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Electroencephalogram channel selection based on pearson correlation coefficient for motor imagery-brain-computer interface

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ABSTRACT

Decryption of Motor Imagery (MI) activity from an Electroencephalogram (EEG) data is a significant part of the Brain-Computer Interface (BCI) technology that allows motor-disabled persons to connect with external devices. Channel selection, feature extraction, and classification are essential requirements for an effective BCI system. Non-stationary EEG data confuses designing EEG-based BCIs. In this study, the Pearson correlation coefficient (PCC) technique is employed for channel selection for EEG signals in the BCI system. It selects the most associated fourteen channels for the sensorimotor area of subject's brain. The popular signal processing technique wavelet packet decomposition (WPD) is employed for feature extraction. After that approximate entropy (ApEn) feature is calculated for selected channels. The proposed study is a novel scheme combining Pearson correlation coefficient-based channel selection technique and wavelet packet decomposition for classifying MI signals. Finally, extracted features are classified with the help of two benchmark techniques, Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN) and achieve maximum accuracy of 91.66% and 90.33%, respectively. The proposed technique is examined on freely available EEG datasets BCI competition-IV-Dataset I to prove its superiority over previously reported approaches. Obtained experimental findings demonstrated advantages over previous methods in terms of classification accuracy.

1. Introduction

Brain-computer interface (BCI) is a technique that allows for communication without using conventional neuromuscular mechanisms [1]. In BCI systems the subject brain signals are usually measured by electroencephalogram (EEG) due to their high resolution and low cost comapred to other modalities, such as fNIRS, fMRI etc. It uses brain impulses to control and communicate information. EEG is a non-invasive popular technique of measuring brain signals [2]. EEG data indicate the fluctuation of electrical potential or voltage. This potential change is measured non-invasively from a person's scalp using sensors called electrodes by international 10/20 electrode placement system [3]. EEG signal is a time series with random amplitude and usually measure in the microvolts [4]. Researchers are mainly interested in sensorimotor rhythm-based BCI systems, which depend on the imagination of the movement of a limb to induce EEG signals in corresponding brain regions [5]. The BCI system uses these captured brain signals to communicate with external applications like prosthetic limbs and robots [6]. One of the issues in developing a successful sensorimotor rhythm-based BCI system is distinguishing between distinct MI activities, such as imagining movement of the limbs. Generally speaking, data preparation, feature extraction, and suitable classifiers are the fundamental pillars of the classification of MI signal in BCI applications. In addition, there is another important factor that researchers often neglect, channel selection or choosing the minimum number of channels that help yield the highest accuracy level of BCI system. It was observed that using more channels might increase classification performance. However, this does not imply that the more, the better. The performance of the BCI system would suffer if a high number of channels were used without first undergoing channel selection since this would result in the addition of noisy and redundant channels. Furthermore, using extra channels raises the cost of the BCI system [7]. Therefore, an efficient method of selecting the most informatics channels from the available set is required. Recently, several researchers have looked at this issue. In most of research, channels have not been manually picked, and they could be chosen via wrapper and filter-based strategies or a combination of both [8]. Filter techniques often depend on criteria, such as the mutual information [9] or fisher criterion [10]. Wrapper techniques

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often combine optimization method with a particular classifier, such as a particle swarm optimization [11] or decision tree [12]. Filter-based strategies are more efficient, do not need a classifier, and are more flexible. However, these advantages are offset by a lower overall accuracy than wrapper-based techniques. In Ref. [13] fifteen out of a total twenty-two channels related sensorimotor area across the motor cortex were chosen at random and obtained appreciable classification accuracy. A channel selection strategy based on the highest fisher score was purposed [14] to enhance common spatial pattern (CSP)-related features for classification EEG signal. Hesam Varsehi proposed [15] Granger causality-based channel reduction technique for a MI-based BCI system. In short, present channel selection strategies are ineffective or lack a neurophysiological foundation.

The traditional approach of MI BCI using EEG data involves features extraction and classification based on numerous machine learning techniques. The feature extraction approaches aim to minimize dataset that provide the most valuable information of EEG signals which improved classification performance. The most prominent feature extraction technique is the CSP [16]. CSP dependency significantly on the frequency range of EEG signals. Other well-known approaches, such as the Wavelet Transform (WT) and Short Time Fourier Transform (STFT) which have excellent multi-resolution and time-frequency localization qualities, have been frequently used in the feature extraction process [17]. These allow the time-frequency features of MI data to be captured dynamically. In terms of signal processing, the wavelet packet decomposition (WPD) the algorithm has proven effective in the time-frequency domain for MI-based BCI systems [18]. However, the aforementioned feature extraction techniques heavily rely on EEG data and are not ideally based on sensorimotor regions of the brain channels for MI BCI system. Furthermore, previous research work could not offer relevant results and compromised the accuracy of EEG signals with selected channels.

To address the identified issues and this study's contribution is:

- To construct an EEG channel selection mechanism based on Pearson correlation coefficient technique.
- Present a popular signal processing technique wavelet packet decomposition for feature extraction in time-frequency domain.
- Compute Approximate Entropy for selected channel which are closely related to sensorimotor region of subject brain.
- Two benchmark classification algorithms SVM and KNN are used for BCI system.
- Compare the research work findings of the proposed technique with previous techniques in terms of accuracy.

Despite the variety of channel selection studies presented but precisely calculating the number and location of channels still have significant problem for EEG-BCI system related to sensorimotor region of brain. This research focuses on Pearson correlation coefficient (PCC) technique, which is used for EEG channels selection related to sensorimotor region of the subject's brain and select fourteen most informatics channels. After that, WPD is applied up to the 8th level and obtains 256 nodes for selected channels. Then selected, 124 nodes which are associated to the sensorimotor frequency range (8–32 Hz) for 14 channels. The approximate entropy (ApEn) most valuable feature is calculated for 124 nodes and computed feature matrix for each trail for selected channels. This research used two benchmark machine-learning techniques (SVM and KNN) to identify MI activities with EEG Data. To our knowledge, the Pearson correlation coefficient channel technique and WPD with approximate entropy feature for BCI competition IV- dataset I have not been implemented till now. Fig. 1 show the schematic block diagram for MI BCI system. The paper is organized as follows: Section 2 explore related work and section 3 illustrates materials and methods. The section 4 is depicted results with discussion, and Section 5 presents conclusion with future scope.

2. Related work

In last two-decades, numerous investigations have explored ability to identify a few mental activities from Electroencephalogram (EEG) data. Richard Caton recorded the first EEG on an animal brain in 1875, and Hans Berger recorded on a human brain in 1929 [19]. The electrical activity of neurons produces the EEG [20]. Electroencephalography is a diagnostic method that permits measuring and recording biological electrical activity in the subject's brain, which is essential for many beneficial applications to enhance the quality of life for a person with disabilities [21]. Motor imagery (MI) signals captured by EEG provide the most realistic basis for constructing BCIs. MI can change the neuronal activity in the central sensorimotor region in the same manner as when an actual body movement occurs. MI-based BCI offers a great degree of mobility, it allows motor-impaired individuals to control the device [22]. The sensorimotor area channels, extracted features, and the classification method significantly impact the MI-BCI system's success [23]. It is necessary to eliminate irrelevant channels using a channel

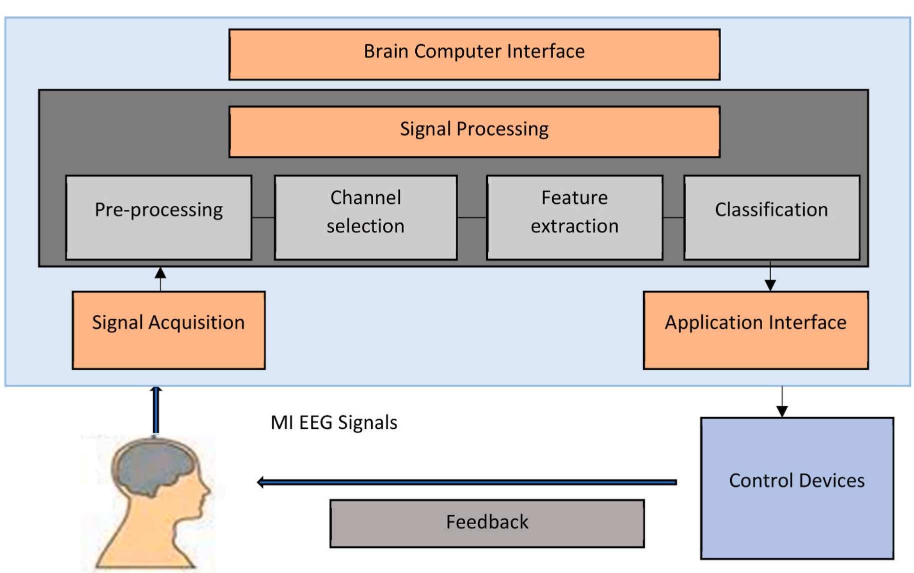

Fig. 1. Schematic block diagram for MI BCI system.

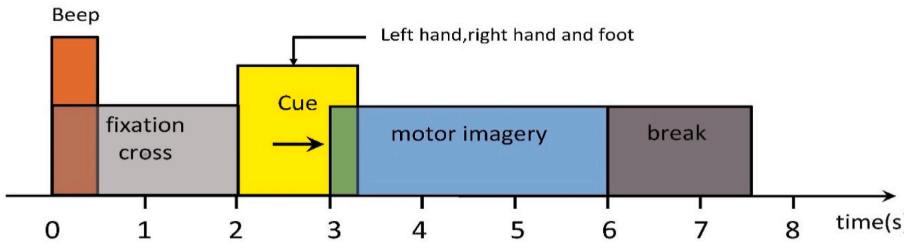

Fig. 2. Show the timeline of MI paradigm.

selection strategy to balance demands for both performance and simplicity in a BCI system. Currently, the three primary groups of channel selection techniques are filter, wrapper, and embedded [24]. The outcome of wrapper-based approaches depends on the accuracy of the used classifier and the characteristics of the channel-sourced features. Although several strategies have been presented to avoid the retraining of classifiers [25]. In comparison to wrapper strategies, the computation complexity of filter-based feature selection methods is lower [26]. Most BCIs are based on EEG because of their non-invasive nature and inexpensive recording equipment, which enables real-time operation [27]. The Motor imagery is a robust simultaneous process for differentiating psychological states related to action by imagining limb motions across the right and left sensorimotor cortex [28] and can be taken as mental practice of action without apparent the motor output. The utilization of multichannel EEG signals often results in excellent classification performance [29]. However, compared to a limited number of ideal EEG channels, multichannel signals often include a lot of unnecessary information, which adds more noise sources and can reduce the performance of motor imagery identification [30]. The channel reduction technique can successfully remove unwanted channels and choose sensorimotor area related channels. Consequently, channel selection is a crucial approach for MI-based BCI [31]. The authors of [32] proposed a novel EEG channel reduction method i.e., particle swarm optimization (PSO) which is applied in a wrapper manner with SVM for classification. Currently, channel selection method used higher-order statistics and selected channels reduces setup time and increases the accuracy and discrete wavelets transform (DWT) used for feature extraction for the BCI system [33]. In Ref. [34] developed a channel reduction technique for MI classification based sequential forward search and Bhattacharyya bound and findings suggested that the approach could notably increase classification accuracy with Bayes classifier. In Ref. [35] proposed a bispectrum-based channel reduction (BCS) strategy for BCI system. The F_score for each channel was calculated using features taken from the bispectrum and channels with appropriate information are chosen based on the F_score. A new approach for EEG channel selection based on Granger causality (GC) analysis was presented, and after sorting channels, CSP was used for features extraction, and a machine learning technique was applied to classify MI activities [36]. For non-stationarity nature of the EEG signals, standard approaches for feature extraction, such as the Fourier transform (FT), do not provide relevant results for processing in BCI application. Wavelet transform (WT) is a time-frequency analytical technique that can decompose signals and divide them into many scales, making it the best option for signal processing [37]. Joseph Fourier discovered the Fourier transformation in the nineteenth century [38]. FT converts signals from the time to the frequency domain. It is effective for stationary signals and unable to measure both time and frequency characteristics. WPD is employed for pre-processing to find features of the EEG signal [39]. Empirical mode decomposition (EMD) and DWT are techniques for analyzing different EEG signal frequency bands containing information about MI actions and they can be employed to decompose EEG in multiscale and multiresolution [40]. The authors of [41] briefly presented the feature extraction approach, which are Auto Regressive Model (AR), Independent Component Analysis (ICA), Principal Component Analysis (PCA). Moreover, the article investigated the signal processing techniques employed for the BCI system. In Ref. [42]showed that WPD gives better performance outcomes than the AR model. In Ref. [43] EEG classification system based on WPD and WPD 8th level decomposition was utilized for feature extraction. Generally, MI-BCIs use machine learning (ML) methods to detect spatial features related to movement simulation with event-related (de)synchronization (ERD/ERS) in 7–30 Hz frequency range of EEG signal, subject in this duration imagines a limbs movement [44]. The CSP algorithm [45] often detects brain activity and uses it as an input to identify the imagined body motions. Linear discriminant analysis (LDA) is commonly employed for MI tasks in BCI system [46]. In Ref. [47] purposed time domain feature extraction techniques have been used to extract most appropriate information for EEG signals related to MI activities. After feature extraction, authors employed Nearest Neighbor (kNN) classifiers to identify MI activities. The authors of [48] proved that SVM is one of the most significant technique in the BCI system and compared it with the outcome of KNN, which is frequently used for MI-EEG data. In Ref. [49] an investigation of the BCI system was discussed. This research paper explored machine learning approaches and described feature extraction methods with the time-frequency domain. In Ref. [50] demonstrated the use of three classifier system (KNN, SVM, LDA) for classifying EEG signals. The aim of this work is to classify MI activities in a more robust manner. In contrast to FT, which has a constant resolution, Wavelet Transform (WT) has multiple resolutions [51]. Therefore, WPD has been selected for this study. It is observed that Person correlation coefficient (PCC) channel selection technique combined with wavelet packet decomposition and approximate entropy has not been implemented till now and this is the main contribution of this study. In this proposed study, the two most popular classifiers, KNN and SVM are used and have many required qualities like adaptivity and noise tolerance.

3. Materials and methods

3.1. Dataset description

BCI competition IV Dataset I is used to evaluate the performance of the proposed technique and this data is publicly available [52]. The dataset was generated from seven people who performed MI activities without receiving feedback. In this study, authors use the two subjects' datasets 'a' and 'b' to estimate results because the data of three subjects are generated artificially, and the other two subjects have picked the same motor activities as subject 'a' and subject 'b'. For this EEG data set, a subject was presented with three MI tasks-both feet, right and left hand and was instructed to pick just two. The timeline of MI paradigm is depicted in Fig. 2, and subjects perform completed MI tasks per cues. EEG dataset were collected at a 1000 Hz sampling rate with bandpass filtered (BPF) between 0.05 Hz and 200 Hz. Each individual conducted 200 trials (100 trials per class) with the 100 Hz downsampled signal. To save computing effort, a version of 100 Hz of the data sampled is employed in the current experiments. Out of 59 EEG channels, 14 channels are chosen for analysis using the proposed Pearson correlation coefficient (PCC) technique with the EEG 10–20 system. Fig. 3 and Fig. 4

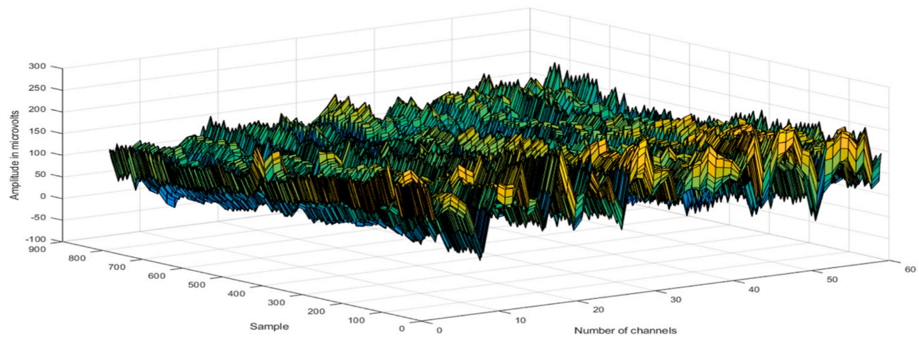

Fig. 3. Show 59 channels pictorial plot in MATLAB.

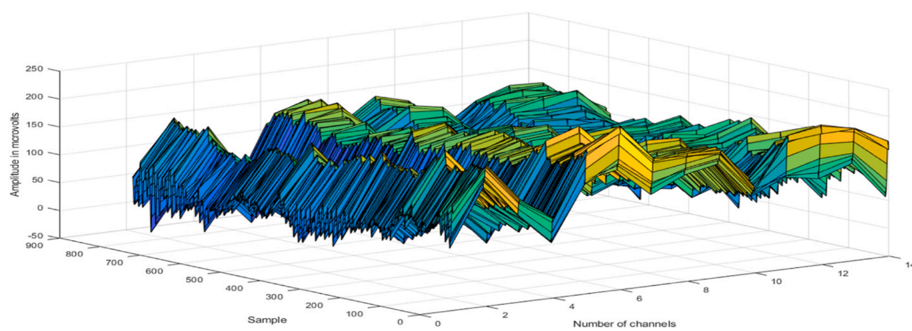

Fig. 4. Show 14 selected channels related to sensorimotor area pictorial plot in MATLAB.

depict a pictorial plot of 59 channels and selected 14 channels. More information is available at http://www.bbci.de/competition/iv/desc 1.html. Table 1 described the dataset used in this study.

3.2. Pearson correlation coefficient (PCC) based channel selection

The correlation coefficient (CC) of motor imagery (MI) channel pair denotes subject-brain connectivity and previous research was examined the similarity between MI signals for two channels [53]. In this study, the author's purpose is to eliminate the extra channels in the given dataset that are relatively uncorrelated with each other across all trials. Pearson correlation evaluations the linear relationship between two variables. The authors in this investigation assume that channels related to motor imagery carry standard information across 200 trials in which subjects execute the same motor imagery activities [54]. The covariance of the A and B (two variables) divided by the sum of their standard deviation (std) is known as the Pearson correlation coefficient.

$$\rho\,(A,B)=\sum_{i=1}^{n}\left(\frac{A_i-\overline{A}}{\rho_A}\right)\left(\frac{B_i-\overline{B}}{\rho_B}\right) \tag{1}$$

Here, $A\ and\ B$ are two observable variables, $\overline{A}$ and $\overline{B}$ are means of both variables and n represents the number of observations. Standard deviation (std) of two variable are σ_A and σ_B. In PCC [55], the value of $\rho\,(A,B)$ range 0–1 which demonstrating correlation low to high. EEG channels CC (correlation coefficient) of each pair is computed. For every trail, correlation computing from C_m (correlation matrix), from C_m mean of every row is calculated. This demonstrates that channel i and other channels have a strong correlation and channel i is most significant.

Table 1
Dataset explanation with subject wise.

S.no.	Subject name	MI Activities Selected	Dataset Size
1	a	Left hand and foot	190594 × 59
2	b	Right and left hand	190594 × 59

According to present rule, authors identified Ch_{ns} channels into one class of greater correlated channels. After that number of trails (t_n), $t_n \times Ch_{ns}$ channels have been obtained, and most channels are repeated. The channels mostly time appear which selected (Ch_{ns}). This method removes the reductant channels and the EEG dataset reduced $t_n \times Ch_n \times X_s$ to $t_n \times Ch_{ns} \times X_s$. Reduced dataset (selected channel) decreased the computation complexity for feature extraction and improve the classification accuracy for MI-BCI system. Table 2 presents the Algorithm for PCC for channel selection MI Dataset.

The authors applied the proposed channel selection method on BCI competition IV-Dataset I. To show convenience of distribution channel for all 200 trails and 14 subject-specific channels are selected for further processing in the MI BCI system which are presented in Table 3.

3.3. Wavelet packet decomposition (WPD)

Wavelet transform (WT) is a popular approach for analyzing MI-EEG signal [56]. WPD is a WT in which the sampled signal is processed through a greater number of filters than a discrete wavelet transform (DWT) [57]. The WPD can deliver multi-level decomposition of a given signal in the time-frequency domain. It allows the simultaneous use of low-frequency information for a long duration and high-frequency for a short span. The selection of number of decomposition and suitable wavelet levels are very vital in investigation of MI-EEG signal with WPD. The original data is the tree's root. The WPD can be seen as an exhaustive binary tree in its entirety and Fig. 5 show 8th level decomposition. This technique offered valuable features for BCI system for classifying MI signals.

The MI EEG signal $w(t)$, WPD is described by Ref. [59].

$$D_0^0 = w(t) \tag{2}$$

$$D_i^{q+1} = \sum_k z_0(k-2t)D_i^q \tag{3}$$

Table 2
Algorithm based on Person correlation coefficient (PCC) for channel selection.

Table no. 2. Algorithm based on Person correlation coefficient (PCC) for channel selection

1 From EEG dataset, select a fixed window of dimension $t_n \times Ch_n \times X_s$
$t_n = number\ of\ trails, Ch_n = number\ of\ all\ channels, and$
$X_s = number\ of\ sample$
2 For $i = 1{:}\ t_n$
3 Dimension =($Ch_n \times X_s$) is Z-score data in each trail.
4 Here, $A_{jk} = k^{th}\ sample\ value\ of\ j^{th}\ channel,$
$mean_i = mean\ value\ of\ j^{th}\ channel.$
and $std_j =\ standard\ deviation\ of\ j^{th}\ channel, S_{jk} =\ (X_{jk} - mean_j)/std_j.$
5 Calculate correlation coefficient (CC) and obtained correlation matrix.
$C_m =\ corrcoef({S_{jk}}^T)$ and T is the transpose of matrix, $corrcoef(.)$ is the person correlation function.
6 Obtain the mean in every row of matrix (C_m) and arrange Ch_n number of all channels in descending order to mean values and $acquire\ first\ Ch_{ns} channels.$
7 End
8 Select Ch_{ns} channels appearing a greater number of times in $number\ of\ trails$ (t_n).

Table 3
Subject-specific selected channel name for MI BCI system.

Subject name	Channel selected based on PCC	Total selected channels
Subject (a)	CFCI, CFC4, C3, C1, C2, CZ C4, C5, CCP3 CCP2, CCP4, CP1, T7, T8	14
Subject (b)	FC1, FC3, FC4, CFC4, C1, C3 CZ, C4, CCP3, CCP1, CCP2, CP1, CPZ, CP2	14

Table 4
Performance of PCC + WPD + ApEn + SVM technique.

Sr.No.	Subject	Accuracy	Sensitivity	Precision	F_Score	MCC
1	(a)	91.66%	92.33%	89.78%	90%	83.10%
2	(b)	90.10%	91.33%	88%	89.20%	82%
5	Mean	90.88%	91.83%	88.89%	89.60%	82.55%

Table 5
Performance of PCC + WPD + ApEn + KNN technique.

Sr.No.	Subject	Accuracy	Sensitivity	Precision	F_Score	MCC
1	(a)	90.33%	92.42%	88.83%	88.33%	83.20%
2	(b)	89.88%	90.83%	87.66%	87.23%	81.33%
3	mean	90.10%	91.62%	88.24%	87.88%	82.26%

Table 6
Comparative analysis of classification accuracy for BCI competition IV-Dataset I.

Sr. No.	Reference	Technique	Subject (a)	Subject (b)
1	[72]	WPD + ApEn + SVM	86.5 ± 4.6%	81.5 ± 3.9%
2	[73]	Blocks Common spatial pattern + SVM	86.10%	74.20%
3	[74]	FFT + Logistic Regression + SVM	67.78%	55.56%
4	[75]	Filter Method Based Channel Selection + CSP	86.69%	69.50%
4	[76]	Common spatial pattern + Stepwise Linear Discriminant Analysis	84.5%	82%
5	PCC + WPD + ApEn + SVM proposed technique		91.66%	90.10%
6	PCC + WPD + ApEn + KNN proposed technique		90.33%	89.88%

$$D_{2i+1}^{q+1} = \sum_k z_1(k-2t)D_i^q \tag{4}$$

$i = 0, 1, 2, \ldots, 2^{q-1}$

WPD coefficients at i^{th} node of q^{th} stage is expressed by D_i^q and $z_0(n)$ and $z_1(n)$ are marked "orthogonal filters" for decomposition. In the time-domain study, $z_0(n)$ and $z_1(n)$ are LPF (Low pass filter) & HPL (High pass filter) that assure following equation:

$$z_1(n) = (-1)^n z_0(n-1) \tag{5}$$

In the present suggested research work, WPD carried EEG signals at 8th level, providing $2^8 = 256$ nodes. The MI tasks are confined in the frequency band related to 8–32 Hz of EEG, total 256 WPD nodes are obtained, and 124 nodes are selected for 14 channels linked to the sensorimotor area of subject brain corresponding to 8–32 Hz frequency band. These 124 nodes are used with selected 14 channels for further processing in the BCI system.

3.4. Feature extraction for brain computer interface

The extraction of correct features is crucial for generation of appropriate commands. This is especially important for use with subjects, as using inferior features for classification could significantly reduce accuracy. The most popular feature is the approximate signal entropy (ApEn) used in the BCI to predict motor imagery activities.

3.4.1. Approximate entropy (ApEn)

The approximate entropy [60] introduced initially by Pincus, is a statistical approach for quantifying fluctuations' unpredictability in stochastic and deterministic data. The (ApEn) is measure the complexity of data. A lower ApEn value is determined from a regular and predictable time-series signal, whereas an unpredictable time series produces a greater positive value for ApEn. The noisy deterministic and stochastic process specialty of ApEn made it valuable in brain states research [61]. The mathematical equation for computing ApEn:

$$ApEn\ (m, r, N) = \varphi^m(r) - \varphi^{m+1}(r) \tag{6}$$

$$\varphi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} ln\ C_i^m(i) \tag{7}$$

$$C_i^m = \frac{N^m(i)}{N-m+1}\ ;\ \ i = 1 \sim N-m+1 \tag{8}$$

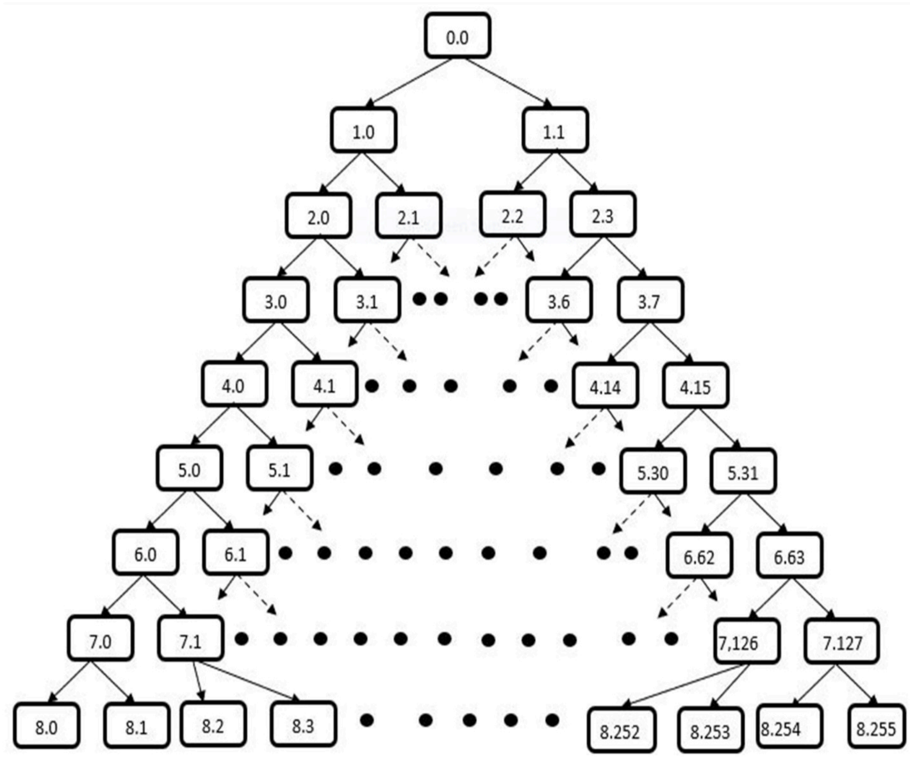

Fig. 5. WPD diagram up to eight -level decomposition [58].

Here, N denotes time series signal, $m = 2$ *and* $r = 0.1 \sim 0.25$ *standard deviation* are two fixed parameters presented in Pincus paper. The author of [62] presented comprehensive computation of ApEn with EEG in BCI system. In this proposed study, ApEn feature is calculated at selected 124 out of $2^8 = 256$ nodes for 14 channels which are strongly associated with the motor imagery activities related to the 8–32 Hz frequency and compute feature matrix of size $14\ \textit{channels} \times 124\ \textit{features} = 1736\ \textit{features}$.

3.5. Classification

Machine learning, often known as ML, is a part of artificial intelligence that systematically uses algorithms to synthesize the fundamental relationships between data and available information. From machine learning, two different classification algorithms are used in this proposed research: support vector machine (SVM) and K-Nearest Neighbors (K-NN).

3.5.1. Support vector machine (SVM)

SVM is a prominent supervised learning method that employs statistical learning theory [63]. It was first suggested for classification the information. The goal is to determine a hyperplane that divides the training data optimally in terms of predicted risk. SVM provides several benefits [64]. SVM has high classification performance because of the maximization margin of hyperplane [65]. SVM is more adaptable than traditional neural networks since it has several parameters that could be modified to attain a higher classification. SVM, unlike other classifiers, is rarely affected by the known "curse of dimensionality." It is a simple classifier. Hyper-plane could be derived by answering the constrained optimization problem well explained in the research paper [66]. The data points $\{(x_1, y_1), \ldots, (x_m, y_m)\}$ includes x patterns having y class labels. Data can be linearly divided, if there exists a vector w and a scalar d such that

$$wx_i + b \geq 1, \textit{if}\ y_i = 1 \tag{9}$$

and

$$wx_i + b \leq 1, \textit{if}\ y_i = -1 \tag{10}$$

Rewrite the above equation as follows:

$$y_i(wx_i + b) \geq 1, i = 1, 2, 3, \ldots n \tag{11}$$

$$wx_i + b = 0 \tag{12}$$

3.5.2. K-nearest neighbor (KNN)

K-NN is a nonparametric approach and simplest machine learning algorithm for classifying object in BCI system [67]. This kind of classier performs well and doesn't need training, especially in the case of two class problems [68]. The feature space contains all feature vectors that were retrieved from the sub-training set. The majority of the k-nearest neighbors from each detected feature vector are used to classify a feature vector that is part of the test data. The performance of KNN is determined by distance metric and the value of the neighbourhood parameter k, which governs the neighbourhood volume. The Euclidean metric is often used as the distance function. The local distribution of feature vectors is significant to the KNN algorithm. This algorithm's success heavily depends on an appropriate similarity function and a fair value for k. If k is too high, massive classes will dominate small classes, and if k is too little, the benefit of the KNN method will be lost [69]. The Euclidean distance between two points $y = (y_1, y_2, \ldots, y_n)$ *and* $z = (z_1, z_2, \ldots, z_n)$. Euclidean k space, y and z are the two points, distance (d) calculate from $z\ \textit{to}\ y$ or from $z\ \textit{to}\ y$ is presented in paper [70]. In this proposed study "k" = 5 and formula for Euclidean distance is as follow:

$$d(y, z) = \sqrt{\sum_i^k (y_i - z_i)^2} \tag{13}$$

4. Results with discussion

The authors of the proposed research have shown that Pearson correlation coefficient (PCC) is a successful approach for channel selection in the sensorimotor region of subject brain for motor imagery EEG signal. The PCC channel selection method selected the highly correlated channels and increased the feature extraction performance with decreased computational process time. The data for participants 'a' and 'b' from Dataset I-BCI Competition IV are employed in present proposed work. The WPD is a remarkable signal process tool for non-stationary EEG data. The WPD is carried out at the eight level, obtaining 256 WPD nodes for 14 channels most informatics channel for each segment of EEG. The motor imagery (MI) activities are confined in an 8–32 Hz frequency band for EEG. Only 124 nodes are selected out of 256 related to an 8–32 Hz frequency range for 14 channels connected to the sensorimotor area of the subject brain for further process in the MI-BCI system. After that approximate entropy (ApEn) feature is computed for 14 channels, with feature vector of size $14\,channels \times 124\,features = 1736\,features$ for each trail. The extracted features are classifying by two benchmark machine learning techniques Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). The SVM and KNN show maximum classification accuracy 91.66% and 90.33% respectively. Fig. 6 depicts the flowchart for the suggested technique for BCI system. Tables 4 and 5 illustrate the performance of the proposed scheme and Table 6 compares the study findings of proposed method with previous research papers. For performance assessment, the five statistical matrixes are developed: classification accuracy, precision, sensitivity, F1_Score and matthew correlation coefficient (MCC) (used as a measure of quality of binary class classification) [71]. Where a confusion matrix can be created to identify the values of TP (true positive), TN (true negative), FP (false positive), and FN (false negative).

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} * 100 \tag{14}$$

$$\text{Precision} = \frac{TP}{TP + FP} * 100 \tag{15}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} * 100 \tag{16}$$

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(FN + FP)(TN + FN)}} \tag{17}$$

$$\text{F1\_Score} = \frac{2TP}{2TP + FP + FN} \tag{18}$$

5. Conclusion with future scope

In this proposed work, the author's investigations on Electroencephalogram (EEG) can be helpful in motor imagery (MI) activities in BCI system. In summary, the first filter-based subject-specific channel selection technique, the Person correlation coefficient (PCC), is used to reduce the data to improve the accuracy of the MI BCI system. The advantages of implementing a channel selection method are that it minimizes computational complexity and improves the effectiveness feature extraction process. Once the channel subset is selected, it also increases the classification accuracy to generate MI control signals. This study uses a popular signal processing technique, wavelet packet decomposition (WPD). The WPD is applied for the 8th level, obtained 256 nodes for 14 most informatics channel for each segment of EEG, and out of 256, only

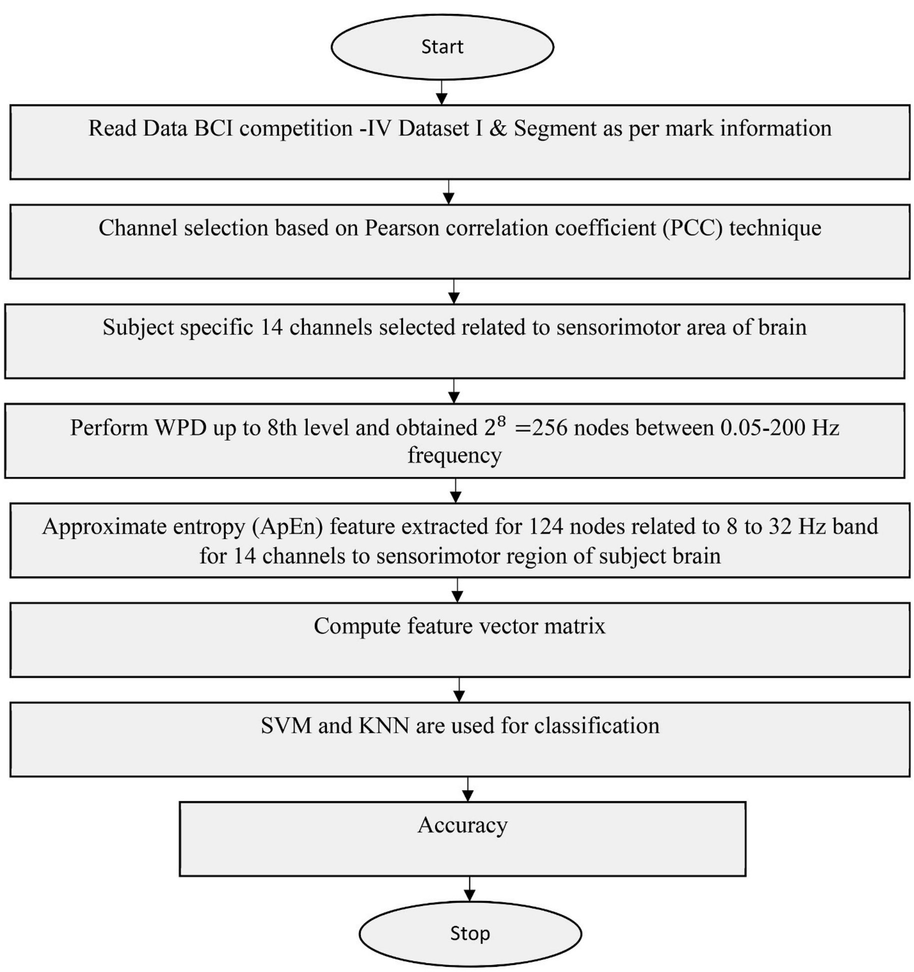

Fig. 6. Flowchart for the suggested technique PCC + WPD + ApEn + SVM/KNN for BCI system.

124 nodes are selected (8 to 32 Hz) for feature computing such as approximate entropy and construct the feature matrix for classification. Two benchmark machine learning techniques (KNN and SVM) are employed to classify motor imagery activities. The dataset employed to evaluate this study is dataset I-BCI competition IV and purposed technique successfully improve the classification accuracy of dataset. This study offers a novel technique for EEG signal processing combined with PCC + WPD + ApEn + SVM/KNN in classification of BCI system. These outcomes demonstrated that suggested technique has the potential to achieve a decent classification of EEG signals, and this proposed study can be implemented in hardware. Although appropriate outcomes are obtained, there are difficulties in a few selections of WPD nodes that must be solve in future research work. Future work should focus on wrapper methods for channel selection. There is scope for feature selection that can improve the classification accuracy and deep learning methods can be applied for classifying EEG signals in BCI system.

CRediT authorship contribution statement

Pawan: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation. **Rohtash Dhiman:** Supervision, Software, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

This investigation uses freely available BCI Competition IV-dataset I to evaluate the proposed research work

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