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Intelligent System For Brain Disease Diagnosis Using Rotation Invariant Features And Fuzzy Neural Network

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Abstract

The characteristic features of the magnetic resonant image (MRI) for Alzheimer's patient's brain image and normal image can be distinguished in terms of dimensional features with the help of wavelet decomposition. From the literature review, it is observed that when datasets used are a combination of the MR images having a very mild cognitive impairment and mild cognitive impairment, the performance of the classifier reduces. Because the features of this kind of MR image are difficult to distinguish from normal brain images. To solve this problem, the lossless feature extraction method along with the feature reduction method having a selection approach is suggested as a solution here. In this paper, the 12 directional, rotation invariant two-dimensional discrete-time continuous wavelet transform (R-DTCWT) and a genetic algorithm (GA) are used for feature selection and feature vector size reduction. The fuzzy neural network (FNN) which is suitable for pattern recognition is used here. The FNN with and without feature reduction is evaluated for identification of combinational dataset, shows satisfactory performance over an artificial neural network (ANN), probabilistic neural network (PNN) classifiers. This method is compared with other state of algorithm to prove the enhanced performance

Keywords- Alzheimer's disease, DTCWT, Feature Classification, Fuzzy Neural Network, Genetic Algorithm, Feature Extraction

1. Introduction

Alzheimer's disease (AD) is a very common neurological disorder observed in old age people. Nowadays it is observed in all age groups. Neurologists claim that increasing stress is the reason for the same. The statistics mentioned in figure 1 give a detailed analysis of the increasing risk of the disease. In brain-related diseases, structure and MRI-based biomarkers indicate structural variations in the grey and white matter tissue. Hippocampal and entorhinal cortical decay is also observed in AD patients. It is difficult for clinicians to detect the smaller changes just by visual assessment. Also, there is a considerable delay between the onset of AD and its diagnosis. Thus the early detection of AD is very difficult and there is a need for intelligent means to support the clinicians for early and accurate diagnosis of the disease.

This paper presented the use of an optimization algorithm over features extracted using the 2D Dual Tree Complex Wavelet Transform (DTCWT) method. The fuzzy neural network (FNN) classifier is used for identifying Alzheimer's disease.

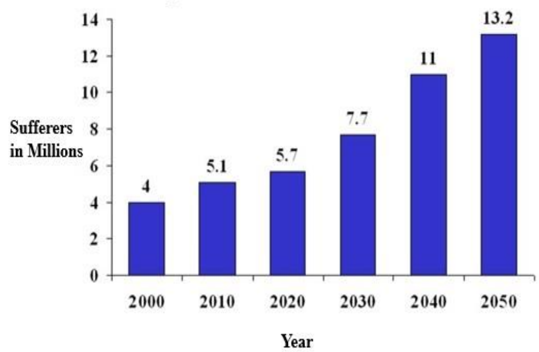

Figure 1. Impact Of Alzheimer's Disease On The Human Brain [1]

The four classes Kaggle database and seven classes. Figshare database is used while identifying Alzheimer's disease. The kaggle [20] Alzheimer's dataset consists of four stages of Alzheimer's disease including very mild AD, mild AD, AD and normal samples. The Figshare [21] database consists of 7 classes of brain diseases including normal, Meningioma, Glioma, Pick's disease, Huntington's disease, Sarcoma, and Alzheimer's disease.

The following section gives a brief about the previous methods with various methodologies. Fusun Er [2] provided a study of the computerized method with a deep learning approach for the identification of MCI due to Alzheimer's disease. The method identifies different brain regions with the use of a three-dimensional Jacobian-based method. The track of the difference between two consecutive brains is easily maintained using this strategy. The method shows an accuracy of 87.2%. Yongsheng Pan [3] identified limitations in various methods involving the neural network-based prediction of dementia from structural MRI images. The unique anatomical characteristic of each brain is ignored while identifying common features. Also, patch-based training focuses on limited regions of interest and hence global structural information about the brain is neglected. The authors provided the use of the attention layer in a CNN-based approach for improving the performance in case of multiple combinations of the datasets. Lei Du et al [4] proposed an analysis method using multitask sparse canonical correlation from multimodal quantitative traits (QT) brain images. The parameter decomposition and multi-task learning advantage is the main outcome of using the method. The genetic image analysis with multi-view using canonical correlation coefficients and weights is the main advantage of the method. Yee Ling Chan et al [5] shown the use of the wavelet method for identifying the brain connectivity parts. The identification of Alzheimer's disease is performed using the method. The motion artifact removal is the main target from fNIRS data. The signal processing approach is used for Alzheimer's disease detection. Authors considered topological constraints in filtering brain networks. Even sparsity present in the network has shown the highest efficiency. M Dadar et al [6] presented a fully automatic segmentation technique. The application considered is a brain MRI image in which the aging effect and AD are to be detected. The white matter hyper intensities are segmented using the linear segmentation method. The automatic segmentation shows almost 93% percent accuracy.

B. S. Mahanand et al [7] presented a method for AD detection with Integer Coded Genetic Algorithm along with the ELM classifier. The morphometric analysis is used with the voxel-based approach in which the respective best features are selected. The classifier shows 91.8% accuracy with 10 features compared to 86.84% accuracy using a support vector machine classifier for AD detection. Luis Javier Herrera et al [8] have discussed two problems in AD detection using MRI images. The first one focuses on the identification of AD and normal images from a dataset of 1000 images. The second problem focuses on the identification of mild cognitive impairment patients, AD, and normal from MRI image datasets. The early diagnosis of dementia is possible using the solution to the second problem developed by the authors. In the feature extraction stage, 2D discrete wavelet transform is used and then principal component analysis (PCA) is applied for further feature reduction. Classification is done by a support vector machine (SVM) based linear kernel classifier. The comparison using two methods of wavelet decomposition is done in which Daubechies and haar wavelet is used. In both the methods performance is evaluated using PCA and without PCA in which Haar wavelet shows the highest performance of 96.23% accuracy and applying PCA improves the processing speed of the classifier but reduces accuracy to 94.79%. M.Evanchalin Sweety et al [9] used an optimization technique for feature selection. The preprocessing with noise removal using Markov random field method is done. The features are obtained from Eigenvectors, mean, standard deviation, variance, area, perimeter, Skewness, eccentricity, and kurtosis. The particle swarm optimization is used for feature selection and feature vector reduction and classification is done using the decision tree.

Stella Vetova et al [1] shown the use of DTCWT for feature extraction from MRI images. The results are evaluated using the multilevel decomposition of DTCWT. In which vector length, time, and wavelet coefficients are considered. The level 4 decomposition even maintains the uniqueness of the features from MRI images when AD disease is concerned. Somkait Udomhunsakul et al [10] shown spatial feature extraction and its application to MRI images. The 5X5 sized filters with 40 sets are used to extract the features which maintain the scale and edge parameters as a characteristic feature. The pre-processing of the image is done using Gaussian 3X3 filters then the impact of noise removal is observed while using Gabor filter banks. Wed Kadhim Oleiwi [11] used a texture-based segmentation method using k-means. The segmented image is further processed using a gray level co-occurrence matrix for feature extraction. The features are then classified in AD and normal sets using K-nearest Neighbor classifier with 86.6% accuracy on the OASIS database. Reem Alattas et al [12] used simple and basic image processing methods such as thresholding, edge detection, and morphological operations to get brain dimensionality. The comparative of brain size is performed for AD patients' brain MRI images and normal brain MRI images in which a dimensional difference study is shown. Huaguang Zhang et al [13] proposed a fuzzy min-max neural network-based classifier on data core. The pattern classification is done with this classifier. It uses this overlapped neuron with a novel membership function based on the data core which differs from contraction processing. Abhijeet V. Nandedkar et al [14] proposed a classification approach, a min-max fuzzy neural network with compensatory neurons. In this classifier approach, pattern classes are represented as hyper box fuzzy sets and a novel compensatory neuron architecture gets activated whenever a test sample appears in the overlapped regions of different classes. P.K. Simpson et al [15] suggested a fuzzy classifier that uses a fuzzy min-max learning system to obtain min-max points. In this, the nonlinear class boundaries in a single pass through the data are cultured easily to obtain the convergence faster. The degree of membership information obtained from the fuzzy set method for pattern classification is proven highly beneficial for high-level decision making. Arun Kulkarni et al [16] suggested FNN for pattern classification. The suggested method is the improvement over the Radial basis function neural network (RBFNN). Here, to obtain the processing nodes in the hidden layers of FNN supervised fuzzy clustering and pruning algorithm to obtain the precise number of clusters with appropriate centroid and width is proposed. Sushmita Mitra et al [17] provided insight into the understanding of fuzzy sets for pattern recognition and its combination procedure for combining with other methods of soft computing.

Thus for Alzheimer's disease detection, various classical methods are suggested previously. In this paper, the 2D DTCWT for feature extraction is proposed. The method is modified to get extra angular features in terms of spatial characteristic coefficients. It is then clubbed with an optimized fuzzy neural network classifier, which gives better performance. Results of comparative analysis are included in the results and analysis section.

2. Experimental Design

The steps involved in the detection of AD are explained in this section and are shown in figure 2. The feature extraction is an integral part of the system which highlights and gathers all important features regarding AD from MR scans datasets. The kaggle [20] Alzheimer's dataset is consisting of four stages of Alzheimer's disease MRI scans with standard images collected from different websites to test the accuracy of the model. It consists of T2 MR Images. The T2 MR images are preferred since they represent maximum details as compared to T1 scans. Figshare [21] database is a seven-class brain-related disease database. The performance of the proposed method is evaluated using these databases.

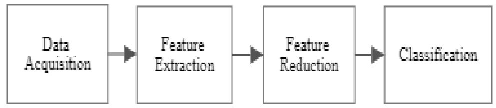

Figure 1. Block Diagram of Processing for Alzheimer's Detection Method

2.1 DTCWT

In earlier conventional tools, the Fourier transform was popular for feature extraction. But the time and frequency feature extraction capability of wavelet transform is very good so it has shown its impact in machine learning applications. The 2D discrete wavelet transform (2D-DWT) decomposes the image into four bands which then reduces the complexity of processing by using each band separately. The complex wavelet transform (CWT) is a complex-valued extension of the standard discrete wavelet transform (DWT). The maximum characteristic features in terms of multi-resolution and sparse representation of CWT, the more unique features can be obtained. The higher degree of shift-invariance in its magnitude is the main reason for obtaining important distinctive features in medical images. A drawback of simple CWT is that it exhibits 2d redundancy in features as compared to a separable (DWT). On the other hand, for image features extraction Kingsbury shown the use of dual-tree CWT (DTCWT) in 1998. In DTCWT, two real DWTs are performed while obtaining the sub-band features, and also it has an imaginary part in second DWT operations.

The features extracted by using the coefficient extraction method should meet the following conditions:

(i)The decomposition should be perfectly reversible to get the original image back which shows lossless decomposition and important features even for a small region of interest after decomposition.

(ii)The decomposed parts of the input vector must be a shift in half-sample of the other. (h_0 and g_0)

(iii)The boundary condition in $h_0(1)$ and $g_0(1)$ must be by one and the only one sample shift.

Orthogonal Q-shift filters were proposed by Kingsbury to meet these conditions for 1D signal vectors. The idea can be extended for 2D by using equations (2) and (3) which describe complex separable wavelet and scaling respectively with the implementation of separable filters on first columns and then on rows in 2D DTCWT.

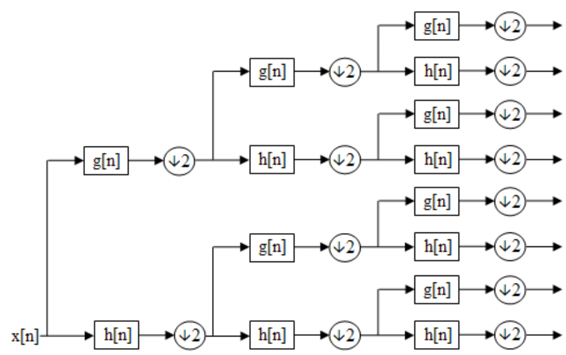

Figure 2. DTCWT Decomposition

$$\psi_1(x,y) = \varphi(x)\psi(y)$$
$$\psi_2(x,y) = \psi(x)\varphi(y)$$
$$\psi_3(x,y) = \psi(x)\psi(y) \quad (1)$$

$$\varphi(x,y) = \varphi(x)\varphi(y) \quad (2)$$

Here ψ (·) and φ (·) are complex wavelets and complex scaling functions respectively.

The proposed method combines four trees on columns and four trees on rows to obtain twelve shift variant wavelets oriented at ±15º, ±30º, ±45º, ±60º, ±75º, ±90º and makes the system rotation invarient.

Two different sets of filters are used in two wavelet transforms to meet 1st condition mentioned earlier. Consider h_0 (n), h_1 (n,) and g_0 (n), g_1 (n) represent low pass and high pass pair of filters for upper and lower separable filter banks respectively. Hence complex wavelet can be denoted as,

$$C(t)=h'(t)+jg'(t) \tag{3}$$
$$g'(t)=Hilbert\{h'(t)\} \tag{4}$$

Where h'(t) and g'(t) are real complex wavelet transforms of h(t) and g(t) respectively.
Equation (4) denotes the relation such that the exact Hilbert transform of h'(t) is g'(t) for the lossless decomposition method. Another advantage of using DTCWT is that there is no involvement of complex arithmetic during its implementation and also, the input data rate is half as to output data rate. In 2D DTCWT the coefficient extraction can be demonstrated as shown in figure 3. Respective 2D DTCWT is applied for the decomposition of input brain MRI image the resulting four-level decomposition is shown in figure 4.

2.2 Fuzzy Neural Network
A fuzzy neural network is a model fusion method, which utilizes the neural network's learning capability with the noise handling ability of FL. FNN is simply a 3 layered feed-forward network namely input layer, hidden layer, and output layer. Input and output layers are used for fuzzification and defuzzification respectively. The hidden middle layer contains fuzzy directions. Generally, the connections between layers contain fuzzy rule sets. Sometimes a fuzzy neural network is a 5-layered network, in that fuzzy sets are contained in the 2^{nd} and 4^{th} layers.

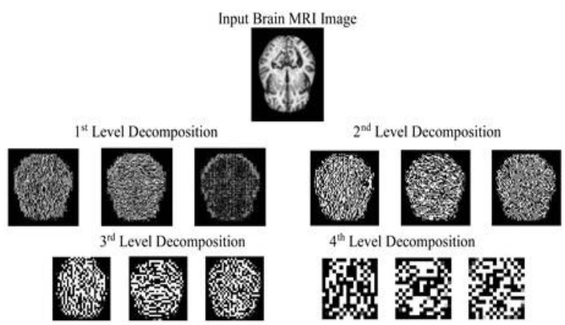

Figure 3. 2D DTCWT Four Level Decomposition

The input fuzzy layer signifies the input connection functions for the fuzzy directions. Enough input initiates the rules in the hidden middle layer to ignite. The weights among the fuzzy layers symbolize the fuzzy sets. The relative weights determine the relationship in each set, that relationship can be varied using various training algorithms similar to the usual neural system. In FNN, the transfer functions are continuous and are used to pass the values to the output layer through the network. It is interpreted as degrees of membership in fuzzy sets. This is according to the fuzzy rules in the hidden middle layer. Fuzzy neural networks use the combination of strengths of neural networks and FL to make the FNN a very commanding hybrid model with the integration of expert knowledge. The use of fuzzy inference like a human makes the system easy to understand. The input from dataset 1[20] consists of four classes in which normal, very mild demented, mild demented, and moderate demented images are used. In dataset 2 [21], seven classes of images are present which are normal, Meningioma, Glioma, Pick's disease, Huntington's disease, Sarcoma, and Alzheimer's disease. The features obtained from 2D DTCWT are very large in number and hence to achieve convergence of FNN in a smaller number of epochs is the main requirement considered. To minimize the convergence iteration count and the system complexity feature reduction technique is applied. The feature reduction is possible by conventional methods such as linear discriminant analysis (LDA), principal component analysis (PCA) and independent component analysis (ICA).
These methods are again having limited capacity to reduce the features and are independent methods that provide output irrespective of classifier requirement. The optimization algorithm is capable of optimizing the convergence during the training process thereby achieving it faster. This approach is used for

optimizing the classifier using a genetic algorithm (GA) for selecting the required features based on the optimal solution and fitness and hence model converges earlier with maximum accuracy of classification.

2.2.1 Genetic Algorithm

The total number of features is required to be reduced for achieving faster convergence in the classifier. On the other hand, the accuracy should remain intact when while selecting the features from a set of a large number of features. For, optimized processing requirements during classification genetic algorithm (GA) can be used for selecting the features. Khehra et al [18] have shown the use of GA for selecting the features. Darwin's 'survival of the fittest principle is used in genetic algorithms. GA involves stages of selection, crossover and mutation in which a new population is generated from the old generation for a predefined number of iterations. Based on fitness function optimum solution is obtained.

2.2.2 Population Encoding

In the proposed method binary-coded GA is used in which 2n possible feature sets are obtained for n number of total features. A binary set of n elements can be obtained by encoding, namely, S = (k_1, k_2, ..., k_m). The feature selection variable k_i can be given as

$$k_i = \begin{cases} 1, & feature\ is\ present\ in\ subset \\ 0\ , & otherwise \end{cases} \tag{5}$$

□□□□□□□□□□□In each defined string or chromosome if the feature is selected, it is nominated as 1 else 0. Considering 8 features for the classifier as the optimal feature set, S = (01001001) can be considered as a feasible solution in which features at 2, 5 and 8 are selected.

2.2.3Fitness of Population

The fitness of the string is given by

$$F(S_i)=CR\ (FNNS_i) \tag{6}$$

where CR is the classification rate of the classifier.

2.2.4 Algorithm

Step 1. Initialize GA parameters,

Population size = P (total number of features obtained from DTCWT), Number of generations = Gmax (this number defines the maximum number of generations to be obtained where operation stops after getting Gmax which is the optimal solution), Probability of mutation = pm, Probability of crossover = pc

Step 2. Obtain P from the feature vector

Step 3. Calculate fitness using equation (6)

Step 4. Apply Roulette wheel selection to select individuals.

Step 5. Apply crossover with respect to pc

Step 6. Mutate based on pm

Step 7. Get new offsprings

Step 8. If maximum iterations reached|| G ≥ Gmax stop Else go to Step 3.

3. Results

The main disease to be detected is Alzheimer's disease from both datasets. The feature extraction which is an integral part of the system which highlights and gathers all important features regarding AD is carried out using R-DTCWT. The classification is carried out using FNN with and without optimization technique. The performance of the proposed system is analyzed using a 2-fold analysis in which the total dataset is divided into two parts. The first part is used for training and the second part is for validation. The operation is applied on both the datasets and performance is evaluated. The performance of a proposed system without optimization and with optimization is evaluated in which accuracy of classification is seen higher in optimization-based method. Also, the results are compared with other classifiers having no optimization process. The classifiers used for comparison are Probabilistic Neural Network (PNN), Artificial Neural Network (ANN). The training parameter configuration is as shown in table 1.

In the case of dataset 2, the performance evaluation is done using a confusion matrix in which true positive (TP) stands for input Alzheimer's and is detected as Alzheimer's. In a true negative (TN) input is Alzheimer's and detected as non-Alzheimer. Similarly, when input is non-Alzheimer then false positive (FP) and false-negative (FN) are detected as Alzheimer's and non-Alzheimer respectively. The formulae for accuracy, Sensitivity and Specificity are given in table 2. The performance values obtained for dataset 1 for very mild, mild and moderate demented images and dataset 2 are given in Tables 3 and 4 respectively.

In the case of dataset 1, there are three subsets of Alzheimer's with variation in stages from very mild to moderate and hence each case has a different approach for considering confusion matrix parameters. The one against all for each Alzheimer's class is considered separately and average performance is calculated to calculate parameters accuracy, sensitivity and specificity.

TABLE 1. PLANNING AND CONTROL COMPONENTS

Parameter	**Configuration Value**
Epochs	1000
Learning Rate	0.001
Number of hidden neurons	10
Gradient	$1e^{-25}$

TABLE 2. PERFORMANCE PARAMETERS

Parameter	**Formula**
Sensitivity	$\boldsymbol{TPR = \frac{TP}{FN + TP}}$
Specificity	$\boldsymbol{TNR = \frac{TN}{FP + TN}}$
Accuracy	$\boldsymbol{ACC = \frac{TP + TN}{TP + TN + FP + FN}}$

TABLE 3. PERFORMANCE OF CLASSIFIERS ON DATASET 1

Method	**Accuracy**	**Specificity**	**Sensitivity**
R-DTCWT+FNN with optimization technique	0.97	0.91	0.91
R-DTCWT+ FNN without optimization technique	0.94	0.875	0.878
ANN	0.899	0.827	0.825
PNN	0.81	0.81	0.80

TABLE 4. PERFORMANCE OF CLASSIFIERS ON DATASET 2

Method	**Accuracy**	**Specificity**	**Sensitivity**
R-DTCWT +FNN with	0.96	0.89	0.91

optimization technique			
R-DTCWT +FNN without optimization technique	0.94	0.91	0.92
ANN	0.82	0.82	0.83
PNN	0.86	0.84	0.82

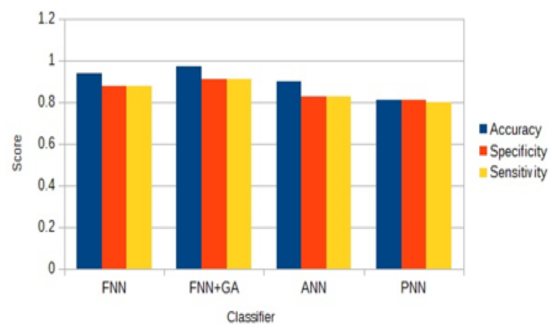

Figure 4. Performance of Different Classifiers on Dataset 1

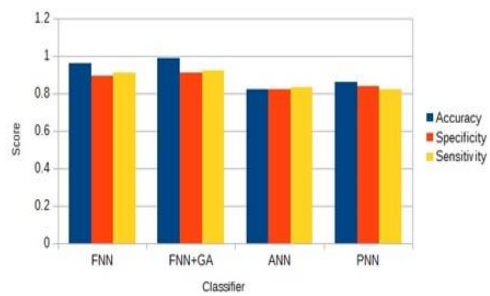

Figure 5. Performance of Different Classifiers on Dataset 2

3.1 Annotations

1. The accuracy of FNN is better than ANN and PNN. The addition of GA also boosts further accuracy due to the unique feature selection mechanism.
2. R-DTCWT is dual tree complex wavelet transform obtained with rotation of wavelet coefficients in 12 various directions which makes the system rotation in variant and thus contributes to improve the performance parameters.
3. PCA, ICA, and LDA reduce feature dimensions up to a certain limit and hence the fitness-oriented selection of features using GA improves the reduction performance with more convergence in the classifier.
4. The performance of the proposed method remains higher even in the case of inclusion of very mild Alzheimer's disease images and also when combined with other disease types.
   The proposed method is compared with the previous methods which used the DTCWT for feature extraction. The comparison is given in table 5.

The efficiency of the suggested algorithm is comparable with the previous techniques proposed by S. Mahanand et al. [7] and Debesh Jha et al. [19] which use DTCWT feature-based classification methods. The classification performance of this method is better when compared with these modern approaches mentioned in terms of accuracy, sensitivity and specificity.

TABLE 5. PERFORMANCE COMPARISON WITH PREVIOUS METHODS ON DATASET 2

Method	Accuracy	Specificity	Sensitivity
DTCWT +ICGA+ELM [7]	91.6	87.9	89.2
DTCWT+PCA+FNN[19]	90.06	92.00	87.78
R-DTCWT+FNN with optimization technique(Proposed)	96.00	89.21	91.05
R-DTCWT+FNN without optimization technique (Proposed)	94.02	91.24	92.16

4. Conclusion

This paper presented the use of an optimization algorithm over features extracted using the 2D DTCWT method. The fuzzy neural network (FNN) classifier has shown better performance for four classes and seven classes applications while identifying Alzheimer's disease. The method shows no impact on performance even if very mild and mild cognitive impairment MRI images are included in the dataset which causes performance degrading problems in existing methods. The performance of GA-based feature selection and reduction is seen as satisfactory when compared over other feature reduction techniques PCA, LDA and ICA. The conventional feature reduction techniques have limited scope for feature size reduction while maintaining the uniqueness of the features on the other hand GA shows better performance by reducing the overall complexity of the system. The overall results are seen as outstanding by using the proposed method.

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