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Two Class Motor Imagery EEG Signal Classification for BCI Using LDA and SVM

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ABSTRACT

By 2021, WHO projects over a billion incapacitated people, with 20% facing daily functional impairments. Brain-Computer Interface (BCI) offers effortless machine control via direct brain-computer interaction, with Motor Imagery (MI) Electroencephalogram (EEG) as the key BCI foundation. The MI EEG signals were collected from the BNCI horizon2020 database for nine participants. The MI EEG data includes four tasks: imaginative movement of the left hand, right hand, feet, and tongue. There are 22 EEG channels with a sampling rate of 250Hz in the data. The MI EEG signals were band-pass filtered with a lower cut-off frequency of 0.5 Hz and an upper cut-off frequency of 100 Hz. Based on the energy count threshold approach (ECTA) nine channels were identified as dominating channels from the filtered MI EEG signals. Energy values for each channel were extracted in the ECTA method for the 3-sec window. And if the energy value of a channel for a particular window is greater than 60% of the maximum channel's energy, then the energy count value will be incremented by one. Finally whichever channels had larger energy counts were identified as a dominant channel. On these nine dominant MI EEG signals discrete wavelet transform using Daubechies 4 mother wavelet a four-level decomposition is applied, and Mu and beta rhythms were extracted. For a 3-sec window from the nine dominant channels, the energy and entropy feature values from the Mu and Beta rhythms were extracted. From the extracted features, 80% of the data is used for training Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) and 20% for testing classifier models. Both the models performed well on the test data and the results obtained had a highest accuracy 91.7±2.7 for subject-9 and these results were compared with the existing methods. The obtained results of MI EEG signals classification using BCI holds potential for revolutionizing assistive technology, stroke rehabilitation, virtual reality gaming, mental health management, human-computer interaction, biometric authentication, sports performance enhancement, and education.

1. INTRODUCTION

As a result of accidents, diseases, or aging, an increasing number of people are experiencing motor limitations or restricted mobility. According to the first-ever global assessment published by WHO and the World Bank, more than one billion people worldwide are disabled today. To help these individuals, BCIs offer a world of possibilities by allowing direct brain-to-computer communication, enabling them to control devices with minimal effort. The EEG patterns vary depending on the activity and mental state, making these signals valuable for BCI applications.

Invasive EEG methods require surgery and have high associated risks. In contrast, non-invasive methods are more practical and do not require any surgical procedures. Among non-invasive BCIs, the EEG-based BCI systems are widely used due to their high time resolution, relatively low cost, and patient convenience [1].

For MI EEG signals, feature extraction often employs Common Spatial Pattern (CSP) [2]. While CSP performs well in two-class classification tasks, it requires many electrodes [3]. Researchers proposed a subject-specific multivariate empirical mode decomposition (MEMD)-based filtering method, SS-MEMDBF, to classify MI-based EEG signals into multiple classes. This method extracts cross-channel and frequency-specific information, using the sample covariance matrix as a feature set, achieving 79.3±14.13% accuracy with 22 EEG channels [4].

In another study, power spectral density was used for two-class MI EEG classification (imagination of left and right movements) with data from the BCI Competition III dataset V, resulting in average accuracies of 61.16% with SVM and 54.06% with Naïve Bayes classifiers [5]. Guan et al. [6] proposed a method utilizing the manifold of covariance matrices from a Riemannian perspective, incorporating a subject-specific decision tree framework (SSDT) and filter geodesic minimum distance to Riemannian mean (FGMDRM) to reduce classification errors. They also developed a feature extraction and classification algorithm combining semi-supervised joint mutual information with general discriminant analysis (SJGDA) and K-Nearest Neighbor (KNN), achieving around 80% accuracy on BCI Competition IV dataset 2a [6].

Another study recorded multichannel EEG with 24 electrodes for left and right leg motor imagery tasks, extracting energy values from delta (1-5 Hz) and Mu (8-13 Hz) bands to train and test SVM and RBF, achieving 76.5% and 77.9% accuracy, respectively [7]. Additionally, 59 EEG channels were used to extract Mu/Beta rhythms, and LDA with CSP projection was employed, yielding results ranging from 57% to 90% accuracy [8].

From the literature survey, it is evident that multiclass MI EEG signal classification accuracy is not highly satisfactory [6, 9-11]. Most studies focus on left- and right-hand movements or hand versus leg movements for classification [5, 7, 12]. In the proposed work, we classify the imagination of left-hand movement and tongue movement, which show significant EEG pattern variation, resulting in better classification accuracy compared to existing methods [4, 5, 7-9].

MI EEG signals exhibit large variations in Mu and Beta rhythms, with LDA and SVM classifiers performing well in this context [13, 14]. The development of real-time, compact BCIs and consumer headsets necessitates optimizing EEG channel selection to reduce channel numbers while retaining essential information about brain processes [11, 15]. Several studies highlight that irrelevant EEG channels can introduce noise and redundant information, potentially reducing signal processing accuracy [15]. Therefore, minimizing EEG channels can improve classification accuracy. However, achieving low computational complexity and high classification accuracy with a minimal number of EEG channels remains a significant challenge in BCIs.

In reviewing current methods for acquiring MI EEG signals, it is apparent that there is a prevalent use of a high number of EEG channels. However, this approach has not introduced innovative channel reduction techniques and still encounters significant limitations in classification accuracy. To address these research gaps, our proposed method aims to optimize EEG channel selection through cutting-edge signal processing algorithms and machine learning techniques. By balancing the trade-off between the number of EEG channels and classification accuracy, our approach is designed to enhance the effectiveness of MI-based BCIs and contribute to a deeper understanding of the underlying neural mechanisms.

In our study, MI EEG signals were collected for nine subjects from the BNCI horizon2020 website. Analysis of the 22 MI EEG signals revealed that nine channels, primarily from the frontal, central, and parietal lobes, were dominant. These nine-channel MI EEG signals were processed using discrete wavelet transform, and Mu and Beta rhythms were extracted using a four-level wavelet decomposition technique. Energy and entropy feature values of the Mu and Beta rhythms were extracted from these dominant channels over a 3-second window. These extracted features were then utilized for training and testing the LDA and SVM classifiers. The performance results obtained with these classifiers were compared with those from existing methods. Furthermore, the classifier outputs can be converted into control commands for external devices such as wheelchairs, exoskeletons, robotic arms, and home appliances, enhancing the applicability of this technology in real-world scenarios.

2. METHOD AND MATERIALS

The strategy and materials used in the proposed work are illustrated in Figure 1. The data were collected from the BNCI Horizon 2020 website, specifically from BCI Competition IV dataset 2a [16]. Each subject's data includes 22 EEG channels and 3 EOG channels, with the left mastoid serving as the reference. Only the EEG channels were used for processing in the proposed work. The collected MI EEG information is shipped off channel determination block where the prevailing channels were recognized from 22 MI EEG channels. The dominant channels were identified using ECTA. In ECTA method the energy of each channel for the 3-seconds window is estimated and which is compared with the 60% of the maximum energy of that particular channel. If the energy value for the 3-seconds window is greater than the threshold value then the count value for that particular channel will be incremented by one. This procedure is repeated for the all the 22 channels and as a result 9-channels were identified as the dominate. These dominant channels are handled utilizing wavelet decomposition method and decomposed into four levels in the signal processing stage as mentioned in the Figure 1. From the extracted rhythms Mu and Beta band is separated. From these two bands Energy and Entropy feature values were extracted from every dominant channel. From the extracted features, 80% of the data was used for training, while the remaining 20% was used for testing classifier models. The results obtained were analyzed and compared with existing methods.

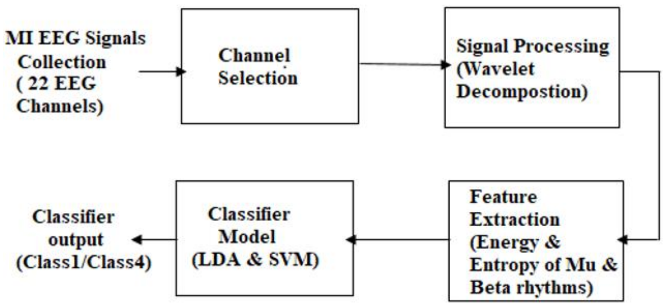

Figure 1. Block diagram of proposed work

2.1 Data collection

The data used in this study was collected from the BNCI Horizon 2020 website, specifically from the BCI Competition IV dataset 2a [16]. This dataset comprises MI EEG signals from nine healthy subjects, each participating in two sessions: a training session and a test session. The recorded tasks include the imagination of movements of the left hand (Class 1), right hand (Class 2), both feet (Class 3), and tongue (Class 4). Each subject's data includes 22 EEG channels and 3 EOG channels, with the left mastoid serving as the reference. Each subject participated in two recording sessions, each consisting of six runs separated by short breaks. Each run included 48 trials (12 trials per each of the four classes), resulting in a total of 288 trials per session.

During the experiment, subjects were seated comfortably in an armchair facing a computer screen. At the beginning of each trial (t = 0 s), a fixation cross appeared on the black screen, accompanied by a brief acoustic warning tone. After two seconds (t = 2 s), a visual cue in the form of an arrow pointing left, right, down, or up appeared on the screen for 1.25

seconds. Subjects were instructed to perform the motor imagery task corresponding to the cue until the fixation cross disappeared.

2.2 Dominant channel selection

One of the major concerns with BCI applications is that when they are implemented in real-time, the number of electrodes used to acquire MI EEG signals must be kept as low as possible so that the subject feels comfortable and can perform well in the activities. Therefore, this in turn helps in getting better MI EEG signals so that these signals can be classified easily and converted into action commands for different applications. So, in the proposed work, we implemented a methodology named ECTA that aids in reducing the number of MI EEG channels. The implementation of this proposed method uses the following steps:

Step 1: Find the maximum energy of each dominant channel for the total duration of the MI EEG signal.

Step2: For every 3-sec window, energy values for each channel were extracted.

Step 3: If the extracted energy value is greater than 60% of the maximum energy of that channel, then increase the energy count value by one (The initial energy count value is zero).

The mathematical condition for the above step is represented as follows:

If $\sum_{n=1}^{22} E_{channel\_n} > (0.6 * E_{\max\ \_channel\_n})$ - then increase the energy count value for the channel number 'n'. Where, $E_{channel\_n}$– Energy of the channel number ranging from 1 to 22 for three seconds window. $E_{\max\ \_channel\_n}$ – Maximum Energy of the channel number ranging from 1 to 22 for total duration of the MI EEG signal.

Table 1 shows the computed energy count for each channel of subject-1, and it can be seen that the energy count ranges from 0 to 46. Based on the energy count value, nine dominant channels were identified. The channels with energy count ranging from 30 to 46 were identified as dominant channels. The remaining eight subjects were analyzed in a similar manner. Based on the ECT approach from the Frontal, Central, and Parietal lobes, nine channels (Fc1, Fcz, Fc2, C3, Cz, C4, P1, Pz, and P2) were identified as the dominating channels for each subject. In the Figure 2 the number (3, 4, 5, 8, 10, 12, 19, 20, and 21) in bold circle represents the dominant channel and other numbers (1, 2, 6, 7, 9, 11, 13, 14, 15, 16, 17, 18, and 22) are rejected channels. Although several of the Centro parietal channels (CP3, CP1, CPz, and CP2) are dominant, they are not employed for further study because channels from the Central and Parietal lobes have already been picked for the feature extraction. In addition, channel 22 is discarded because the signal level of the Occipital region can be altered by visual impacts. As described in the Data Collection section, the MI EEG recordings were conducted with subjects seated comfortably in an armchair in front of a computer screen. The motor imagery task was prompted by visual cues in the form of arrows pointing left, right, down, or up, which appeared on the screen and remained for 1.25 seconds [16]. Therefore, as this visual effect can affect signal intensity in channels from the occipital lobes, channels from this lobe are not examined for feature extraction. The proposed method of selecting dominating channels reduces computational complexity while simultaneously could provide significantly more comfort to the subject during real-time recording and implantation of proposed work.

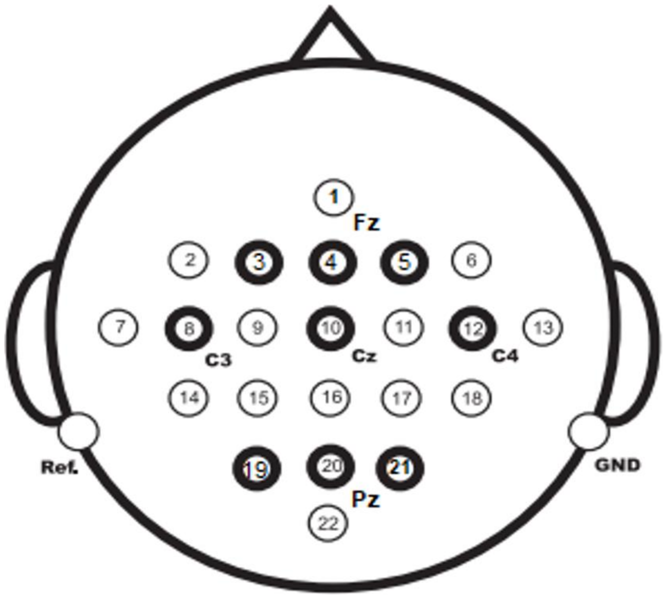

Figure 2. 10-20 Electrode system

Table 1. Energy count of each channel

Channel Number - Name	Energy Count Value (Energy > 60% of Maximum Energy)
1-F_z	13
2-Fc3	19
3-FC1	35
4-FCz	46
5-FC2	39
6-Fc4	26
7-C5	0
8-C3	37
9-C1	25
10-Cz	39
11-C2	29
12-C4	30
13-C6	4
14-CP3	35
15-CP1	33
16-CPz	36
17-CP2	35
18-CP4	20
19-P1	46
20-Pz	43
21-P2	44
22-POz	45

2.3 Discrete wavelet transform

MI EEG signals are non-stationary signals in the traditional sense. Short-time Fourier transforms (STFTs) were used to analyze EEG data as a time-frequency analysis method, although it was found that the window selection is crucial for the short-time Fourier transform. The wavelet transform, which is a multi-resolution analysis approach, provides a solution to this problem and could provide a more precise temporal localization. For non-stationary signals, the Wavelet transform is a new two-dimensional time-scale processing approach [17]. Its primary benefit is that it provides simultaneous information on the frequency and temporal location of signal characteristics in terms of signal representation at several resolutions corresponding to various time scales. The Discrete Wavelet Transform (DWT) produces two coefficients, Di and Ai, which are the down sampled outputs of the high-pass and low-pass filters at each decomposition level [18]. A four-level decomposition employing a Daubechies wavelet of order 4 (db4) is applied to the nine dominating MI-EEG signals. Because db4 wavelet stands as a widely employed choice for EEG signal decomposition due to its advantageous properties such as compact support, orthogonality, and vanishing moments, facilitating effective analysis and feature extraction of both transient and oscillatory components in EEG signals. Higher-order mother wavelets, possessing more vanishing moments, offer increased localization in both time and frequency domains, potentially improving resolution in signal decomposition and enabling finer detail capture in MI-EEG signal dynamics. Two rhythms, the Mu band and the Beta band, were extracted from MI-EEG data using the wavelet decomposition approach.

In the flow diagram of Figure 3, the approximated and detailed coefficients of the MI-EEG signals utilizing four-level wavelet decomposition are shown. The Energy and Entropy features were derived from the wavelet coefficients (Cad3 and Cad4), which had a frequency range of 15.6Hz to 31.2Hz for Cad3 and 7.81Hz to 15.6Hz for Cad4, as shown in the Figure 3.

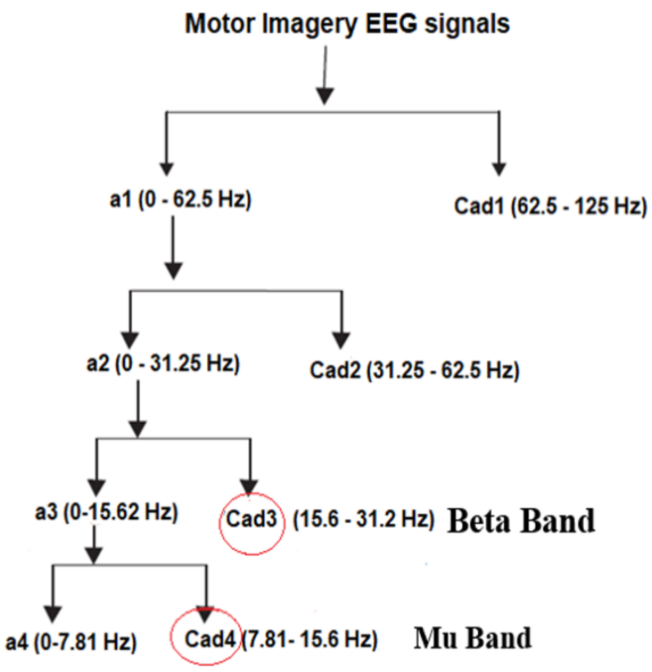

Figure 3. Frequency representation of approximated and detailed coefficients of MI-EEG signals

2.4 Feature extraction

In BCI literature, the most commonly used features in MI-based BCI applications for the classification of multiple MI tasks are power spectral density and energy of Mu and delta band. In the proposed work for all the 9-subjects two different features namely, energy and entropy from Mu and Beta bands were extracted for 288 trials per session from a 3-seconds window. The features were extracted only from 9-dominant channels (Fc1, Fcz, Fc2, C3, Cz, C4, P1, Pz, and P2) using the following mathematical expressions:

$$\text{Energy} = \sum_{i=1}^{n} S_i^2 \qquad (1)$$

where, S is the MI-EEG signal.

$$\text{Entropy} = -\sum_{k=1}^{n} P_k * log_2(p_k) \qquad (2)$$

where, P_k is the probability of occurrence of k^{th} EEG sample.

The extracted features from all the nine subjects were used for testing and training both LDA and SVM classifiers. Eighty percent of the features were used to train the classifiers, while twenty percent of the data was utilized to test them. The resulting results were compared to existing approaches. The performance of each subject with both the classifiers is explained in the next section. In the following section, we will look at how each subject performed with both classifiers.

2.5 Classification

In BCI literature, LDA and SVM are frequently used for categorizing MI EEG tasks, often achieving better classification accuracy compared to other models. SVM, in particular, is regarded as a highly promising tool for classifying single EEG trials [13, 14]. Ma et al. [14] highlighted that SVM effectively addresses issues related to small sample sizes and high-dimensional data, resulting in improved classification accuracy.

LDA and SVM are also used in the proposed method to classify two classes of MI EEG data. The extracted features from the data set are loaded into excel sheet. The excel sheet file with the energy and entropy features were fed as input to the different classifiers using Classification Learner App in MATLAB software. This App in MATLAB offers the advantage of intuitive and interactive model building for classification tasks, simplifying the process for users without extensive programming or machine learning expertise.

LDA is a popular supervised learning method that is widely used for dimensionality reduction as well as classification tasks, particularly in the context of two-class classification situations (Class1, Class4). Through statistical modeling of feature distributions and subsequent computation of an optimal decision boundary that maximized between-class distance while minimizing within-class variance, LDA worked by identifying the best linear combination of proposed features that effectively separated the classes (Class1 and Class 4). This illustrated a linear border in the feature space and is the quintessential LDA. Specifically, LDA is a strong technique that works well for binary classification problems where classes can be clearly defined by a linear border. When faced with new data, LDA allocated class membership based on the highest posterior probability relative to this decision boundary.

In the proposed work, an SVM model with a linear kernel function is utilized. Using a linear kernel in SVM is a powerful method for binary classification tasks. SVM maximizes the margin, which is the distance between the hyperplane and the closest data points, or support vectors, by identifying the optimal hyperplane in the feature space. By calculating dot products between feature vectors, the linear kernel function in SVM effectively transforms the data into a higher-dimensional space where class separation is feasible. The objective is to identify a hyperplane that minimizes the risk of overfitting while effectively classifying data and generalizing well to unseen data. New data points are classified based on their position relative to the hyperplane. In summary, SVM with a linear kernel provided a reliable and effective solution by determining the best decision boundary.

3. RESULTS AND DISCUSSION

In this study, LDA and SVM classifiers are trained and tested using distinct features extracted from the Mu and Beta bands. Both networks are trained with 80% of the data, with the remaining 20% of the data being utilized to test the classifiers. For each subject, the findings achieved using both networks are listed below. Two methods were used to classify MI EEG tasks in the proposed research work. Only the energy of Mu and Beta bands from 9 separate dominant channels was collected and utilized to train and evaluate both classifiers in method-1. Similarly in method-2 the Energy and Entropy of Mu and Beta rhythms were extracted and also tested both the classifiers (LDA and SVM). The results obtained with both methods were analyzed, compared, and tabulated below.

Table 2. LDA and SVM classifier accuracy

Subject	LDA		SVM	
	Avg. Accuracy±SD with Energy Feature	Avg. Accuracy±SD with Energy and Entropy Feature	Avg. Accuracy±SD with Energy Feature	Avg. Accuracy±SD with Energy and Entropy Features
1	86.6±2.36	89.1±3.7	81.4±5.36	83.8±0.7
2	61.3±4.31	66.8±4.6	65.35±0.9	68.4±8.5
3	88.78±3.2	89.8±1.4	89.92±1.45	91.2±2.16
4	78.94±5.13	74.62±2.4	77.56±6.01	79.6±1.5
5	57.2±4.41	65.9±3.4	67.72.18±2	68.4±3.01
6	62.46.18±4.75	68±3.7	66.68±4.48	69.5±5.3
7	84.22±4.48	85.6±7.3	84.92±1.98	86.6±3.1
8	79.3±6.86	80.6±3.3	81.04±3.99	82.8±1.9
9	87.38.3±1.45	89.6±2.7	89.92±1.45	91.7±2.7

Table 3. The average energy and entropy of mu and beta bands for subject 2

Channel Number - Name	Subject 2 – Class 1				Subject 2 –Class 2			
	Avg. Energy of Mu Band	Avg. Energy of Beta Band	Avg. Entropy of Mu Band	Avg. Entropy of Beta Band	Avg. Energy of Mu Band	Avg. Energy of Beta Band	Avg. Entropy of Mu Band	Avg. Entropy of Beta Band
3-fc1	19.06	20.20	1.93	2.12	18.26	15.62	1.96	2.15
4-fcz	21.37	20.76	1.89	2.09	20.50	16.32	1.90	2.12
5-fc2	20.80	20.66	1.89	2.09	19.69	16.14	1.91	2.13
8-c3	14.05	19.13	2.08	2.22	13.37	14.49	2.09	2.24
10-cz	20.43	20.96	1.88	2.10	19.69	16.47	1.89	2.13
12-c4	19.62	20.65	1.92	2.11	17.98	15.94	1.95	2.16
19-p1	14.00	18.55	2.06	2.24	14.27	14.56	2.05	2.25
20-pz	16.11	19.08	1.98	2.20	15.91	15.06	2.00	2.21
21-p2	16.23	18.90	1.97	2.19	15.93	14.90	2.01	2.21

Table 4. The average energy and entropy of mu and beta bands for subject 9

Channel Number - Name	Subject 9 – Class 1				Subject 9 – Class 2			
	Avg. Energy of Mu Band	Avg. Energy of Beta Band	Avg. Entropy of Mu Band	Avg. Entropy of Beta Band	Avg. Energy of Mu Band	Avg. Energy of Beta Band	Avg. Entropy ofMu Band	Avg. Entropy of Beta Band
3-fc1	27.61	9.37	1.83	2.30	43.93	11.79	1.65	2.10
4-fcz	31.21	9.97	1.77	2.25	48.20	12.42	1.60	2.09
5-fc2	31.39	9.68	1.75	2.29	47.39	11.95	1.59	2.13
8-c3	31.68	9.71	1.81	2.35	69.02	16.64	1.47	1.98
10-cz	36.50	10.08	1.70	2.26	62.24	13.62	1.54	2.03
12-c4	42.53	11.64	1.66	2.21	83.23	18.78	1.42	1.91
19-p1	53.19	9.72	1.60	2.28	106.27	15.70	1.40	2.02
20-pz	63.33	11.17	1.54	2.20	111.93	16.24	1.41	2.00
21-p2	65.17	11.39	1.53	2.20	108.78	16.06	1.41	1.98

In the proposed Method 2, classification results using extracted features of energy and entropy from Mu and Beta rhythms show improvement compared to the first method. From the result in Table 2, it is noticed that the LDA and SVM accuracy is around 90% for some of the subjects (Subject 1, 3, and 9), for some subjects (Subject 4, 7, and 8) the classification accuracy is around 80% but for the few subjects (subject 2, 5 and 6) the classification accuracy is around 65% only. The extracted features Energy and Entropy of Mu and Beta bands were shown significant variation for the two-class MI tasks. So, the classification accuracy of some subjects (Subject 1, 3, 4, 7, 8 and 9) is far better than that of subjects 2, 5 and 6.

The Extracted feature values from Mu and Beta band for subject-2 and subject-9 are projected in Table 3 and Table 4. For subject-2 most of the feature values of Mu and Beta band of Class-1 and Class-2 were similar. As the some of the feature values were similar between class-1 and class-2, Therefore, both proposed classifier models misclassified Class 1 as Class 2 and Class 2 as Class 1 for some inputs. Because of the misclassification of the classifier models, the average classifier accuracy obtained for subject-2 is 66.8±4.6 with LDA and 68.4±8.5 using SVM. Whereas the same feature values of Mu and Beta band for Class-1 and Class-2 of subject-9 were shown much difference in Table 4, as a result, the classifier accuracy of this particular subject is 89.6±2.7 using LDA and 91.7±2.7 with SVM. From these two cases it is clear that the subjects (Subject 1, 3, 4, 7, 8 and 9) who had much variation in feature values for both the classes could able to produce better accuracy and others (subject 2, 5 and 6) were not able to give better performance. And also, it is clear that the subjects were required enough training to produce better MI EEG signals. If the subjects could able to produce better MI EEG signals for different tasks, the classifier models can produce better accuracy.

The study of each subject using LDA and SVM classifiers is shown in Figure 4. Subjects 1, 3, 7, 8, and 9 did better than the other subjects, according to this proposed method-1. Another feature entropy is extracted to improve classification accuracy, and the results achieved with the approach are presented in Figure 4. In comparison to proposed method-1, the classification accuracy improves after adding another new feature Entropy, as seen in Figure 5.

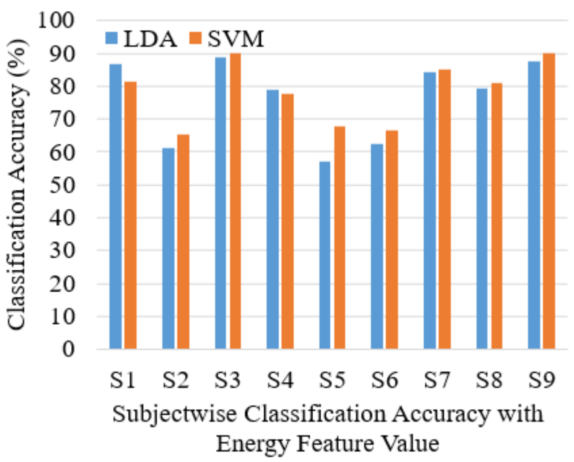

Figure 4. Performance evaluation of proposed system based on energy

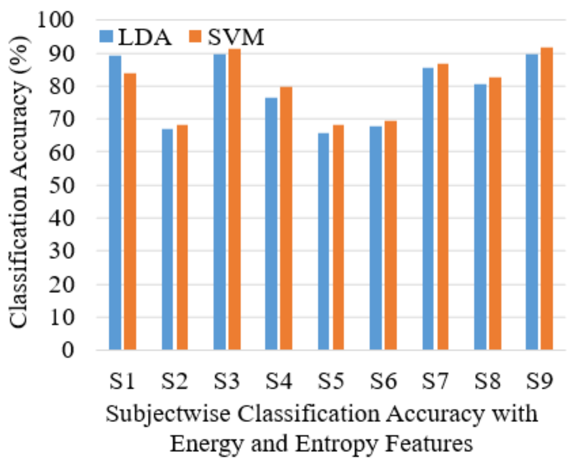

Figure 5. Performance evaluation of proposed system based on energy and entropy

The proposed method achieved better results for two-class MI EEG task classification using the BCI Competition IV data compared to previous research [4, 5, 7, 19, 20]. In study [21], sparse Common Spatial Pattern (SCSP) features and regularized discriminant analysis (RDA) were utilized for motor imagery EEG classification, which improved feature selection and the robustness of classification. However, the model's reliance on extensive parameter tuning and its lower performance on synthetic data may restrict its generalizability. For MI EEG tasks, classification accuracy can be enhanced if subjects remain focused on the tasks, leading to more distinct EEG data for different MI tasks. Consequently, further improvements in accuracy can enable the classification results to effectively control external devices such as wheelchairs, exoskeletons, and robotic arms.

4. CONCLUSION

In this study, MI EEG data was acquired from the BNCI Horizon 2020 website. The dataset comprises 22 EEG channels. The primary innovation of our approach lies in the reduction of EEG channels from 22 to 9 using the energy count thresholding technique. This reduction significantly decreases computational complexity while enhancing the classification accuracy of proposed models. Subsequently, the nine dominant MI EEG channels were employed for extracting MU and Beta rhythms, which served as the basis for deriving feature values pertaining to energy and entropy. These extracted feature values were used to train and test LDA and SVM classifiers. The obtained results were benchmarked against analogous existing models. Notably, our study reveals that employing merely two minimal features, namely energy and entropy, is adequate to achieve over 90% accuracy with our proposed classifier models, outperforming conventional methods. Moreover, the utilization of only two features for LDA and SVM testing indicates a reduction in classification time. Consequently, our proposed methodology excels over existing approaches in terms of the reduced number of channels and features utilized, as well as superior classification accuracy.

In the proposed methodology, it is evident from Table 2 showcasing classifier performance that there remains room for improvement in the classification accuracy for certain subjects (subject 2, 5 and 6). Additionally, although the current approach focuses solely on a two-class MI EEG classification, there exists potential to expand the number of classes in future investigations. Moreover, there is a crucial objective to implement this method in real-time for various BCI applications, enabling control over external devices such as wheelchairs, exoskeletons, robotic arms, home appliances, and more.

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