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Wavelet Filter for Alzheimer's Classification from MRI Images using Adaboost

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Abstract

Alzheimer's Disease (AD) is a disorder of the brain which is progressive, destroying memory and the ability to think. The patients of AD suffer from problems such as lack of initiative, change in personality and behavior which is seen in their daily functions either at work or home and also in taking care of oneself which eventually results in death. One widely used technique for diagnosing of the AD is Magnetic Resonance Imaging (MRI) owing to its non-invasive nature and is widely adopted in several hospitals to examine certain cognitive abnormalities. The MRI images are processed using image processing techniques to identify the AD. Image processing techniques extract features from the images and classify them as either normal or abnormal (AD). The primary reason for the robustness of the Wavelet Transform is its flexibility in choosing bases and also its low level of complexity of computation. The basic idea behind the AdaBoost algorithm was that it was a combination of the weak classifiers to build a robust classifier. In this work, an improved wavelet filter is proposed to classify Alzheimer's using MRI images with a modified AdaBoost.

Keywords: *Alzheimer's Disease (AD), Wavelet transform, Magnetic Resonance Imaging (MRI), AdaBoost algorithm Minimum*

1. INTRODUCTION

Alzheimer's Disease (AD) has not always been related to aging. It is a classification of dementia which results in issues connected to memory, behavior, and thinking patterns. The actual signs of AD develop quite slowly and get worse over time. This can, at times, get very severe and can also interfere with daily life and may also lead to death. Until today, there has been no cure that is identified for this disease. Identification of AD in the early stage helps in slowing the progress of disease.

Another very promising research area to detect the AD is neuroimaging. There have been multiple processes of brain imaging that may be used for the identification of brain abnormalities which include the PET, the MRI, and the CT scans. Every scan includes a new and unique technique that detects certain structures, as well as abnormalities identified in the brain.

A fusion of such techniques will improve the accuracy of classification. Almost all recent approaches to computer-aided machine learning make use of a fusion of techniques of neuroimaging and a similar model for classification is applied to the

Patients that do not have tailoring of any diagnostic decisions as they tend to assume the biomarkers to be readily available at the same time [1].

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Magnetic Resonance Imaging (MRI) is a scanning device that employs magnetic fields along with computers for capturing brain images on the film. It does not make use of x-rays. It further provides pictures obtained from different planes that permit the doctors to ensure a three-dimensional tumour image is created. The MRI also detects all signals that are emitted from both normal and abnormal tissue, thus providing clear images of the tumours. This has now become the method that is most commonly used, and has medical imaging of high quality, especially for brain imaging as the soft tissue are seen in contrast. The radiologists further examined the MRI based on visual interpretation for films in identifying abnormal tissues. MR brain images and their diagnosis indicate critical tasks. Any wrong diagnosis may provide certain types of results for healthy patients. The human brain has been characterized by complexity, and this can make analysis extremely hard. Additionally, both the analysis and the viewing expert can be quite limited in comparison to large amounts of the MR images.

The wavelets are recently considered to be a strong tool used for de-noising the image. An individual wavelet can make the image into a small group of coefficients that are composed of an image with a multi-scale model. A distinct wavelet transform for the signal is expressed as x(n), and this is computed by using a low pass filter along with an impulse response g(n). This signal will now concurrently break it down by using the high pass filter which is h(n), and provide coefficient details.

There have been several techniques that were proposed for the classification of the MRI. All methods will have image features that are different, and they represent determinant information that is the classifier input vectors. The extraction of features has a crucial role as features that are effective and good will be able to provide higher levels of accuracy. Typically, the techniques can be grouped into two categories which are supervised and unsupervised. The former will need some more information classes and will perform the earlier model from their training sets. However, image processing found in unsupervised methods will not require any particular training data. They are fast and will not need a training step. At times, they can be inefficient [2].

From among the different algorithms that were proposed for statistical classification, the AdaBoost, a meta-algorithm that sequentially chooses the weak classifiers (the ones not performing well when being used on their own) to form a candidate pool with weights based on errors, thus significantly improving the quality of output (classification). A weak learner, on the other hand, denotes a statistical classifier performing better by chance. Every iteration of the AdaBoost will assign something known as the "importance weight" to every example. The example that has a higher weight which is classified wrongly in the earlier iterations receives more attention for all subsequent iterations, thus tuning weak learners to challenging examples. The testing of examples with the AdaBoost is a weighted vote for the weak learners. The remainder of the investigation is organized in the following manner: Section 2 makes a discussion of the work which is available in the literature. The methods used are explained in Section 3. The results of the experiment are analyzed in Section 4, and the conclusion is made in Section 5.

2. LITERATURE SURVEY

Both visualizing, as well as interpreting the Convolution Neural Networks (CNNs), becomes a crucial task for increasing trust in the systems of medical decision making. Rieke et al [3] had trained the 3D CNN for detecting Alzheimer's disease, and this was based on the structural MRI scans of the brain. After this, there are four occlusion-based, and gradient-based methods of visualization explain the decisions using highlighting some relevant areas. The methods are compared both qualitatively and also quantitatively. It is found that all the four methods will focus on the regions of the brain which are involved in AD, which may be either inferior or middle temporal gyrus. While methods based on occlusion have been focusing on more specific regions, the methods based on gradients tend to pick up the relevance patterns. In addition to this, it can be found that the relevance distribution can vary across different patients. To summarize, it is shown that the application of various methods of visualization

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which makes it crucial to understand CNN decisions which are an important step for increasing their clinical impact and trust in the decision support systems that are based on computers.

The analysis of MRI used to detect neurodegenerative diseases have been investigated and further reported for this work. This was based on the Discrete Wavelet Transform (DWT), which was combined with various fractal analysis. Bhandari et al [4] had proposed a new method that contained two different stages. The first one contained pre-processing images that included the enhancement of images, skull stripping, and region of extraction. The next state had the pre-processed image converted to the wavelet domain, and a study was performed to extract features with fractal analysis. Lastly, the work also was experimented using an image dataset that was publicly available with mild cognitive impairment, an Alzheimer's, and a healthy patient. This support vector machine classifier had achieved an accuracy of classification of about 89.7 +- 0.6. This paved the way to develop a new system for the diagnosis that was computer-aided on certain neurological diseases.

Acharya et al [5] aimed at developing a new system called Computer-Aided-Brain-Diagnosis (CABD) to determine whether the brain scan can show early signs of the Alzheimer's disease. This method employs the MRI, which is used for classifying various techniques of feature extraction. The images are acquired with T2 imaging sequence. This paradigm has a series of quantitative techniques. They are filtering, extraction of features, Student's t-test feature selection, and the k-Nearest Neighbour (KNN) classification. In addition to this, there was another comparative analysis which was done using implementing some more procedures of feature extraction that have been described in the literature. Findings have suggested the technique of feature extraction known as the Shearlet Transform (ST) was able to offer better results for the diagnosis of Alzheimer's compared to the other alternative methods. The tool proposed known as the CABD along with the technique known as the ST + KNN had provided an accuracy of about 94.54%, a precision of about 88.33%, a sensitivity of about 96.30% and finally a specificity of about 93.64%. Also, the tool had provided accuracy, precision, sensitivity, and finally specificity of about 98.48%, 100%, 96.97% and 100% using the benchmark MRI database.

Nayak et al [6] made a presentation of an automated system of Computer-Aided Diagnosis (CAD) which was used for the Brain Magnetic Resonance (MR) based image classification. This system had employed a two-dimensional Discrete Wavelet Transform (2D DWT) for extraction of features from images. Once the normalization of the feature vector is complete, Probabilistic Principal Component Analysis (PPCA) will be employed for the reduction of feature vector dimensionality. All the reduced features will be applied to a classifier for categorizing the MR images as either normal or abnormal. The scheme makes use of the AdaBoost algorithm using random forests as their base classifier. There are three other benchmarks MR image datasets which are: Dataset-66, Dataset-160, and Dataset-255 that are employed for validating this system. The results of simulation have been compared to the schemes in existence, and it observed that the scheme proposed had outperformed the others for all three datasets.

A new system had exploited the Discrete Wavelet Transform (DWT) and the Bag-of-Words (BoW) for the extraction of image features in Ayadi et al [2]. The Support Vector Machine (SVM) has been used in the step of classification. There were 256×256 images employed from three different datasets (DS-66, DS-160, DS-255) that were provided by the Harvard Medical School, for evaluation of this method. There was a 10*k-fold technique of stratified Cross-Validation (CV) which was applied for the validation of the system performance. The accuracy level was 100%, 100%, and 99.61% for the DS-66, DS-160, and the DS-255 datasets. The overall time taken for computation was about 0.027s for every MR image. There was a comparative study with different work made to prove the robustness and efficiency of the scheme.

Lama et al [7] proposed the AD diagnosis with structural Magnetic Resonance (sMR) images for the discrimination of subjects with AD, MCI, and the Healthy Control by employing the Support Vector

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Machine (SVM), Import Vector Machine (IVM), and the Regularized Extreme Learning Machine (RELM). There was also a discriminative approach that was kernel-based which was adopted for dealing with such complex data distributions. The performance of the classifiers was compared for the volumetric sMR image data obtained from the Alzheimer's disease Neuroimaging Initiative (ADNI) datasets.

Alzheimer's disease normally affects the hippocampus region in the brain. Rangini and Jiji [8] presented a level set approach for identification of the AD. Once the segmentation was done, the features in the segmented region were computed. Features like the intensity, the gradients, the curvatures, the 1-D, the 2-D, and the 3-D Haar filters, the mean filters, and finally, the standard deviation were estimated. The Hierarchical AdaBoost with the Support Vector Machines (SVM) was employed. These segmentations were favorably compared to the manual segmentations. How the segmentation and its accuracy were dependent on the training set size was also evaluated.

3. METHODOLOGY

The section detailed the Wavelet Transform, the Fast Fourier Transform, the AdaBoost and the Classification and Regression Tree (CART) techniques used in this investigation.

3.1 Fast Fourier Transform

This is the Fast Fourier Transformation (FFT) is very efficient in computing and its reverse is the Discrete Fourier transformation (DFT). This is a very robust tool that classifies fast and owing to its effectiveness, the FFT is used in various areas of research like analyzing signals or forecasting the consumption of energy in the buildings [9], the detecting of epileptic seizures in a condition of electroencephalography (EEG) and forecasting of water demand [10]. DFT further decomposes the sequence of input data (such as data in sliding windows for a particular time series data for patients) for the extraction of information on frequency and prediction of the condition of patients. Even before the Fast Fourier transformation was performed, all input variables were scaled with a technique of normalization. These normalized variables will take on the values inside the interval [0, 1]. This normalization was performed based on equation (1):

$$D_{norm} = \frac{D_{Orig} - D_{\min}}{D_{Max} - D_{\min}} \tag{1}$$

In this, D_{norm} denotes normalized data value, D_{Orig} denotes original raw data, the $D_{\min}$ and D_{Max} denote minimum and maximum values for the whole dataset. If $x(t)$ is a time series which is bonded by the sliding window, Discrete Fourier Transformation of the $x(t)$ is defined as per equation (2):

$$X(c^{jw}) = \sum_{t=-\infty}^{\infty} x(t) c^{-jwt} \tag{2}$$

Wherein t denotes the discrete-time index, w is the frequency. T is the input time series $x(t)$, and so a transform pair of DFT is as per equation (3) [11]:]:

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$$X(P)=\sum_{t=0}^{T-1}x(t)W_T^{tp}\Leftrightarrow x(t)=\frac{1}{T}\sum_{p=0}^{T-1}X(P)W_T^{-tp}$$
$$\textit{where } \mathrm{W}=\mathrm{c}^{-j2\Pi/T} \tag{3}$$

3.2 Wavelet Transform

Wavelet Transform is a novel and integrated technique of signal processing used for complex problems. This has a performance of analysis which is excellent with the traits of multi-resolution, making it worthy of processing images. For localization and analysis of the multi-resolution of signals, we can use the wavelet transform. Also, this can be applicable to the complicated images for edge detection, which is accurate [12]. Wavelet transform has been defined as the linear operation where the signal decomposes as mechanisms like in the case of altered scales. The wavelet functions (t) were well-defined within a space that has measurable functions which are absolution and are square integral as depicted in equation (4 and 5):

$$\int_{-\infty}^{+\infty}|\psi(t)|\,dt<\infty$$
$$\int_{-\infty}^{+\infty}|\psi(t)|^2\,dt<\infty \tag{4, 5}$$

These conditions of the zero mean and the square norm one have been gratified [17]:

$$\int_{-\infty}^{+\infty}\psi(t)dt=0$$
$$\int_{-\infty}^{+\infty}|\psi(t)|^2\,dt=1 \tag{6, 7}$$

Wavelet transform of function $f(t)\in L^2(R)$ at scale a and position τ in equation (8) [5]:

$$Wf(a,\tau)=\frac{1}{\sqrt{2}}\int_{-\infty}^{+\infty}f(t)\Psi^*(\frac{t-\tau}{a})dt \tag{8}$$

An asterisk * will signify a complex conjugation. In equation (8) the analysis of the signal f(t) gets convolved with the stretched or the dilated copies of a mother wavelet (t). For the a < 1, a wavelet will be contracted, and data for transform stretches approximately as the particulars of f(t). For the a > 1, a wavelet will enlarge, and the transform will give a view of the same signal. If a scale parameter which is a = 2j with j ∈ Z, Z denotes a set of integer, the wavelet will be called a dyadic wavelet. A wavelet transform will be in continuous time on the functions and also in the discrete-time on the vectors. In the case of continuous-time, wavelet coefficients will originate using assessing an integral as per equation (5). In the discrete-time, coefficients originate through passing the vector (x(n), n integer) employing a bank that has two filters and one is low-pass whereas the other denotes a high-pass.

3.3 Classification and Regression Tree (CART)

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The CART algorithm is based on a statistical methodology for the classification that had categorical outcomes with regression having continuous ones [13]. This denotes a tool of data mining which is like the case of binary recursive partitioning. Constructing the CART was similar to the ID3. In a classification tree, there is a measure of impurity calculated with the Gini criterion for the best split. The split's goodness is defined to be the reduction in impurity as per equations 9 and 10):

$$\Delta i(t) = i(t) - p(t_l)i(t_l) - p(t_r)i(t_r) \tag{9}$$

$$i(t) = 1 - \sum_j p_j^2 \tag{10}$$

Wherein the $i(t)$ is the node impurity t with them $p(t_l)$ and $p(t_r)$ is the probability that an object may fall either to the left and the right of the node t. p_j Denotes the proportion of the cases falling in category j. $i(t_L)$ and $i(t_R)$ Denote impurities of that of the left and the right nodes. Now choose a predictor variable and a split point that has the highest reduction in performing the split of parent nodes for the two nodes that are based on a selected split point. The process is made by making use of the node like the new parent node until such time the tree which has a maximum size. Once the maximal tree CART is generated by using the technique of pruning of an optimal tree.

The procedure of pruning will develop another sequence of some smaller trees to compute the complexity of cost for every tree. Based on the parameter of cost-complexity, pruning will determine an optimal tree that has high accuracy. For this, complexity was given by equation (11):

$$R_\alpha = R(T) + \alpha |\tilde{T}| \tag{11}$$

Wherein the R (T) denote a re-substitution estimated error, $|\tilde{T}|$ denotes the terminal nodes for the tree, and this determines the tree and its complexity. α denotes the complexity of cost, which is associated with the tree. R (T) will be given by an error of misclassification computed using the equation below (12):

$$R(T) = \frac{1}{N} \sum_{i=1}^{N} X(d(x_n) \neq j_n \tag{12}$$

Wherein X denotes an indicator function, and this is equal to 1 in case the statement is $X(d(x_n) \neq j_n$ which is true and 0 in case it is false, and d(x) denotes a classifier. The complexity parameter value in pruning falls typically between 0 and 1. The procedure of pruning will develop a new group of trees that make use of several other values of the complexity of a parameter with different tree sizes. From among a group of trees of various sizes, for value α, a tree that has a smaller size with a high level of accuracy. An optimal tree will be one that a small prediction error for the newer samples. There is a prediction error measured by making use of an independent test set and sometimes a Cross-Validation (CV).

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At the time a dataset is not big enough to split data into either training or testing data, there is a V-fold validation which is used. The cross-validation will be repeated V number of times with different training data and testing data subsets and develop V number of trees that are varied. Among all the V different trees, the tree which is the simplest and has the lowest rate of Cross-Validation error (CV error) will be chosen to be the optimal tree.

3.4 AdaBoost Classifier

Owing to its ineffectiveness and complexity, the method of MRI image classification has to boost the yields of identical, accurate, and explicit classification. The AdaBoost classifier can be called the most standard and successful pattern found in ensemble learning. For the machine learning algorithms that attempt at generating the sets of base learners, this is collected. Ensemble denotes the process which boosts weak learners in making a strong classifier.

A technique of machine learning algorithm where a ‘weak classifier' becomes a learner and is similar to the true labels where the strong classifier is near to its true label is Adaptive Boosting. A prominent supervised algorithm of boosting which repeats usage of base learning algorithms or weak algorithms is employed. An expression of the sum for a weak classifier or the classification of a suitable combination of a weak classifier can be obtained.

$$H(x) = sign\sum_{i=1}^{T} \alpha_t h_t(x) \tag{13}$$

For this process, there are several distributions of the sample sets that are used with the weak classifier. In subsequent training, the misclassified classifier gets a large training. Once various training is complete, they may get the greatest weight. For obtaining a strong classifier from this one, the training sample has to be sufficient, and the error of classification has to be minimal.

The AdaBoost is an efficient algorithm used for boosting the classification performance of weak learners. This was by combining a set of functions of different weak classifiers to form a strong one. Here, the weak classifiers are considered for distributing the training sample weight for ensuring more weight is featured to samples that are misclassified under the other iterations.

An ultimate strong classifier will obtain a perception which is a weighted combination of weak classifiers [15]. The AdaBoost will explicitly look to minimize errors based on the distribution of weights for every iteration.

4. RESULTS AND DISCUSSION

Table 1 to 3 and figure 1 to 3 shows the results of classification accuracy, sensitivity, and specificity respectively. For the experiments, AD, MCI and CS images were used. 80 AD, 55 MCI, and 40 CS MRI images are considered.

Table 1. Classification Accuracy of Wavelet Transform – AdaBoost

Number of features	**Classification Accuracy**
Fast Fourier Transform - CART	61.14
Wavelet Transform -CART	72.57

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Fast Fourier Transform - Adaboost	67.43
Wavelet Transform -Adaboost	78.86

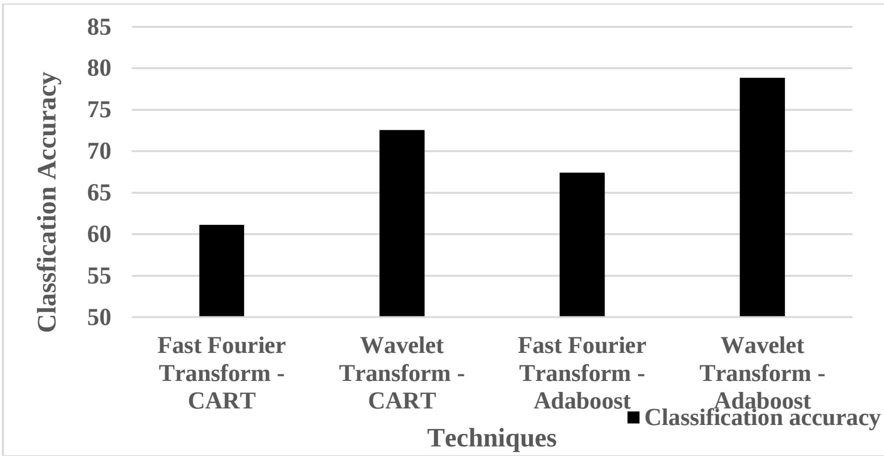

Figure 1. Classification Accuracy of Wavelet Transform – AdaBoost

Table 1 and figure 1 shows that the classification accuracy of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively.

Table 2. Sensitivity of Wavelet Transform – AdaBoost

Number of features	**Fast Fourier Transform - CART**	**Wavelet Transform - CART**	**Fast Fourier Transform - Adaboost**
AD- Sensitivity	0.6125	0.7625	0.6875
MCI - Sensitivity	0.5818	0.6909	0.6545
CS-Sensitivity	0.65	0.7	0.675

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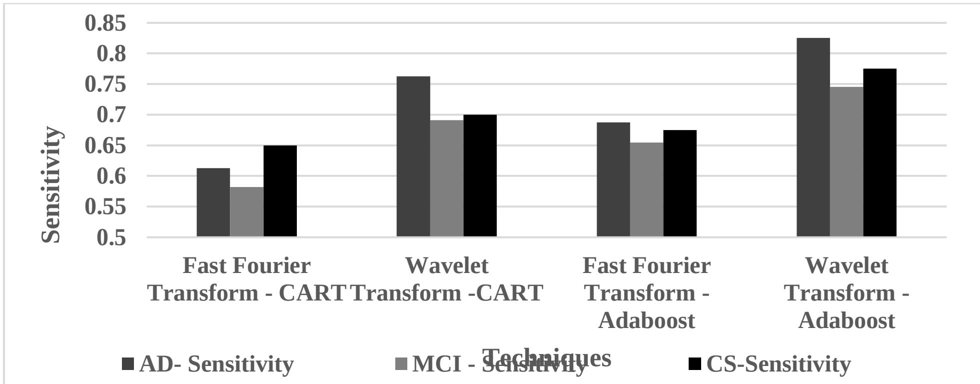

Figure 2. Sensitivity of Wavelet Transform – AdaBoost

Table 2 and figure 2 shows that the sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively for AD - Sensitivity. The sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively for MCI – Sensitivity. The sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively for CS – Sensitivity.

Table 3. Specificity of Wavelet Transform – AdaBoost

Number of features	**Fast Fourier Transform - CART**	**Wavelet Transform - CART**	**Fast Fourier Transform - Adaboost**
AD- Specificity	0.7436	0.8148	0.7778
MCI - Specificity	0.7895	0.8476	0.8283
CS- Specificity	0.7431	0.8534	0.8053

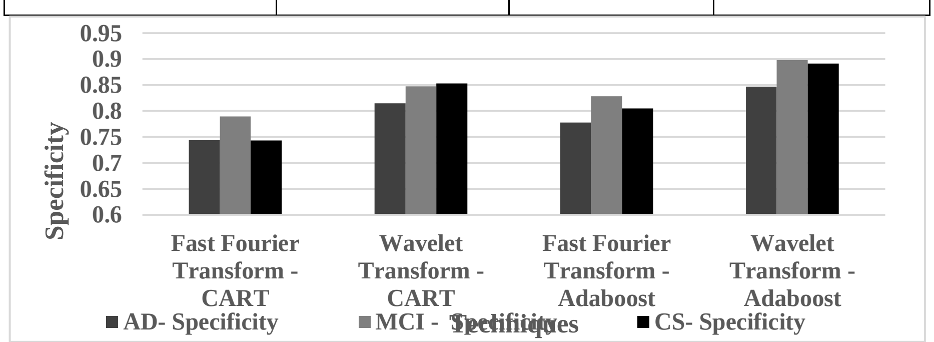

Figure 3. Specificity of Wavelet Transform – AdaBoost

Table 3 and figure 3 shows that the sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast

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Fourier Transform – Adaboost respectively for AD - Sensitivity. The sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively for MCI – Sensitivity. The sensitivity of wavelet transform – Adaboost classifier performs better by %, by % and by % than Fast Fourier Transform – CART, Wavelet Transform – CART and Fast Fourier Transform – Adaboost respectively for CS – Sensitivity.

5. CONCLUSION

Alzheimer's disease (AD) is one type of dementia for which machine learning techniques are developed for diagnosis, such as the automated MRI segmentation and classification. The AdaBoost algorithm has been used for classification of the features obtained from the MRI images classifying as normal, MCI or AD. In this investigation, the focus is on to evaluating the efficacy of various feature extraction and classifiers for diagnosing AD. The results have proved that in the accuracy of classification of a wavelet transform – the AdaBoost classifier shows better performance by %, by % and by % compared to the Fast Fourier Transform – CART, the Wavelet Transform – CART and the Fast Fourier Transform – AdaBoost respectively. Further work will explore optimizing the feature extraction techniques and classifiers to improve the classification accuracy.

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