of neural network algorithm, is recognized as high quality classifier to resolve the multidimensional problem and it brings minimized computational time than the other neural network algorithms.

Related work

Many classification methods are present to classify the Alzheimer's disease, other diseases based on their own theory. Since these methods are used in different population, environments and the disease severity, the conclusion about the working of those methods are difficult to determine. Hence this paper brings the performance evaluation of selectively taken ten of those methods and techniques[5]. In those ten methods three methods based on cortical thickness, five voxel-based methods and two methods based on the hippocampus. This experiment is done in a same set of data, environment and images. The ADNI database is used for this performance analysis.

The paper proposes a framework that recognize and classifies the Alzheimer's disease (AD) automatically from the MRI (Magnetic Resonance Images)[6]. This method concentrates on the visual features of the image region and slows down the fusion process that maximizes the precision rate. The images required for the classification are taken from the Alzheimer's disease Neuroimaging Initiative (ADNI) database. The method is examined along with the contrast images from the Bordeaux dataset. The final performance analysis of the proposed method compared with the Normal Control (NC) shows that the proposed method proves better efficiency than the existing methods and brings accurate classification.

Alzheimer's disease becomes the most serious issue in many countries. In order to diagnosis this disease, various methods have been proposed. The author proposes a new method that also automatically diagnosis the AD but the difference here is that the classification is done using the Binary Support Vector Machine[7]. This classification discriminates the Alzheimer's disease, mild cognitive impairment patients and the elderly control subjects' patients. All this process for classification takes much computational time, so that the proposed system used the Java Agent DEvelopment Framework JADE multi agent platform which results in better efficiency and improvement in parallelization.

Early diagnosis of mild cognitive impairment (MCI) stage in the Alzheimer's disease supports the medical expert to give prior treatment to the patients. This classification of disease is usually done using machine learners with the multi-modal biomarkers. However the accuracy becomes a major problem with these methods. The author proposed a multi model Bayesian kernelization (MBK), a novel diagnosis algorithm which maximize the local neighborhood affinity by the biomarker and detect the disease by synthesizing the output probability of disease[8].

The author proposes the modalities of biomarkers namely FDG-PET, MRI and CSF which is used to differentiate Alzheimer's disease and MCI[9]. This is the first method which is used for AD classification using the multi modalities. In depth analysis of this method has been analyzed and it used the PET images and MRI images and nearly 93 features are extracted and use the atlas warping algorithm for the classification. This classification is evaluated using the linear Support Vector machine. This proposed method is compared with the many existing efficient algorithms and methods and proves that the

proposed method achieves better performance than the other methods.

A local patch based subspace ensemble method is proposed that overcome the single classifier problem and implements the multiple classifiers which work according to the local patch subset. These subsets are huge in number that is integrated together into a single result for the better accuracy of diagnosis[10]. In addition, the sparse representation based classifier is used to detect and transform the weak classifier to strong one which adds additional advantage to the proposed system.

The paper proposes the Alzheimer's disease classification system[11] by observing the ADNI dataset. It observes and fuse the overlap based similarity and registration based measures and enhances a matrix using self-smoothing technique. This is the matrix of pair-wise affinities between the data points leads to the enhanced matrix, using this enhanced matrix, the accuracy is improved in the Alzheimer's disease classification. This classification gives the output as normal, Alzheimer's and the mild cognitive impairment.

Proposed Methodology

The proposed system performs the feature extraction SMRI by using popular 2D Gabor Wavelet (GW) approach. The extracted features are sub-selected using Genetic algorithm, where selected optimized features are fed into Extreme Machine Learning Classifier (EMLC) that classifies the given SMRI image of AD into any of the three stages namely Normal, MCI and the AD. This proposed system is depicted in the figure 1.

2D Gabor Wavelet (GW) Feature Extraction

The refine study of functional and structural brain image is of great significance in the early recognition of Alzheimer's disease (AD) and Mild cognitive impairment (MCI). The MCI is simply a small drop in thinking ability and is popularly known as the early stage of Alzheimer's disease (AD).In this paper, a 2D GW examination methodology is connected to Structural MRI (SMRI), for appropriate early diagnosis of Alzheimer's malady (AD). GWs were presented in image processing due to their computational properties and biological relevance[12]. The images from the SMRI tool are normalized and combined with the 2D log-Gabor wavelet filter along with different scales and orientations. 2D Gabor wavelet transfer function along with Gaussian function is defined as follows:

$$\varphi_{u,v}(\vec{z}) = \frac{1}{2\pi}\frac{\|\vec{K}_{u,v}\|^2}{\sigma^2}\exp\left(\frac{-\|\vec{K}_{u,v}\|^2((x)^2+(y)^2)}{2\sigma^2}\right)exp(j\vec{k}_{u,}\vec{z}) \quad ...(1)$$

Where σ is the standard deviation of the transfer function

$$\vec{K}_{u,v} = 2\pi f_u \exp(j\theta_v) \quad ...(2)$$

$$\theta_v = \frac{v}{V}\pi, \qquad v = 0, \ldots, V-1 \quad ...(3)$$

$$f_u = \frac{\sqrt{2}}{\sqrt{2^u}}, \qquad u = 0, \ldots, U-1 \quad ...(4)$$

Where θ_v and f_u are the scale and orientation of the Gabor Wavelet method, and $\vec{K}_{u,v}$ is the wave vector. By using the eq. (1-4), the

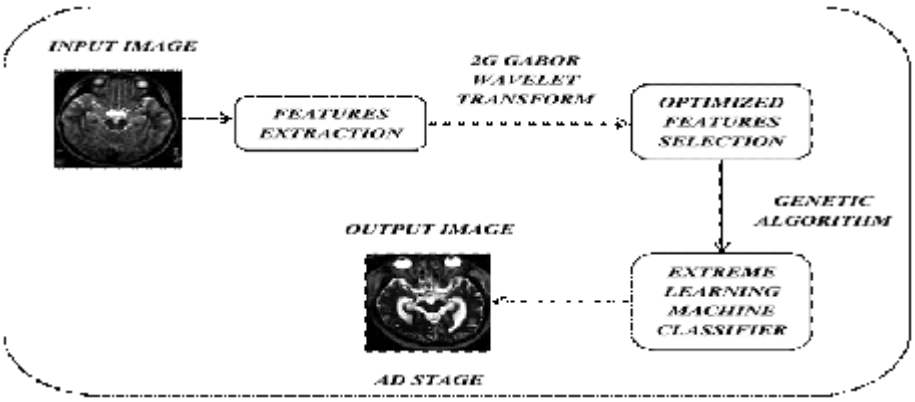

Fig. 1. Architecture of Proposed System

2D wavelets set of an image can be calculated. The experiment takes the 4 scales and 6 orientations and assume that the odd symmetric and even symmetric filters be M_{so}^{odd} and M_{so}^{even} at the scale s and the orientation o[13]. By using the different orientation and scales, the texture features of the AD affected area are obtained. Then the response vector is calculated as

$$[E_{so}(x,y), O_{so}(x,y)] = [I(x,y) * M_{so}^{even}, I(x,y) * M_{so}^{odd}] \quad ...(5)$$

Utilizing the given orientation and scale, the amplitude and the phase of the response can be calculated as

$$Amplitude_{so} = \sqrt{E_{so}(x,y)^2 + O_{so}(x,y)^2} \quad ...(6)$$

$$Phase_{so}(x,y) = a\tan\left(\frac{O_{so}(x,y)}{E_{so}(x,y)}\right) \quad ...(7)$$

Many features of the SMRI image regarding AD are extracted using the 2D Gabor Wavelet such as Mean, Variance, Energy, Entropy, Skewness, contrast, Absolute Value, correlation, inverse difference and inertia. Textural features such as Sum Average, Dissimilarity, Auto Correlation, Cluster Prominence and moment. Mean is an average value of the image. Variance is the variation around the mean. Energy is the sum of square elements that is calculated using the 2D Gabor Wavelet transform. It is also called as Angular Second Moment. Entropy is a measuring the uncertainty in the random variable. Uniformity of the mean value is the skewness. Contrast is the difference between the bright and dark area in the image. Correlation is simply finding the difference between the image pixels. Inverse difference measures the changes in the image texture. Homogeneity is a state of being homogeneous. The following table 1 gives the formula for the features extracted by the 2D Gabor Wavelet (GW) transform methodology.

Genetic Feature Subset Selection

The features from the image are extracted using the 2D Gabor Wavelet (GW) transform methodology and listed in the above table. The purpose of feature extraction is to minimize the complexity of the classification and that makes the classification process easier. Since the classification does not require all the features extracted from the image, the appropriate subset selection of features are required. Hence the genetic algorithm is used to reduce the unwanted features from the set of extracted features. The genetic algorithm is a procedure for finding the optimized points in the search space. Consider a search space of many points (features extracted) and the randomly generated chromosomes. Taking these chromosomes as initial population, the genetic algorithm initiates its searching process to find the best optimal features. This algorithm has the three step processes namely selection, crossover and finally mutation. The final points from the search space represent the optimal features.

Before the process of feature subset selection, the fitness value of each feature is calculated and it is based on the accuracy of the feature and the size of the feature[14]. Integrating the feature size and the accuracy gives raise to the fitness function as

$$fitness\ value = 10^4 Accuracy + 0.4 * Zeros \quad ...(8)$$

Where the accuracy represents the accuracy range of each individual point and Zeros represent the number of zeros in the chromosome. The higher the accuracy, the higher the fitness is. The less number of feature selected leads to the higher number of zeros in the chromosomes and it results in the higher fitness value.

The genetic algorithm for selecting the optimal features consists of three steps[15]. First is initial population where each initial point in the search space is generated randomly and contains the value that are scattered haphazardly in the chromosomes. Second step is crossover where the qualities from two different features are combined and form the new feature that gives higher fitness value. In order to make the process straightforward, uniform crossover is used here. Third step is mutation where the selection process actually starts. It restore the genetic material that was lost unconditionally and selects the optimal best features which are having the higher fitness value among the original and offspring features.

The selected features set from the original extracted features set is represented as $C = \{F^1, F^2, \ldots, F^n\}$ and the final combination of optimal best feature sub set is represented as $F_{ss} = \{< f_{k1}^1, f_{k1}^1, \ldots, f_{kp}^n >\}$.

The final optimal feature extracted from this feature selection process are *contrast, mean, homogeneity, Sum average, auto correlation and variance.*

Classification using Extreme Machine Learning Algorithm

The classification of Alzheimer's disease into three stages namely normal, AD and mild are performed using the specific features selected in the previous sub section. This classification is done using the Extreme learning machine algorithm. This algorithm is minimizes the cost function and maintain the constant/moderate accuracy and computing speed with a reasonable range. A new machine leaning algorithm knows as the Extreme Learning Machine comprises of an input layer with neurons of specific weights, hidden layer neurons to minimize the cost function and this algorithm maintains the computing speed, cost and classification accuracy within an acceptable range.

Similar to the neural network, the Extreme Learning Machine is based on the Single hidden Layered Feed Forward Neural Networks (SLFNs)[16]. The algorithm selects and fixes the parameters of the hidden nodes where the output weights of each hidden nodes are calculated. Final output weights are obtained by using the inverse operation of the output matrixes of the hidden layer. The SLFN network takes the $"p"$ number of hidden nodes where in the $"N"$ pairs of input/output values are processed and results in zero error. The purpose of using this SLFN network is that it selects the input neuron weights and the hidden neuron weights without using the training set. Hence the training time is reduced when compared to the other networks which are using training set data. In addition, the SLFN network avoids the use of kernel based design; instead it uses the additive neuron design which is used to select the parameter randomly. The sigmoid function is used which is a non-linear activation function and can be written as

$$G(a_i, x_j, b_i) = \frac{1}{1 + e^{-(-a_i x_j + b_i)}} \quad ...(9)$$

The procedure of Extreme Machine Learning Algorithm in SFLN works as follows:

Let the training set be represented as $N = \{(x_i, t_i) \mid x_i \in R^n, t_i \in R^m, i = 1, \ldots, N\}$, hidden neuron N and the kernel function $f(x)$.

i) Select the suitable activation function. Here the sigmoid Eq (9) is used with the hidden neurons for the optimized classification.

ii) Fix the input weight and the hidden neuron weights

iii) Compute the hidden layer output matrix and can be written as

$$H = \begin{bmatrix} G(a_1, x_1, b_1) & G(a_1, x_1, b_1) & \ldots & G(a_1, x_1, b_1) \\ G(a_1, x_2, b_1) & G(a_2, x_2, b_2) & \ldots & G(a_p, x_2, b_p) \\ \vdots & \vdots & \ldots & \vdots \\ G(a_n, x_N, b_n) & G(a_n, x_N, b_n) & \ldots & G(a_n, x_N, b_n) \end{bmatrix}$$

Where, $H\beta = T$

iv) The final output of the Extreme Machine Learning classifier is computed as

$$\beta = H^{1}T \quad ...(10)$$

Based on this β value, the normal, MCI and serious stages of Alzheimer's disease is classified.

(i) Choose the selected features on by one and place it in the input neurons

(ii) The weights for the features in the input neurons and the hidden layer neurons are assigned based on the optimization level.

(iii) Calculate the output of the hidden layer in the form of matrix.

$$H = \begin{bmatrix} G(a_1, x_1, b_1) & G(a_1, x_1, b_1) & \ldots & G(a_1, x_1, b_1) \\ G(a_1, x_2, b_1) & G(a_2, x_2, b_2) & \ldots & G(a_p, x_2, b_p) \\ \vdots & \vdots & \ldots & \vdots \\ G(a_n, x_N, b_n) & G(a_n, x_N, b_n) & \ldots & G(a_n, x_N, b_n) \end{bmatrix}$$

Where, $H\beta = T$

(iv) Use the hidden layer output and add some weights based on the hidden layer result, find the classified stages of the AD in the output of the final layer $\beta = H^{1}T$.

RESULTS AND DISCUSSION

The proposed system works on the dataset images which are real human brain images. The input data set consists of 120 images which are the AD patients' brain images and their ages vary between 20 to 85 years. The goal of the proposed system is to classify input images into

Table 1. Features and their formulae Extracted by the 2D Gabor Wavelet Transform Methodology

Feature	*Formula*
Mean	$\sigma^2 = \sum_{I=0}^{G-1} ip(i)$
Variance	$\sigma^2 = \sum_{I=0}^{G-1} (i-\mu)^2 P(i)$
Energy	$\sum_{i,j=0}^{N-1} (p_{i,j})^2$
Entropy	$H = -\sum_{I=0}^{G-1} p(i) log_2[p(i)]$
Skewness	$\mu_3 = \sigma^{-3} \sum_{I=0}^{G-1} (i-\mu)^3 p(i)$
Contrast	$\sum_{i,j=0}^{N-1} p_{i,j}(i-j)^2$
Absolute Value	$\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \lvert i-j \rvert p(i,j)$
Correlation	$\sum_{i,j=0}^{N-1} p_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$
Inverse Difference	$\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{p(i,j)}{1+(i-j)^2}$
Inertia	$\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-j)^2 p(i,j)$
Sum Average	$TSA = \sum_{i=0}^{2N_x-2} i\, p_{x+y}(i)$
Dissimilarity	$TDM = \sum_{i,j=1}^{S} C_{ij} \lvert i-j \rvert$
Auto Correlation	$AC(p,q) = \frac{MN \sum_{i=1}^{M-p} \sum_{j=1}^{N-q} f(i,j) f(i+p, j+q)}{(M-p)X(N-q) \sum_{i=1}^{M} \sum_{j=1}^{N} f^2(i,j)}$
Kurtosis	$\mu_3 = \sigma^{-4} \sum_{I=0}^{G-1} (i-\mu)^4 p(i) - 3$
Homogeneity	$\sum_{i,j=0}^{N-1} \frac{p_{i,j}}{1+(i-j)^2}$
Angular Second Moment	$\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} [p(i,j)]^2$
Maximum Probability	$TMP = Max_{i,j}(p(i,j))$

three different stages such as normal, MCI and AD. The images are collected from the ADNI database. The dataset is collected and fed into the proposed system. As describes in the previous sections, the input images are fed into the 2D GW which extracts 17 features. Since the minimum optimal features are enough for the classification purpose, these features are processed using the genetic algorithm for the extraction of optimal features for further classification. Seven optimal features are given to the Extreme Machine Learning Classifier which classifies the different stages of the AD disease.

The images of the Alzheimer's disease are taken through the Structural MRI scan from the ADNI database. The sample images are given in the below figure 2.

The performance assessment of the methodologies used in the proposed system is done in this section. The feature extraction of the ADNI database images is done using the 2D Gabor wavelet method. The table 2 shows the extracted features and their corresponding values using the 2D Gabor wavelet transform method. The resultant feature values shows that the 2D Gabor wavelet transform method performs better feature extraction process when compared to the other existing methods.

The comparison of 2D Gabor Wavelet method with the existing Gray-Level Co-occurrence

Table 2. Values of the Extracted Features

Features	Values
Mean	0.8462
Variance	0.9746
Energy	0.9653
Entropy	0.7581
Skewness	0.8652
Contrast	0.7263
Absolute Value	0.9365
Correlation	0.9123
Inverse Difference	0.7821
Inertia	0.8259
Sum Average	0.7615
Dissimilarity	0.7784
Auto Correlation	0.8635
Kurtosis	0.9365
Homogeneity	0.8555
Second Angular Moment	0.7777
Maximum Probability	0.8523

Matrix is shown in the figure 3. It shows that the 2D Gabor Wavelet method extracts the features from the images with more accuracy and speed.

The methodologies used for classification of different stages of Alzheimer's disease in the previous works are compared here with the proposed EMLC classifier. The figure 4 shows that the proposed system has attain the high accuracy in predicting the sensitivity of disease.

This section describes the performance evaluation of the methods employed in the proposed system. The assessment of these methods is done in terms of accuracy, specificity and the sensitivity. These three assessment terms are specified in the following forms.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN)*100\% \quad ...(11)$$

$$\text{Specificity} = TN / (TN+FN) * 100\% \quad ...(12)$$

$$\text{Sensitivity} = TP / (TP+FN) * 100\% \quad ...(13)$$

Where,

TP (True Positives) = correctly classified positive cases,

FP (False Positives) = incorrectly classified negative cases,

TN (True Negative) = correctly classified negative cases,

FN (False Negative) = incorrectly classified positive cases.

Accuracy is chance of the methods performed correctly. Specificity also called as true

Table 2. Analysis of proposed methodologies

Techniques	TN	FN	TP	FP	Specificity	Sensitivity ± SD	Accuracy ± SD
2D GW+GA	17	3±1	34±1	0	100	91.87±2.69	94.44±1.85
2D GW+GA+EMLA	17	2±1	35±1	0	100	94.6±2.7	96.29±1.85

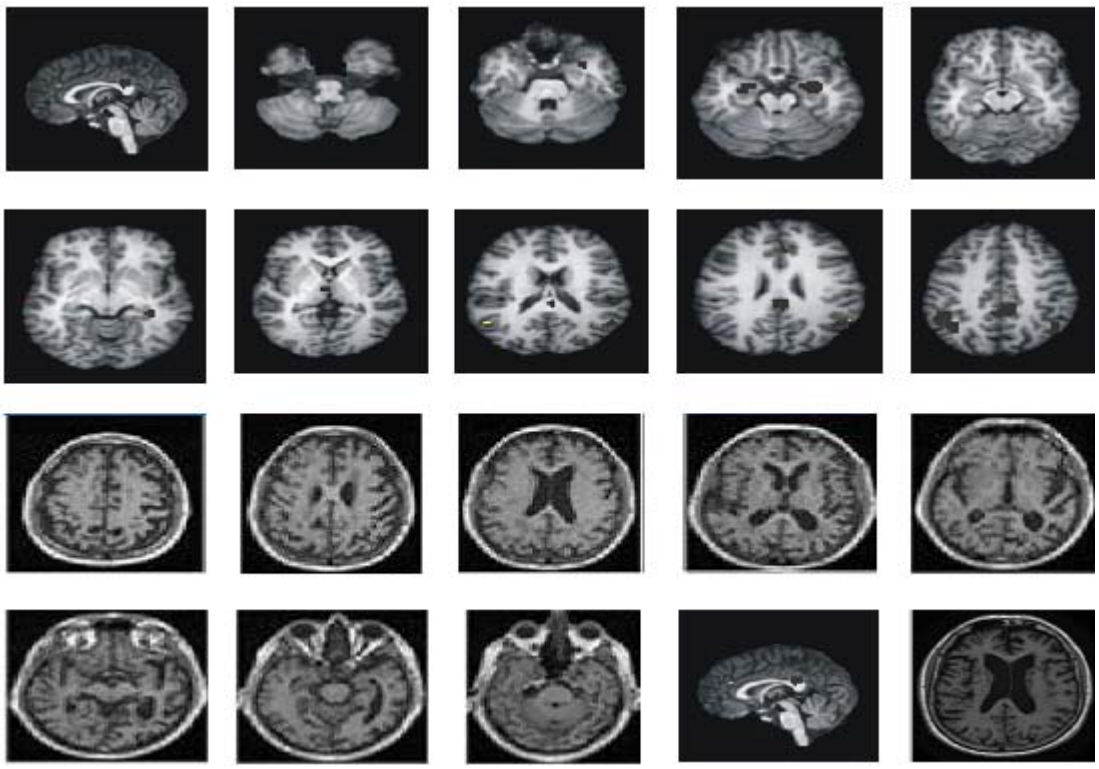

Fig. 2. Sample Images

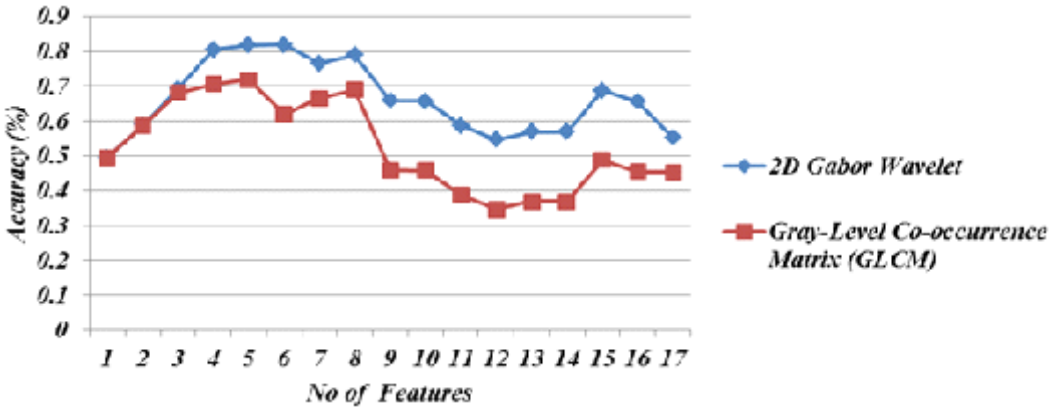

Fig. 3. Comparison of 2D Gabor Wavelet with existing Gray-Level Co-occurrence Matrix method

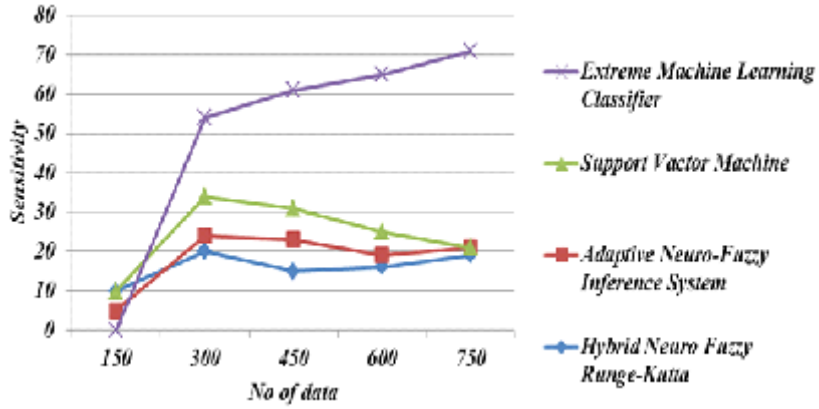

Fig. 4. Comparison of previous classification methods with proposed EMLC classifier

negative fraction is that the results of the tests are negative (i.e.) the person is not having the particular disease. Sensitivity is also called as true positive fraction is that the results of the tests are positive (i.e.) the person is having the chance of that particular disease.

The methodologies used in the paper are to classify the Alzheimer's disease into three different stages. In order to assess the performance of the methods used in the proposed system, the methods are compared with other existing methods used for the same purpose. The table 2 shows the classification range of the proposed techniques based on the parameters taken for determining the sensitivity, accuracy and the specificity.

The table explains that the high accuracy classification and the minimized computational cost are achieved by the 2D Gabor Wavelet feature extraction. The accuracy rate is ranging from 96% to 98% which is not possible in the existing hybrid methodologies. This makes the additional advantage to the proposed system and acts as a medical image analysis device that supports the medical experts to classify the AD's prodromal stages.

CONCLUSION

In this paper, the Alzheimer's disease classification is done using Extreme Machine Leaning algorithm from the SMRI images. This disease is classified as normal, mild and AD stages. The features are extracted from the SMRI scan images using the 2D Gabor Wavelet (GW) Transform methodology. Since the classification does not need all the extracted features to classify the disease stages, the features are reduced into less in number. This feature dimensionality reduction is done using the genetic algorithm. Then the EML Classifier is used to classify the disease stages and uses the SLFN network for the minimization of time, computational cost and

maintains the constant accuracy. The proposed feature extraction method is compared with the existing feature extraction method used in the previous work and shows that it performs better. The classification method in the proposed system is compared with the methodologies of previous work and shows that the proposed classification method brings the result with more sensitivity and accuracy. The feature extraction and feature selection methods are evaluated in terms of accuracy, sensitivity and the specificity and proves that they brings the enhanced performance than the existing combination of techniques.

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