Motor Imagery EEG Classification Using Random Subspace Ensemble Network with Variable Length Features

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Abstract: *Classification of electroencephalography (EEG) signals for brain-computer interface has great impact on people having various kinds of physical disabilities. Motor imagery EEG signals of hand and leg movement classification can help people whose limbs are replaced by prosthetics. In this paper, random subspace ensemble network with variable length feature sampling has been proposed for improving the prediction accuracy of motor imagery EEG signal classification. The method has been tested on eight different subjects and a hybrid dataset of two subjectsdata combined. Discrete wavelet transform based de-noising scheme has been adopted to remove artifacts from the EEG signal. For sub-band selection, dual-tree complex wavelet Transform has been employed. Mutual information scoring has been used for univariate feature selection from the feature space. A comparative analysis has been carried out where random subspace ensemble network outperformed other classification models. The maximum accuracy obtained by the model was 90.00%. Furthermore, the model showed better performance on the hybrid dataset with an average accuracy of 86.00%. The findings of this study are expected to be useful in artificial limb movements through brain-computer interfacing for rehabilitation of people with such physical disabilities.*

Keywords: *Electroencephalography, Brain computer interface, Random subspace ensemble network, Discrete wavelet transform, Dual tree complex wavelet transform.*

Introduction

Brain-computer Interface (BCI) is a bridge between the human brain and the computer. We can study the human brain with the aid of BCI and can make important decisions about how our brain works to communicate and control [13, 18]. There are two kinds of BCI systems that control the exoskeleton, i.e., BCI based on Motor Imagery (MI) and BCI based on Steady-state Visual Evoked Potentials (SSVEPs) [17]. The main advantage of SSVEP based control is that it requires less time to train but the limitation of this system is that it results in higher false detection. Another drawback is that it aims to communicate with environment neglecting functional rehabilitation [19].

Previous efforts were concentrated on categorizing the MI EEG signals into phenomena of Event-related Desynchronization (ERD) and Event-related Synchronization (ERS) [20]. On the other hand, band power, interval variance, autoregressive model, spectral decomposition, temporal spectral evolution task-related power increase and decrease etc. [23] are included in quantification measurements of ERD/ERS [5, 30].

Time, frequency, and time-frequency, all three domains of EEG signals were analyzed during the motor imagery EEG classification [9]. Extracted features from these domains were analyzed with Linear Discriminant Analysis (LDA) algorithm to obtain the optimal features. Then these features were used for ANN classifier which resulted in 83.6% accuracy. Authors in [4], tried to classify imagined words with conventional methods, sonification, textification, and compared the performance of these three methods. While textification outperformed conventional and sonification approaches by an average accuracy of 83.34%. STFT images were extracted from the EEG signals and used to train a multi-input CNN for classification in [26]. In [7], authors showed the effects of gender on Event-related Potentials. There are other applications of EEG signal, such as, classification alcohol decency [6], drowsiness detection [29], Alzheimer's patients classification [29], epilepsy detection [28], various event detection in sleep [2], etc. In this paper, we plan to denoise EEG signals using Discrete Wavelet Transform (DWT), Dual-tree Complex Wavelet Transform (DTCWT) to select sub-band. Suitable features can be extracted from this sub-band for effective classification. As the size of the features are expected to be large, its dimensionality is planned to be reduced by using a univariate feature selection scheme based on mutual information score. Random Subspace Ensemble (RSE) method has shown effectiveness for nonstationary signals [8, 14]. Therefore, Neural Network Ensemble with Random Subspace Feature Aggregation can be useful in EEG based motor imagery classification. In this study, the selected features are applied to the ensemble network for the classification of the signals. Finally, a comparative study will be done to assess the performance of the proposed method relative to conventional models. The rest of this paper is organized as follows: in section II, the proposed methodology is discussed. The next section contains a detailed analysis of the result and finally a conclusion of this work is drawn.

Proposed methodology

The methodology of this work is based on three steps: denoising EEG signal and sub-band selection, feature extraction and selection, and classification. At first, the signal was preprocessed using DWT, and the noise was removed. Then DTCWT was used for EEG sub-band selection. After that, features were calculated from selected EEG sub-band. Then the univariate feature selection scheme was used for optimizing the classification process. For classification, RSE network was used. The overall methodology used in this paper is given in Fig. 1.

For noise removal of biomedical signals which are easily contaminated with artifacts [12], wavelets are utilized with shapes similar to the corresponding signal class. In this scheme, by applying DWT, the signal is decomposed into its wavelet coefficients [22]. Mallat [16] introduced quadrature mirror filters for an efficient way of implementation by passing the signal through a series of low-pass (LP) and high-pass (HP) filter pairs.

In this work, orthogonal Coiflets 2 (coif2) wavelets were used in DWT to remove noise from EEG signals and a shrinkage function based soft thresholding is used because hard thresholding generates artifacts due to discontinuity [16].

Although DWT is widely used in EEG classification tasks, it has several drawbacks. Authors in [25] pointed out four major drawbacks of DWT, namely: oscillation, shift-invariance, aliasing, and lack of directionality. They proposed DTCWT. DTCWT overcomes the limitations of DWT. DTCWT structure is similar to Wavelet Packet Transform (WPT) but the wavelet in DTCWT is complex in nature. The complex wavelets are the main reasons to overcome the limitations of DWT. For EEG sub-band selection, we used level three decomposition using DTCWT and the absolute value of detailed coefficients was used (Fig. 2).

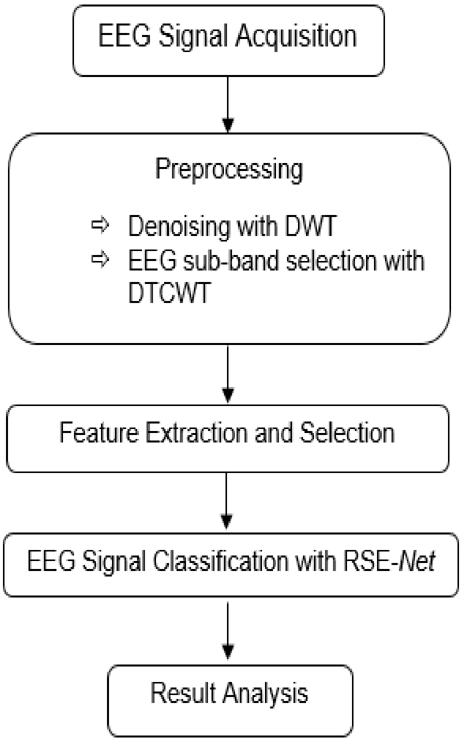

Fig. 1 Proposed methodology

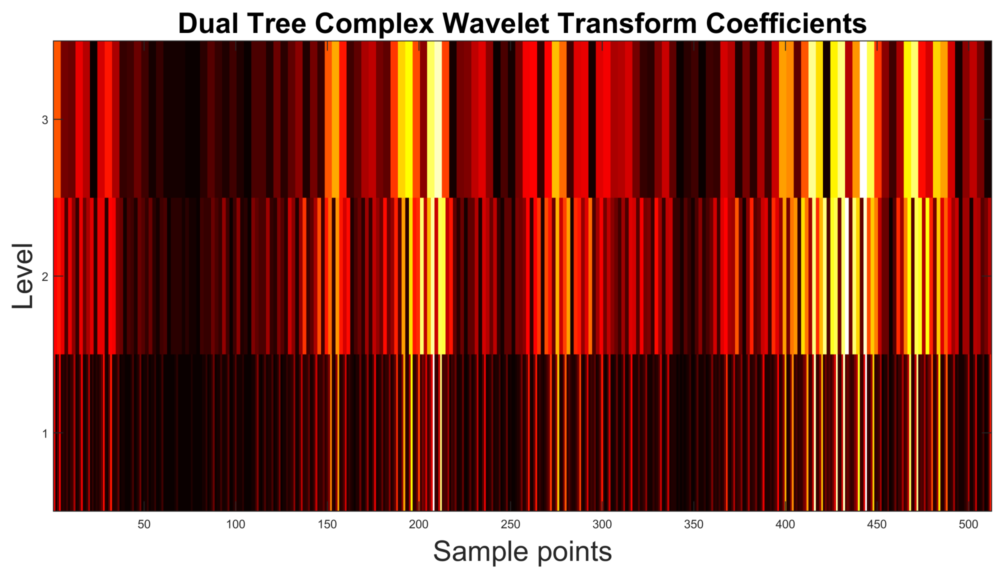

Fig. 2 Heat map of DTCWT coefficients

Feature extraction and selection

Features from both time and frequency domain can be used for EEG classification. But random features can decrease the performance of classification. Initially 19 features per channel were calculated from the EEG signal. Then on the basis of mutual information, best-performing features were selected. The feature selection method is described in the next section. List of features [1] with mathematical definitions are listed below.

2^{nd} Spectral Moments ($SM2$) is a statistical approach to extract the power spectrum of EEG signal and it is defined as:

$$SM2 = \sum_{i=1}^{n} P_i f_i^2. \tag{1}$$

Waveform Length (WL) is used to measure the complexity of EEG signal and is defined as:

$$WL = \sum_{i=1}^{n-1} |x_{i+1} - x_i|. \tag{2}$$

Absolute Energy is the sum of squared values:

$$E = \sum_{i=1}^{n} x_i^2. \tag{3}$$

Augmented Dickey Fuller is a hypothesis test method. Three types (teststat, p-value, usedlag) of statistic tests were used.

Autocorrelation is defined as:

$$\frac{1}{n-1} \sum_{l=1}^{n} \frac{1}{(n-l)\sigma^2} \sum_{t=1}^{n-l} (X_t - \mu)(X_{t+1} - \mu), \tag{4}$$

where n, σ^2 and μ are length of time series X_t, variance and mean, respectively.

Binned Entropy (BE) is calculated as:

$$BE = - \sum_{k=0}^{min(max\_bins, len(x))} P_k log(p_k),\ where\ p_k > 0. \tag{5}$$

$C3$ was proposed as a measure of non-linearity in time-series [24], is formulated as:

$$C3 = \frac{1}{n-2lag} \sum_{i=0}^{n-2lag} x_{i+2lag}^2 . x_{i+lag} . x_i. \tag{6}$$

CID is used to calculate the complexity of data:

$$CID = \sqrt{\sum_{i=0}^{n-2lag} (x_i - x_{i+1})^2}. \tag{7}$$

As the name implies Count Above Mean and Count Below Mean count the number of times the signal appears above and below the mean respectively.

Average amplitude change (AAC) is formulated as:

$$AAC = \frac{1}{N}\sum_{i=1}^{N-1}|x_{i+1} - x_i|. \tag{8}$$

Mean Second Derivative Central ($MSDC$) is defined as:

$$MSDC = \frac{1}{n}\sum_{i=1}^{n-1}\frac{1}{2}(x_{i+1} - 2x_{i+1} + x_i). \tag{9}$$

Zero Crossing is used to calculate number of times the sample signal changes its sign. Sample entropy estimates the entropy of the samples. LOG or Log detector is a non-linear detector which is changed based on logarithm [21]. Variance is the measure of how far a random variable is spread out, and Time Reversal Asymmetry Statistic ($TRAS$) can be written as:

$$TRAS = \frac{1}{n-2lag}\sum_{i=0}^{n-2lag}(x^2_{(i+2lag)}x_{(i+lag)} - x_{(i+lag)}x^2). \tag{10}$$

After feature extraction was performed, feature selection was carried out. Feature selection is necessary because feature importance varies subject to subject and also across channels. In our approach, a univariate feature selection scheme based on mutual information score was used to select optimum feature space for training with k highest scoring features. The mutual information is calculated between features and target set. From a feature dimension of 95 (5 channels) and 114 (6 channels), a sparse feature set was generated with the most important 30 features.

Classification method

To improve the prediction accuracy of the classifier RSE is introduced by Ho [10]. This method works on a subspace randomly selected from the original feature space. The problem of dimensionality is optimized in this reduced space as the number of subjects per feature grows and useful features are retrieved [15]. In the next few paragraphs, we will visit our implementation of RSE-Net with variable feature-length in a detailed manner.

RSE [14] modifies the training dataset by sampling features, this modified dataset is used to build a classifier, majority voting or weighted averaging technique is utilized to reach the final decision. For each of the channels per training sample, 19 features were calculated. Based on these features over all of the channels, the feature vector X_i was generated which was used for the RSE method along with the corresponding label y_i for training.

Let, each training data point $X_i = (x_{i1}, x_{i2}, ..., x_{ik})$ in the data set $X = (X_1, X_2, ..., X_n)$ be a vector of dimension k for k features, where $i = 1, 2, 3, ..., n$. In RSE, randomly $\tilde{k}$ features are selected $(\tilde{k} < k)$, thus $\tilde{k}$ dimensional random subspace is obtained from the k dimensional feature vector.

Thus, the original dataset is modified to: $\tilde{X}^t = (\tilde{X}^t_1, \tilde{X}^t_2, ..., \tilde{X}^t_n)$, where each data point now contains $\tilde{k}$ dimensional training objects $\tilde{X}^t_i = (\tilde{x}^t_{i1}, \tilde{x}^t_{i2}, ..., \tilde{x}^t_{ik})$ where $i = 1, 2, ..., n$ and $\tilde{k}$ features $x^{\tilde{k}}_{ij}(j = 1, 2, ..., \tilde{k})$ are selected randomly. The classifier is built upon the new random subspace $\tilde{X}^t$ and aggregation is performed t times to reach the final prediction accuracy. In this work, we have introduced variable length feature-sampling with random subspace aggregation method to introduce more variation in the subspace feature set which results in less correlated classifier blocks in the ensemble network. A variable $\tilde{k}$ is chosen to sample the features to improve the performance of RSE-Net.

Algorithm : Variable Length Feature Sampling in Random Subspace

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I **INPUT**: Training set X, Label set y, Minimum subspace dimension $\tilde{k_1}$, Maximum subspace dimension $\tilde{k_2}$, No. of classifiers T

II **for** $t = 1, 2, ..., T$

(a) Select feature length $\tilde{k}$ such that $\tilde{k_1} \leq \tilde{k} \leq \tilde{k_2}$ from uniform distribution.

(b) Generate $\tilde{k}$ dimensional random subspace feature set $\tilde{X}^t$ from k dimensional feature space X

(c) Build a classifier $C^t(x)$ on $\tilde{X}^t$

III Merge classifiers $C^t(x), t = 1, 2, ..., T$

The RSE-Net is benefited from combining the classifiers and using random subspace for feature generation. In the case of training, data points being relatively small compared to the feature dimension, the problem of small sample size is solved by generating classifiers on random subspace. The model also performs better on datasets with redundant and noisy features [27].

From Fig. 3, RSE-Net was used with seven classifiers. The ensemble model contains around 80000 parameters in total. As the number of training samples is small, dropout is used in the classifier blocks to avoid over-fitting. Rectified linear activation function (ReLU) was used and a maximum batch size of 512 was chosen. All the features are fed simultaneously to the single classifier. The model is built iteratively from the classifiers. The model was trained with Adam optimizer with a learning rate of 0.02 for 100 epochs. In Fig. 4 classifier architecture is presented.

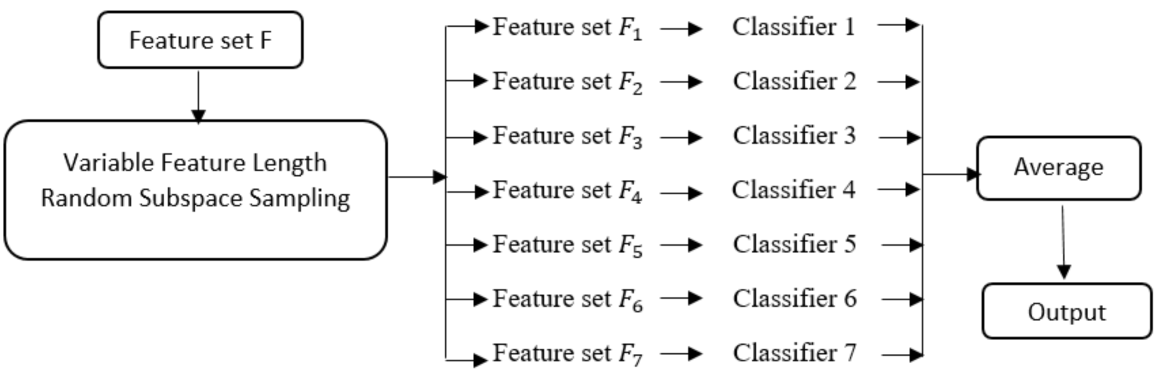

Fig. 3 Architecture of RSE-Net

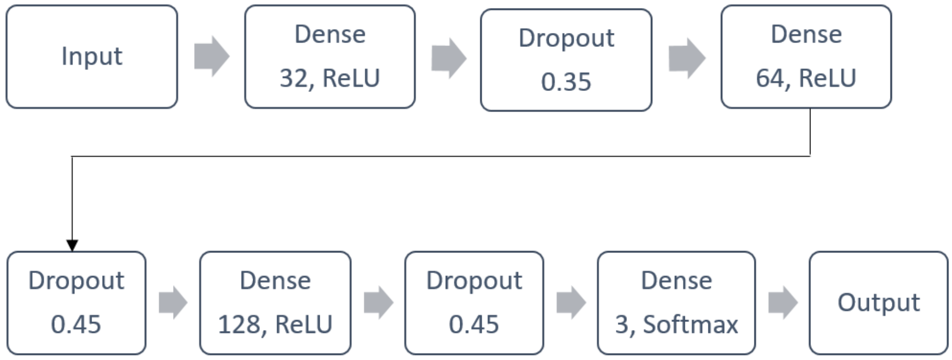

Fig. 4 Classifier architecture

Result analysis

The dataset from Dr. Cichocki's Lab (Laboratory for Advanced Brain Signal Processing) was used [11]. The cue-based data recording paradigm consisted of MI tasks, specifically the imagination of movement of the left hand (LH), right hand (RH) and both feet (F). In this dataset, g.tec (g.USBamp), and Neuroscan (SynAmps RT) were used for recording the EEG signals.

Band pass filter was used with low and high cut-off frequency of 2 Hz and 30 Hz respectively with sampling rate of 256 Hz with a notch filter at 50 Hz for g.tec and for Neuroscan device bandpass filter between 0.1 Hz and 100 Hz with sample rate of 250 Hz was used. The signals were measured in μV and V for Neuroscan and g.tec, respectively.

The application of proposed RSE-Net on EEG data was demonstrated on dataset SubA_5chan_-3LRF, SubB_5chan_3LRF, SubC_5chan_3LRF, SubD_5chan_2LR, SubE_5chan_2LR, SubF_-6chan_2LR, SubG_6chan_2LR and SubH_6chan_2LR from Dr. Cichocki's Lab (cued motor imagery data with three classes: right hand, left hands and feet from 8 subjects) and on a hybrid dataset by combining data of subjects A and C. The signals were denoised with DWT with coif2 wavelets by decomposing into level 3. For each of the 5 channels 19 features were calculated, in total a feature vector of length 95 for 5 channels and for 6 channels, 114 features were generated. As the feature importance varies subject to subject and also across channels, best 30 features were selected based on mutual information score.

From Fig. 5, the selected features are highly correlated which can be observed in the correlation matrix. The scatter plot for these features after t-SNE is shown in Fig. 6. For the hybrid dataset, two clusters of features can be observed which also demonstrates the complexity for classifying the samples. Selected Feature Importance Statistics has been shown in Fig. 7. Mutual information score is a good indicator of the importance of the individual features.

A comparative performance analysis was investigated between conventional machine learning models such as Decision Tree, SVM with linear kernel, KNN, Random Forest, AdaBoost and proposed RSE-Net for MI EEG signal classification. RSE-Net outperformed all other methods for subject A (86.67%), subject B (79.91%), subject C (89.44%), subject F (90.00%), subject G (77.50%), subject H (74.82%) and hybrid set (dataset A & C combined) (86.00%), for subject D and E, RSE-Net reached very close to maximum performance achieved by SVM and AdaBoost. For all the models, a 10-fold cross validation was evaluated on the dataset to show the robustness of the proposed approach. The results are given in Table 1.

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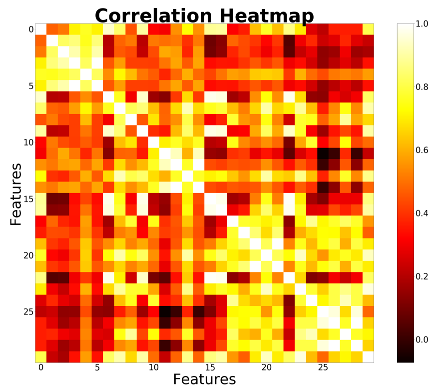
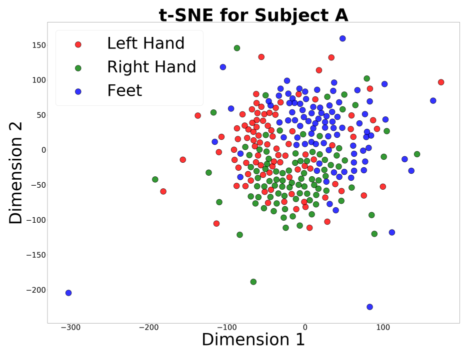
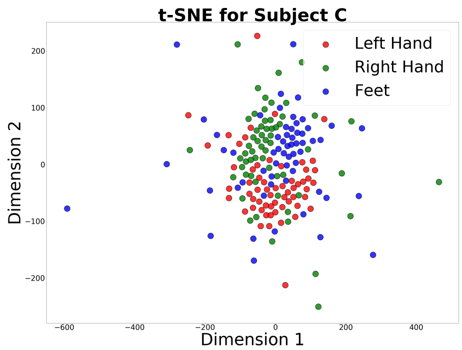


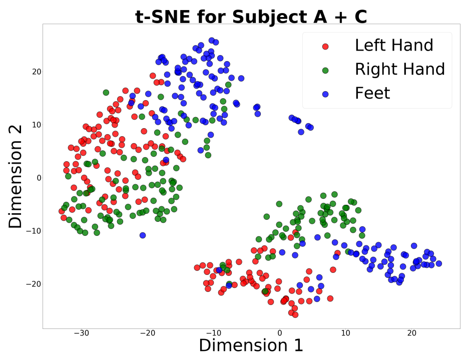
Fig. 5 Pearson correlation heat map of features for hybrid dataset



(a) t-SNE for subject A



(b) t-SNE for subject C



(c) t-SNE for hybrid subject A+C

Fig. 6 t-SNE scatter plot for subject A, C, A+C

From Table 1, we can say that all the algorithms showed mixed performance. But there is an important factor that must be evaluated which is the number of features. As mentioned earlier, initially there are 95 features (for subject A, B, C, D, E) and 114 features (for subject F, G, H) whereas after dimensionality reduction with feature selection, there are only 30. From Fig. 5, the features are highly correlated. So, number of features had an impact on the performance of the algorithms. For RSE-Net, another observation is that in case of relatively small training objects compared with number of features, RSE solved the small sample size problem by constructing classifiers in random subspace with lower feature dimension. So, when the data contains many redundant features this method performs better in random subspace than in original feature space. The combined decision of the classifiers outperforms single classifiers built on the original training dataset with complete feature space. Hence, the RSE-Net was able to

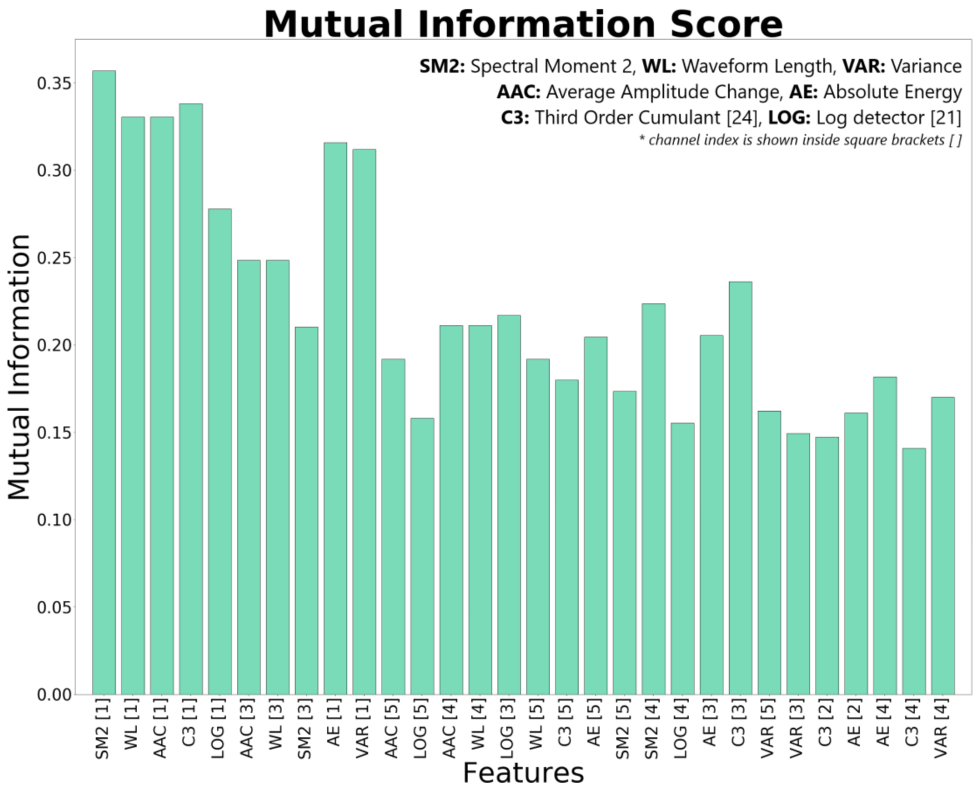


Fig. 7 Mutual information between features and targets of hybrid dataset

Table 1. Comparative study between various types of classification model for 10 fold cross-validation

Method		Accuracy % (10-fold CV)								
		Sub A	Sub B	Sub C	Sub D	Sub E	Sub F	Sub G	Sub H	Sub A+C
SVM	mean	85.55	76.67	89.44	51.25	**89.17**	77.5	69.17	57.68	81.78
	± std	4.82	11.12	7.64	15.26	**11.82**	14.58	11.82	11.21	7.425
KNN	mean	79.62	67.89	86.11	56.25	80.00	62.50	67.50	53.75	80.89
	± std	4.755	12.14	10.32	10.08	15.46	15.81	10.84	11.96	6.83
Decision Tree	mean	72.59	66.33	78.33	55.00	87.50	67.50	65.83	50.36	74.89
	± std	6.02	11.65	10.38	13.92	17.18	12.75	13.15	11.57	6.29
Random Forest	mean	79.26	67.78	86.11	62.50	87.50	63.75	64.17	59.29	81.33
	± std	7.81	11.18	7.56	13.70	15.48	18.07	14.46	14.24	6.61
AdaBoost	mean	76.30	65.89	77.78	**67.5**	85.00	57.50	62.50	58.21	73.78
	± std	8.64	12.91	12.425	**20.31**	17.00	21.07	16.35	10.73	8.82
RSE-Net	mean	**86.67**	**79.91**	**89.44**	63.75	77.5	**90.00**	**77.50**	**74.82**	**86.00**
	± std	**8.32**	**8.4**	**6.31**	16.25	19.74	**9.35**	**14.93**	**12.07**	**4.67**

generalize even with sparse feature set after feature selection and random subspace sampling with smaller number of model parameters.

Conclusion

In this paper, we proposed Random Subspace Ensemble Network for classifying MI EEG signals and found that this method performs better in classification task with reduced dimension than commonly used models such as Decision Tree, Random Forest, AdaBoost, SVM and KNN. The main contribution of this work is that, we tried to find a method which generalizes across multiple subjects, multiple channel combinations with different feature dimensions. RSE-Net showed better generalization with few trainable parameters as the hyper-parameters were chosen very carefully to train the network. The model was also faster to train due to small number of parameters. We intend to improve the model's performance by using more classifiers in ensemble network and hyparameter-optimization, which will be an important aspect of real time EEG classification for Brain Computer Interface.

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