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Enhanced Motor Imagery Classification through Channel Selection and Machine Learning Algorithms for BCI Applications

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Abstract

Brain-Computer Interface (BCI) applications utilizing Electroencephalography (EEG) signals have garnered significant attention for their potential to facilitate through communication between the brain and external devices. EEG-based BCIs offer a non-invasive means to interpret neural activity, enabling a range of applications in healthcare, gaming, and cognitive neuroscience. This study explores motor imagery (MI) EEG signals classification, employing a variety of signal processing techniques as well as machine learning algorithms to increase accuracy and reliability. Using data from the BCI Competition IV dataset, the proposed methodology involves EEG band separation via Butterworth bandpass filters, channel selection through a wrapper method using K-nearest neighbors (KNN), and classification of motor imagery tasks. The study demonstrates a high classification accuracy of 98% across different motor imagery tasks, highlighting the effectiveness of the proposed approach. This method not only shows promise for BCI applications aimed at assisting individuals with motor disabilities but also for gaming and potential security applications such as user authentication. Future work will focus on further enhancing the model's accuracy and exploring its integration into diverse practical applications.

Keywords: Motor Imagery, KNN, Machine Learning, BCI Application.

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1. Introduction

BCI applications utilizing EEG signals have gained considerable attention due to their potential to facilitate direct communication between the brain and external devices. EEG-based BCIs offer a non-invasive means to interpret neural activity, enabling a range of applications across various domains. In healthcare, EEG-based BCIs hold promise for assisting individuals with motor disabilities by enabling them to control prosthetic limbs, wheelchairs, or computer interfaces using their brain signals alone. Moreover, EEG-based BCIs are being explored for neurological rehabilitation, aiding in the recovery of motor function after stroke or spinal cord injury. Beyond healthcare, these BCIs find applications in gaming, where users can interact with virtual environments using their brain activity, and in cognitive neuroscience research, allowing for the investigation of neural correlates of cognitive processes in real-time. The continuous advancements in signal processing techniques and machine learning algorithms further enhance the accuracy and reliability of EEG-based BCIs, paving the way for their integration into everyday life for diverse applications.

A range of studies have explored the motor imagery EEG signals classification. Chang (2022) [1] introduced a dual channel attention module migration alignment with convolution neural network, achieving an 86.03% classification recognition rate. The multivariate variational mode decomposition method was used to find common patterns in the frequency domain across all EEG channels. Various features from each EEG signal, including those related to time, frequency, nonlinear characteristics, and shape were extracted. To improve the classification of different motor imagery EEG signals, a mix of feature selection methods has been used, combining wrapper and filter techniques, and tested different channel combinations. [2]. Channel oriented techniques used for classification of motor imagery actions are discussed in the paper [3]. CNN based deep learning model is proposed in the article [4]. The classification accuracy of 69.2% is achieved in this method. Residual network is proposed to separate the motor imagery actions in [5]. 91.6% of accuracy was achieved. Statistical features and nonlinear parameters are taken as features for the prediction of multiple MI tasks. Ensemble method of machine learning is employed in the classification [6]. Temporal-Spectral-attention with wavelet method is used in [7] to get important discriminative characteristics between MI tasks by weighting features of EEG on time-frequency maps. Principle component analysis is used to select the importance channel selection and kernel extreme learning machine is employed in the motor action classification in [8]. LSTM and CNN based hybrid deep learning network is used for classification in [9]. The time domain EEG signals are converted to images using Continuous wavelet transform (CWT) for better classification results. Spatial representation fusion method is used in decoding motor imagery EEG signals in [10].

2. Methodology

2.1 Data Description

The Motor Imagery EEG signals used in the proposed work was obtained from BCI competition IV data set [11]. Nine volunteer's EEG data were recorded on the scalp using AgCl – 22 channel electrodes. During EEG recording, the volunteers are asked to imagine one out of four different actions to record the motor imagery task EEG. The four different tasks are Left, Right hand movements, Foot movement and Tongue movement. Total 288 motor imagery trials were recorded with 72 trials per motor imagery task. The Montage of EEG electrode fixing is given in Figure 1. In the proposed experiment, an EEG recording machine with 22 scalps EEG electrodes built on international 10–20 system is used. The electrodes including Frontal "(Fz, FC3, FC1, FCz, FC2, FC4)", central"(C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2, CP4)" and Parietal "(P1, Pz, P2, and POz)" Electrodes, and two references (Left mastoid, and right mastoid grounding), the REF and GND are taken as reference points. The data sampling rate is 250 Hertzs and 50Hz notch filter is used to filter the power system line noise. Figure 2 shows the flow diagram of the proposed.

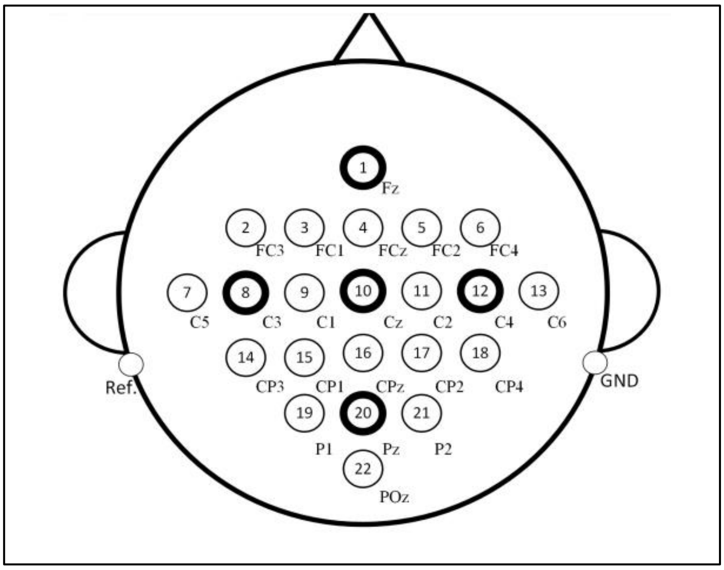

Figure 1. Montage of EEG Electrodes. [13]

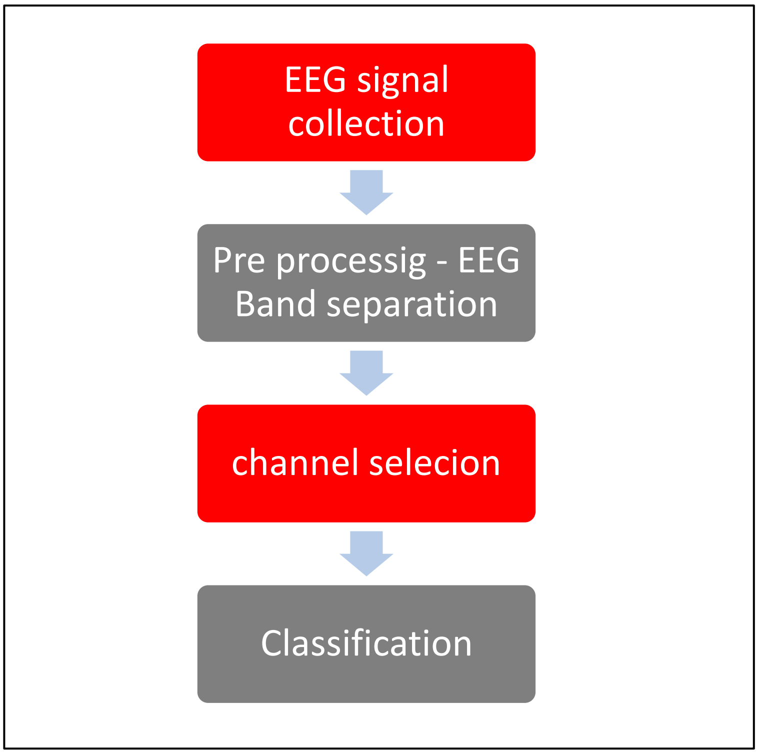

Figure 2. Flow Diagram of Proposed Work

2.2 EEG Band Separation

Frequency EEG bands are determined using the EEG signal's frequency characteristics, which are analyzed using spectral analysis techniques. Hans Berger [12] discovered EEG signals and he discovered that the Alpha and Beta waves (8-30 Hz) are present in the brain during conscious states. William Grey Walter, a British neurophysiologist, further expanded the understanding of EEG patterns. He stated the theta waves (4–7 Hz) and delta waves (0.5–3.5 Hz) and studied their relationship with different states of consciousness. Butterworth Band pass filter with order n=12 is used to separate the bands from combined EEG signal. The transfer function of the filter is given in,

$$H(z) = k\,\frac{(1-z(1)z^{-1})(1-z(2)z^{-1})\ldots\ldots(1-z(n)z^{-1})}{(1-p(1)z^{-1})(1-p(2)z^{-1})\ldots\ldots(1-p(n)z^{-1})} \quad (1)$$

Where z-Zeros, p-poles and k is gain.

2.3 Channel Selection

The EEG signals are non-stationary signals and they showed better classification accuracy in the distance based classification algorithm like KNN. But the distance-based classification algorithms are greatly affected by the 'dimensionality' problem. When the training data has too many dimensions, it can cause the machine learning classifier to overfit, leading to lower classification accuracy on test data. In order to deal with this problem, dimensionality reduction or feature reduction is applied in this proposed work. In this EEG data, the EEG electrodes or channels are considered as features. The number of channels is limited based on their ability to classify the motor imagery tasks. Filter Methods, Wrapper Methods, Embedded Method, Principal Component Analysis, Linear Discriminant Analysis, t-distributed Stochastic Neighbor Embedding, Auto encoders are some popular techniques used for feature dimension reduction. In this proposed work, wrapper method is employed. A model is used in the proposed method to identify the best and worst performing features and recursively eliminate the least important features based on classification accuracy. K-nearest neighborhood (KNN) algorithm is used as the model. The features are ranked based on classification accuracy. This method provides a simple way to rank features based on their importance in a KNN classifier.

2.4 Classification

KNN is a nonparametric algorithm where there are no explicit assumptions about the functional form of the underlying data content distribution and the algorithm does not build a model during the training phase but instead memorizes the training dataset. For a given test instance, KNN identifies the K closest training samples in the feature set and predicts the output based on the majority class. A smaller value of K makes the model sensitive to noise, while a larger value smoothens the decision boundaries. The distance between instances is typically calculated using the Euclidean distance.

$$\text{Euclidean\_Distance} = \sum_{i=1}^{n} (x_i - y_i)^2$$

2.5 Performance Metrics

The accuracy of the proposed model is evaluated by BCI -2A data set. The accuracy is calculated for every action. The Accuracy is calculated using the formula given below.

Accuracy %= Number of correct predicted actions/ Total number of actions.

2.6 Results and Discussion

2.6.1 Pre processing

The recorded EEG signal is separated into EEG bands as Delta(0.5 to 4Hz), Theta(4-8 Hz), Alpha(4- 8 Hz), Beta(8-13 Hz),Gamma(13-30 Hz) using Butterworth band pass filter. The original EEG and Delta, Theta, Alpha, Beta, Gamma bands are illustrated in Figure 3(a),(b),(c),(d),(e),(f).

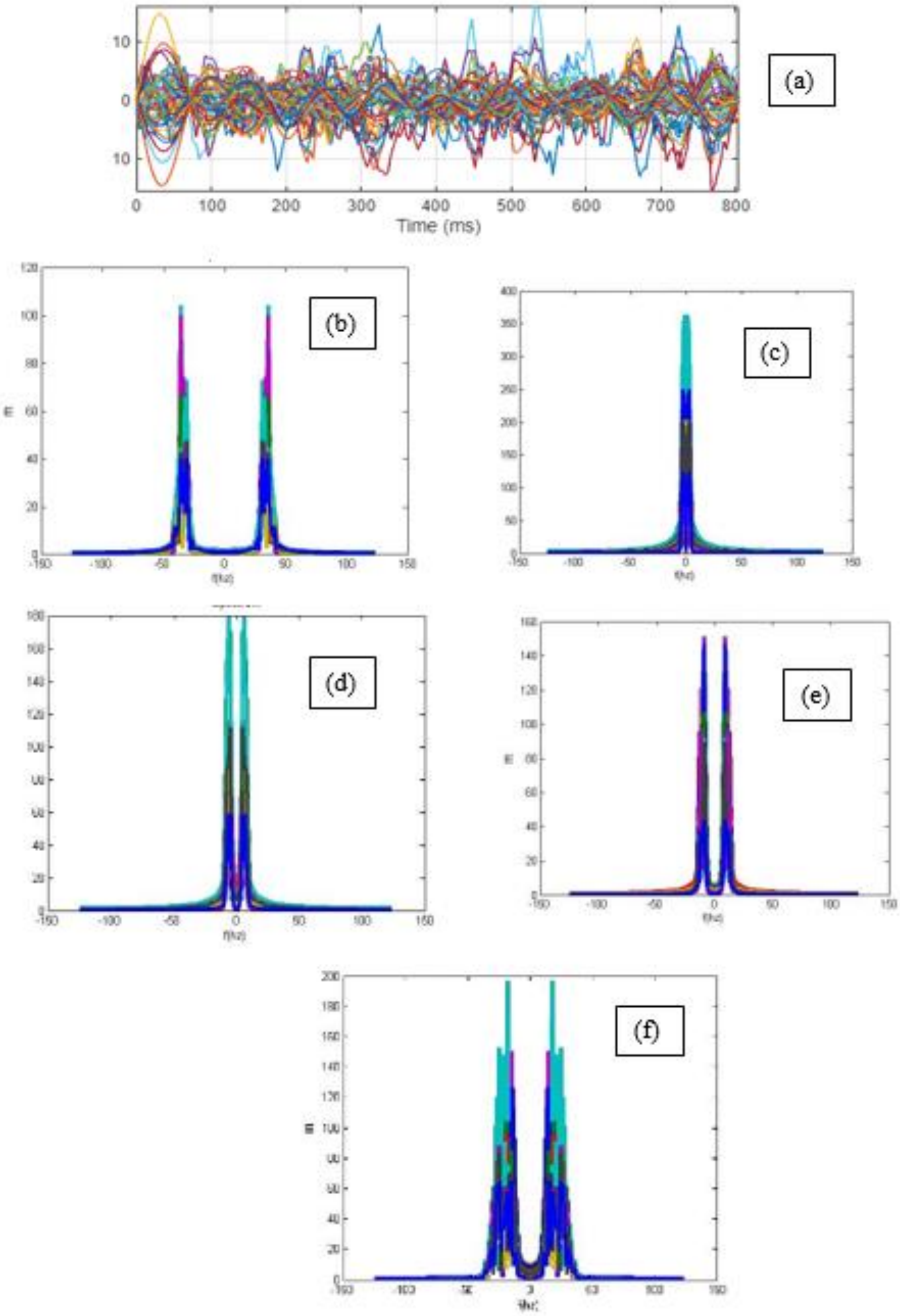

Figure 3 (a)- Original EEG, (b)-Delta Band, (c)-Theta Band, (d)- Alpha Band, (e)Beta band, (f)-Gamma Band

Figure 3. Preprocessing

2.6.2 Channel Selection

Feature selection KNN algorithm is applied to each band of EEG signals. The top 3 important channels are tabulated in Table 1. The K-values is taken as 3. Among the 22 channels, 5 channels (C4, C5, C3, CZ and C6) are selected for further processing. The Table 1 shows the three important features in each of the EEG band.

Table 1. Top 3 Important Features in Each of EEG Band.

Patient no	**alpha**	**beta**	**theta**	**Delta**	**gamma**
Patient 2	channel 5,6,13	channel 6,7,8	channel 6,7,8	channel 1,5,6	channel 4,5, 10
Patient 3	channel 7, 10,13	channel 6,7, 13	channel 9, 10,15	channel 3,8,15	channel 6,7, 11
Patient 4	channel 7,8,15	channel 13, 21,5	channel 7, 13,16	channel 9,13, 18	channel 4,15,20
Patient 5	channel 2,6,21	channel 2,7, 8	channel 6,7,8	channel 13,18,21	channel 1,8,21
Patient 6	channel 7,13, 22	channel 2,7, 13	channel 2,3,12	channel 1,2,13	channel 1,3,9
Patient 7	channel 1,7,13	Channel 1,7,16	Channel 7,10,13	Channel 1,10,13	Channel 6,13,14
Patient 8	Channel 6,7,13	Channel 7,10,13	Channel 5,6,7	Channel 1,7,13	Channel 2,5,11
Patient 9	Channel 6,7,22	Channel 7,8,10	Channel 7,8,13	Channel 7,13,22	Channel 2,13,14
EEG_channel 6-FC4; EEG_Channel 7- C5; EEG_channel 8- C3; EEG_channel 10-CZ; EEG_channel 13- C6					

2.6.3 Motor Task Classification

The selected channels's EEG Band signals are given to KNN classifier for motor imagery task classification. The sample classfication is given in the Figure 4. Every band of EEG signals are classified separately, and based on the voting method the motor imagery action of EEG signal is determined.

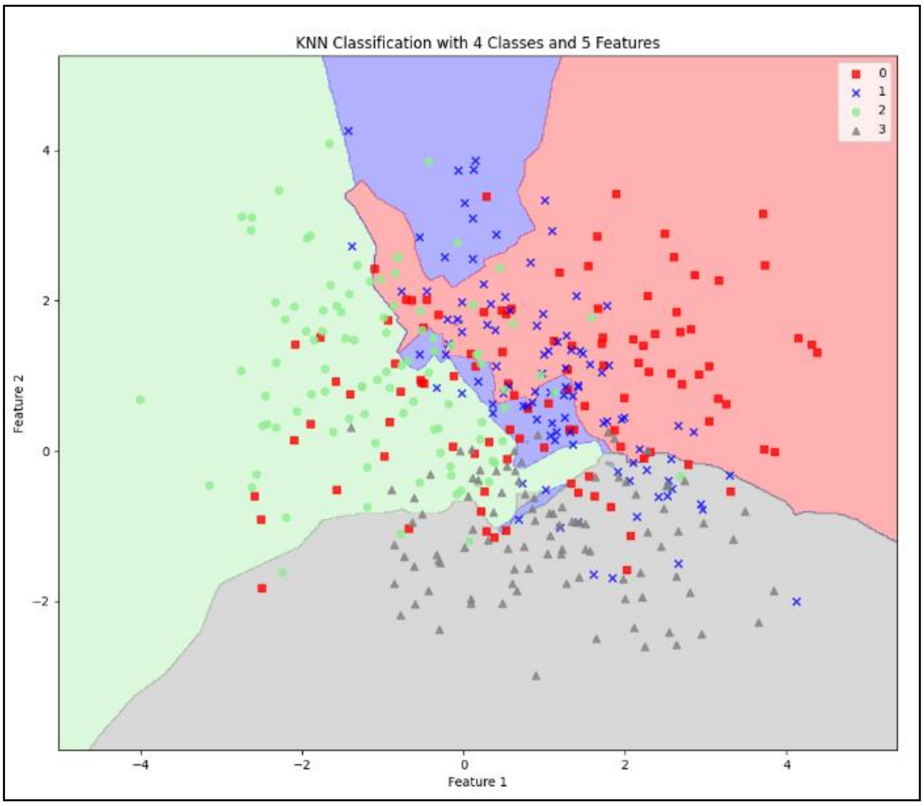

Figure 4. KNN Classification Results

Figure 4 shows the classification results of four motor imagery actions in a five-dimension feature space.

3. Performance Validation

The proposed method is validated using the BCI 2a dataset [16], which is one of the datasets available under the BCI Competition IV dataset. Open-source machine learning libraries (Tensorflow, Keras) were used to simulate the proposed model in Python language at google colab environment. The sample dataset of test dataset is given in Figure 5.

patient	time	label	epoch	EEG-Fz	EEG-0	EEG-1	EEG-2	EEG-3	EEG-4	EEG-5	EEG-C3	EEG-6	EEG-Cz	EEG-7	EEG-C4	EEG-8	EEG-9	EEG-10	EEG-11	EEG-12	EEG-13	EEG-14	EEG-Pz
1	-0.1	tongue	8	-1.68141	2.245496	-0.15835	1.163765	-1.52366	-0.57527	3.299057	3.928189	0.673606	0.972209	-2.34059	-2.5622	0.758116	3.441785	0.305517	1.137473	-1.27576	-2.89836	0.656704	-2.01006
1	-0.096	tongue	8	0.420417	0.587559	1.65051	0.970672	1.505904	0.891796	3.838386	2.514392	1.798873	1.316225	0.347175	-1.82755	1.541586	-0.07162	0.258909	-1.4482	0.142472	-1.96841	-1.73365	-2.93558
1	-0.092	tongue	8	0.551365	1.499758	0.121302	2.859433	2.613414	4.636026	2.162693	1.522294	-0.07213	0.861236	2.577732	2.600268	2.649097	-2.13794	-1.6121	-1.61022	-0.41017	-0.27496	-4.77653	-5.09955
1	-0.088	tongue	8	3.054916	-1.80724	1.843603	2.286812	5.995872	6.651295	2.078354	-1.98001	0.136497	-1.02974	4.446518	3.248351	6.031554	-5.24962	-2.673	-3.45237	0.189081	1.593829	-6.08158	-5.47686
1	-0.084	tongue	8	2.50671	-2.4531	0.221178	0.127278	4.519931	6.249573	0.309444	-3.3583	-2.02304	-2.16389	4.337764	4.946238	7.827097	-5.30955	-2.48878	-3.70761	1.447515	4.268278	-4.38369	-4.21843
1	-0.08	tongue	8	1.150619	-2.05138	-0.40249	0.529	3.554466	4.551686	0.711166	-1.73587	-0.98655	-1.95748	2.884018	5.738585	8.082335	-3.88243	-1.35464	-2.71995	0.823847	3.986407	-3.83548	-3.52373
1	-0.076	tongue	8	-1.53715	-2.15125	-2.94377	-0.49861	1.062012	4.061185	-3.63676	-1.83575	-2.6001	-1.66673	0.879845	5.736366	5.736366	-1.34559	-1.50334	-1.59912	2.725924	4.521297	-0.37091	-0.20564
1	-0.072	tongue	8	-2.9798	-4.76578	-4.82587	-3.30845	-1.50368	1.934942	-1.80792	-2.30184	-2.52907	-3.25586	-0.26984	5.221451	8.395279	1.362151	0.667289	-0.06325	1.234447	4.934116	2.043867	1.379053
1	-0.068	tongue	8	-4.74205	-2.96358	-6.09984	-3.31289	-5.07258	1.49105	-0.88463	0.379272	-3.31476	-3.11382	-3.00865	4.191621	4.48459	4.580368	-0.4602	0.518244	1.718289	4.734365	4.041381	2.79063
1	-0.064	tongue	8	-5.06165	-1.96482	-5.05226	-5.3903	-6.27108	-1.8559	0.358272	1.670997	-1.68124	-2.16389	-3.52356	1.77241	0.747019	5.383813	1.270982	2.102939	0.080327	2.461637	5.626076	3.887043
1	-0.06	tongue	8	-4.97287	-3.5362	-4.32872	-6.57105	-4.57098	-3.4761	3.425566	1.710948	-0.17645	-3.53995	-2.40939	-0.97084	0.982282	5.423763	3.605855	0.824529	-1.53988	-0.23279	7.423838	3.926993
1	-0.056	tongue	8	-4.80197	-3.07233	-3.91368	-5.27711	-3.66766	-2.37747	4.475371	1.78419	-0.1032	-2.34366	-2.28732	-2.75307	-1.38588	4.569271	2.849019	0.311834	-1.12484	-1.4779	6.862315	4.097892
1	-0.052	tongue	8	-3.31937	-2.51747	-1.55217	-4.62459	-1.50146	-3.97104	6.543908	1.801946	1.477051	-1.73997	-0.12113	-3.85836	-2.97945	4.879995	3.745681	-0.06104	-2.57193	-4.19452	4.878117	2.553148
1	-0.048	tongue	8	-2.17635	-0.44671	-1.82516	-0.79602	0.471635	0.443465	3.536539	1.431296	0.227495	0.233129	0.582438	-2.03175	-2.61768	2.165596	1.177765	0.398393	-1.23359	-2.7097	3.042624	0.082888
1	-0.044	tongue	8	-1.20201	0.185837	0.565194	-0.65175	1.494806	0.880699	2.411273	0.403686	0.713556	0.133253	1.019671	-0.71561	-0.32498	1.040329	1.077889	-0.7757	-1.18698	-2.56544	0.598998	-0.99355
1	-0.04	tongue	8	-1.44393	0.0904	-0.50681	-0.69836	0.471635	0.687606	1.143961	1.040671	0.08101	0.770238	-0.19881	0.263177	0.312005	1.286689	0.884796	-0.2852	-1.57539	-1.92845	-0.42417	-0.35656
1	-0.036	tongue	8	-2.66241	-0.68863	-1.48115	-2.74692	-1.57693	-1.11682	-1.2464	-0.27547	-0.16091	-0.00879	-0.88019	-0.02757	0.411881	-0.32242	0.691703	-0.08767	1.454173	1.198765	1.091718	1.989405
1	-0.032	tongue	8	-2.68461	1.974722	0.107985	-0.91365	-3.11279	-2.89682	-2.09867	0.337102	-0.03662	1.87331	-1.14652	-0.24508	-2.97945	0.436636	0.864821	1.843262	0.992526	0.004695	1.118352	2.504319
1	-0.028	tongue	8	-3.00643	2.19001	-0.55563	0.57117	-4.55766	-2.73036	-5.39901	-0.08238	-1.23735	1.990941	-3.66561	-1.05518	-5.15675	0.358955	-1.65427	3.425737	2.135548	1.294201	1.870749	4.135623
1	-0.024	tongue	8	1.796482	1.03589	2.001185	0.344785	-2.0985	-4.90987	-4.20938	-2.1154	1.221813	1.6669	-0.86465	-2.30696	-3.08821	-1.82055	-0.22049	1.68568	1.909163	0.97016	-0.35759	2.493222
1	-0.02	tongue	8	3.141475	3.650415	3.785631	3.789387	-0.06991	-3.0766	-4.03626	-0.62392	1.346103	3.890799	-0.39856	-1.5479	-4.77056	-2.67283	-1.31691	1.907626	0.861577	-0.27274	-2.52822	-0.31218
1	-0.016	tongue	8	6.297548	5.68344	5.183891	6.115381	1.963113	-1.04357	-3.07745	0.090742	1.523659	4.21484	0.36493	-1.85863	-5.52074	-3.7648	-2.36005	0.278542	0.502025	-0.77877	-5.37801	-1.8436
1	-0.012	tongue	8	6.870168	4.937701	5.512371	4.979018	2.731046	-1.39869	0.620168	-0.16672	1.705655	1.760117	1.621145	-1.9696	-3.09265	-2.65507	-1.78743	-0.17423	-1.36676	-1.96397	-5.87961	-2.83348
1	-0.008	tongue	8	7.380644	2.469662	6.4623	4.171134	3.632147	-2.30423	-1.94553	-1.51171	2.362615	1.098718	1.252715	-4.24233	-5.60951	-3.56061	-0.3004	-0.15203	-0.41683	-1.84412	-3.61132	-1.1023
1	-0.004	tongue	8	5.010261	0.001622	3.896604	2.044891	3.068404	-2.13555	-1.19091	-2.22194	1.652388	-0.88104	0.933112	-4.46427	-4.31779	-1.53646	0.893674	0.114302	-1.56651	-2.94497	0.512439	1.410126
1	0	tongue	8	4.091404	1.865969	2.294154	4.836972	2.442516	1.388955	-5.38125	-0.40642	0.00111	3.082916	-0.13223	-1.28157	-6.11555	-0.59985	-0.56229	1.588024	-1.94826	-3.91265	-0.40642	-0.33881
1	0.004	tongue	8	6.528372	2.64278	5.02409	7.615736	5.074796	3.435298	-7.87593	-1.28976	1.07089	3.908555	0.400442	-1.33483	-6.6571	-3.14335	-0.66439	0.118741	-2.19684	-4.99131	-0.85031	-1.56395
1	0.008	tongue	8	9.28938	3.841288	6.613223	8.66776	5.199086	2.241228	-6.77507	-0.67719	2.757679	4.325813	0.280591	-3.16367	-9.26719	-1.26125	0.875919	0.340687	-5.19755	-7.40608	-1.11664	-2.17208
1	0.012	tongue	8	10.81415	1.557464	7.503227	7.604639	6.186745	1.324591	-7.00812	-3.15633	3.501199	2.627926	1.707704	-3.64085	-4.91039	-3.74039	0.838188	-1.30837	-3.57512	-5.14889	-2.08211	-2.60044

Figure 5. Sample Dataset from BCI-2a Data Set.

Table 2. Classification Accuracy of Proposed Model

Action	Classification Accuracy
Left movement	98%
Right movement	98%
Tongue move	97%
Foot movement	98%
Overall accuracy	98%

The Table 2 shows that, the motor imagery brain actions are predicted by our proposed model and the overall accuracy is greater than 96%.

Table 3. Comparison with Existing Methods

Reference	Methodology	Classification accuracy
[14]	Riemannian geometry + feed forward neural network	96%
[15]	Transformer encoder-based neural network	95%
Proposed model	Feature selection+ KNN classifier	96%

The Table 3 reveals that, the proposed model is on par with the modern deep learning methodologies. It exhibits 96% classification accuracy.

4. Conclusion and Future Scope

The BCI utilizes the EEG signals, into control signals which is used to control the devices. For individuals with paralysis, BCIs offer a potential means of communication and control, which can significantly improve their quality of life and sense of presence. This proposed model, utilizes EEG signal to convert in to four different types of action. The overall accuracy of the proposed methodology is 98%. This type of classification can be employed not only in BCI but also used for Gaming applications. The enhanced version of this work may lead to security application like user authentication.

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