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Classification of EEG Signals using various Dimensionality Reduction Techniques

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Abstract

The electroencephalogram (EEG) signals play an eminent role in identifying the complexities of brain activities. It provides a monitoring method to record the electrical activity of the brain. This paper deals with the various channel selection techniques for selecting the subset of channels. We have provided the various dimensionality reduction techniques which can reduce the computational cost and engross the training of the model. Firstly, this paper will go through the variety of channel selection algorithms and then it will use those channel compression techniques. We have worked on PCA, ICA, LDA, and various types of DCT waves. We have proposed a unique algorithm for classification of signals which resulted in the accuracy of 92% on test data. The course for making a distribution contains various stages: (a) Pre-processing of a signal, (b) Channel Selection, (c) Applying compression algorithms to reduce the dimension of the dataset and

(d) classification using the feed-forward neural network. The results show that the proposed method has the ability to be used in various domains.

Keywords: Brain Computer Interface, EEG, PCA, ICA, DCT, Neural Network.

I. INTRODUCTION

The notion of ANNs is built on the fact that functioning of the human brain by crafting the right connections, has a great possibility to be mimicked by replacing neurons and dendrites with wires and silicon. Neurons are the building blocks of the human brain: a brain consists of nearly a 100 billion of these miniscule units Axons join the other cells of the brain to the neurons. Stimuli from external environment or inputs from sensory organs are accepted by dendrites. The inputs from our sensory organs, or some external stimulus when fed to dendrites electric impulses that are electric in nature. These impulses traverse the neural network with very high velocities. Messages are then exchanged or interchanged between various neurons, which now have the task to decide whether to address the issue or prohibit it from further traversal in the network. In a similar contexture, here, multitudinous nodes, which form an analogy with biological neurons that are present in the brain, form the building blocks of an Artificial Neural Network. Interaction is carried out amongst neurons through associations or links which are constructed between them. A variegated amount of operations can be carried out on the data which is input or fed to the multitudinous nodes. Interaction is made possible between neurons by passing output of these operations to another neuron. Neurons. At every node, there exists a result, which is termed as activation value in this context, it might be useful to add that a term called "weight " is associated to every link in the neural network. By modifying or changing these values associated to each link, the process of learning can be implemented in an ANN. One of the most observable benefits from a large pool of advantages that an ANN offers is the ability to learn by merely undergoing the process of observing and studying different data sets. Thus, in this particular context , ANN can be put into use as a tool for approximating the values of random functions, which assist in reckoning and estimating an optimal and cost effective procedure while distributions or computational methods are defined and specified. Computing. The cost and time effectiveness strategy of ANNs can be attributed to the fact that in place of the taking the data set as an entirety, it takes samples of data as the input. ANNs can be thought of as fairly apt mathematical models that aim to enrich and ameliorate existing data analysis technologies. An interconnected system of three layers forms an ANN. Input nerve cells or neurons make up the primary layer. Neurons from the primary layer transmit data to the second layer, which in turn transmits them to the last layer neurons send data on to the second layer, which in turn sends the output neurons to the third layer. Selecting from permitted models which have a variegated number of models linked to them forms the basis to train an artificial neural network.

II. BRAIN-COMPUTER INTERFACE

Brain-computer interfaces (BCIs) implement three important steps: signal acquisition, signal anatomization, and restating them into instructions which are redirected to output devices so as to perform suitable actions. The paramount purpose of BCI is to substitute or rejuvenate workable function to the individuals impaired by neuromuscular complications like cerebral palsy, epileptic disorders, brain stroke, or damage to the spinal cord. Brain-computer interfaces have the competence to turn out to be practical for cure and healing after critical brain disorders like stroke. In the years to come, performance of surgeons or other medical professionals can be escalated by using BCI's. BCI is an approach to gauge and apply signals produced as a result of electric current produced by the nerve cells of the central nervous system. So, for example, a communication system which uses any other methods of triggering other than neurons, like muscle – driven or voice triggered system, cannot be considered as a BCI .Also, an electroencephalogram (EEG) machine alone can't be thought of as a BCI because it only gathers and examines brain signals but does not result in a yield that takes note of the user's surroundings. To assume that a BCI can manipulate the mind or terming it as a mind reading device can be labeled as a misconception. Brain-computer interfaces empower individuals to act on the environment by making use of brain signals rather than muscles and on the contrary, they do not manipulate human mind so that information might be withdrawn using coercion. Frequently, it is observed that an individual, after a tenure of training has the ability to produce brain signals which encompass and encode the thoughts and intentions, and the BCI, also after training, has the competence to decode the signals and restate them into well laid out instructions to an output device that executes what the user desires or wished for.

III. RELATED WORK

If we take the past few years in deliberation, prominent and variegated research tactics methodologies have been administered and customary and satisfactory results have been obtained. Detection using neural network systems have been put forth and proposed by a variegated and very large number of researchers. Thomas Lal [1] proposed methods towards Invasive Human Brain Computer Interfaces. It proved to be useful in processing data. T. N. Lal [2] worked on Support vector channel selection in BCI and it turned out to be a great contribution to the community. M. Arvaneh [3] helped in optimizing the Channel Selection and Classification Accuracy in EEG-Based BCI. M. Schroder [4] worked on Automated EEG feature selection for brain computer interfaces. G. Pfurtscheller [5] contributed in current trends in Graz brain-computer interface (BCI) research and these trends led to further improvement by other leading researchers in this field. B. Blankertz [6] worked on the BCI competition III: validating alternative approaches to actual BCI problems. The approaches put forth by this paper gave various alternatives to the existing approaches and it proved to be of immense importance in problem solving. D'Alessandro [7] worked on epileptic seizure prediction using hybrid feature selection over multiple intracranial EEG electrode contacts: a report of four patients. H. Ramoser [8] worked on optimal spatial filtering of single trial EEG during imagined hand movement. A. Rakotomamonjy and V. Guigue [9] worked in BCI Competition III: Dataset II-

Ensemble of SVMs for BCI P300 Speller. Z. Lin, C. Zhang, W. Wu and X. GAO [10] proposed a frequency recognition based on canonical correlation analysis for SSVEP-based BCIs. Xiaorong GAO, Dingfeng Xu, Ming Cheng and Shangkai GAO [11] worked in a BCI-based environmental controller for the motion-disabled. Tian LAN [12] provided Salient EEG Channel Selection in Brain Computer Interfaces by Mutual Information Maximization. G. Bin, X. GAO, Y. Wang, B. Hong and

S. GAO [13] worked on VEP-based brain-computer interfaces: time, frequency, and code modulations, this paper proposed various modulations based in time and frequency in BCI context. D. Garrett [14] provided a comparison of linear, nonlinear, and feature selection methods for EEG signal classification. C. Guger [15] provided rapid prototyping of an EEG-based brain- computer interface (BCI). M. Pregenzer and G. Pfurtscheller [16] worked in frequency component selection for an EEG-based brain to computer interface.

M. Murugappan, R. Nagarajan and S. Yaacob [17] gave a comparison of different wavelet features from EEG signals for classifying human emotions. R. Scherer [18] researched in an asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate. K. Ansari-Asl, G. Chanel and T. Pun [19] gave a channel selection method for EEG classification in emotion assessment based on synchronization likelihood. J. J. Vidal [20] gave a Real-time detection of brain events in EEG. R. Scherer, F. Lee, A. Schlogl, R. Leeb, H. Bischof and G. Pfurtscheller [21] worked toward Self- Paced Brain–Computer Communication: Navigation through Virtual Worlds. Yijun Wang [22] gave a practical VEP-based brain-computer interface. M. Murugappan [23] worked on human emotion classification using wavelet transform and KNN. Wenjie Xu [24] gave a High accuracy classification of EEG signal. D. Nie, X. W. Wang, L. C. Shi and B. L. Lu [25] worked in EEG-based emotion recognition during watching movies. A. Kachenoura, L. Albera, L. Senhadji and P. Comon [26] worked on Ica: a potential tool for bci systems. M. Murugappan [27] researched in appraising human emotions using Time Frequency Analysis based EEG alpha band features. I. Iturrate, J.

M. Antelis, A. Kubler and J. Minguez [28] gave a Noninvasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation. B. Blankertz [29] worked in the BCI competition 2003: progress and perspectives in detection and discrimination of EEG single trials. G. Pfurtscheller,

G. R. Müller-Putz, R. Scherer and C. Neuper [30] focused on rehabilitation with Brain-Computer Interface Systems. N. Birbaumer [31] proposed the thought translation device (TTD) for completely paralyzed patients. G. Pfurtscheller [32] compiled 15 years of BCI research at graz university of technology: current projects. G. Pfurtscheller and C. Neuper [33] worked in motor imagery and direct brain-computer communication. A. Al-Ani and A. Al-Sukker [34] compared the effect of Feature and Channel Selection on EEG Classification. P. C. Petrantonakis and L. J. Hadjileontiadis [35] gave an emotion Recognition from EEG Using Higher Order Crossings. Yijun Wang, Zhiguang Zhang, Xiaorong GAO and Shangkai GAO [36] focused on lead selection for SSVEP-based brain- computer interface. Q. Wang and O. Sourina [37] gave a Real-Time Mental Arithmetic Task Recognition from EEG Signals. X. Liao, D. Yao, D. Wu and C. Li [38] Combined Spatial Filters for the Classification of Single- Trial EEG in a Finger Movement Task. S. P. Kelly, E. C. Lalor, R. B. Reilly and J. J. Foxe [39] worked on a visual spatial attention tracking using high-density SSVEP data for independent brain-computer communication. Xinyi Yong, R. K. Ward and G. E. Birch [40] focused on a sparse spatial filter optimization for EEG channel reduction in brain-computer interface. C. W. Anderson,

E. A. Stolz and S. Shamsunder [41] worked on multivariate autoregressive models for classification of spontaneous electroencephalographic signals during mental tasks. C. C. C. Pang, A. R. M. Upton, G. Shine and M. V. Kamath [42] gave a comparison of algorithms for detection of spikes in the electroencephalogram. T. Kalayci and O. Ozdamar [43] focused on a wavelet preprocessing for automated neural network detection of EEG spikes. Kostov and M. Polak [44] worked in parallel man-machine training in development of EEG- based cursor control. R. Leeb, F. Lee, C. Keinrath, R. Scherer, H. Bischof and G. Pfurtschelle [45] worked on a Brain–Computer Communication: Motivation, Aim, and Impact of Exploring a Virtual Apartment. K. Q. Shen, C. J. Ong, X. P. Li, Z. Hui and E. P. V. Wilder- Smith [46] worked in a Feature Selection Method for Multilevel Mental Fatigue EEG Classification. T. M. Vaughan [47] provided the The wadsworth BCI research and development program: at home with BCI. L. Chisci [48] provided real-Time Epileptic Seizure Prediction Using AR Models and Support Vector Machines. P. Jahankhani, V. Kodogiannis and K. Revett [49] worked on EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks. Y. Li [50] focused on an EEG-Based BCI System for 2-D Cursor Control by Combining Mu/Beta Rhythm and P300 Potential.

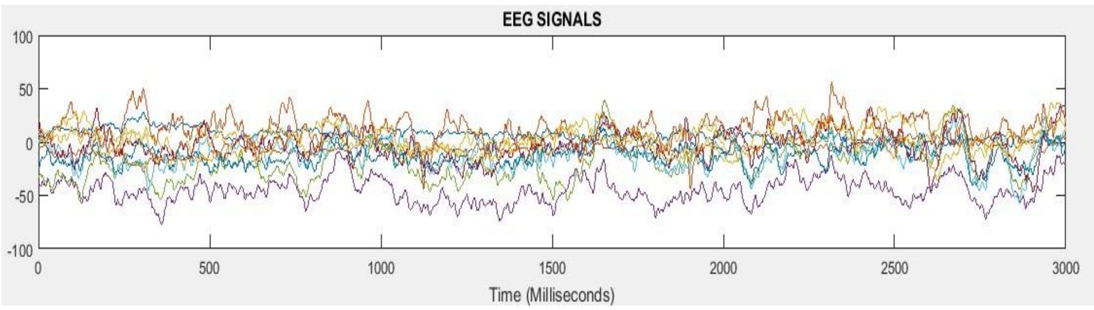

Fig. 1: EEG signal of 1 trial with 10 channels

IV. DATA ACQUIREMENT

The dataset we have worked on has been taken from the 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 experiment. 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.

V. PROPOSED METHOD

STEP 1.

Pre-processing and filter are applied on signals. These filters are used for removing the noise and unwanted signals from the dataset. Input BCI competition dataset signal are in a 3D matrix configuration, so we have flattened the 3D matrix into the 2D matrix to reduce the computational cost, and then this signal is passed through the low-pass filter designed using MATLAB tools which remove some unwanted noise components from the signals dataset. EEG Signal obtained from the Dataset is operated on the Matlab Software and after that, we visualized data using a Matlab internal plot function. In 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 displayed only 10 channels, for the purpose of better presentation.

STEP 2.

After pre-processing, the next step would be selecting appropriate channel from the EEG signals dataset. In our data, there are 278 experiments done on subject and for each experiment there are 64 channels signal, and each channel consists 3000 milliseconds of data activity of the subject, 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 studied various channel selection

a) *Implanted methods:* These channel selections select the channels by working over the elimination of Channels recursively over the each iteration. Have implemented the recursive feature elimination (RFE), and zero-norm optimization algorithms based on the training of SVMs this method was appraised on the motor imaginary dataset of thetechnique.signal. The recursive feature elimination and zero-norm optimization are proficient of lessening the number of channels without growing the error rate, but it was discerned that it cannot only be used fortunately for channel selection in particular subjects. Still, it is used in channel selection technique, we used this technique because our dataset [ref] is also motor-imaginary dataset, and recursive feature elimination can perform well with our dataset.

b) *Filtering techniques:* There are various techniques to filter the channels over the large dataset. But using statistical approach was best technique that is used over the time again and again. Common spatial pattern technique is the most suitable technique that has resulted to be good technique without affecting the accuracy of the model. The method uses classification sordid on the sorting of common spatial pattern (CSP) filter coefficients variable. This method is also called CSP-rank, is based on a filtering strategy with an incessant search procedure for subset channel preference. So, it uses two common spatial pattern filters for two classes corresponding to data set target classes. First of all, it orders the arbitrary value of the filter coefficients and for every filter, it then chooses the electrode with the subsequent highest coefficient from the two spatial filters.

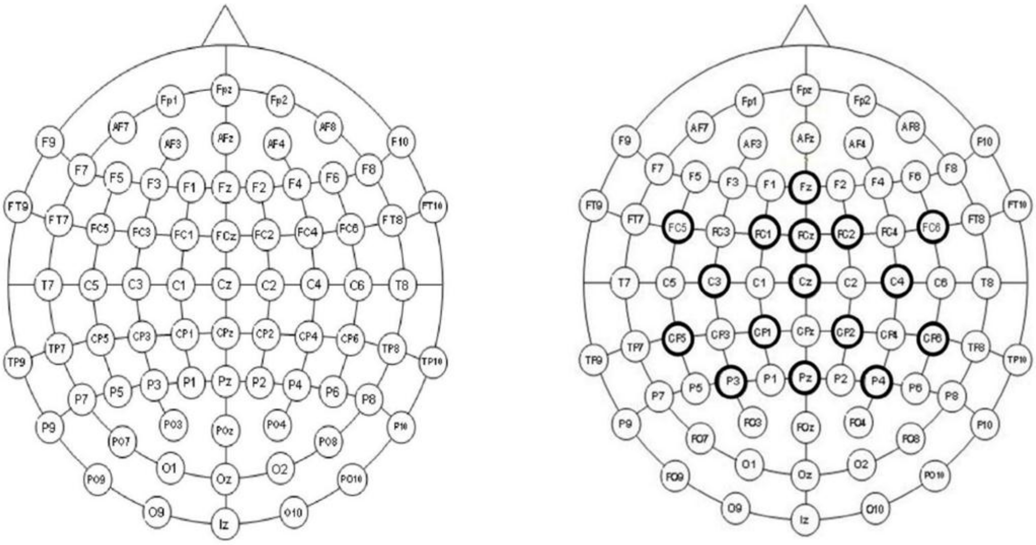

Fig. 2: (left) Position of different Electrodes present at scalp of human Brain

(Right) BCI Competition III uses these highlighted electrodes for generating 64 channels signals wave.

c) Power-based Techniques: The channels are selected using power ratios performed over the various channels signals, where each experiment has its own channel power spectrum. Each experiment is presented a subject-specific channel selection method based on standards inferred from Fisher's discriminant analysis to measure the acumen power of time-domain parameter (TDP) features extracted from different channels and different time domain for classification of two motor imagery tasks, left- hand small finger, and their tongue. This method adopts a power based approach with pre-specified subset channel selection depending on experience. This method adopted a power based approach with a random search strategy for subset channel selection. Then, it extended the particle power optimization algorithm shown to handle two objectives: minimizing the number of selected channels and maximizing the accuracy over the dataset using suitable classifier. The method gave the accurate result on the neural network. In our proposed model we are going to use the neural network as a classifier for classification of the signal, so this channel selection technique can be helpful for further steps.

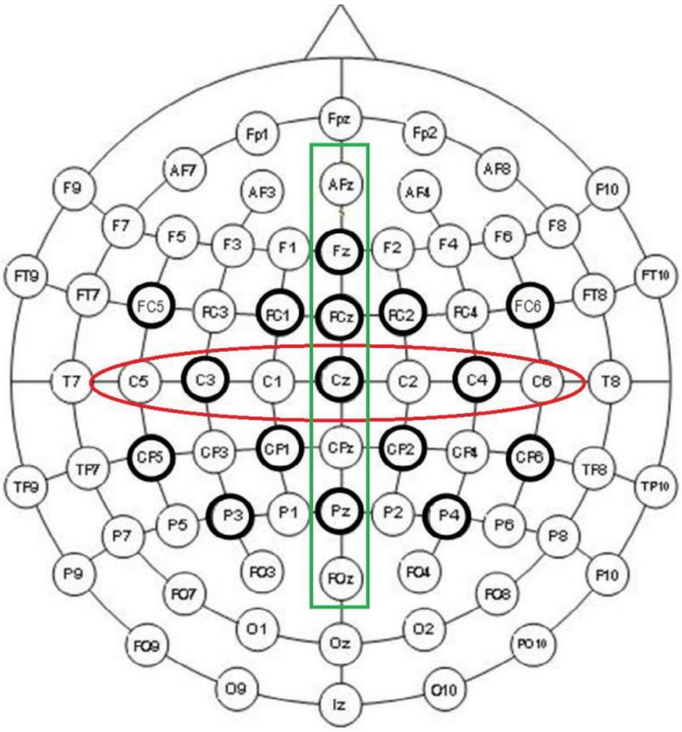

Fig. 3: Selected Electrodes from the total number of electrodes.

d) Hybrid techniques: These techniques are combination technique dependent on statistics and some manual technique for selecting the subset of channels from the Signals datasets. In our proposed model we have worked on these kinds of techniques more as this makes the algorithm accuracy increase and improve the prediction of Signal. A hybrid technique is a combination of a filtering technique and a wrapper technique attempting to take advantage of both in avoiding the pre-specification of a stopping criterion, but the performance sensitivity should be studied with different types of classifiers. These hybrid technique may use as a manual channel selection based on behavior observation from the different channels signals.

Thus, these are the technique that we used to select and analyze the various channels from the dataset, but sometimes selecting appropriate channel may be helpful for just one subject and not applied to other subjects. The figure 2 shows the position of different electrodes on the head of scalp. Each channel is formed from the Electrode, where each electrode pair forms the channel dataset signal for that particular experiment. The figure 2 on right side also shows the highlighted electrodes which are selected in BCI competition [ref], whereas figure 3 shows the most eminent electrodes marked under the red and green area which contributes the most in classification technique. These electrodes are figured out using above channel selection techniques

Hence, Electrodes Cz, C3, C4, Pz, FCz, Fz and Fc1 are the selected electrodes for providing the channel signals and rest the electrodes are removed from the signal dataset.

The total channels selected from the BCI competition are 47 which are further processed for compression technique which will be discussed in next step.

STEP 3.

After applying the channel selection algorithm, the signals are compressed using various Techniques. We have worked on, Linear Discriminant Analysis, Independent Component Analysis, Principle component Analysis, Discrete Cosine Transform, Inverse Discrete Cosine Transform, and Differential Pulse Code Modulation which are discussed as below:

a) Independent component analysis (ICA) is an analytical and computational technique for unveiling hidden variables that are further used assets for random factors, measures or signals. ICA defines a productive model for the analysed multivariate data, which is taken from a large database of samples. In the model, the data variables are formed from the linear mixtures of some concealed latent variables, and the mixing operation is also concealed. The latent variables are followed by non-gaussian and mutually independent factors, and these are known as independent components of the data set.

Hence, these independent components are also called factors that can be found using Independent component analysis. ICA is related to principal component analysis and factor analysis, but ICA is a much more powerful technique for finding the underlying factors where Principal Component Analysis fails. ICA are mostly used for identifying the unique components from the mixed Signals wave, which also concludes that it can be used for brain waves recorded by multiple ECOG sensors. So we have used ICA in our proposed methods and results in the reduction of the signal from 3000 milliseconds to almost 1500 milliseconds. Figure 4 shows the compressed signal by Principal Component Analysis. Although Signal is compressed but it makes the signal a much smoother than the original signal. Independent component analysis (ICA) is an analytical and computational technique for unveiling hidden variables that are further used assets for random factors, measures or signals. ICA defines a productive model for the analysed multivariate data, which is taken from a large database of samples. In the model, the data variables are formed from the linear mixtures of some concealed latent variables, and the mixing operation is also concealed. The latent variables are followed by non-gaussian and mutually independent factors, and these are known as independent components of the data set. Hence, these independent components are also called factors that can be found using Independent component analysis. ICA is related to principal component analysis and factor analysis, but ICA is a much more powerful technique for finding the underlying factors where Principal Component Analysis fails. ICA are mostly used for identifying the unique components from the mixed Signals wave, which also concludes that it can be used for brain waves recorded by multiple ECOG sensors. So we have used ICA in our proposed methods and results in the reduction of the signal from 3000 milliseconds to almost 1500 milliseconds. Figure 4 shows the compressed signal by Independent Component Analysis and Signal is compressed as compared to the original signal.

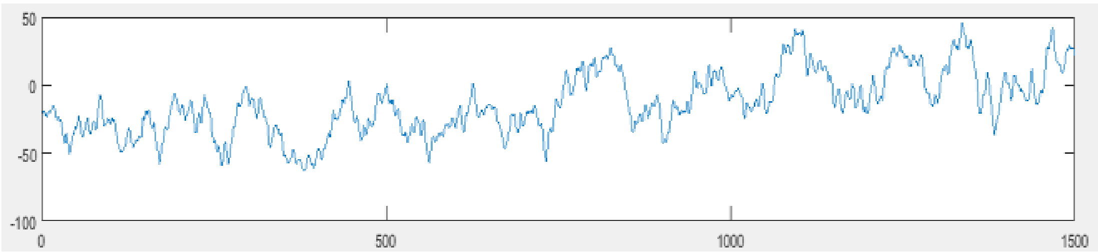

Fig. 4: Signal compressed using ICA

b) Using Principal component Analysis on EEG signals is a method of analysis which involves finding the straight blending of a set of mutable that has the highest change and eliminating its effect, repeating this iteratively over each trial. Principal component Analysis is also used for dimensionality reduction of the data so that computational cost should be low and classifier performs training of model faster. We have applied PCA to each trial and for every signal data, the score is obtained these scores are arranged in using values of eigenvectors of channels. This results in the reduction of the signal from 3000 milliseconds to almost 1500 milliseconds. Figure 5 shows the compressed signal by Principal Component Analysis. Although Signal is compressed but it makes the signal a much smoother than the original signal.

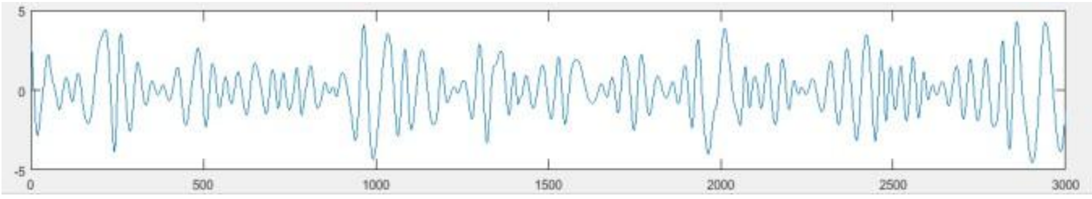

Fig. 5: Signal compressed using PCA

c) Linear Discriminant Analysis (LDA) is another technique similar to PCA and most commonly it is used as dimensionality compression technique in the feature generation for pattern classification, this also results in reduce computational costs and consume less time for a train a model. The overall LDA approach is very alike to a Principal Component Analysis but additionally we have worked on the axes that maximize the separation between multiple classes (LDA). In our dataset we have only 2 class for data separation for the linearly Distinguish the data Signal from the different data points. LDA helps in finding the data points which are more responsible for predicting the Signals. So we have used LDA in our proposed methods and results in the reduction of the signal from 3000 milliseconds to almost 1500 milliseconds. Figure 6 shows the compressed signal by Linear Discriminant Analysis and Signal is compressed as compared to the original signal.

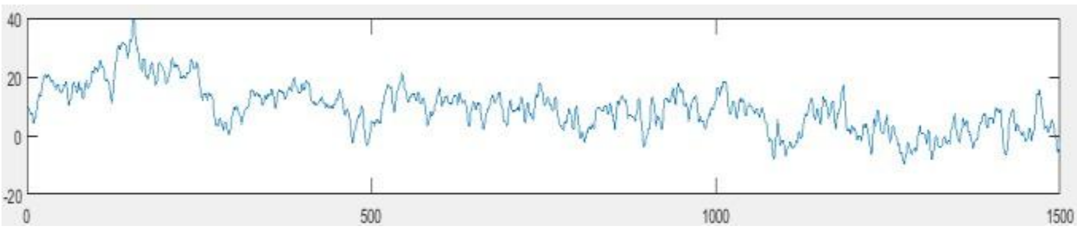

Fig. 6: Signal compressed using LDA

d) Discrete cosine transform (DCT) expresses a finite sequence of data points where the sum of cosine functions oscillating at different frequencies. These are the suitable technique for analyzing the spectral channels from the mathematical explication of partial differential comparisons. These only make use of cosine function and other functions like sine functions are used internally for compression of signals and since it turns out that there are only some cosine functions which are capable of compressing the signals and each function has its own boundary conditions defined over calculus. The DCT are based on Fourier-related transform which further used the concept of discrete Fourier transform (DFT). Fourier order coefficients are calculated by periodically and symmetrically sequence data points, and this makes DCTs are similar to DFTs. There are 8 DCT transforms coefficients but only 4 DCT have worked well on our proposed model. Below we have given the wave formed from the four DCT and DCT wave was different from the previous wave generated from the Set of channels. Hence we have used DCT compression in our proposed methods and all the four wave results in the reduction of the signal from 3000 milliseconds to almost 1500 milliseconds.

Figure 7 – 10 shows the compressed signal by various discrete cosine transform and Signal is compressed as compared to the original signal.

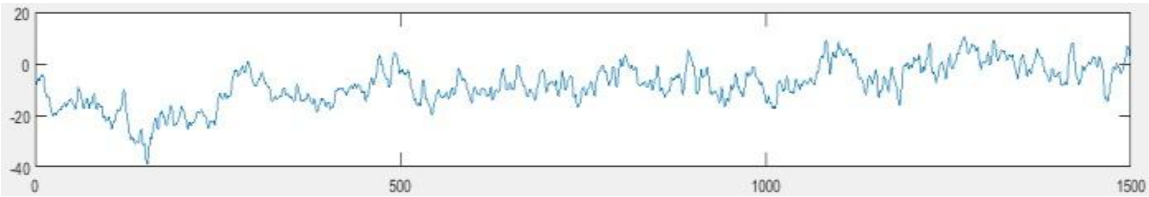

Fig. 7: Signal compressed using DCT-I

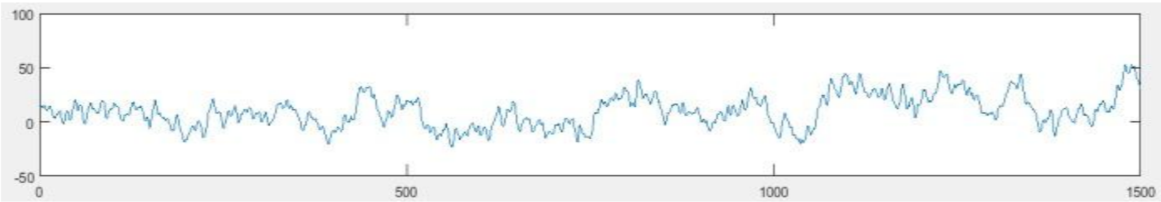

Fig. 8: Signal compressed using DCT – II

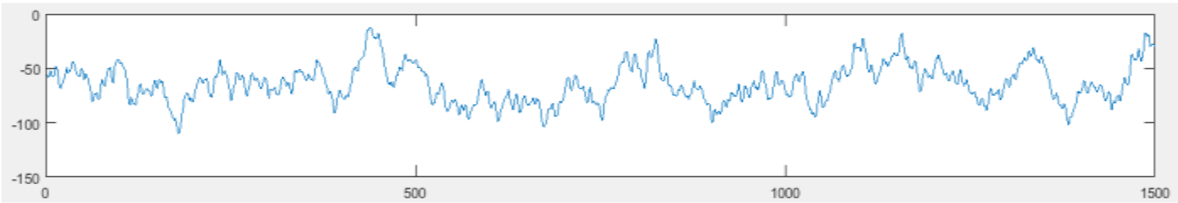

Fig. 9: Signal compressed using DCT – III

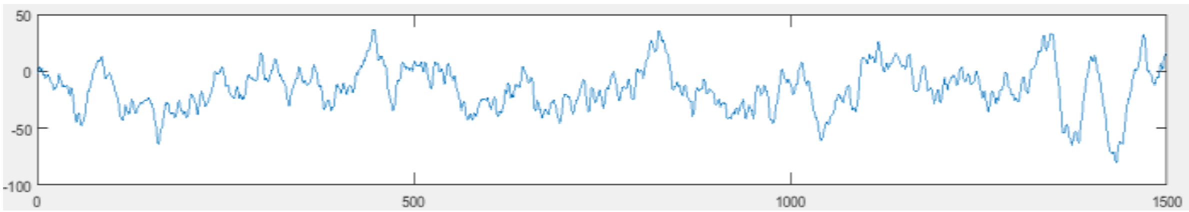

Fig.10: Signal compressed using DCT - IV

STEP 4.

In this step, we are going to use the features generated in step 3 further as an input to the feedforward neural network. For training of neural network, we have used Scaled Conjugate Gradient backpropagation algorithm, where for every epoch it sets the weights to steepest descending direction also this algorithm, was used because it takes less time for the train of a model on patterns and has high classification accuracy. In our proposed method, the neural network consists of N inputs, 15 hidden layer, and Y outputs, where N is the size of the feature vector which is 70500 and Y are the number of classes that is 2. We have partitioned the data into training, test, and validation data, where training data is 70%, and both test and validation are 15% of full data. Figure 11 illustrate the neural network input, output, and hidden layers.

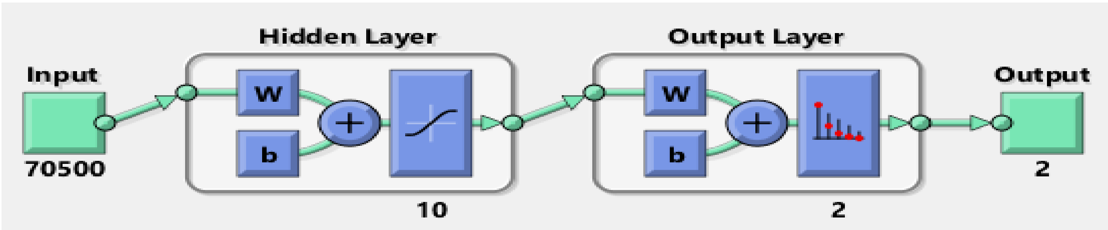

Fig. 11: Feed Forward Neural Network

This network is trained on the features generated by Independent Component Analysis, and the classifiers accuracy is obtained on Test data. Below is the figure 12 shows overall performance on test data.

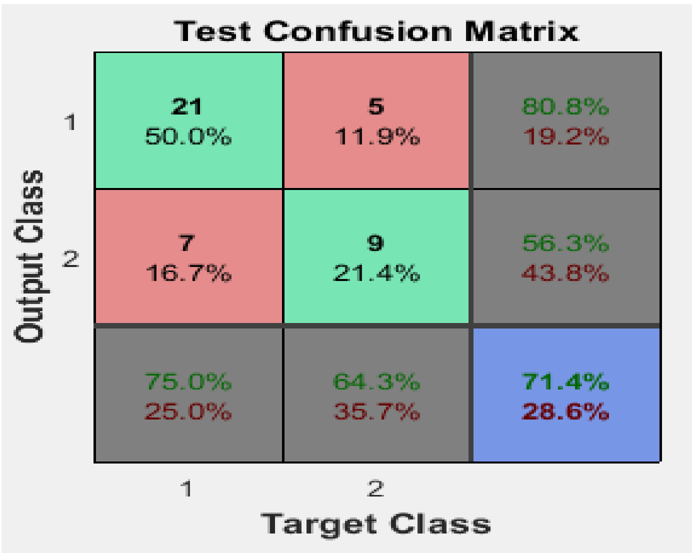

Fig. 12: Empirical mode decomposition

Similarly, now the network is trained using features generated by Principal component Analysis and classifiers accuracy is obtained on Test data, then again network is trained using features generated by Linear Discriminant Analysis, and Discrete cosine transform methods and for both the features classifiers accuracy is obtained on Test data. All these accuracies are examined in the Table. 1

Table 1: Accuracy of various methods on Test data.

Methods		Accuracy (%)
DCT	*Discrete cosine transform - I*	88
	Discrete cosine transform - II	84
	Discrete cosine transform - III	86
	Discrete cosine transform - IV	86
Principal component Analysis		92
Linear Discriminant Analysis		88
Independent Component Analysis		71.4

VI. 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. Figure 13, clearly shows the comparison between various accuracies obtained in various discrete cosine Transform. Higher the bar graph, higher is the accuracy. Discreet cosine transform-1 in the results show the highest accuracy among all the compared cosine transforms. Then we have done comparison in figure 14 which shows the comparison of Accuracy obtained in PCA, LDA, and ICA. As we can see that Principal component analysis show the highest accuracy among all the compared. LDA has a lower accuracy than PCA but has a higher accuracy than ICA. ICA has the lowest accuracy among all these three techniques. Now Figure 15 compares the best outcomes obtained in previous figures, figure 13 and figure 14. This is done so that we can decide which method provides the most accuracy in the entire spectrum of methods that we have used to obtain the high classification accuracy rates. As we can see that principal component analysis still outperforms the best outcome of figure 13 and wins over the entire spectrum by giving the unbeatable 92% accuracy in classifying the EEG signals. Figure 17 shows the confusion matrix for training data and as we can see the accuracy obtained in this case is 100%. Now figure 18 shows the confusion matrix of validation data. Here we have been able to achieve 81% accuracy. Although this accuracy is not very high as the allotted dataset for validation was quite smaller than the overall dataset which was very large. We can see that in figure 19, a very high accuracy of 92.4% was achieved on the test data. As we know that there are three types of divisions in classification, one is the training data, second is the validation data and third is the test data. So we have demonstrated the all the accuracies obtained in all three types of division although the matter of importance goes to test data classification accuracy only. Figure 20 shows the confusion matrix for all data including training and test data.

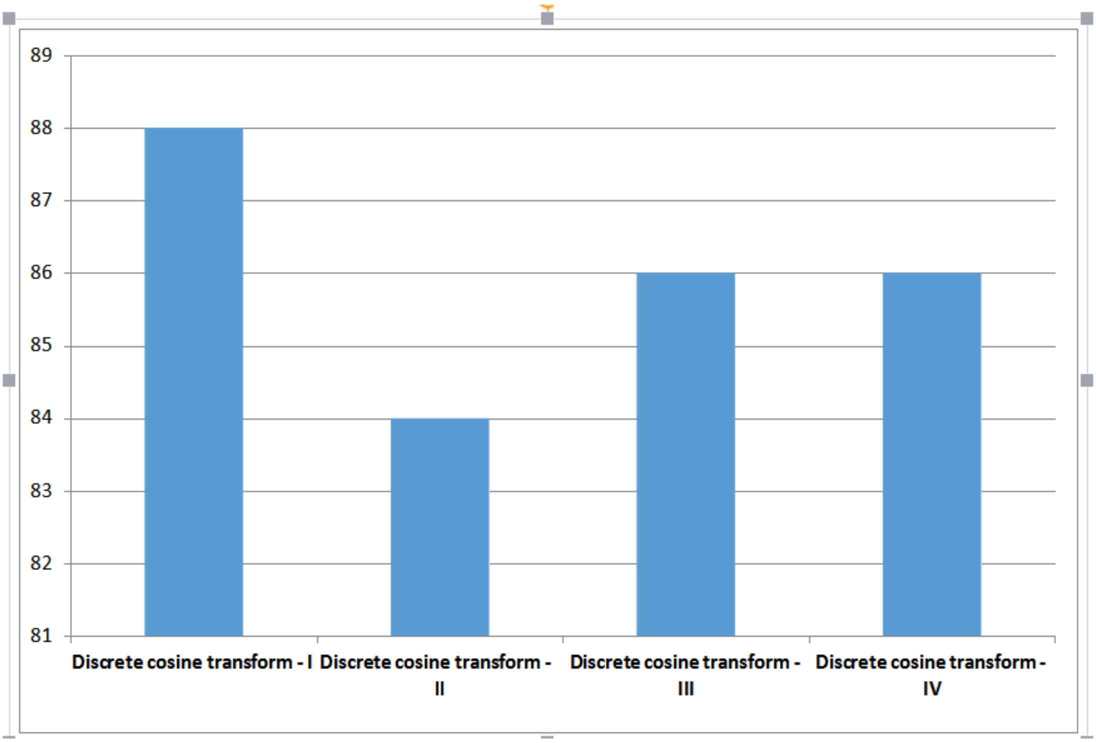

Fig. 13: Comparison of Accuracy obtained in various discrete cosine Transform

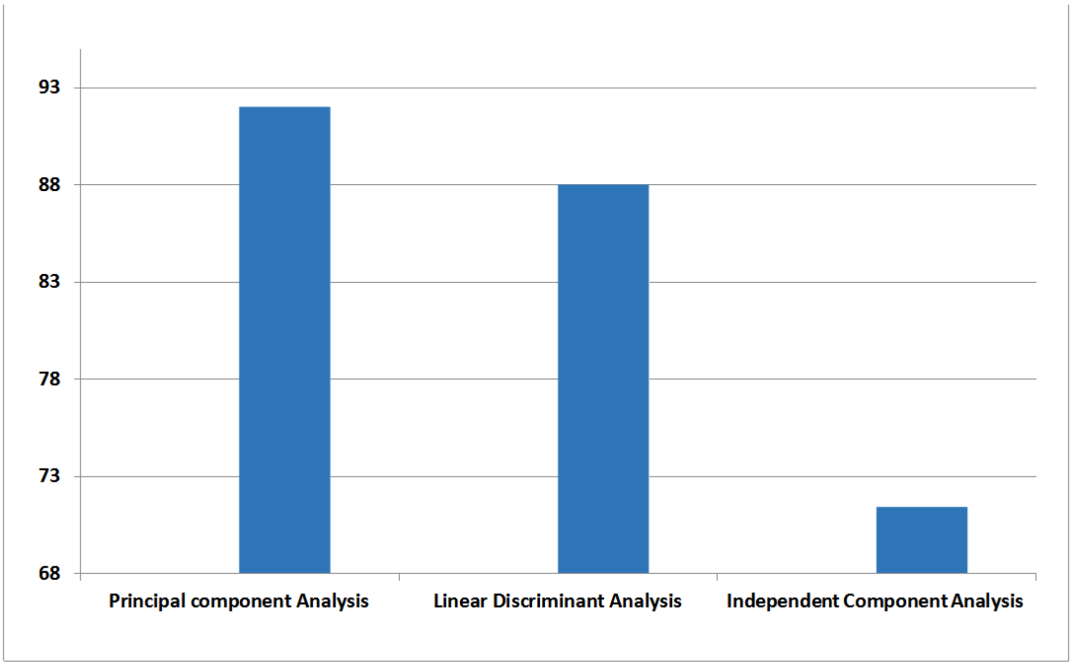

Fig. 14: Comparison of Accuracy obtained in PCA, LDA, and ICA

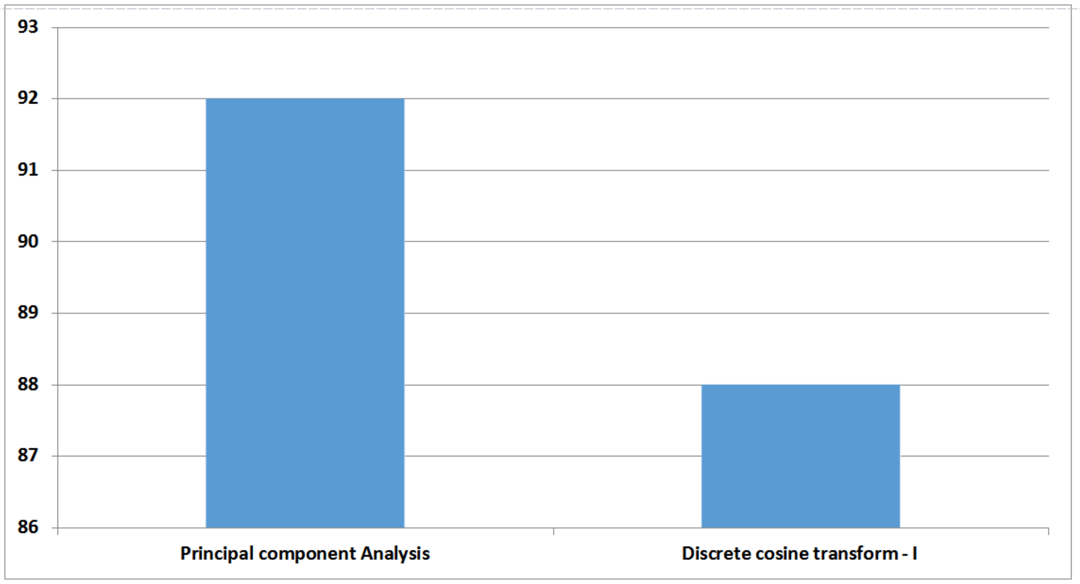

Fig. 15: Comparisons of PCA and DCT - I

Fig. 16: Confusion matrix for training data

Fig. 17: Confusion matrix for Validation data

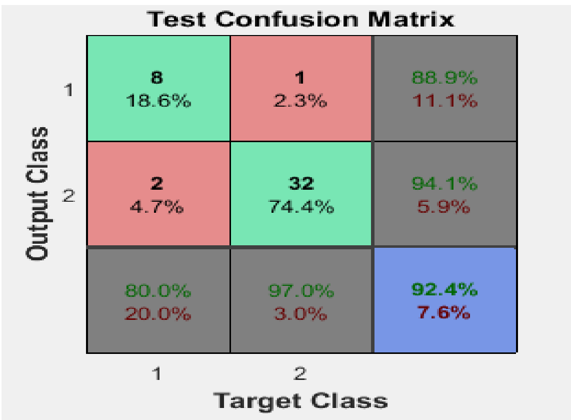

Fig. 18: Confusion matrix for Test data

Fig. 19: Confusion matrix for all data, Includes both training and test data

VII. CONCLUSION

We have suggested a channel selection method which prefers the most befitting channels based on the computation of the probability of the channel. Selecting apt channels help boost the computational operations and diminishes the dimensionality of the data. Later we constricted the signals using Empirical Mode Decomposition(EMD), and a array of Discrete Wavelet Transform(DWT) families and Lifting Wavelet Transform(LWT) schemes. Finest intrinsic mode function of Empirical Mode Decomposition has been designated for the feature achievement, whereas in Discrete Wavelet Transform disparate families of DWT were acknowledged, also LWT schemes have been worn to wrap the EEG signals without any casualty of information. All of these compressions of EEG signal aids in curtailing the computational charge and requires a lower time to case the EEG signals. In forthcoming work, we can work on enhancing the results by employing a variety of alternative compression algorithms and processing the signal to excerpt more admissible features which can make our model extra potent and ready to be exercised in a variety of real world applications.

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