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IMAGE & SIGNAL PROCESSING

Earlier detection of Alzheimer disease using N-fold cross validation approach

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Abstract
According to the recent study, world-wide 40 million patients are affected by Alzheimer disease (AD) because it is one of the dangerous neurodegenerative disorders. This AD disease has less symptoms such as short term memory loss, mood swings, problem with language understanding and behavioral issues. Due to these low symptoms, AD disease is difficult to recognize in the early stage. So, the automated computer aided system need to be developed for recognizing the AD disease for minimizing the mortality rate. Initially, brain MRI image is collected from patients which are processed by applying different processing steps such as noise removal, segmentation, feature extraction, feature selection and classification. The captured MRI image has noise that is eliminated by applying the Lucy–Richardson approach which examines the each pixel in the image and removes the Gaussian noise which also eliminates the blur image. After eliminating the noise pixel from the image, affected region is segmented by Prolong adaptive exclusive analytical Atlas approach. From the segmented region, different GLCM statistical features are extracted and optimal features subset is selected by applying the hybrid wrapper filtering approach. This selected features are analyzed by N-fold cross validation approach which recognizes the AD related features successfully. Then the efficiency of the system is evaluated with the help of MATLAB based experimental results, in which Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset images are utilized for examining the efficiency in terms of sensitivity, specificity, ROC curve and accuracy.

Keywords Alzheimer disease (AD) · Lucy–Richardson approach · Prolong adaptive exclusive analytical Atlas · Hybrid wrapper filtering approach · N-fold crosses validation

Introduction

Alzheimer Disease (AD) is one of the dangerous neurodegenerative (nerve) disease that affects people upto 60–70% [1]. According to the survey 110 million people are affected by this nerve related disorder in their old age. Not only the old age people, now days most of the people suffer from this Alzheimer disease [2] at their middle age such as 40's and 50's. The AD disease affected people suffered by short term memory loss and other nervous related issue. This Alzheimer disease is detected by several symptoms [3] such as mood swings, difficulty to recognize language, loss of self-motivation, fail to manage their self-care also having behavioral issues. The serious AD issue leads to affect the function of entire body that leads to death. Most of the time, the AD disease having 70% risk [4] because it created due to the genetic mutations, depressions, head injuries, hypertension that affects the tangles, plaques in brain. So, the AD disease risk factor is further reduced by performing the medical examination, behavioral examination and neurological examination [5] process. During this process, brain functions are analyzed in terms of using different medical imaging methods such as single-photon emission computed tomography (SPECT), computed tomography (CT), positron emission tomography (PET), magnetic resonance imaging (MRI) which are more useful to detect the seriousness present in the brain as well as computing the Alzheimer disease [6]. According to the National Institute of Neurological and Communicative

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Disorders and Stroke (NINCDS) and Alzheimer Association includes the brain function detection process [7] and testing methodologies to detect the Alzheimer disease along with their symptoms. The computed medical examination used to predict the orientation related problem solving, memory issues, perceptual related skills, constructive abilities and functional abilities related issues. The conducted physical and medical examination resultant medical imaging is examined using different image processing and machine learning techniques [8] because that used to predict the affected region, related functions with effective manner. Various methodologies such as Gaussian filter, median filter, mean mode method, weiner filters are used to eliminate the noise from the captured medical image. Further those medical images are examined using segmentation, feature extraction, selection and disease recognition steps. The affected part is further segmented with the help of dual clustering, soble operator, canny edge operator, and so on. From the region various features are extracted that are processed by effective machine learning techniques [9] such as support vector machine, K-nearest neighbor, neural network and so on. Even though these methods are successfully recognizing the AD disease, the system has high computational complexity as well as high computation consumtion time. So, this paper introduce effective optimized techniques such as hybridized wrapper filtering approach along with N-fold cross validation approach for detecting Alzheimer disease with effective manner. Then the excellence of the system is evaluated with the help of experimental results and the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset images are utilized for examining the efficiency in terms of sensitivity, specificity, ROC curve and accuracy.

Then the rest of the section is arranged as follows, first section examines the related works on Alzheimer disease detection, second section explains hybridized wrapper filtering approach along with N-fold cross validation approach, Alzheimer disease detection system, fourth section evaluates the efficiency of hybridized wrapper filtering approach along with N-fold cross validation approach for detecting Alzheimer disease and fifth section gives a conclusion on the findings made.

Related works

This section discusses about the various authors opinions, regarding Alzheimer disease detection process, (Alam et al. 2017) [10] by Implementing Alzheimer disease detection system using support vector machine techniques. During the AD detection process, brain structural magnetic resonance image is collected from patient by applying the CIVET toolbox. From the brain image, various features are extracted and irrelevant features, dimensionality of the features are reduced by applying kernel principle component analysis method. The selected features are processed by defined classifier that successfully recognizes the AD disease with 93.5% accuracy. Akgül et al. (2009) [11] developed Alzheimer detection system by applying supervised learning methodologies. Initially, the brain MRI images are collected from people by conducting visual similarity and user feedback process. The gathered images are analyzed and various features are derived which are fed into the K-Nearest Neighbor approach. This approach examines the similarity between the features by computing the distance measure which is done with the help of support vector machine approach. According to the distance, similarity, features are estimated that are ranked and AD disease related features are computed with effective manner.

Savio et al. (2009) [12] analyzed the Alzheimer disease from MRI brain image by applying different neural networks such as Learning Vector Quantization Neural Networks (LVQ), Neural Networks (NN), Radial Basis Function Networks (RBFN), Back Propagation Neural NEtworks (BPNN) and Probabilistic Neural Networks (PNN). Before processing these networks, brain images are examined and affected part is segmented by voxel based morphometric clustering process. From the cluster different features are extracted that are fed into mentioned networks for recognizing the AD disease in an effective manner. The efficiency of the system is evaluated by using Open Access series of imaging studies database which consists of collection brain MRI image that have collected from 98 females. The collected images are processed by above defined neural network methods for recognizing AD disease in an effective manner. Lahmiri and Boukadoum (2013) [13] Examined the FMRI brain image for detecting the Alzheimer Disease. During this process, FMRI image of brain is collected from 93 patients, which are analyzed by multiscale analysis method that extract 6 different scales of features. The extracted fractal feature is analyzed by support vector machine that successfully classifies the normal and abnormal AD related features with 99.18% accuracy.

Tejeswineea et al. (2017) [14] Created Parkinson's and Alzheimer disease detection system from neuro-degenerative data using different data mining techniques. Initially, the brain data is collected from patients, which are huge in dimension that is difficult to process while analyzing AD disease. The dimensionality of the features is selected by computing the correlation between the data which is done with the help of correlation based feature selection approach. The selected feature investigated by genetic variants approach classifies AD disease with 93% of accuracy. Sivapriya et al. (2015) [15] analyzing brain features by applying Merit Merge feature selection approach and multivariate analyze method. Initially, the brain images are collected; effective features are extracted from image. From the extracted s optimized features are selected by defined approach, that reduces the computation complexity. The selected features are processed by different ensemble classifiers such as support vector machine, random forest, C4.5 feature search, naïveBayes approach. In addition

to this, the method searches the features in search space according to particle swarm optimization approach. This optimized process improves the Alzheimer detection system upto 98.7% accuracy. According to the above discussions, Alzheimer detection process is improved by applying effective techniques because the huge dimensionality of the feature is set. So, this paper examines the optimized techniques for improving Alzheimer disease detection process which are discussed is as follows.

Alzheimer disease detection using N-fold cross validation approach

In this section the early detection of Alzheimer Disease (AD) detection system using N-Fold Cross Validation Approach is analyzed. During this process, the system follows several steps such as image preprocessing, region segmentation, feature extraction, feature selection and disease detection. By using the above steps, the main intension of the work is explained.

Objective of the work

In this work Alzheimer's disease Neuroimaging Initiative (ADNI) dataset images are used to analyze the AD disease in earlier stages. The collected brain images are processed by effective Lucy–Richardson approach which examines each and every pixel which eliminates the Gaussian noise from the image. From that image, prolong adaptive exclusive analytical Atlas approach based region is segmented and related features are derived. After extracting the features from the image which is huge in dimension that is difficult to process with minimum time accurate prediction of AD is too difficult. So, in this work hybrid wrapper filtering approach is used to get the feature subset. Normally, the wrapper approach select the feature subset train the model to get the subset but it consumes more computational complexity, while filtering approach analyze the features in terms of mutual information, the point wise mutual information, Pearson product-moment correlation coefficient that helps to get the important feature from the set of features. But the filtering approach, select the feature with very low computational complexity but the prediction rate is very low. So, in this work, this approach is hybridized which means, analyze the features according to the filtering approach and create the train model based on wrapper method for getting the effective feature subset from the collection of feature that helps to improve the overall AD prediction rate. Further the N-fold cross validation approach is applied to classify the AD disease which is done by spilting the dataset into two half validating dataset and training set.

Materials and methods

Image acquisition

The first phase of Alzheimer disease (AD) detection process is an image acquisition in this work, Alzheimer's disease Neuroimaging Initiative (ADNI) (http://adni.loni.usc.edu/about/) dataset is used to collected MRI brain image. The dataset capture the longitudinal structural image by 1.5 T scanner and dual echo T2 weighted sequences process. The ADNI captures MRI brain image by conducting experiments in Laboratory of Neuro-Imaging (LONI) at University of Southern California. In 2013, the ADNI consists of around 7 million brain images with related clinical data. The data is collected by recruiting the people who have age 55 to 90 from 57 cities in Canada and US. The gathered data helps to examine 12 different diseases such as Alzheimer disease, bipolar disorder, depression and schizophrenia. According to the discussions, the normal and Alzheimer Disease (AD) brain image is shown in Fig. 1.

According to this discussion, MRI brain image is collected from Alzheimer's disease Neuroimaging Initiative (ADNI) dataset and AD disease has been detected from this, related processing structure is shown in Fig. 2.

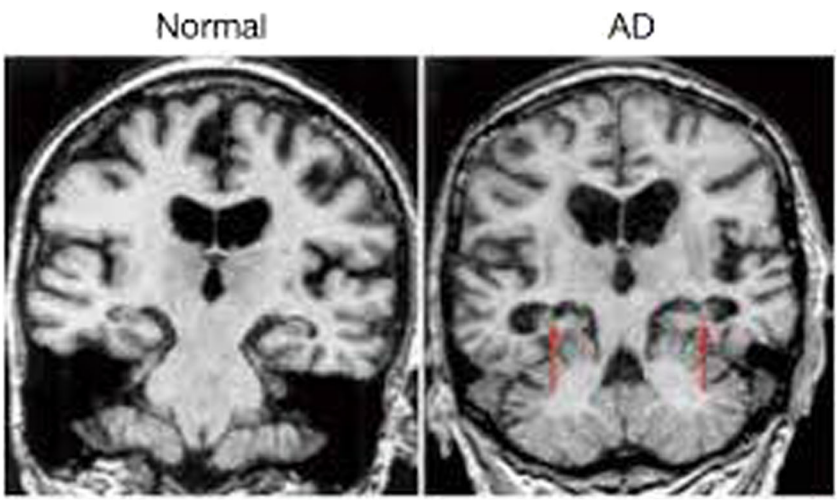

Fig. 1 Sample AD and normal brain MRI image

Brain MRI image pre-processing using Lucy–Richardson approach

After collecting MRI brain image from ADNI dataset, it has been analyzed pixel by pixel because the brain image may contain noise pixel. In addition to this, brain image have deblur pixel, Gaussian noise that need to be removed from image for improving AD disease detection process. So, in this work Gaussian noise [16] has been eliminated from the image by applying the Lucy-Richardson algorithm [17]. The LR method removes the noise by utilizing the point spread function which successfully deblur the image also eliminate the noise. First, each pixel in brain image is examined to predict the spread value of pixel that is computed as follows.

$$d_i = \sum_j p_{ij} u_j \quad (1)$$

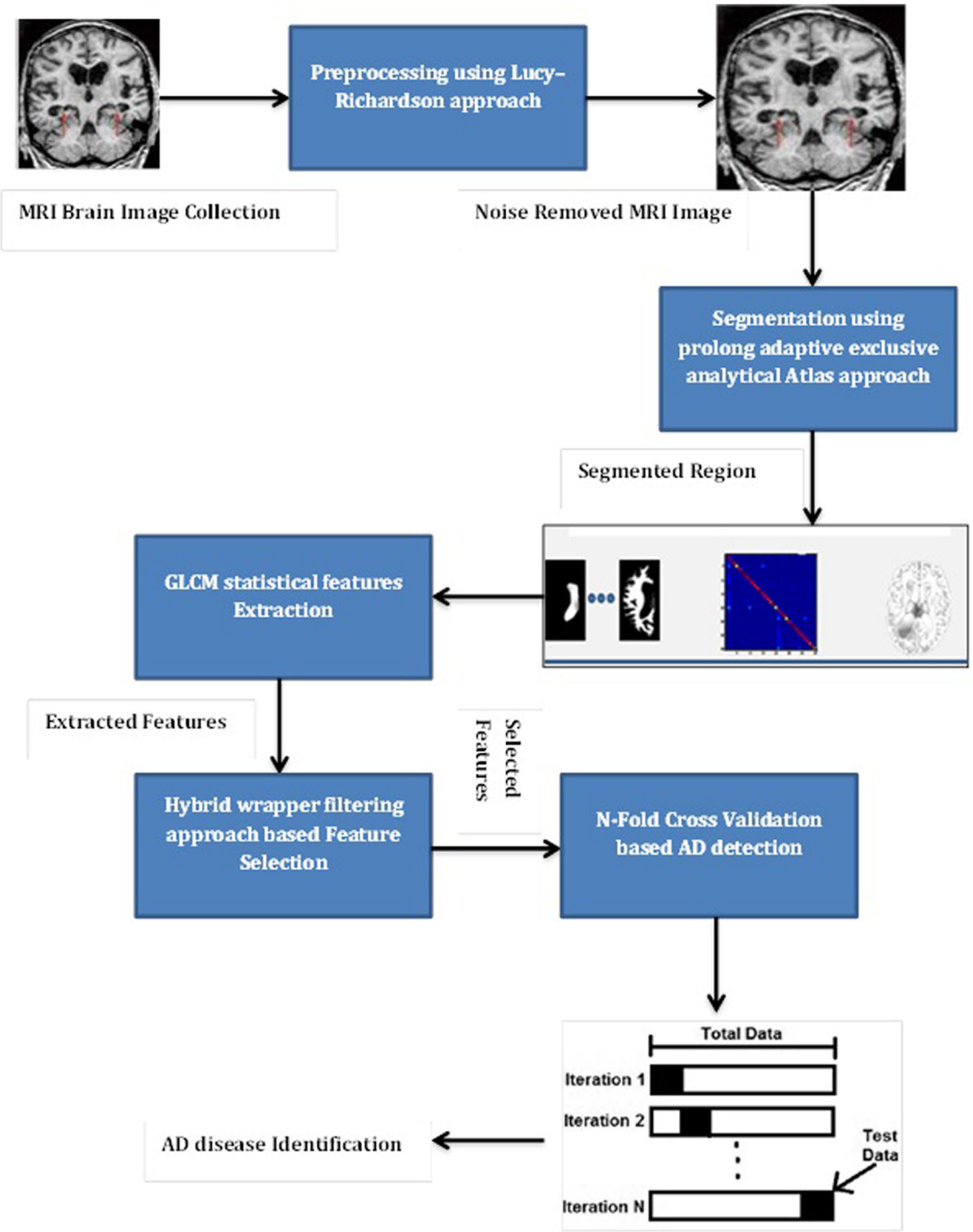

Fig. 2 N-fold cross validation based AD detection structure

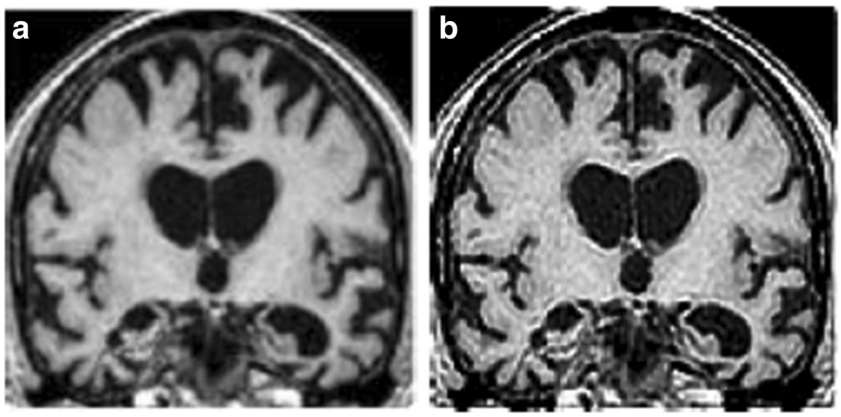

Fig. 3 MRI brain pre-processing (**a**) original (**b**) noise removed image

In the above Eq. (1), p_{ij} is the point spread function value of each pixel.

u_j is the location of each pixel in latent images, d_i is the observed pixel value.

According to the pixel value, the distribution of the pixel is computed which helps to how the pixel is varied from normal pixel to noise pixel. The distribution of the pixel is determined as follows.

$$u_j^{(t+1)} = u_j^{(t)} \sum_i \frac{d_i}{c_i} p_{ij} \tag{2}$$

$$c_i = \sum_j p_{ij} u_j^{(t)} \tag{3}$$

With the help of the pixel distribution, pixel spread value is identified until to estimate the maximum likelihood value of u_j.

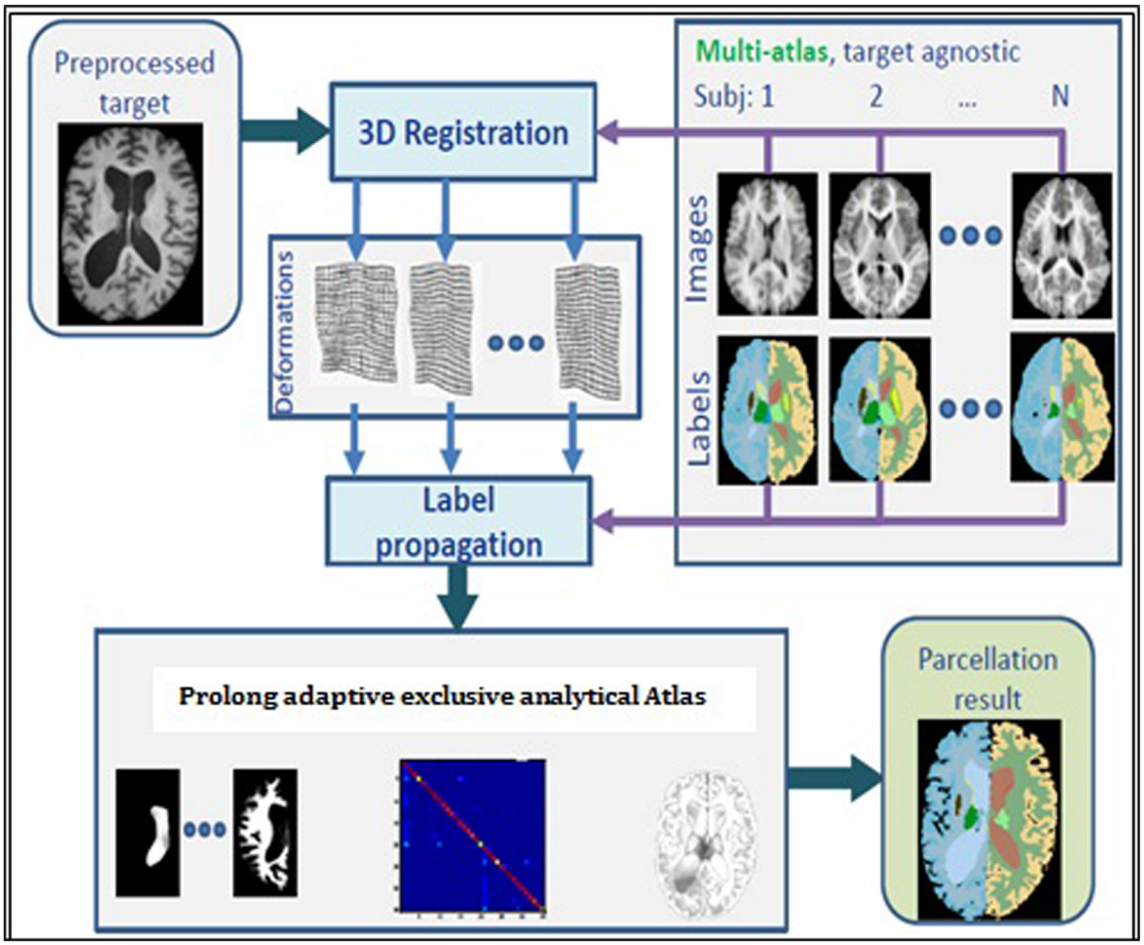

Fig. 4 Function of PAEA segmentation process

$$u^{(t+1)} = u^{(t)}.\left(\frac{d}{u^{(t)} \otimes p} \otimes \hat{p}\right) \quad (4)$$

Based on the likelihood value, noise value is estimated (maximum likelihood value) and it is replaced by using the pixel point spread value. This process is repeated continuously until to eliminate the noise also deblur the image with effective manner. Then the pre-processed MRI brain image is shown in Fig. 3.

MRI brain image segmentation using prolong adaptive exclusive analytical Atlas approach

Next step of this work is to detect, segment the particular affected region by applying Prolong Adaptive Exclusive Analytical Atlas (PAEA). It is one of the division process which means, the image is split into different region and form particular preparation set. The PAEA method analyze the image in terms of cerebrum of K-structure (K = 1,…..K) of quantity of voxels in MRI image N (I = 1,….N). After dividing different regions, affected parts are examined by Gaussian Mixture Model which segment the region using different blending coefficients π_ik and θ_k = (μ_k,σ_k^2), where σ_k^2 and μ_k are indicated as the differences and means, correspondingly. The genuine name for voxel I is connoted as z_i, while the earlier likelihood that voxel I has a place with development k is indicated as pi = (p_i1;…; p_iK), and its back likelihood as w_ik. Earlier on z_i's is joined to the total functioning model is shown in Fig. 4.

Then the brain MRI image affected region is examined using following function,

$$f(Z, X|\pi, \theta) = \frac{1}{Norm}\prod_{i=k}^{N}\prod_{k=1}^{k}(\pi_{ik}G(x_i;\theta_k))^{z_{ik}}\exp\left\{-\beta\sum_{j\in N_i}\sum_{l=1,l\neq k}^{K} z_{ik}z_{jl}\right\} \quad (5)$$

Where x_i is the force in target picture at voxel I, G(x_i;θ_k) is the GMM of structure k, Norm is the MRI normalizer span and N_i is the six-connected neighborhood of voxel I. This process is repeated continuously until to detect the particular region from MRI brain image. After detecting various region GLCM features are derived from MRI image that is discussed as follows.

Table 1 Texture based features and related formulae

Features	Related formula
Entropy	$\sum_{i,j=1}^{n-1} -\ln(P_{ij})P_{ij}$
Correlation	$\sum_{i,j=0}^{n-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$
Energy	$\sum_{i,j=0}^{n-1} (P_{ij})^2$
Contrast	$\sum_{i,j=0}^{n-1} P_{ij}(i-j)^2$
Cluster shade	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\left(i+j-\mu_x-\mu_y\right)^3 \cdot p(i,j)$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(i-\mu)^2 \cdot p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i \cdot p_{x+y}(i)$
Cluster prominence	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\left(i+j-\mu_x-\mu_y\right)^4 \cdot p(i,j)$
Intensity related features	
Inertia	$\sum_{i,j=0}^{n-1}(i-j)^2 \cdot p(i,j)$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(i-\mu)^2 \cdot p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i \cdot p_{x+y}(i)$
Skewness	$\sigma^{-3}\sum_{i=0}^{n-1}(i-\mu)^3 \cdot p(i)$
Kurtosis	$\sigma^{-4}\sum_{i=0}^{n-1}((i-\mu)^4 \cdot p(i)) - 3$

MRI GLCM and statistical feature extraction

The third step of the AD detection process is MRI brain image GLCM [18] and Statistical Feature Extraction. During the feature extraction process, image is examined in terms of intensity, texture and statistical manner for deriving various effective features. The feature set includes cluster (or) region prominence, region shade, energy, variance, contrast, mean, correlation information. Then the derived features are listed in Table 1.

According to the above Table 1, the features are derived from MRI image which helps to detect AD disease in an effective manner. But the extracted features are huge in dimension which consumes high computational complexity as well as high computation time. So, the extracted features are processed by effective feature selection method to select the optimized features that reduce the computation complexity as well as improve the AD disease detection process with minimum time.

Hybrid wrapper filtering approach based MRI feature selection method

The next important step is feature selection, because it analyze the extracted feature, reduce the dimensionality of the feature also eliminates the irrelevant AD disease related features that enhance the overall AD disease diagnosis process. The extracted features also process the AD disease but it degrade the efficiency of the AD disease process, also have complexity while classifying the AD features. So, the feature selection process played a key role in this AD disease recognition process. For making the feature selection [19], this work utilizes the hybrid wrapper filtering approach for selecting feature subset. This hybridized approach selects the features in terms of mutual information, the point wise mutual information, Pearson product-moment correlation coefficient that helps to get the important feature from the set of features. Initially, wrapper approach is applied to the extracted features; build the train model using those features. Rank

the feature according to the importance that helps to improve the classification process, also minimizes the time complexity. From the ranked features, high ranked features are formed as subset. After ranking the features, it has been examined in terms of mutual information, point wise mutual information, Pearson product-moment correlation coefficient value. First the mutual information of the feature is computed because it helps to determine how the features are important in the AD disease recognition process. The mutual information of the feature is estimated as follows:

$$I(X,Y) = \sum_{x,y} PXY(x,y) log \frac{PXY(x,y)}{PX(x)PY(y)} \quad (6)$$

$$PX(x) = \sum_{y} PXY(x,y) \quad (7)$$

In Eqs. (6 and 7) X,Y represented as the two features, $\boldsymbol{PXY(x,y)}$ is joint probability distribution, $\boldsymbol{I(X,Y)}$ is mutual information between two features.

After computing the mutual information, point wise mutual information is computed because it helps to estimate the association of the feature with AD disease recognition process that is computed as follows,

$$pmi(x;y) = log \frac{p(x,y)}{p(x)p(y)} \quad (8)$$

In Eq. (8) $\boldsymbol{pmi(x;y)}$ represents the point wise mutual information of features.

In addition to this mutual information, point wise mutual information, Pearson product-moment correlation coefficient value is computed for estimating the correlation between two features. The correlation of the feature is estimated as follows.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (9)$$

In Eq. (9), cov denoted as the covariance of the feature, $\boldsymbol{\sigma_X}$ is represented as standard deviation of X, $\boldsymbol{\sigma_Y}$ is standard deviation of Y. The above parameters are estimated as follows.

$$cov(X,Y) = E[(X-\mu x)(Y-\mu y)] \quad (10)$$

According to this relation between features, optimized features are selected from the extracted feature set. These selected features are processed by classification method for recognizing the AD disease in an effective manner. Then the detailed AD disease recognition process is explained.

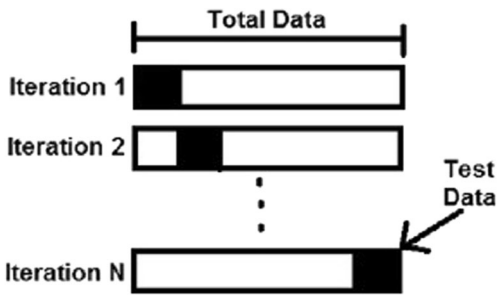

Fig. 5 N-fold cross validation process

N-fold cross validation based AD disease recognition process

The last step of this work is to classify AD disease recognition which is done by applying N-fold cross validation process [20]. This method works according to the model validation process that analyzes each and every feature and predicts the AD disease related features by dividing the feature set into equal validating and training set. The divided sample is shown in Fig. 5.

During the AD recognition process, the method compute the feature fit value according to the training set that helps to optimize the AD disease diagnosis process. At the time of fitting estimation process, the system needs to reduce the mean square error rate because it indicates that effective AD recognition process. Then the training set means square error rate has been estimated as follows.

$$\frac{1}{n}\sum_{i=1}^{n}\left(y_i - a - \beta^T x_i\right)^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - a - \beta_1 x_{i1} - \ldots\ldots - \beta_p x_{ip}\right)^2 \quad (11)$$

In Eq. (11), a and $\boldsymbol{\beta}$ is the training set parameter values. From the divided parts, one part is considered as the validating or testing set. The testing set feature is compared with the training set features and AD disease related features are computed with minimum error rate. This process is repeated continuously until to recognize the AD disease effectively. Then the excellence of the system is evaluated with the help of experimental results and discussions.

Results and discussion of AD disease recognition process

This section evaluates the excellence of N-Fold Cross validation based AD disease recognition process. The efficiency of the AD disease recognition process is evaluated using Alzheimer's disease Neuroimaging Initiative (ADNI) dataset. The dataset consists of collection MRI brain images that are used to examine the different brain diseases such as Alzheimer disease, bipolar disorder and so on. According to ADNI discussions, the sample MRI brain image is shown in Fig. 6.

The Fig. 6 shows that sample MRI brain image of ADNI dataset helps to recognize different brain diseases. In this work, the MRI image is used to detect the Alzheimer disease (AD) by using the N-fold cross validation method. Initially, brain MRI image is processed pixel by pixel for eliminating Gaussian noise and deblur the image with effective manner. After removing image, the affected region is examined using Prolong adaptive

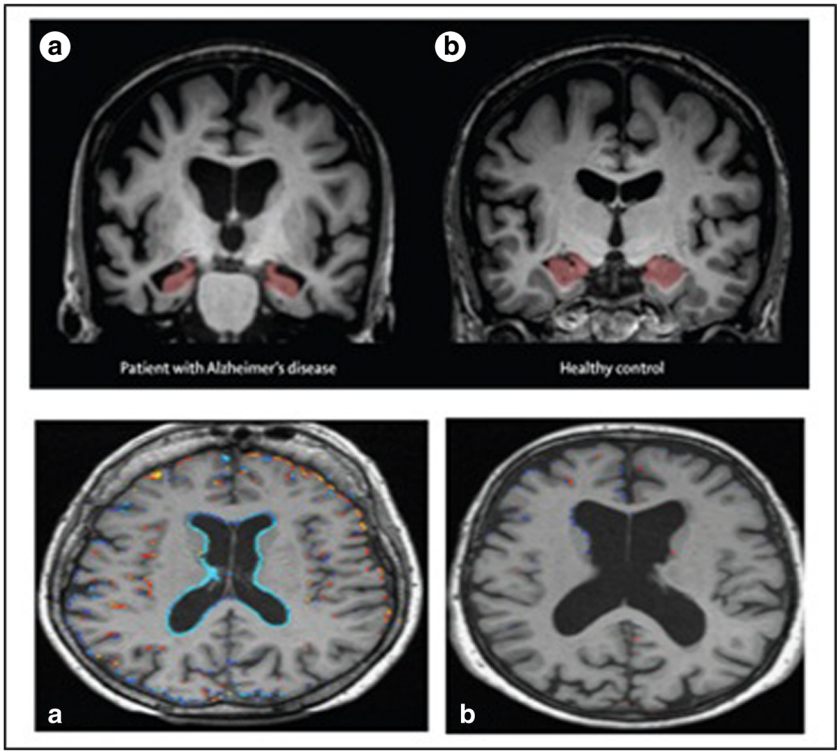

Fig. 6 ADNI dataset brain MRI image

exclusive analytical Atlas (PAEA) that successfully segments the region by using Gaussian mixture model (GMM). From the region, various features are extracted and optimized features are selected in terms of computing mutual information, point wise mutual information by Pearson product-moment correlation coefficient value. The selected features are processed by dividing training and validating set using N-fold cross validation approach. This process helps to analyze the AD disease with effective manner. Then the efficiency of the system is evaluated using following performance metrics.

True Positive rate (TP)

$$= \frac{\text{Numbers of AD features detected} \times 100}{\text{Number of presented features}} \tag{12}$$

False Positive rate (FP)

$$= \frac{\text{Number of false feature detections} \times 100}{\text{Number of featuredetected} + \text{Number of false feature detection}} \tag{13}$$

False Negative Rate (FN)

$$= \frac{\text{Number of feature missed} \times 100}{\text{Number of presented features}} \tag{14}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{15}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{16}$$

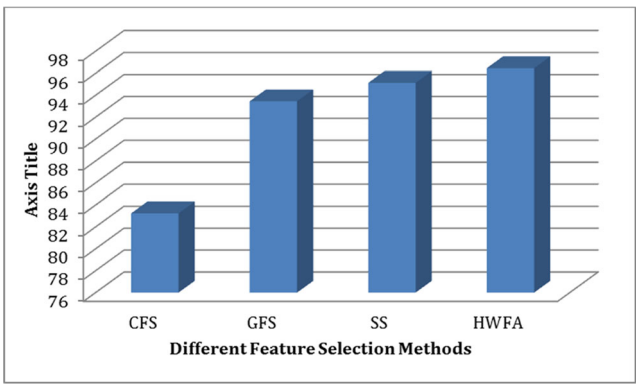

Fig. 7 Accuracy of selected features

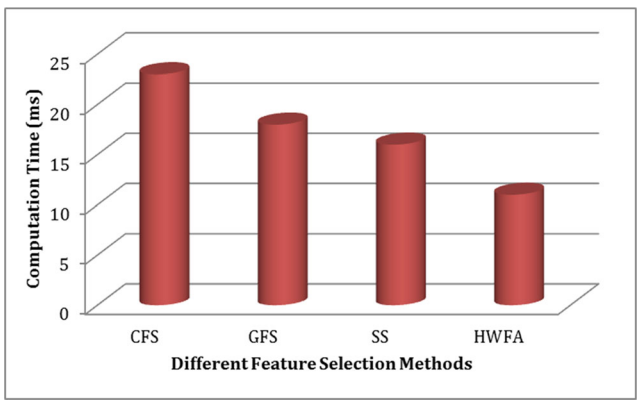

Fig. 8 Computation time of feature selection process

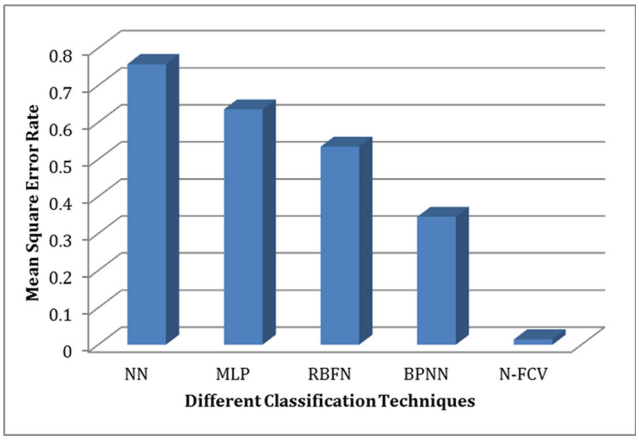

Fig. 9 Performance of the means square error rate

$$\text{Accuracy} = \frac{\text{number of true positive} + \text{number of true negative}}{\text{number of true positive} + \text{false positive} + \text{false negative} + \text{true negative}} \quad (17)$$

According to the performance metrics, efficiency of N-fold cross validation based AD disease recognition process is evaluated. Before performing the classification process, Hybrid wrapper filtering approach based MRI Feature Selection Method is performed for selecting optimized features. The efficiency of the Hybrid wrapper filtering approach (HWFA) based MRI Feature Selection is compared with the different feature selection methods such as Correlation Feature Selection (CFS) [21], Greedy Forward Selection (GFS) [22] and Scatter Search (SS) [23]. The obtained accuracy of feature selection is shown in Fig. 7.

According to the Fig. 7 it clearly shows that Hybrid wrapper filtering approach (HWFA) based MRI Feature Selection process, effectively selects optimized and relevant AD disease features with high accuracy (96.45%) when compared to other methods such as Correlation Feature Selection (CFS) (83.24%), Greedy Forward Selection (GFS) (93.45%) and Scatter Search (SS) (95.13%). In addition to this, Hybrid wrapper filtering approach (HWFA) selects the features with minimum computation time that leads to reduce complexity while classifying AD

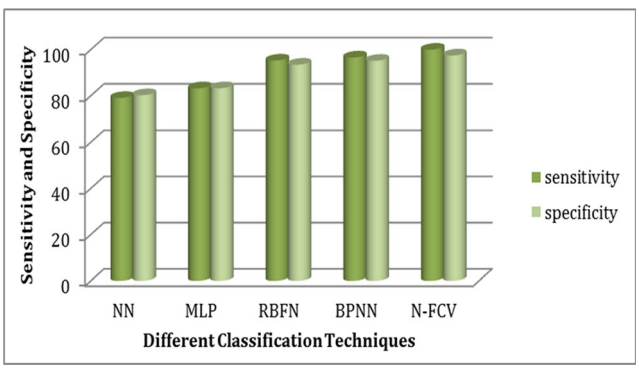

Fig. 10 Performance of sensitivity and specificity

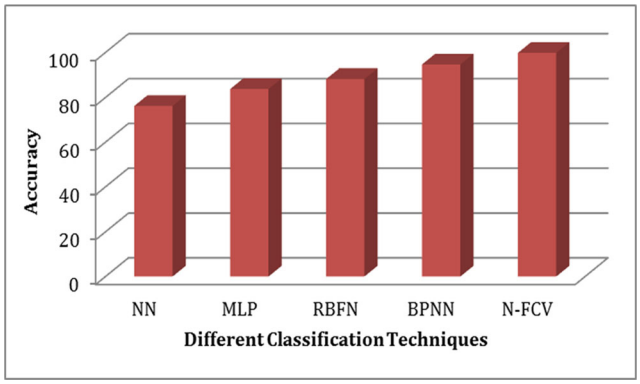

Fig. 11 AD disease recognition accuracy

disease. Then the obtained computation time of the Hybrid wrapper filtering approach (HWFA) is shown in Fig. 8.

From the Fig. 8, shows that the Hybrid wrapper filtering approach (HWFA) select the optimized features with minimum computation time. The less computation time improves the overall AD disease classification process. The selected features are processed by N-fold cross validation approach which recognizes the disease with high accuracy. The N-fold cross validation (N-FCV) approach recognize the disease with minimum error rate when compared to traditional methods such as Neural Networks (NN) [24],Multilayer Perceptron (MLP) [25], Radial Basis Neural Networks (RBFNN) [26] and Back Propagation Neural Networks (BPNN) [27] which is shown in the Fig. 9.

Thus above figure clearly shows that the N-fold cross validation method consumes the minimum error rate while classifying the Alzheimer disease from extracted MRI brain features. This minimized error rate increased the classification process which is shown in the Fig. 10.

The above Fig. 10 clearly shows that N-fold cross validation approach selects the AD disease related features and classifies the disease in an effective manner that is examined in terms of using sensitivity and specificity metrics. The increased sensitivity and specificity value leads to improve the overall AD disease

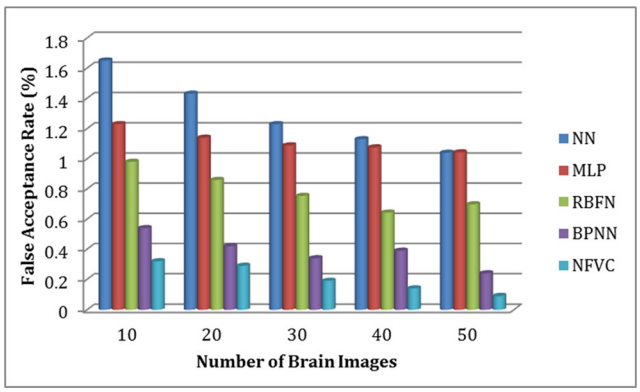

Fig. 12 ROC curve

recognition accuracy. Then the obtained AD disease classification accuracy is shown in Fig. 11.

Thus the proposed system successfully recognizes the AD disease from the extracted, selected features with 99.26% accuracy when compared to other traditional methods due to the minimum error rate. Further efficiency of the system is examined in terms of using ROC curve which is used to examine how the N-fold cross validation approach selects the AD related features successfully that is computed from the true positive rate and false positive rate and the obtained result is shown in Fig. 12.

The above Fig. 12, clearly shows that ROC curve attains minimum false acceptance rate that indicates that NFVC method effectively recognize the AD disease related features effectively. According to the above discussions, N-Fold cross validation approach recognizes the Alzheimer disease in an effective manner. Overall the N-fold cross validation method successfully recognizes the AD disease from the Alzheimer's disease Neuroimaging Initiative (ADNI) dataset with effective manner.

Conclusion

This paper analyzes the Alzheimer Disease detection system using Hybrid Wrapper Filtering along with N-Fold Cross Validation approach. Initially, the MRI brain image is collected from Alzheimer's disease Neuroimaging Initiative (ADNI) dataset, which are processed applying effective techniques. Initially, the images are collected, pixel by pixel analyzed using Lucy–Richardson approach that successfully removes the Gaussian noise and also deblur the image. From the image, affected region is segmented with the help of Prolong adaptive exclusive analytical Atlas (PAEA) that successfully segments the region by using Gaussian mixture model (GMM). From the region, various features are extracted and optimized features are selected in terms of computing mutual information, point wise mutual information, Pearson product-moment correlation coefficient value. The selected features are processed by dividing training and validating set using N-fold cross validation approach. At last the efficiency of the system is evaluated with the help of the ADNI database. These database images are classified using the introduced AD disease recognition method which ensures high accuracy (99.26%) with minimum rate when compared to the traditional methods which also minimize the computation complexity.

Compliance with ethical standards

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

In the work development, all the ethical requirements prescribed by Resolution 466/12 of the Brazil National Health Council and its complementary ones were fulfilled, being approved by the Research Ethics Committee of the Medical School of Ribeirão Preto of the University of São Paulo, Certificate of Presentation for Ethical Assessment 44813815.6.0000.5440 and 69187617.7.0000.5440.

This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Conflict of interest None.

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