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Classification of EEG Signals Using Novel Algorithm for Channel Selection and Feature Extraction

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Abstract

The electroencephalogram (EEG) signals play an eminent and consequential role in the diagnosis of epilepsy. In our previously published papers. We have worked on numerous problems that can be analyzed by neural networks. In this paper we have chosen EEG signals due to its application in medical industry. EEG recordings complied and anthologized over the duration of an extensive time frame encompasses a gargantuan quantum of EEG data. The study, unearthing and decomposition of these signals activity is, therefore, a very arduous and onerous course of operation that necessitates a circumstantial and particularized assessment of the comprehensive expanse of the EEG data. We have proposed a unique classification of signals in which we have analyzed variety of wavelet functions. The procedure for making a resolution contains four stages: (a) extraction of signal, (b) signal preprocessing, (c) compression using Empirical mode decomposition or discrete wavelet Transform families and (d) classification using artificial neural network enforcement. The outcomes acquired advocate the fact that there exists a potentiality in the proposed algorithm for the classification of EEG signals.

Keywords: Brain Computer Interface, EEG, Empirical Mode Decomposition, Discrete Wavelet Transform, Channel Selection, Neural Network.

INTRODUCTION

The electroencephalogram (EEG) encases a time series data of elicited electrical potentials which arise from the methodical neural operations of the brain. The human EEG's are captured and recorded by planting the electrodes over the scalp. These are plotted as a Y-X graph of voltage against time. The electric voltage of the EEG signal conforms to the amplitude. Conventionally, the voltage range of the EEG lies between 10 and 100 µV. In adolescents, the more frequent range is in the interval of 10 and 50µV. If we throw light on the frequency spectrum range of the EEG, its range extends from ultra-slow to ultra-fast constituents of frequency. The frequency values lying at the extremities do not play a momentous purpose in the clinical EEG. For the classification purpose, we only need a frequency range between 0.1Hz and 100Hz. The above acquired range is customarily assorted into multiple frequency components, the delta rhythm (lies between 0.5 and 4Hz), theta rhythm (lies between 4 and 8Hz), alpha rhythm (lies between 8 and 13Hz) and the beta rhythm (lies between 13 and 30Hz). Considering the case of normal adults, the very quick (>30Hz) and the very slow range (0.3 -7Hz) are exiguously portrayed, and medium (8 - 13Hz) and fast (14 - 30Hz) elements prevail.

A neural network is a mathematical model which derives its foundation from the cell structure of a neuron, present in the biological nervous system. The neural network can apprehend the data by incorporating learning algorithm. These Networks contain highly interconnected and veritable processing units which are fabricated to replicate and model the way the human brain executes a particular operation. Each element or unit is called a neuron. The network computes a weighted addition of its inputs and to it, a constant term which is called bias is added. This sum is made to go through a transfer function (for example linear, sigmoid or hyperbolic tangent). During the evolution of neural architecture, one of the most exigent and pressing problems is the selection of the number of hidden layers and the number of neurons in each layer. To successfully discover the optimal network architecture, various combinations must be computed and calculated. These combinations may include networks encompassing disparate number of hidden layers, distinct number of elements in each layer and unalike nature of transfer functions. Artificial neural networks (ANNs) are comprised of cells. Simulating the low-level operations of biological neurons. In ANN, intelligence and knowledge about the enigmatic problem is divided in neurons and connections weights of associations between neurons. The neural network should be seasoned and conditioned to acclimate the connection weights and biases so that the desired mapping is obtained. The feature vectors are provided and applied as input to the network at the training stage and then, the network adapts and fits the parameters of the varying quantities, the weights and biases, to record the association and relationship among the input patterns and outputs. ANNs are especially serviceable for complex pattern recognition and classification operations. ANNs are widely implemented in the field of bio medics' field for replication, reproduction, modeling, data analysis and diagnostic classification. There are various disparate domains, types and architectures of neural networks which differ fundamentally in the process through which they undergo the process of learning.

BRAIN-COMPUTER INTERFACE

Brain-computer interfaces avouch the competency to control tools and effectuate duties and tasks without the necessity of lifting an arm. These interfaces can be used even by patients who have lost the ability to move their limbs. On this account, the brain-computer interface is an area of research of great fascination to scientists. Implementing variegated techniques, it is realizable to gauge electric activity in the brain. The signals are then processed and distinguishable characteristics of required interest are evoked. Afterwards, these peculiarities may be elucidated as instructions to a connected device using the assistance of a translation algorithm. There exist numerous methods to measure brain activity. These procedures vary in means of accomplishment as well as precision and exactitude some methodologies are invasive, warranting the electrodes to be inserted into the brain. These methods quite regularly furnish precise signal data, but the physical presence of a foreign substance inside the brain may cause tissue to scar and is thus normally disadvantageous. Invasive strategies are thus seldom performed on humans. Other tactics, like electroencephalography (EEG), are noninvasive. The activity on the scalp is calculated and measured by EEG. It is noninvasive: applied on the outside of the head, thus not leading to any physical damage. As an outcome of its externality, EEG continually delivers less veracious data than the invasive strategies. Consequently, the competency to process such data with great precision is of utmost importance. EEG provides an opportunity to record motor imagery, consenting a subject to mentally impart a movement, which can then be illustrated and replicated by a machine. With the propitious applications of EEG, it is of majestic value to be able to classify EEG signals precisely. In this report, we study the classification of EEG signals using machine learning techniques.

RELATED WORK

Detection using neural network systems have been put forth and proposed by a variegated and very large number of researchers. We have previously done research work on neural networks and made classifiers based on the dataset we are working on. Our models have done prediction based on neural networks [2]. Optimization of number of inputs to classify Breast cancer using neural networks has been performed by us [3]. Hong Wang, Hai-bin Zhao, Chun-sheng Li, Chong Liu [4] have used Probabilistic Neural Network for Classifying EEG signals, whereas [5] Dat, Tran Huy, Louis Shue, and Cuntai Guan have used time-frequency decomposition technique for generating the eminent features. Deepajothi, S., and S. Selvarajan [6] have worked on improving the performance of SVM-RBF for classification of EEG signals. Demirer, R. Murat, Mehmet Sirac Ozerdem, and Coskun Bayrak [7] have worked on hybrid approach for classification which produced remarkable results in classification. [4-7] have worked on the [20] dataset and Hence, only Demirer gave the remarkable classification accuracy for EEG signals. Although, there are numerous other articles which have worked on the other dataset of EEG signals. SGüler, Inan, and Elif Derya Übeyli [8] have used fuzzy inference technique for classification, they have used wavelet coefficients for generating Fuzzy logic relation. Work by Fengyu Cong [9] was very appreciable where he used Tensor flow decomposition on EEG signals. Ram Bilas Pachori [10] did analysis of variety of EEG signalsusing empirical mode decomposition. Feature Extraction by Shufang Li [11] was also studied in detail. Ram Bilas Pachori's [12] work on different mode functions was also studied and it proved to be very valuable for our own research work. Balamareeswaran M, Ebenezer D. [13] present the various techniques for Denoising of EEG signals using Discrete Wavelet Transform Based Scalar Quantization, which later on proves to be good Decompression technique. Alotaiby, Turky, et al. [14] commenced various channel selectiontechnique to improve the computational cost and less time engrossed, also [15] have worked on various DWT families which put forth various comparisons of Daubechies family. Chatterjee, Rajdeep, Tathagata Bandyopadhyay, and Debarshi Kumar Sanyal [16] have also worked on the wavelet feature generation from the EEG signals. Subasi, Abdulhamit [17-19] have provided various techniques for classification of EEG signals. Subasi, Abdulhamit, and Ergun Ercelebi [17] have extracted the features using lifting-based discrete wavelet transform (LBWT) and then they have used the neural network and logistic regression as a classifier, LBWT demonstrated to be here better feature extraction algorithm. Subasi, Abdulhamit have worked on a variety of feature

Extraction techniques wavelets transform of the Signals [18], and PCA, ICA, LDA [19] which are further served as input to the neural network for classification of signals.

DATA ACQUIREMENT

The dataset we have worked on has been taken from the [20] BCI III competition, in which, a subject was asked to do imagined actions of either their left small finger or their tongue. The time series data of the electrical brain activity has been collected during 278 experiments using an 8x8 ECoG platinum electrode layer which contributed 64 channel pairs from electrodes for every registered experiments. All registrations had been performed with a sampling rate of 1000Hz. Data was recorded for 3 seconds duration. All the dataset was processed using the Matlab software.

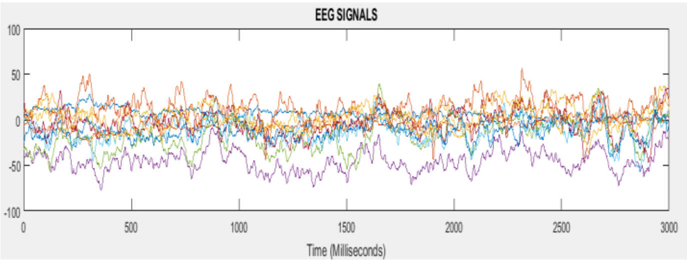

Figure 1: EEG signal of 1 trial with 10 channels

PROPOSED METHOD

EEG Signal acquired from the Dataset is loaded in the Matlab Software and after that we visualized data using a plot function. In the figure 1, we have shown the EEG signals of 1 trial with 10 channels. Although we have worked on all 64 channels in this paper, we have shown only 10 channels, for the sake of good visuality. Now the steps for the processing have been explained as follows:

STEP 1.

To make the signals more relevant for analysis, the first step is pre-processing and filtering. Input EEG signals are in 3D matrix configuration, so we have converted the 3D matrix into 2D matrix to reduce the computational cost, and then this signal is passed from the low-pass filter which removes some unwanted components from the signals.

STEP 2.

After filtering, the next step would be channel selection from the EEG signals dataset. In our data, there are 278 trials for one subject and for each trial there are 64 channels signal, and each channel consists 3000 milliseconds of data information, this makes the computational cost very high and may consume more time for classifying the signals, further it may result in low accuracy. So to address these issues we need a robust channel selection algorithm. In our paper, we have worked on our own method of channel selection. Following are the steps followed for selecting appropriate channels:

a) First, each channel is marked with a probability of selection. The more is the probability, the better the chances for selection of a channel. Initially, all channels are marked with equal probability. Probability of a channel is given by:

$$P\left(Ch_i\right) = ½\ ,\ \forall\ i\ \in\ \mathrm{Z}\ ,$$

$P\left(Ch_i\right)$ denotes the probability of ith channel, where i =1, 2, 3… 64 (total number of channels), for every trial the same probability is assigned.

b) For every trial, we have 64 channels, where each channel has their respective EEG waves and each wave, out of 64 waves, has 3000 data points associated with it. Out of these 64 waves, our method derives 2 waves. We define these 2 waves as upper threshold wave (above x-axis i.e. y=0 line) and lower threshold wave (below x-axis). Upper threshold wave is formed by taking the average of data points which are lying above the x-axis, whereas Lower threshold wave is formed by taking the average of data points which are lying below the x-axis.

So if

$D_{(i,j)}$ Data point is taken on i^{th} trial and in the j^{th} channel. Then for every channel, out of 64 channels, we check whether

Value of ($D_{(i,j)}$) > 0 or Value of ($D_{(i,j)}$) < 0

Then for all 64 parallel data points D, we take the "average" of those data points whose $D_{(i,j)}$ was greater than zero and we plot the value of that "average". Similarly we do it for all "n" data points in each channel, out of 64 channels, and after parsing all these data points, the plotted curve that we get is called "Upper threshold wave".

Likewise, for all remaining 64 parallel data points D, we take the "average" of those data points whose $D_{(i,j)}$ was less than zero and we plot the value of that "average". Similarly we do it for all "$3000-n$" data points and after parsing all these data points, the plotted curve that we get is called "Lower threshold wave". j ranges from 1, 2, 3… 3000 milliseconds, figure 2 illustrates the 2 waves formed using this step.

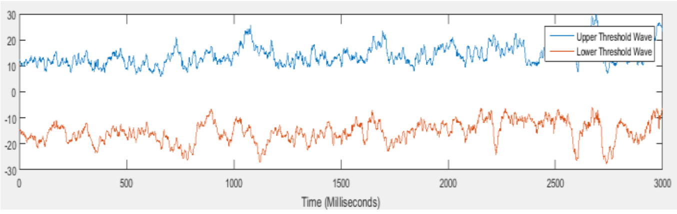

Figure 2: Upper and Lower threshold waves for a trial

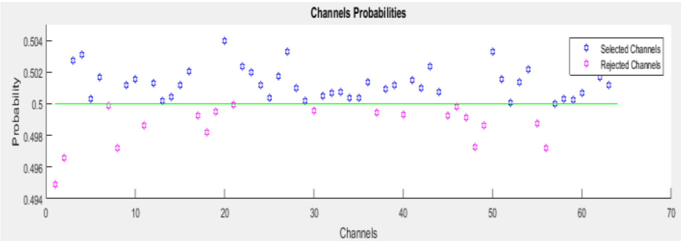

Figure 3: Channels probability lying above the line are selected, whereas the channels lying below are rejected

c) Then, waves formed in b) are used to assign the probabilities to the different channels in the signals. Here we define a "closed space region". This region is defined as the region between the lower limit of upper threshold wave and upper limit of lower threshold wave. Any data point lying outside this region is said to reside in "open spaced region". For signals of every channel, we find which data points of signal lie in which region. The catch is that, we need to filter out the relevant information and weed out the irrelevant information. We found out that any data point which will lie in the "closed space region" will be irrelevant to our analysis of EEG signal. We now define an overhaul factor which is used to update the channel probability. The factor is given by this formula:

$$\gamma = (m - n) \times \left(\frac{1}{2 \times T \times Ch \times R} \right)$$

Where,

m is the number of data point lie outside threshold range,

n is the number of data point lie in threshold range,

T is the number of the trials of a subject,

Ch is the number of channels in each trial,

R is the range of the signals of the channel.

Notice that the factor of ½ is present in the overhaul factor which ensures that channel probability should remain in the range of 0 to 1. Thus, this overhaul factor is further used to update the channel probability, which is given by following formula:

$$P(Ch_i)_{new} = P(Ch_i)_{old} + \gamma$$

Where,

$P(Ch_i)$ denotes the probability of i^th^ channel, γ is the overhaul factor.

Thus, this formula is used to update the probability of all channels one by one.

d) Steps b) and c) are repeated for every trial and probability of each channel is updated.

e) After completion of above steps, the final probability of each channel is obtained. The channels having probability greater than 0.5 are selected.

The above method when applied to the EEG signals, results in selecting the 43 channels out of 64 channels. These selected channels are further processed for the classifying the signal data, figure 3 plots the final channels probabilities obtained, channel's probability lie above the green line are selected.

STEP 3.

After applying the channel selection algorithm, the signals are compressed using various Techniques. We have worked on Empirical Mode Decomposition, Discrete Wavelet Transform Families, and various LWT schemes which are discussed as below:

a) Using Empirical Mode Decomposition on EEG signals produces various IMFs out of which IMF wave with less information loss was chosen for further analysis. figures 4 – 9 shows the various EMD waves of 1 trial with 1 channel data signal.

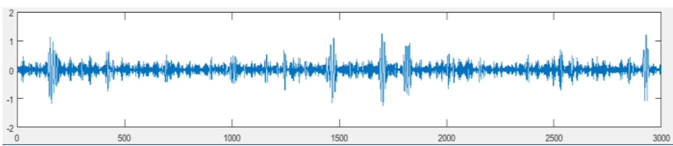

Figure 2: IMF 1

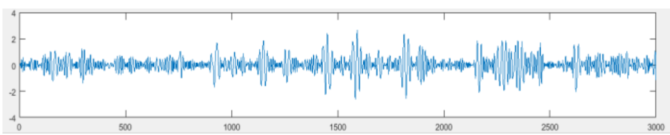

Figure 3: IMF 2

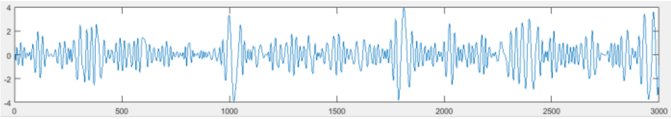

Figure 4: IMF 3

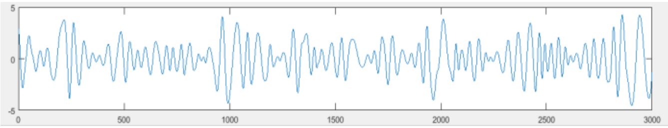

Figure 5: IMF 4

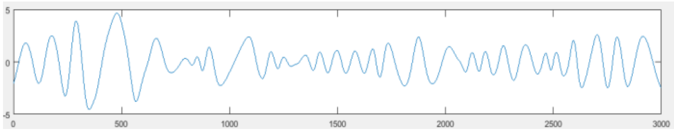

Figure 6: IMF 5

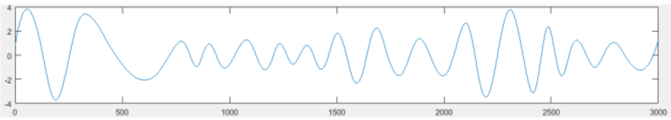

Figure 7: IMF 6

b) DWT is a wavelet transform in which wavelets are discretely sampled. This is another approach which can be used as compressing technique. Using Discrete Wavelet Families, [15] provide effective techniques for the compression of signals with less information loss. We have applied Daubechies order 5, Coiflets order 5, Biorthogonal order 1.5, Symlets order 5 and Reverse biorthogonal wavelets order 1.5. All the DWT families compressed the signal from 3000 millisecond to almost 1500 millisecond. Following figures 10-14 illustrate the Different Wavelet Compression of signal.

c)

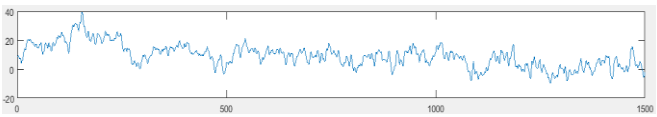

Figure 8: Symlets order 5

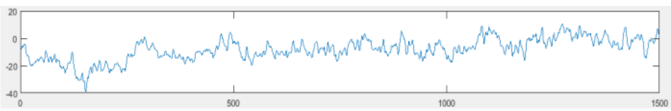

Figure 9: Daubechies order 5

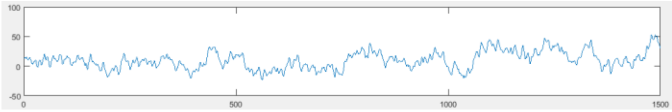

Figure 10: Biorthogonal order 1.5

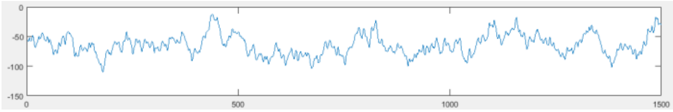

Figure 11: Coiflets order 5

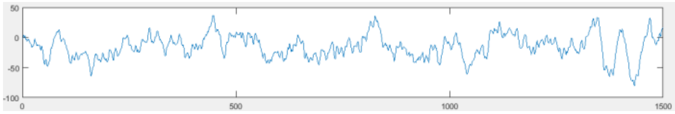

Figure 12: Reverse biorthogonal order 1.5

d) LWT is a scheme factorizes any discrete wavelet transform with restricted separates into a series of primary convolution operators are called lifting steps, due to this number of arithmetic operations diminishes by approximately a factor two. This is another approach which can be used as compressing technique. Using Lifting Wavelet Transform, [17] provide effective techniques for the compression of signals with less information loss. Here we have used various LWT schemes, these are Cohen-Daubechies-Feauveau order 1.5, Haar,Daubechies order 5, Coiflets order 5, Biorthogonal order 1.5, Symlets order 5 and Reverse biorthogonal wavelets order 1.5. All the LWT schemes are performed at LEVEL 1 which compressed the signal from 3000 milliseconds to 1500 millisecond. Following figures 15-21 illustrate the Different Wavelet Compression schemes of signal.

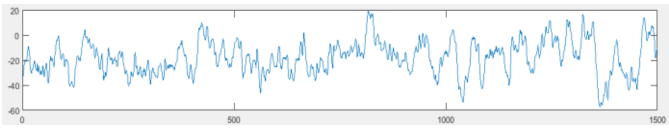

Figure 13: Cohen-Daubechies-Feauveau order 1.5

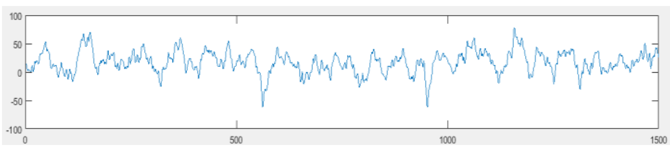

Figure 14: Haar

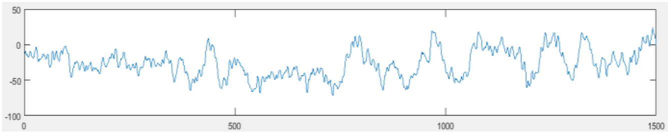

Figure 15: Symlets order 5

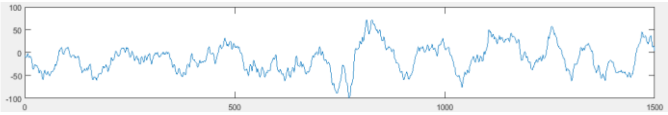

Figure 16: Daubechies order 5

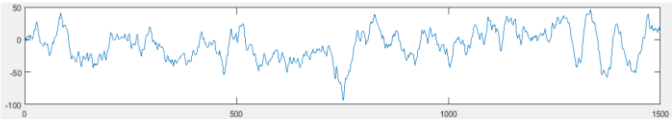

Figure 17: Biorthogonal order 1.5

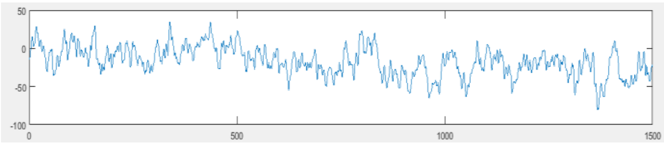

Figure 18: Coiflets order 5

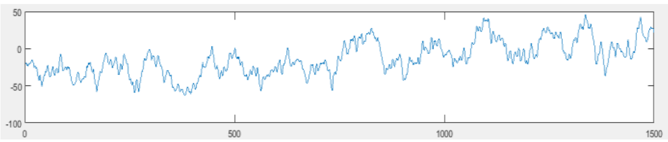

Figure 19: Reverse biorthogonal order 1.5

STEP 4.

The signals are then fed into a feedforward neural network consisting of N inputs, 15 hidden layer, and Y outputs, where N is the size of the feature vector which is 64500 and Y is the number of classes that is 2. Scale conjugate gradient backpropagation method is used for training the Neural Network. The percentage of data used for training is 70%, test is 15%, and validation is 15%. figure. 22 shows the neural network configuration.

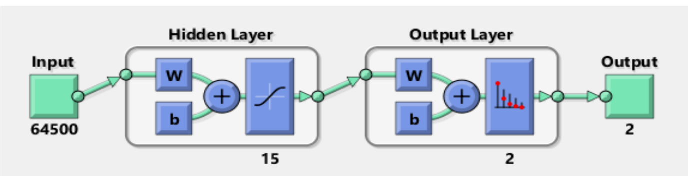

Figure 20: Feed Forward Neural Network

This network is trained on the features generated by Empirical Mode Decomposition, afterward the classifiers accuracy is obtained on Test data. Figure 23 illustrates confusion matrix of test data.

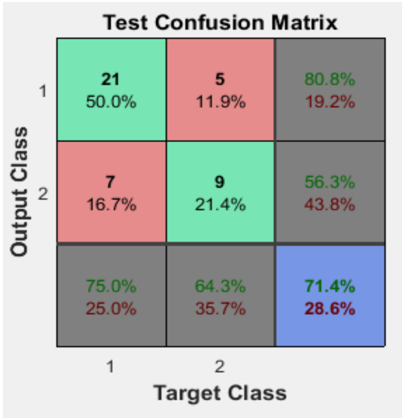

Figure 21: Empirical mode decomposition

Similarly, now network is trained using features generated by Discrete Wavelet Transform families and classifiers accuracy is obtained on Test data, then again network is trained using features generated by LWT schemes and classifiers accuracy is obtained on Test data. All these accuracy are further compared in the Table. 1

Table 1. Accuracy of various methods on Test data.

Methods		Accuracy (%)
Empirical Mode Decompostion		71.4
DWT	*Daubechies wavelet function*	78.65
	Symlet wavelet function	85.7
	Biorthogonal wavelet function	83.33
	Coiflets wavelet function	81
	Reverse biorthogonal wavelet function	82.95
LWT	*Cohen-Daubechies-Feauveau wavelet scheme*	88.1
	Haar wavelet scheme	75.82
	Symlets wavelet scheme	84
	Daubechies wavelet scheme	83.91
	Biorthogonal wavelet scheme	83.85
	Coiflets wavelet scheme	81
	Reverse biorthogonal wavelet scheme	79.38

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RESULTS

Classification of EEG signals are done using neural network classifier using the feature generated by the EMD, DWT families, and LWT schemes. We have compared all the results in the form of easy to understand bar graphs. As we can see in Fiigure 24 we have shown the comparison of Accuracy obtained on test data set among all Discrete Wavelet Families which include the accuracy of Daubechies order 5, Coiflets order 5, Biorthogonal order 1.5, Symlets order 5 and Reverse biorthogonal wavelets order 1.5. We infer from this figure that the highest accuracy is achieved by Symlets wavelet function of order 5. In the figure 25, we have shown the comparison of accuracy obtained on test data set among all Lifting Wavelet Transform schemes which include the accuracy of Cohen-Daubechies-Feauveau order 1.5, Haar,Daubechies order 5, Coiflets order 5, Biorthogonal order 1.5, Symlets order 5 and Reverse biorthogonal wavelets order 1.5 schemes. We infer from this figure that the highest accuracy is achieved by Cohen-Daubechies-Feauveau order 1.5. We finally conclude that all in DWT families the Daubechies order 5 and Coiflets order 5 didn't results to give the good accuracy, also in LWT schemes the Haar,Coiflets order 5, and Reverse biorthogonal wavelets order 1.5 schemes didn't performed well, whereas Symlets wavelets families in DWT and Cohen-Daubechies-Feauveau order 1.5 in LWT transform performed well with our channel selection algorithm. To decide the highest accuracy among all the scenarios that we have chosen the highest accuracy each from figures 24 and figure 25, which are further compared with the Empirical mode Decomposition in figure 26. Our results show that we are able to get 88.1 percent accuracy on test data using LWT schemes i.e. *Cohen-Daubechies-Feauveau wavelet scheme 1.5.* Although we have worked on empirical mode decomposition but it didn't result in a good fit for our channel selection algorithm, this also infers that removing the spikes from the signal may have result in low accuracy for EMD compression. Figure 28 - 31 illustrates the brief summary of our work on Cohen-Daubechies-Feauveau wavelet scheme by using Neural Network Classifier.

In our proposed method, channel selection algorithm is a novel technique for selecting suitable channels based on their selection probability. Further, this channel selection algorithm fits best with Lifting wavelet Schemes i.e. Cohen-Daubechies-Feauveau wavelet scheme 1.5 to classify the EEG signals using Neural Network. To prove that our algorithm is efficient, we compared it with other existing methods proposed by Hong Wang, Hai-bin Zhao, Chun-sheng Li, Chong Liu [4] and Deepajothi, S., S. Selvarajan [6] in the figure 27. Thus, figure shows that our proposed method has higher accuracy than other models.

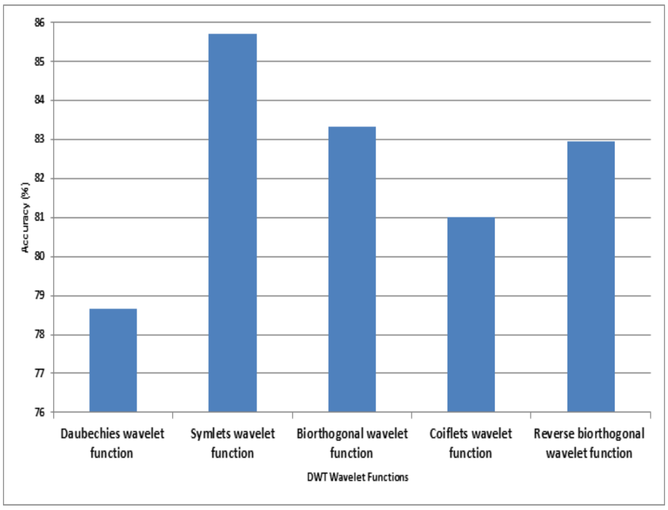

Figure 22: Comparison of Accuracy obtained in various DWT Wavelet Functions

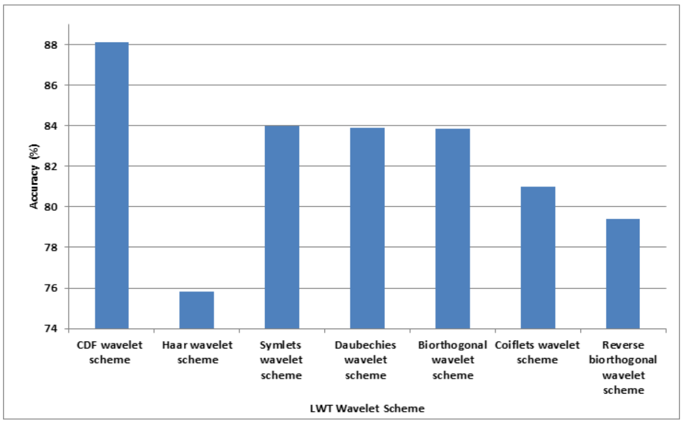

Figure 23: Comparison of Accuracy obtained in various Lifting Wavelet Transform schemes.

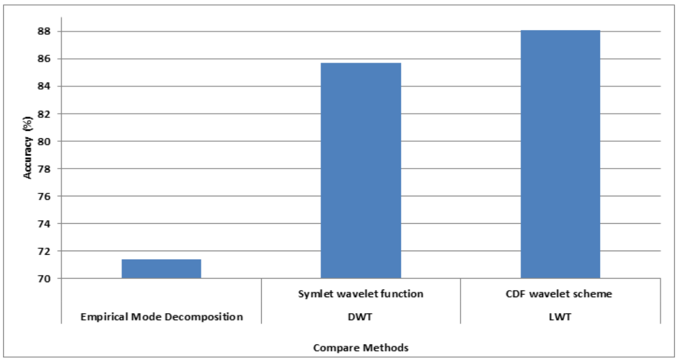

Figure 24: Comparisons of EMD, DWT and LWT transform

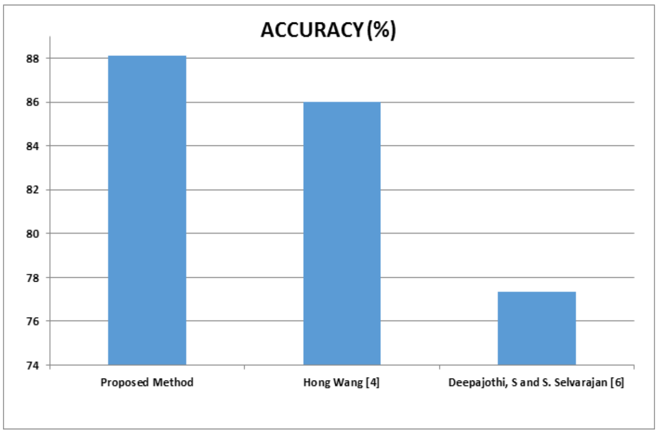

Figure 25: Accuracy comparison among three models.

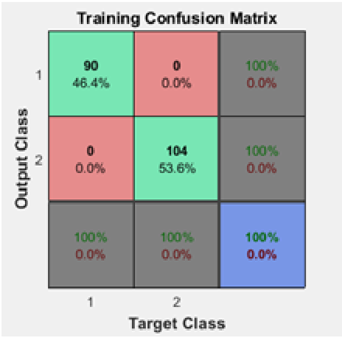

Figure 26: Confusion matrix for training data

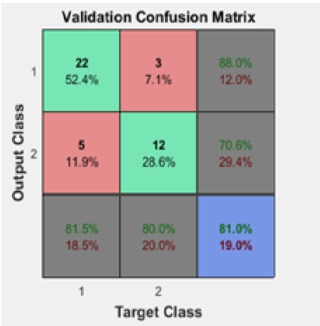

Figure 27: Confusion matrix for Validation data

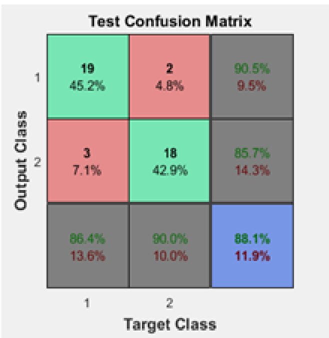

Figure 28: Confusion matrix for Test data

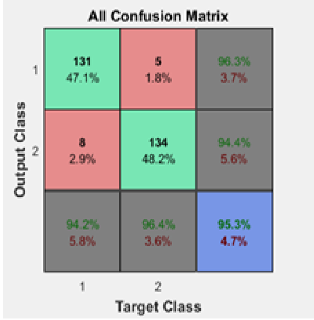

Figure 29: Confusion matrix for all data, includes both training and test data

CONCLUSION

We have proposed a method a channel selection method which select the most appropriate channels based on the computation of probability of channel. Selecting appropriate channels helps speed up the computational operations and reduces the dimensionality of the data. We then compressed the signal using Empirical Mode Decomposition, and variety of Discrete Wavelet Transform families and Lifting Wavelet Transform schemes. Best intrinsic mode function of empirical mode decomposition has been chosen for the feature generation, whereas in Discrete wavelet Transform different families of DWT were considered, also LWT schemes have been used to compress the EEG signals without any loss of information. All of these compressions of EEG signal helps in reducing the computational cost and require less time to process the EEG signals. In future work, we can work on improving the results by applying variety of other compression algorithms and processing the signal to extract more relevant features which can make our model more robust and ready to be applied in variety of real world applications.

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