Alzheimer Disease Detection and Classification using Probabilistic Principal Component Analysis and Long Short-Term Memory Classifier

Halebeedu Subbaraya Suresha, Srirangapatna Sampathkumaran Parthasarathy

Abstract: The automatic recognition and classification of Alzheimer disease utilizing magnetic resonance imaging is a hard task, due to the complexity and variability of the size, location, texture and shape of the lesions. The objective of this study is to propose a proper feature dimensional reduction and classification approach to improve the performance of Alzheimer disease recognition and classification. At first, the input brain images were acquired from Open Access Series of Imaging Studies (OASIS) and National Institute of Mental Health and Neuro Sciences (NIMHANS) databases. Then, the image pre-processing and feature extraction were attained by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) and Discrete Wavelet Transform (DWT) approach to denoise and extract the feature vectors from the images. In addition, Probabilistic Principal Component Analysis (PPCA) was applied for diminishing the dimension of the extracted feature vectors that significantly lessen the “curse of dimensionality” issue. At last, Long Short-Term Memory (LSTM) classifier was employed for classifying the brain images as Alzheimer disease, normal, and Mild Cognitive Impairment (MCI). From the experimental result, the proposed work attained better performance compared to the existing works and showed 3-11% improvement in recognition accuracy.

Keywords: Alzheimer disease detection and classification, discrete wavelet transform, long short term memory, normalization, probabilistic principal component analysis.

I. INTRODUCTION

Alzheimer disease is a degenerative brain disorder, which leads to memory loss and the difficulties like language or problem solving, and thinking that extremely affect the individual’s daily life [1-2]. Currently, the neuroimaging techniques are extensively utilized in Alzheimer disease recognition and classification, which delivers a way for physicians to investigate the functional and structural changes in the brain [3-4]. Commonly used modalities in Alzheimer disease recognition are Magnetic Resonance Imaging (MRI), positron emission tomography, functional MRI, diffusion tensor imaging, etc. [5-6]. In that, MRI gains more attention among the researchers, because of its easy access in the clinical settings, and the functional and structural changes in the brain related to Alzheimer disease are non-invasively evaluated by utilizing MRI [7-8]. However, the manual analysis of Alzheimer disease by the clinicians may not be accurate and consumes more time for detection. So the automatic recognition of Alzheimer’s disease has made an impression in the research community [9-10]. In recent times, several methodologies are developed by the researchers for Alzheimer disease detection such as Support Vector Machine (SVM) [11], L2 norm equalization [12], ensemble classifier [13], Gaussian process regression [14], Back-propagation artificial neural network [15], etc. The conventional methodologies are not effective in recognising the medical images, due to the semantic space between the extracted features, and the nonlinear nature of the feature vectors.

In this work, a new deep learning based supervised system was proposed for enhancing the performance of alzheimer disease detection and classification. For the experimental study, the brain images were acquired from two databases such as OASIS and NIMHANS. After the acquisition of brain images, pre-processing was accomplished by applying normalization and CLAHE technique. The major benefit of normalization approach was that it brings the range of intensity value to the normal distribution that makes the image looks better for the visualizer. In addition, CLAHE technique estimates several histograms for redistributing the tightness of the image pixel values, which enhances the color contrast and edges of the brain images. After image denoising, DWT technique was applied to extract the feature values from the denoised brain images. The undertaken denoising DWT technique effectively reveals the local feature vectors of the images that helps in the reduction of feature degradation. After feature extraction, PPCA was applied to lessen the dimension of the extracted features. Usually, PPCA utilizes only a limited number of feature vectors for representing the data that significantly diminish the “curse of dimensionality” issue. Then, the output of PPCA was given as the input for LSTM classifier to classify the brain images as normal, MCI, and alzheimer disease. Finally, the proposed work performance was compared with the existing works by means of False Omission Rate (FOR), False Discovery Rate (FDR), sensitivity, error rate, accuracy and specificity.

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This research paper is prepared as follows. In section II, a few research papers related to alzheimer disease recognition and classification are surveyed. Section III detailed about the proposed work with mathematical expressions. In section IV, the result and discussion is done with graphical comparisons. Conclusion is made in the section V.

II. LITERATURE REVIEW

T. Altaf, et al. [16] developed a new automated system for alzheimer disease detection and classification. In this paper, the input brain images were acquired from Alzheimer’s disease Neuro-imaging Initiative (ADNI) database. Then, the texture feature descriptors like histogram of gradient, gray level co-occurrence matrix, local binary pattern, and scale invariant feature transform were applied for extracting the feature values from the acquired brain images. Hence, the features extracted from the white matter, cerebrospinal fluid, and grey matter were utilized to classify the images as three classes such as normal, MCI, and Alzheimer’s disease. In this research study, the classification phase was validated with dissimilar approaches like decision tree, K-Nearest Neighbor (KNN), SVM, and ensemble classifiers. Related to other classifiers, the KNN showed better performance with 79.80% of classification accuracy. Still, the semantic space between the extracted texture features were very high that leads to the poor classification of the images.

D. Jha, et al. [17] developed a new supervised system for alzheimer disease recognition on the basis of PCA, Feed Forward Neural Network (FNN), and Dual Tree Complex Wavelet Transform (DTCWT). Initially, DTCWT approach was used to extract the feature values from the brain images that were acquired from the OASIS database. Then, PCA was applied to lessen the dimension of the extracted feature values. These feature values were given as the input for FNN for distinguishing the healthy and alzheimer disease individuals. From the experimental study, the developed system attained better performance in terms of specificity, sensitivity, accuracy, and precision. Hence, the FNN classifier was related to application domain, so it was limited to static concerns due to its feed forward structure.

D. Jha, et al. [18] presented a new framework for alzheimer disease classification on the basis of DTCWT, PCA, Linear Discriminant Analysis (LDA) and ensemble classifier. In the clinical support system, the early recognition of alzheimer disease was essential for medical physicians to customize a treatment program for managing the growth and progression of the diseases. In recent times, numerous efforts were made for diagnosing the neuro-degenerative disorders in the early periods. In this literature paper, a new cascade model was developed to distinguish the healthy and alzheimer disease patients. At first, DTCWT method was utilized for extracting the features from the acquired images. Then, PCA and LDA were employed for lessening the dimension of the features. Finally, the extracted feature vectors were classified by using ensemble classifier in order to distinguish the healthy and alzheimer disease patients. In contrast, the computational complexity of the developed system was automatically increased by combining two or more dimensional reduction methods.

J. Samper-Gonzalez, et al. [19] developed a new methodology for alzheimer disease recognition. Initially, the brain images were collected from three online datasets such as ADNI, OASIS, and Australian Imaging Biomarkers and Lifestyle Flagship study of ageing (AIBL). In this paper, the developed system contains three stages: image denoising, feature extraction and classification. Here, the image pre-processing was accomplished utilizing statistical parametric mapping 12 and positron emission tomography-partial volume correction software’s. Then, the region and voxel feature values were extracted from the pre-processed images. Finally, SVM, logistic regression, and random forest classifiers were applied to distinguish the normal, MCI, and Alzheimer’s disease. The experimental segment validated that the developed system was only suitable for single modality classification problem.

V. Sachnev, and S. Suresh, [20] developed a diagnosis system for alzheimer diseases identification on the basis of Extreme Learning Machine (ELM) and sample balanced genetic algorithm. The developed system majorly consists of two phases: voxel selection and alzheimer diseases classification. At first, the robust voxel subsets were chosen by using sample balanced genetic algorithm, which maintains a high generalization performance of alzheimer diseases detection in several scenarios. Then, the classification was accomplished by employing ELM algorithm to classify the classes of images (normal, MCI, and Alzheimer’s disease). From the experimental simulation, the developed system achieved better performance compared to the existing systems in light of accuracy. However, the ELM algorithm includes a few drawbacks like imbalanced class distribution and over-fitting problem.

To address the above stated issues, a new supervised system is proposed in this paper for improving the performance of alzheimer diseases classification.

III. PROPOSED SYSTEM

Currently, the alzheimer disease is the 5th leading cause of death in India and more than four million people are affected from the alzheimer disease and other dementia diseases. Still, there is no proper treatment is available to stop the growth of alzheimer disease. However, the early recognition of alzheimer disease helps in determining the progression and also enhances the quality of life for alzheimer disease patients. In this study, a deep learning based supervised system is proposed for the early recognition of alzheimer disease. The proposed work majorly consists of five phases such as image collection, image denoising, transformation, dimensional reduction, and classification. The graphical illustration of the proposed work is represented in figure 1.
A. Image collection

In this research study, OASIS and NIMHANS (real time) datasets are utilized to acquire the brain images. The OASIS dataset comprises of 416 individuals (whose age ranges from 18-96). In this work, totally 126 individuals are considered that includes 98 healthy subjects and 28 alzheimer disease patients. The statistical information about the individuals undertaken in this research study are detailed in table 1. The OASIS dataset consists of information about the individual’s demographics such as number of patients, education, socioeconomic status, age, gender, Mini Mental State Examination (MMSE) score, and Clinical Dementia Rating (CDR). The MMSE is a questionnaire test, which is utilized for monitoring the dementia and cognitive impairment. Correspondingly, CDR is used to measure the severity of dementia on the basis of individual care, community affairs, orientation, residence and hobbies, and memory [21]. The sample images of OASIS dataset are represented in figure 2.

Similarly, the NIMHANS dataset comprises of 99 individuals (60 normal controls and 39 alzheimer disease patients), who’s age ranges from 55-87 years. In the undertaken dataset, all the individuals are assessed on NNB - E, which contains the tests for working memory, visuo and verbal spatial memory, executive function, construction, and language [22]. The sample images of NIMHANS dataset is denoted in figure 3.

B. Image pre-processing

After image collection, image pre-processing is performed by using normalization and CLAHE techniques. Initially, image normalization is applied to alter the image pixel intensity values to improve the quality of acquired brain images by lessening the machinery and impulse noises from the brain images. Then, identify the deformations and alterations occurred in the brain images due to imprecise image capture. During image normalization, the acquired brain image is converted into pre-determined variables. The formula to estimate image normalization is mathematically denoted in Eq. (1).

\[
IN = (1 - M \min) + \frac{newMax - newMin}{Max - Min} + newMin
\]

Where, \( I \) is represented as input brain image, \( IN \) is indicated as normalized image, \( newMax - newMin \) is stated as intensity range of normalized image, and \( \min = 0, and Max = 255 \) is indicated as pixel intensity range of input brain image.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Alzheimer diseases</th>
<th>Healthy control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of patients</td>
<td>28</td>
<td>98</td>
</tr>
<tr>
<td>Education</td>
<td>2.57 ± 1.31</td>
<td>3.26 ± 1.31</td>
</tr>
<tr>
<td>Age (years)</td>
<td>77.75 ± 6.99</td>
<td>75.91 ± 8.98</td>
</tr>
<tr>
<td>MMSE score</td>
<td>21.67 ± 3.75</td>
<td>28.95 ± 1.20</td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>2.87 ± 1.29</td>
<td>2.51 ± 1.09</td>
</tr>
<tr>
<td>CDR</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Gender (Male/Female)</td>
<td>9/19</td>
<td>26/72</td>
</tr>
</tbody>
</table>
The sample normalized brain images of OASIS and NIMHANS datasets are indicated in the figures 4 and 5.

Fig. 4. Sample normalized images of OASIS dataset

(a) (b) (c)

Fig. 5. Sample normalized images of NIMHANS dataset

(a) (b)

After image normalization, CLAHE technique is used to further enhance the quality of normalized images in order to achieve the detailed information about the images. Initially, the normalized brain images are divided into non-overlapping contextual regions, named as sub-images or blocks [23]. Generally, the CLAHE technique consists of two key parameters such as clip limit and block size. Hence, the clip limit is used to smooth the low intensity pixel values and the block size improves the colour contrast of the grayscale images. Additionally, the block size and clip limit identifies the maximum entropy curvature in order to provide good quality of images using image entropy. Step by step process of CLAHE technique is detailed below.

- At first, the input variables are initialized for image enhancement such as distribution parameter type, number of regions in row and column direction, clip-limit, and dynamic range (no of bins utilized in histogram transfer function).
- The normalized brain images are divided into blocks or sub-images and then employ grey level mapping and clipping in the sub-images.
- The no of image pixels is equally divided into grey levels in the contextual regions. Therefore, the average number of image pixels are estimated by utilizing the Eq. (2).

\[
n_{\text{avg}} = \frac{C_y - y_p \times C_x - x_p}{n_{\text{grey}}}
\]  

(2)

- After estimating the actual clip-limit, Eq. (2) is updated as shown in Eq. (3).

\[
n_{\text{CL}} = n_{\text{avg}} \times n_{\text{CLIP}}
\]  

(3)

Where, \(n_{\text{avg}}\) is indicated as average number of image pixels, \(n_{\text{grey}}\) is represented as number of grey-levels in the contextual regions, \(n_{CR} - x_p\) and \(n_{CR} - y_p\) are denoted as number of pixels in \(x\) and \(y\) directions of the contextual regions.

- At last, incorporate the grey-level mapping using four pixel clusters, where the resultant image is the enhanced image. The enhanced brain images of OASIS and NIMHANS datasets are specified in the figures 6 and 7.

Fig. 6. Enhanced brain images of OASIS dataset

(a) (b) (c)

Fig. 7. Enhanced brain images of NIMHANS dataset

(a) (b)

C. Image transformation

After denoising the brain images, image transformation is accomplished by using DWT approach for revealing the local features of the enhanced images that helps in eliminating the irrelevant image features. The two dimensional DWT approach includes a few advantages like low computation, good energy compression and low redundancy. The two dimensional DWT approach is a “rescaled square-shaped function” that generates a wavelet family for separating the low frequency image components from the high frequency image components. Initially, transform the brain images into sub-images in different image resolution levels for preserving the both high and low level frequency information that assists DWT to extract the useful data from the denoised brain images.
The square integral function $f(x)$ and the wavelet transforms are determined as the inner product $f$ and the real valued function $R(x)$ that are mathematically denoted in Eq. (4).

$$w[f(s, \tau)] = \left( f, R^s_{\tau} \right) = \int \overline{f(x)} R^s_{\tau}(x) \, dx$$

(4)

Where, $R^s_{\tau}(x) = \left( 1 \sqrt{4\pi R^s_{\tau}(x-\tau) / \tau} \right)$ is represented as wavelet family, $s \in \tau, z$ and $k \in \{v, h, d\}$ are stated as scale, translation, and orientation parameters. The orientation parameters $v, h$, and $d$ are indicated as vertical, horizontal and diagonal directions. In the next segment, the Dyadic wavelet decomposition is undertaken, where $s = 2^j \land \tau = 2^\ell, n, j, n \in z$. Then, the scaling and wavelet families are generated by using the wavelet function $R(x)$, and scaling function $\xi(x)$ that are mathematically denoted in the Eqs. (5) and (6).

$$R^s_{\tau}(x) = \frac{1}{\sqrt{2^j}} \xi \left( \frac{x-2^j n}{2^j} \right)$$

(5)

$$\xi^h_{\tau}(x) = \frac{1}{\sqrt{2^j}} \xi^h \left( \frac{x-2^jn}{2^j} \right)$$

(6)

Generally, the orthonormal sub-spaces are related to the resolution $2^j$. Henceforth, the wavelet atom is estimated by utilizing the mother atoms $R^s$, $R^v$ and $R^d$, which are determined as tensor product of two dimensional $\xi(x)$ and $R(x)$ that are stated in the Eqs. (7) and (8).

$$\xi(x) = \xi(x_1) \xi(x_2), R^v(x) = R(x_1) R(x_2)$$

(7)

$$R^d(x) = \xi(x_1) R(x_2), R^d(x) = R(x_1) \xi(x_2)$$

(8)

The two dimensional DWT technique is executed by utilizing filter banks and down-samplers. Normally, the digital filter bank comprises of high-pass $g$ and low-pass $h$ filters, and the number of filter bank is assumed as per the resolution in the wavelet configuration. For instance, the enhanced brain image $A_{2^n, f}$ at resolution $2^{n+1}$ is transformed into four sub-bands in the frequency domain. In the available four sub-bands, three sub-bands are brain images $D_{2^n f}, D_{2^n f}$ and $D_{2^n f}$ at the resolution of $2^j$ in vertical, diagonal, and horizontal directions. The remaining one sub-band is approximation image $A_{2^n, f}$, which is in the coarse resolution format. Though, the entire brain image $A_{2^n, f}$ is mathematically indicated in Eq. (9).

$$A_{2^n, f} = D_{2^n f} + D_{2^n f} + D_{2^n f} + A_{2^n, f}$$

(9)

The transformed brain images are in the form of two dimensional orthogonal wavelet.

The wavelet transformation outcome is resultant into four orthogonal sub-bands such as low-high, high-low, low-low and high-high that corresponds to the sub-images $D_{2^n f}, D_{2^n f}$ and $D_{2^n f}$ and $A_{2^n, f}$. A sample wavelet transformed brain image is stated in figure 8.

D. Feature dimensional reduction

After feature extraction, dimensional reduction is performed by applying PPCA [24]. Let us consider $x_i = \left( x_{i1}, \ldots, x_{ip} \right)^T$ as the feature vectors, which are extracted from the DWT for the $i^{th}$ subject $i = 1, \ldots, n$. The probabilistic representation of PCA is mathematically stated in Eq. (10).

$$x_i = \mu + w_i + \varepsilon_i, \quad i = 1, \ldots, n$$

(10)

Where, $\mu_i$ is denoted as principal components, and $w$ is stated as $p \times q$ matrix with elements $w_{j, p}, j = 1, \ldots, p, h = 1, \ldots, q$. In addition, the term $u$ is stochastically independent from $\varepsilon$, and it is mathematically denoted in Eq. (11).

$$u_i \sim N(0, I_q)$$

(11)

Where, $I_q$ is indicated as identity matrix of order $q$. In addition, the error is assumed to be zero centered Gaussian with covariance matrix $\Psi, \varepsilon_i \sim N(0, \Psi)$. Then, the multivariate distribution is obtained by using the Eq. (12),

$$x_i \sim N(\mu, C), \quad C = w w^T + \Psi$$

(12)

Also, assume $\Psi = \psi I_q, \psi \in R_+$, so the elements of $x_i$ are conditionally independent to given $u_i$. The parameters $\mu = \left( \mu_1, \ldots, \mu_p \right)^T$ allows location shift fixed effect and the marginal log likelihood is mathematically denoted in Eq. (13).
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\[ l(\theta; X) = -\frac{n}{2} \left\{ p \log(2\pi) + \log |C| + \text{tr} \left( C^{-1} S \right) \right\} \]  

(13)

Where, \( S = \left( \frac{1}{n} \sum \mathbf{x}_i \mathbf{x}_i^T \right) \) and the parameter \( \theta = (\pi, \mathbf{w}, \psi) \) are estimated by the maximum likelihood estimation Eqs. (14), (15) and (16).

\[ \hat{\mu} = \frac{1}{n} \mathbf{X}^T \mathbf{1}_n \]  

(14)

\[ \hat{\omega} = \mathbf{H}_q \left( \mathbf{L}_q - \mathbf{y} \mathbf{I}_q \right)^{\frac{1}{2}} \mathbf{R} \]  

(15)

\[ \hat{\psi} = \frac{1}{p-q} \sum_{i=q+1}^{p} \delta_i \]  

(16)

Where, \( \mathbf{X} = (\mathbf{x}_i)^T \) is denoted as response matrix, \( \mathbf{1}_n \) is stated as \( n \times 1 \) vector, \( \mathbf{H}_q \) is indicated as principal eigenvectors of the covariance matrix, and \( \mathbf{R} \) is represented as orthogonal rotation matrix. At last, the individual score is predicted by utilizing best linear prediction as shown in Eq. (17).

\[ \hat{u} = E(u | x) = \left( \mathbf{w}^T \mathbf{w} + \mathbf{\Psi} \right)^{-1} \mathbf{w}^T (x - \mu) \]  

(17)

E. Classification

After dimensionality reduction, classification is accomplished using LSTM classifier to classify the images as normal, MCI, and alzheimer disease. Generally, the LSTM classifier works on the basis of learning the features that significantly enhances the mapping performance related to the manually predicted values. For feature learning, stack auto encoder approach is used for analysing the variations in data. In LSTM classifier, the stack auto encoder comprises of three layers; input, recurrent hidden and output layers. In LSTM classifier, the temporal state, cell of multiplicative gathering unit and couple of versatile are used to control the stream of data in the memory block.

At first, the consistent error carousels are activated with self-associated direct unit for describing the memory cell state. The multiplicative gate-ways along with consistent error carousels are used for finding the error constant of the system. Then, the forget gate is included in memory block for improving the bound development and for preventing the inner cell values. Restart the memory block, once the consistent error carousel weight replaces the multiplicative forget gateway activation and the data stream is outdated. The architecture of LSTM classifier is represented in figure 9.

![Fig. 9. Architecture of LSTM architecture](image-url)

The input of the model is represented as \( x = (x_1, x_2, ..., x_T) \), and the output sequence is indicated as \( y = (y_1, y_2, ..., y_T) \), where \( T \) is stated as recognition period. Based on prior information, the optimal features are recognized without affecting the previous steps, which is deliberated as a major benefit of LSTM. In order to accomplish this objective, the travel time is iteratively calculated by utilizing the Eqs. (18-23).

\[ i_t = \Theta(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}C_{t-1} + b_i) \]  

(18)

\[ f_t = \Theta(W_{ fx}x_t + W_{ fm}m_{t-1} + W_{ fc}C_{t-1} + b_f) \]  

(19)

\[ C_t = f_t \Theta C_{t-1} + i_t \Phi g \left( W_{cx}x_t + W_{cm}m_{t-1} + b_c \right) \]  

(20)

\[ O_t = \Theta(W_{ ox}x_t + W_{ om}m_{t-1} + W_{ oc}C_{t} + b_o) \]  

(21)

\[ m_t = O_t \Phi h(C_t) \]  

(22)
\[ y_i = W_{si}m_i + b_y \]  

(23)

Where, \( \Theta(\cdot) \) is stated as sigmoid function of standard logistics and \( \Phi \) is represented as vector scalar product. Hence, the sigmoid function \( \Theta(\cdot) \) is calculated by applying the Eq. (24).

\[ \Theta(X) = \frac{1}{1 - e^{-X}} \]  

(24)

Where, \( a_{im} \) is signified as activation vectors of every cell and memory blocks, \( b \) is represented as bias vectors, and \( W \) is indicated as weight matrices. Additionally, \( H(\cdot) \) is stated as sigmoid function of centered logistic that ranges from [-3, 3], which is indicated in Eq. (25).

\[ H(X) = \frac{4}{1 - e^{X}} - 3 \]  

(25)

Where, \( c(\cdot) \) is denoted as sigmoid function of centered logistic that ranges from [2, -2], which is mathematically stated in Eq. (26).

\[ C(X) = \frac{2}{1 - e^{X}} - 2 \]  

(26)

By adjusting the truncated back propagation and real time recurrent learning, the LSTM classifier is trained. Before entering into linear consistent error carousel, the truncated errors reaches the output of memory cell and the square errors are limited. For time management in LSTM classifier, the self-assertive time slacks are developed with long dependency. The global features are selected by utilizing PPCA and it is given as the input to LSTM classifier. In this work, the weight of neural system is controlled by Adam optimizer, because it is productive in computation, easy to implement, invariant to rescaling diagonal gradients, and requires fewer memory space.

IV. RESULT AND DISCUSSION

In the result and discussion segment, MATLAB (2018a) was utilized for experimental simulation with Intel (R) Core (TM)i5 CPU @ 3.10 GHz and 8 GB (RAM). In this study, the proposed work was compared with a few existing works (D. Jha, et al. [17], D. Jha, et al. [18], and V. Sachnev, and S. Suresh, [20]) on OASIS database to assess the efficacy of the proposed work. Here, the proposed work performance was evaluated by means of FOR, FDR, error rate, sensitivity accuracy and specificity. The general formula for estimating FOR, FDR, sensitivity, accuracy, error rate and specificity were indicated in the Eqs. (27), (28), (29), (30), (31), and (32).

\[ FOR = \frac{FN}{TN + FN} \times 100 \]  

(27)

\[ FDR = \frac{FP}{TP + FP} \times 100 \]  

(28)

\[ Sensitivity = \frac{TP}{FN + TP} \times 100 \]  

(29)

\[ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \]  

(30)

\[ Error\ Rate = 100 - Accuracy \]  

(31)

\[ Specificity = \frac{TN}{FP + TN} \times 100 \]  

(32)

Where, \( TP \) was indicated as true positive, \( FP \) was stated as false positive, \( TN \) was specified as true negative, and \( FN \) was denoted as false negative.

A. Quantitative study on OASIS dataset

In this subsection, OASIS dataset is used for analysing the performance of the proposed work. In table 2, the proposed work performance is assessed in light of specificity, sensitivity and classification accuracy. Here, the performance valuation is done for 75 images (25 images for normal class, 25 images for MCI class, and the remaining 25 images for Alzheimer disease class) with 20% testing of images and 80% training of images. In addition, the performance validation is done with dissimilar classification methods such as LSTM, Deep Neural Network (DNN), and Convolutional Neural Network (CNN). From the experimental investigation, the sensitivity of LSTM is 98.43% and the comparative deep learning classification methodologies (DNN and CNN) achieved 93.78% and 90.14% of sensitivity. Similarly, the specificity value of LSTM is 98.01% and the comparative methodologies (DNN and CNN) attained 92.49% and 90.89% of specificity. Furthermore, the accuracy of LSTM methodology is 98.78%, and the available deep learning classifiers (DNN and CNN) achieved 92.29% and 91.48% of accuracy. The graphical comparison of the proposed work in light of accuracy, specificity and sensitivity on OASIS dataset is denoted in figure 10.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>93.78</td>
<td>92.49</td>
<td>92.29</td>
</tr>
<tr>
<td>CNN</td>
<td>90.14</td>
<td>90.89</td>
<td>91.48</td>
</tr>
<tr>
<td>LSTM</td>
<td>98.43</td>
<td>98.01</td>
<td>98.78</td>
</tr>
</tbody>
</table>

Table II: Performance validation by means of accuracy, specificity and sensitivity on OASIS dataset
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In table 3, the proposed work performance is assessed in light of error rate, FOR, and FDR. Correspondingly, the error rate of LSTM approach is 1.22% and the comparative deep learning classification methodologies (DNN and CNN) attained 7.71% and 8.52% of error rate. Likewise, the FOR value of LSTM is 2.12% and the comparative methodologies (DNN and CNN) attained 8.56% and 12.23% of FOR value. In addition, the FDR value of LSTM approach is 1.14% and the undertaken deep learning classifiers (DNN and CNN) achieved 7.97% and 9.12% of FDR value. The graphical comparison of the proposed work by means of error rate, FOR, and FDR on OASIS dataset is indicated in figure 11.

Table- III: Performance validation by means of error rate, FOR, and FDR on OASIS dataset

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Error rate (%)</th>
<th>FOR (%)</th>
<th>FDR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>7.71</td>
<td>8.56</td>
<td>7.97</td>
</tr>
<tr>
<td>CNN</td>
<td>8.52</td>
<td>12.23</td>
<td>9.12</td>
</tr>
<tr>
<td>LSTM</td>
<td>1.22</td>
<td>2.12</td>
<td>1.14</td>
</tr>
</tbody>
</table>

As mentioned above, feature dimensionality reduction and classification are the integral steps in automatic recognition and classification of Alzheimer disease. After feature extraction, dimensionality reduction is performed to lessen the “curse of dimensionality” issue, where the dimensionally reduced feature vectors are fit for better Alzheimer disease classification that is shown in table 4. In this consequence, the performance of the proposed work is validated with dissimilar methods such as LDA, PCA, Independent Component Analysis (ICA), Kernel-PCA (KPCA) and PPCA. The experimental investigation shows that the PPCA algorithm shows higher performance in terms of FOR, FDR, sensitivity, classification accuracy, error rate and specificity on OASIS dataset. Hence, the PPCA algorithm improved the recognition accuracy up to 2-24% related to other algorithms in Alzheimer disease detection and classification.

Table- IV: Performance valuation of the proposed work with dissimilar dimensionality reduction algorithms on OASIS dataset

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Error rate (%)</th>
<th>FOR (%)</th>
<th>FDR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICA</td>
<td>74.24</td>
<td>71.05</td>
<td>72.73</td>
<td>25.76</td>
<td>23.29</td>
<td>27.05</td>
</tr>
<tr>
<td>LDA</td>
<td>78.19</td>
<td>76.02</td>
<td>77.79</td>
<td>21.81</td>
<td>20.49</td>
<td>25.07</td>
</tr>
<tr>
<td>PCA</td>
<td>96.34</td>
<td>96.21</td>
<td>97.35</td>
<td>3.66</td>
<td>3.82</td>
<td>2.92</td>
</tr>
<tr>
<td>KPCA</td>
<td>82.97</td>
<td>83.51</td>
<td>81.19</td>
<td>17.03</td>
<td>12.14</td>
<td>13.26</td>
</tr>
<tr>
<td>PPCA</td>
<td>98.78</td>
<td>98.01</td>
<td>98.01</td>
<td>1.22</td>
<td>2.12</td>
<td>1.14</td>
</tr>
</tbody>
</table>

B. Quantitative study on NIMHANS dataset

In this segment, NIMHANS dataset is used to analyse the performance of the proposed work. In table 5, the proposed work performance is assessed in light of specificity, sensitivity, accuracy, error rate, FOR, and FDR. Here, the performance evaluation is done for 50 images (25 images for normal class, and 25 images for Alzheimer disease class) with 20% testing and 80% training of the brain images. From the experimental inspection, the recognition accuracy of LSTM is 95.88%, and the existing deep learning classification approaches (DNN and CNN) achieves 87.12%, and 90.75%. Correspondingly, the specificity, sensitivity, error rate, FOR, and FDR value of LSTM approach is 94.15%, 93.02%, 4.12%, 6.32% and 5.79%. Hence, the undertaken classification methodologies (DNN and CNN) achieves minimum sensitivity and specificity, and maximum error rate, FOR, and FDR value compared to LSTM classifier. The graphical comparison of the proposed work in light of sensitivity, accuracy, error rate, FOR, and FDR on NIMHANS database is represented in the figures 12 and 13.

Table- V: Performance validation by means of sensitivity, accuracy, specificity, error rate, FOR, and FDR on NIMHANS dataset

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
<th>Error rate (%)</th>
<th>FOR (%)</th>
<th>FDR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>89.19</td>
<td>88.74</td>
<td>87.12</td>
<td>12.88</td>
<td>15.56</td>
<td>12.19</td>
</tr>
<tr>
<td>CNN</td>
<td>89.78</td>
<td>91.57</td>
<td>90.75</td>
<td>9.25</td>
<td>10.35</td>
<td>13.54</td>
</tr>
<tr>
<td>LSTM</td>
<td>93.02</td>
<td>94.15</td>
<td>93.88</td>
<td>4.12</td>
<td>6.32</td>
<td>5.79</td>
</tr>
</tbody>
</table>

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In table 6, the proposed work performance is analysed with dissimilar dimensionality reduction algorithms on NIMHANS dataset. From the inspection, the recognition accuracy of PPCA is 95.88%, and the existing approaches (ICA, LDA, PCA and KPCA) achieves 71.35%, 75%, 91.87% and 85.46% of accuracy. Similarly, the specificity, sensitivity, error rate, FOR, and FDR value of PPCA is superior related to other approaches. Though, the PPCA includes a few key benefits like effectively dealing with missing values in the dataset, and appropriate for model class conditional densities.

Table IV: Performance valuation of the proposed work with dissimilar dimensionality reduction algorithms on NIMHANS dataset

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Error rate (%)</th>
<th>FOR (%)</th>
<th>FDR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICA</td>
<td>71.35</td>
<td>68.72</td>
<td>69.99</td>
<td>28.65</td>
<td>34.59</td>
<td>32.29</td>
</tr>
<tr>
<td>LDA</td>
<td>75</td>
<td>73.58</td>
<td>71.46</td>
<td>25</td>
<td>32.41</td>
<td>28.21</td>
</tr>
<tr>
<td>PCA</td>
<td>91.87</td>
<td>92.88</td>
<td>92.19</td>
<td>8.13</td>
<td>7.81</td>
<td>8.47</td>
</tr>
<tr>
<td>KPCA</td>
<td>85.46</td>
<td>81.54</td>
<td>80.79</td>
<td>14.54</td>
<td>16.39</td>
<td>18.43</td>
</tr>
<tr>
<td>PPCA</td>
<td>95.88</td>
<td>93.02</td>
<td>94.15</td>
<td>6.12</td>
<td>6.32</td>
<td>5.79</td>
</tr>
</tbody>
</table>

C. Comparative study

Table 7 indicates the comparative study of proposed and existing works performance. D. Jha, et al. [17] developed a new supervised system for alzheimer disease recognition on the basis of PCA, FNN and DTCWT. The performance of the developed work was verified on OASIS database. The experimental outcome shows that the developed work attained 90.06% of recognition accuracy in alzheimer disease recognition and classification. In addition, D. Jha, et al. [18] presented a new framework for alzheimer disease classification based on DTCWT, PCA, LDA and ensemble classifier. The extensive experiment shows that the developed work achieved 95.72% of recognition accuracy in alzheimer disease recognition and classification on OASIS dataset. V. Sachnev, and S. Suresh, [20] presented a new diagnosis framework for alzheimer diseases identification on the basis of ELM and sample balanced genetic algorithm. Extensive experiments were performed on OASIS dataset, the developed framework attained 98.78% of recognition accuracy. Compared to these existing works, the proposed work attained 98.78% of accuracy that was superior. In the proposed study, feature dimensionality reduction is the fundamental part of alzheimer disease recognition and classification. Every brain MRI images comprises of several feature vectors that leads to “curse of dimensionality” issue. So, feature dimensionality reduction is vital for optimizing the feature vectors that are suitable for better classification.

Table VII: Comparative study of proposed and existing works

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Dataset</th>
<th>Recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA, FNN and DTCWT [17]</td>
<td>OASIS dataset</td>
<td>90.06</td>
</tr>
<tr>
<td>DTCWT, PCA, LDA and ensemble classifier [18]</td>
<td>OASIS dataset</td>
<td>95.72</td>
</tr>
<tr>
<td>ELM and sample balanced genetic algorithm [20]</td>
<td>OASIS dataset</td>
<td>87</td>
</tr>
<tr>
<td>Proposed work</td>
<td>OASIS dataset</td>
<td>98.78</td>
</tr>
</tbody>
</table>

V. CONCLUSION

An effective deep learning based supervised system is proposed in this article for the automatic recognition and classification of Alzheimer disease. The purpose of this work is to classify the brain images as normal, MCI, and alzheimer disease by proposing a proper feature dimension reduction and classification algorithm. In this study, PPCA algorithm is employed to lessen the dimension of the extracted features. The obtained active discriminative feature vectors are classified by applying a deep learning classifier (LSTM). Compared to the prior works, the proposed work attained a better performance in Alzheimer disease recognition and classification by means of sensitivity, accuracy, specificity, error rate, FOR, and FDR. From the experimental investigation, the proposed work attained 98.78% of accuracy in OASIS dataset and 95.88% of accuracy in NIMHANS dataset, which are greater related to the existing works. In the future work, an optimization algorithm is considered to improve the performance of Alzheimer disease recognition and classification.
Alzheimer Disease Detection and Classification using Probabilistic Principal Component Analysis and Long Short-Term Memory Classifier

REFERENCES


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