Received: January 20, 2022. Revised: March 5, 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Hybrid Feature Extraction for EEG Motor Imagery Classification Using Multi-Class SVM

Vishwesh Jayashekar[1]* **Raviraj Pandian[2]**

[1]*Department of Computer Science & Engineering, GSSS Institute of Engineering and Technology for Women, Mysuru, Affiliated to VTU, Belagavi, Karnataka, India*
* Corresponding author's Email: vishweshj@gsss.edu.in

Abstract: The cerebral activity identification of imagined motor movement is a significant task due to the translation of actions into control signals through Brain-Computer Interface (BCI) based applications. The existing models showed lower performances because of the absence of detailed information in the signal. The pre-processing tasks are performed based on the 6th order butter worth filter and sliding window for the Electroencephalogram (EEG) signal decomposition. From the pre-processed signals, the feature extraction is performed by using the Hybrid Common Spatial Pattern (CSP) and Convolution Neural Network(CNN) coefficients. The hybrid feature extraction combines the diagonal and directional-based features to avoid Overfitting risk reduction and speed up in training. The extracted hybrid features are undergone for the classification of test signal using Multi Support Vector Machine (Multi- SVM). The Multi SVM overcomes the problem of misclassification during the process of training. The extracted features are fed for the various classifiers that classified the signals into multi classes such as left, right, tongue, and feet movements. The proposed model obtained 89.6% of better accuracy when compared to existing models such as Sub-Band Common Spatial Patterns with Sequential Feature Selection obtained 86.50%, 3D Convolutional Neural Network of 52.173 %, Space-Frequency Localized Spatial Filtering of 78.1%, Dual-Tree Complex Wavelet and Neighbourhood Component Analysis of 84.02%, and Ensemble RCSSP of 82.64 %.

Keywords: 6th order butter worth filter, Hybrid common spatial pattern, Convolution neural network, Motor movement, Multi support vector machine.

1. Introduction

The BCI is a computer-based system that is used to evaluate brain signals. The brain signals received are translated to commands which are relayed based on the output for responding to the stimulus. Remote communication, mind-reading, self-regulation, education, marketing, security, games, entertainment are a few of the BCI contributions to the society that showed understanding among the users and the surrounding system. The contributions of BCI are more appreciable in medical fields to prevent neuronal rehabilitation for serious injuries [1, 2]. The detection of electrical activity occurring in the brain is determined by using a non-invasive EEG signal through BCI. The collections of electrical signals received for the BCI will translate the brain activity signals to generate an output for controlling non-muscular channels. Motor Imagery (MI) is a common mental rehearsal where the participants will be directed for imaging the specific motor activities like foot or hand, tongue movement without any activation of muscles [3]. The EEG signals are analysed based on the motor imagery signals, as it is subjected to imaging obtained through BCI. It will translate the participant's intention to pre-specified control commands that help disabled persons to drive the wheelchairs or autonomous driving. Recognizing the correct patterns from EEG signals plays a crucial role in a Motor Imagery BCI system [4]. The EEG signals are having a high temporal resolution feature which is not possible using the latest techniques like Magnetic Resonance Imaging or Computed Tomography image that making EEG an important tool for the diagnosing of brain function and disorders [5].

The existing model uses the Motor Imagery BCI system based on the CSP filtering that is combined with the band power that forms the feature vectors [6]. The Linear Discriminant Analysis (LDA) with the CNN model was employed for the classification of MI signals to two types of movements such as left and right-hand movements [7]. But, the feature vectors are alleviated with heavy computation and overfitting gave rise to high dimensional space. However, the main challenge occurred when exploiting the similar things among the brain responses for passive movements attempted improving [8]. Thus, to overcome the problem, deep neural networks are used for EEG signal classification based on training more data gives good performances [9, 10]. The hybrid feature extraction combines the diagonal and directional-based features to avoid Overfitting risk reduction and speed up in training. The extracted hybrid features are undergone for the classification of test signal using Multi Support Vector Machine (Multi- SVM). The Multi SVM overcomes the mistake work that limits the misclassification on the preparation set. Classification of extracted features is fed for different classifiers and obtained 4 classes such as left, right, tongue, and feet movements.

The structure of the paper is as presented as follows: Section 2 describes the existing models involved in motor imagery detection. Section 3 describes the proposed hybrid feature extraction with the multi- SVM model. Section 4 describes the results and discussions involved in the proposed research. The conclusion and future work of this research work is presented in Section 5.

2. Literature review

The existing researches involved in the classification of EEG motor imagery is presented as follows:

Javeria Khan [10] developed the multiclass EEG motor imagery classification using sub-band CSP. The existing models used the practical applications that were used by BCI showed difficulty in decoding the imagery-based brain signals. The classes obtained by the multi-class classification were non-stationary. The developed Sub-Band CSP with Sequential Feature selection (SBCSP-SBFS) showed improvement in the classification accuracy. Yet, the optimal channel selection was important and required more improvement.

Xinqiao Zhao [11] developed the Multi branch 3D CNN for EEG-based MI classification. The features were used to the various EEG signal dimensions for classification included 3D EEG representation. The multi-branch 3D CNN shows a corresponding for the classification. However, MI for performing the classification task obtained an overfitting issue due to the small training dataset.

Haider Alwasit and Kamran Raza [12] developed a Motor imagery classification using deep Metric Learning for MI classification. The Triplet network classifies the motor imagery signals to frequency domain results with an improvement in the DML model and LSTM model obtains in terms of accuracy. However, the BCIs used were dependent on the CNS regions that needed to execute a unique task from the user which showed throughout development.

Vangelis P. Oikonomou [13] developed a robust classifier by combing the Sparse Representations and Grouping Structures for the MI classification. The developed model used the sparse representation for performing the classification extended the current sparse schemes exploited the relevant features and group of sparsity. However, each test signal showed a linear combination for training that required further constraint that belonged to the motor Imagery of the same class.

M. Rahman and M. A. M. Joadder [14] developed a Space-Frequency Localized Spatial Filtering (SFLSF) to perform the MI classification. The SFLSF divided the EEG channels from the scalp faced the problem of overlapping the spatial windows. The filter bank divided the signals into local frequency bands but the noise was sensitive for the model showed overfitting problem resulted in dimensionality problems.

N.S. Malan and S. Sharma [15] developed a dual Tree Complex Wavelet and Neighbourhood Component Analysis (NCA) for MI EEG based on Spectral-Spatial Feature Optimization. The developed model utilized optimization approach that was tested and optimized the spectral and spatial features showed improvement by selecting the most relevant window time. However, the model required more dimension to present the model and structural tensor data was required to be analysed.

Mohammad Norizadeh Cherloo [16] developed an Ensemble Regularized Common Spatio-Spectral Pattern (ensemble RCSSP) approach for MI for EEG signal classification. The developed model decreased the overfitting probability in the CSP model by introducing an improved Ensemble RCSSP model that showed improvement better when compared to other CSP models. The developed model obtained better accuracy in terms of reliability and robustness for MI EEG data. However, only one frequency band related to MI task was considered in the CSP yet still in various subjects the valuable information contained were not extracted.

Thus, the existing models employed for classifying the MI signals into distinct movements showed alleviation due to feature vectors heavy computation. This showed over-fitting in the data for higher dimensional space. The present research work utilizes the hybrid features that consisted of dimensional and directional features overcame overfitting problem. The proposed hybrid set of features fed for the model automatically detected the significant features based on the convolution on patches to their adjacent pixels.

3. Methodology

The present research work steps to be followed are shown in Fig. 1. The block diagram consists of a dataset known as the BCI dataset. The obtained data is now undergone for pre-processing the signals using Sliding window and 6th order butter worth filter. The pre-processed signals are now undergone for the process of feature extraction by hybridizing the Common Spatial Pattern and Convolution Neural Network. The obtained hybrid features are undergone for the classification using M-SVM. The multi classifier used will obtain the multiple classes such as right hand left hand, feet movement, and tongue movements are classified based on the motor imagery signals.

3.1 Dataset

3.1.1. BCI dataset

The proposed method evaluated the experiment by using the BCI Competition IV Dataset 2a was recorded from 4 human subjects performing motor imagery tasks. Each subject chose to perform four classes of motor imagery tasks from the left hand, right hand, tongue, or foot movements. As the task begins, a visual signal will be displayed on the monitor screen of a computer from where the subject starts to perform a motor imagery task which uses 4s. A total of 200 motor imagery tasks were performed for maintaining a balance among the two classes.

The subjects are followed by the voice commands given by an instructor for performing a task that

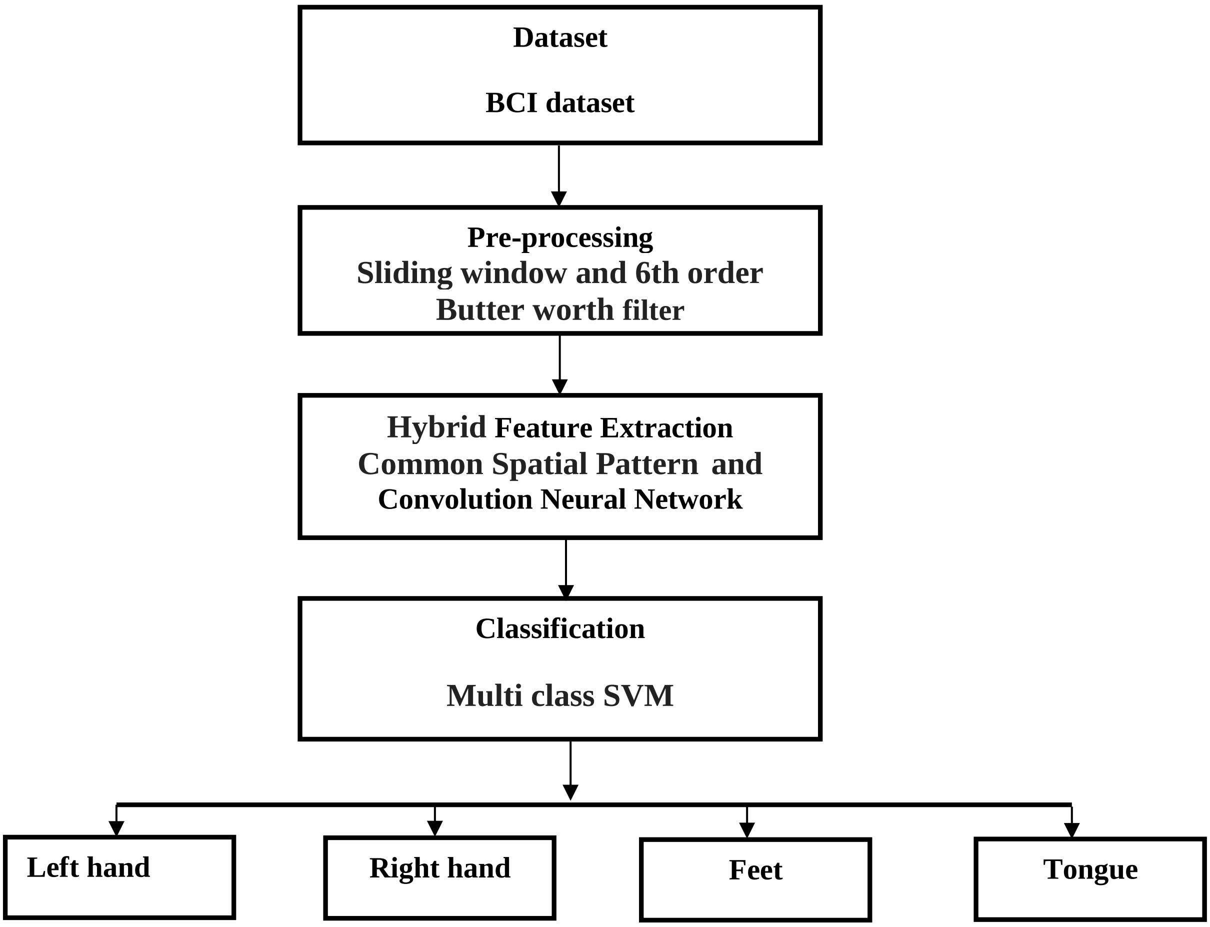

Figure. 1 Block diagram of the proposed method

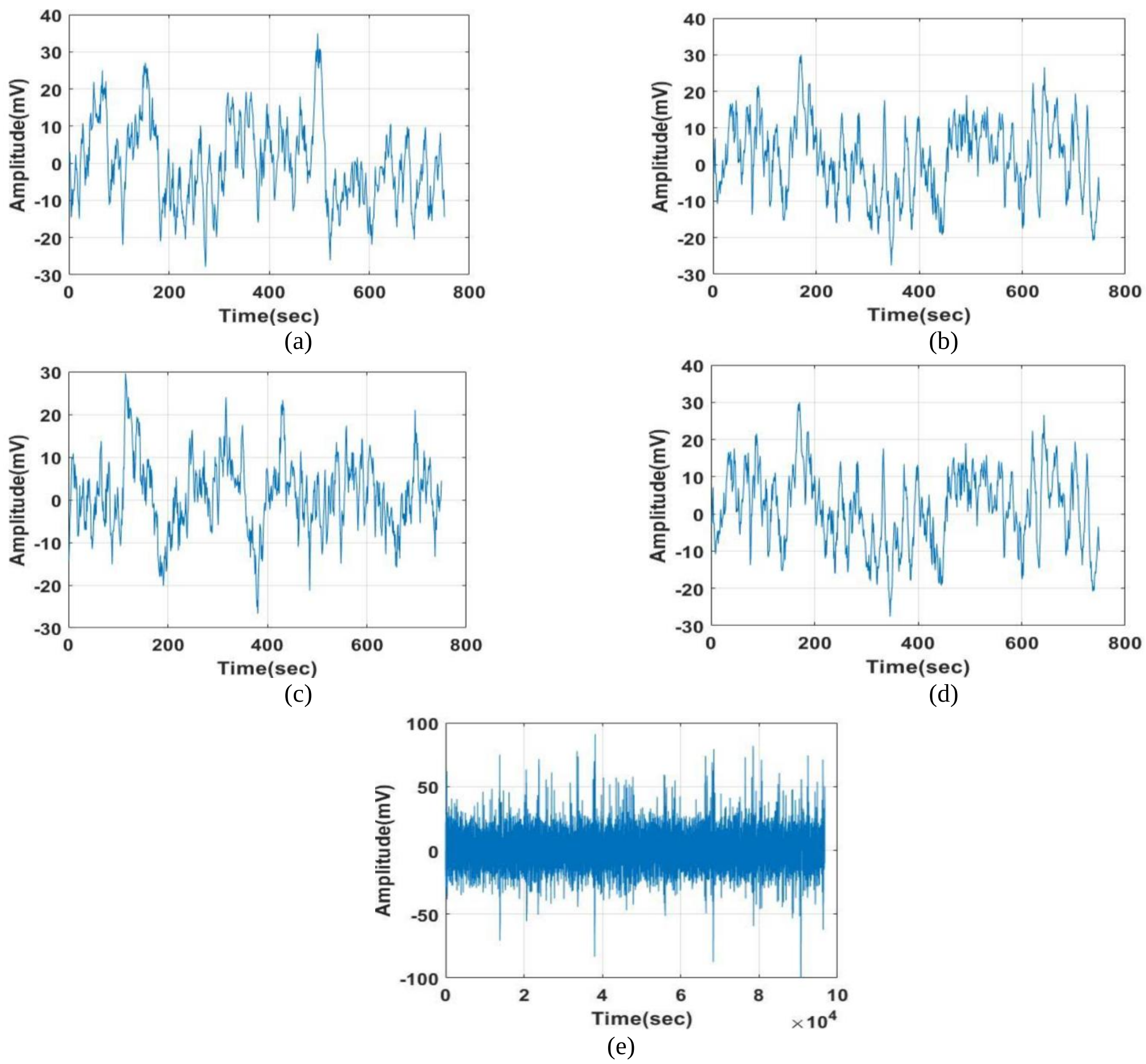

Figure. 2 Sample images: (a) Left hand, (b) Feet, (c)Right hand, (d) Tongue, and (e) Input signal obtained from electrode 1

varies the time length of 1.5 s to 8 s. The four human subjects are referred to as "a," "b," "f," and "g" classes are used in the work. Fig. 2 shows the sample images taken from the dataset.

3.2 Pre-processing

The EEG records are consisting of noises or artifacts that are captured by the skin electrodes and recorded by BCI. Thus, elimination of such kinds of disturbances are in the form of noises that are to be detected and should be removed using the pre-processing technique. The pre-processing technique is used for the detection of noise accurately to distinct components which played an important role. The signal is consisting of high and low frequency noise components. The noise was of high-frequency components that have EMG signal and power line interference etc. that consisted of low frequency based Electrooculography (EOG) signals. Thus, elimination of such kind of disturbances are in the form of noises are detected and removed using the pre-processing technique. The pre-processing stage helps to detect noise accurately so that different components could be extracted which plays an important role for further process. Fig. 3 shows the Sliding window for the Electrode 1 signals. Fig. 4 shows the obtained Prepossessed images.

The sixth order Butter worth filters are utilized to filter the unwanted noises. The neighbour entries form patterns and such patterns are known as Window. The window slides over the entire signal when the Butter worth filters run to the signal. Thus the length of the signal after filtering remains the same before undergoing pre-processing. The signal processing concept includes the statistics has a window function that is mathematically expressed. The mathematical function is zero-valued outside of

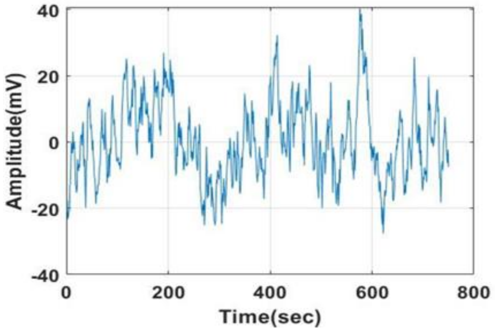

Figure. 3 Sliding window for the electrode 1 signals

that of the chosen interval. It is symmetric to the middle interval reaches a maximum and tapers away from the middle value. The general equation for the butter worth filter is given by $H(jw)$ the Maximum Passband Gain is expressed as shown in Eq. (1).

$$H(jw) = \frac{1}{\sqrt{1+\varepsilon^2 (\frac{w}{w_p})^{2n}}} \tag{1}$$

Where n is the order of the filter, Ω is equal to $2\pi f$, Epsilon ε is the maximum passband gain, (Amax of 3 dB).w is the stopband frequency, w_p is the passband frequency.

3.3 Proposed hybrid feature extraction using CSP-CNN

CSP is included for the extraction of features from the multi-channel in EEG when the hand movements are imagined. The main aim of the CSP model is to consider the weights from each of the channels present row vice. The performed transformation maximizes the effect of variance among the two classes (hand and foot) of a covariance matrix. The CSP model is based on the diagonalization of both classes of the covariance matrix. The details of the algorithm are described as follows by explaining with an example. The classification of single-trial EEG was performed for hand and foot movements. This normalized spatial covariance of EEG is expressed using the following Eqs. (2) and (3).

$$R_H = \frac{X_H X_H^T}{trace(X_H X_H^T)} \tag{2}$$

$$R_F = \frac{X_F X_F^T}{trace(X_F X_F^T)} \tag{3}$$

X_H and $X_F$are the pre-processing EEG matrices that come under the hand and foot conditions having the dimension $N \times T$. Where N is the number of channels, T represents the total number of samples

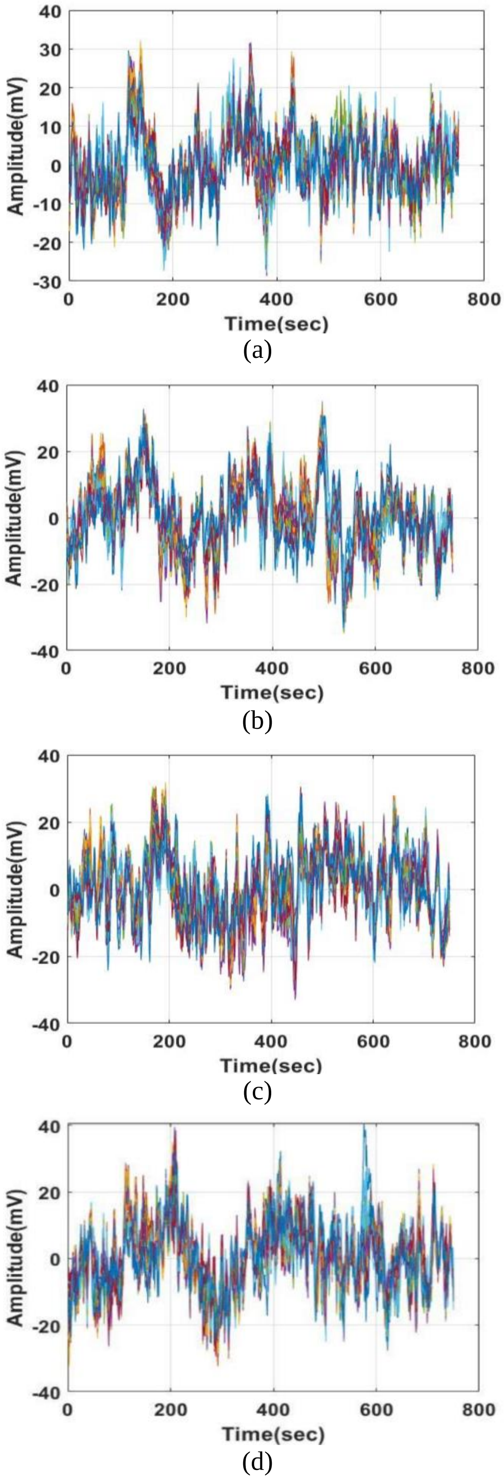

Figure. 4 Prepossessed images: (a) Left hand, (b) Right hand, (c) Foot, and (d) Tongue

per channel. X^T is the transpose of X and the sum of the matrix diagonal elements is computed. The averaged normalized covariance matrix is calculated by averaging the overall trials in each group which is represented as $\bar{R}_H$ and $\bar{R}_F$. The composite factorized function is calculated by using the Eq. (4).

$$R = \bar{R}_H + \bar{R}_F = U_0 \Sigma U_0^T \tag{4}$$

U_0 is known as the matrix of eigenvectors and $\sum$ is known as the diagonal matrix for the Eigen values. Another whitening transformation matrix generated is represented as shown in the Eq. (5).

$$P = \sum^{-\frac{1}{2}} U_0^T \quad (5)$$

Transform the covariance matrix as shown below:

$$S_H = P\bar{R}_H P^T \quad (6)$$

$$S_F = P\bar{R}_F P^T \quad (7)$$

S_H and S_F derives the common eigenvectors and the corresponding sum of the Eigenvalues for the corresponding matrix will be always equal to 1 as shown in Eqs. (8) to (10).

$$S_H = \mathrm{U}\sum_{\mathrm{H}} U^T \quad (8)$$

$$S_F = U\sum_F U^T \quad (9)$$

$$\sum_H + \sum_F = 1 \quad (10)$$

The Eigenvectors have the largest eigenvalues for S_H that having the smallest eigenvalues for S_F and it is transverse. The whitened EEG is transformed to some eigenvectors that are corresponded to a large eigenvalue optimally separates the variances for the two signal matrices. The projection matrix is denoted as shown in Eq. (11).

$$W = U^T P \quad (11)$$

The original EEG is transformed to components uncorrelated with the projection matrix W is denoted as shown in Eq. (12).

$$Z = WX \quad (12)$$

Where the projection matrix W is known as the spatial pattern matrix that explains the largest variance for the smallest variance of the other.

3.3.1. Feature extraction using convolution neural Network

The CNN will extract the prominent features from the signals to process furtherly the task. The CNN model will extract features related to data classifies the high dimension data. The CNN will be designed specifically for reorganizing the 2D shapes with a higher degree of variance for scaling, translation, and other forms of distortions. The structure includes the process of feature mapping from the sub-sampling layers. The CNN model has convolution with sub-sampling layers that are followed by a fully connected output layer. The propagation algorithm uses the model to train where the CNN tries to imitate the structure. The extraction of features will be similar to that of the input space unless the standard techniques are used for the manual extraction of features. These features are provided for the classifier for performing the classification. The high dimension data is involved to estimate the parameters of large numbers. The training data used will be large in number will give rise to the overfitting of the data. The CNN will handle the problems related to local connectivity, pooling or subsampling, and local connectivity.

3.3.2. Local connectivity

The signal will be divided into equal-sized units known as patches or blocks. The blocks obtained from the signal are called the receptive fields. The blocks are overlapped and non-overlapped in nature. The overlapping block will share the signal's common part but the non-overlapping blocks would not share the signals. Every signal will be divided into equal-sized units known as patches or blocks. The blocks from the signal are also known as the receptive field. The smooth features are extracted and the blocks that are overlapping will be considered. The hidden unit will be associated with one input signal block that will extract the features from each of the image blocks. The local features will be extracted from the exact feature location that will become less important. Thus, it is important to extract the local features as it is important until the other features are preserved in the relative location.

3.3.3. Parameter sharing

Each computational layer in the network comprises some feature maps and the main idea is to share the parameter to allow distinct neurons for parameter sharing. Thus, the hidden neurons are organized to map and share the parameters. The hidden units within the feature map will cover distinct blocks from a signal for sharing and extracting the same type of features from distinct blocks. Every block of the signal will be located with the multiple feature maps and neurons with the distinct feature will map the features from the same block. The activation values from the hidden unit results with weights from the input channel maps the features. The obtained features are multiplied by the input vector. The operation of convolution is concerned basically with the process of discrete convolution.

3.3.4. Pooling and subsampling

The neural network has the pooling layer and convolutional layer pairs from where the features are extracted. The convolution layer results with its name which converts the data using the operation of convolution. The collection of digital filters is used in two ways such as average and max pooling. The window will be having a predefined size that will select both of the methods. In the max pooling, the maximum activation value considers the window and the activation values from the average pooling in a window will be considered.

The present research work uses fully connected layers to perform dimension reduction. This fully connected layer is considered a traditional neural network. The CNNs are used for analyzing the image data and operations are performed on these layers to the 2D plane. The regression or classification is performed based on the data features where the output is generated. The threshold is obtained from the pooling layer to perform dimensionality reduction. Thus, the operations of the Convolution and pooling layers are performed to the 2D planes using the convolution layers.

3.4 Classification using multi-SVM

The extracted spectral features from fully connected layers are fed to the multiclass SVM for obtaining the classification rate in terms of accuracy that classified the total number of motor imagery acquired from the BCI dataset. The Multiclass SVM classified them into 4 types directly. The results are obtained using a one-against-one classification of SVM obtained better classification results. The results obtained also showed both the valence and arousal cases yield a higher value of accuracy compared to the other direct four-class classification. The model is based on the scheme which has two level binary classifiers that were used. There is no difference among the arousal and valence which are applied for the first level to perform a comparison. An advantage of using MSVM is that, as it is the model-based scheme obtained an average accuracy which will be better by using a multi-class classifier in a solid step process to decrease the computation complexity present in the system. By comparing MSVM with the existing SVM classifier, binary classes for motor activities are performed. The SVM model is applied for performing the binary classification which will divide the data points as 1 or 0. The multi-class classification is performed from the principle utilized. The multi-class problem will break down the multiple binary classification cases which are known as one vs one which distinguishes from the remaining classes. The number of classes needed for one vs one classification is evaluated using the Eq. (13).

$$Number\ of\ classifiers = \frac{n\,(n-1)}{2} \tag{13}$$

From the above equation, n is known as the class that is considered.

From the above equation, the number of SVM classifiers will be used for determining the forms of MSVM. The equation for the SVM is represented using Eq. (14).

$$n = \min_{w^{ij},b^{ij},\xi^{ij}} \frac{1}{2}\left(w^{ij}\right)^T\left(w^{ij}\right) + C\sum_t \zeta_t^{ij} \tag{14}$$

Where,

$$\left(w^{ij}\right)^T \phi(x_t) + b^{ij} \geq 1 - \xi_t^{ij} \text{ if } y_t = i$$
$$\left(w^{ij}\right)^T \phi(x_t) + b^{ij} \leq -1 + \xi_t^{ij} \text{ if } y_t = j$$
$$\xi_t^{ij} \geq 0$$

From the above Eq. (14), ξ_t^{ij} is known as the distance for correcting the margin. Where, $t = 0,1 \ldots n$

C is known as the regularization parameter

$\phi(x_t)$ is known as the Transformed input space vector

$\left(w^{ij}\right)^T\left(w^{ij}\right)$ is the obtained product for the normal vector

b^{ij} is known as the bias parameter which correctly predicts

w^{ij} is known as the optimal value.

From the above expression, $\left(w^{ij}\right)^T\phi(x_t) + b^{ij}$where x is for the i^{th} the class will vote for the class as one. Thus, j^{th} the term is also increased by one. The term x is in the class which will predict the value as the largest vote. Based on the voting approach the strategy of max win is used for finding the largest vote which classifies into 4 motor imagery classes.

4. Expected outcomes

The proposed hybrid CSP-CNN feature extraction technique with Multi SVM model is applied to the BCI dataset.

4.1 Simulation setup

The MATLAB R2018 software tool and system requirement of 16 GB RAM with i7 processor is used to implement the proposed hybrid CSP-CNN feature

Received: January 20, 2022. Revised: March 5, 2022.

with Multi SVM model. The performance measures used to analyse the classified arrhythmia signals in terms of Accuracy, F-measure, Sensitivity, Specificity.

4.2 Performance analysis

4.2.1. Accuracy

The accuracy performance measure is defined as the ratio of the correctly predicted observation for the total number of observations. The accuracy is calculated using Eq. (15).

$$Accuracy(\%) = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 10 \quad (15)$$

4.2.2. Specificity

Specificity is the measure of the ratio of correctly identified negatives which is expressed as shown in Eq. (16).

$$Specificty(\%) = \frac{TN}{TN+FP} \times 100 \quad (16)$$

4.2.3. Sensitivity

Specificity is known as the correctly identified positives which are expressed as shown in Eq. (17).

$$Sensitivity(\%) = \frac{TP}{TP+FN} \times 100 \quad (17)$$

4.2.4. F-measure

F-measure is the evaluation metric for finding out the abnormality effectiveness and normality effectiveness of the EEG signals. The F-measure equation is given in the Eq. (18).

$$\mathrm{F} - measure(\%) = \frac{2TP}{(2TP+FP+FN)} \times 100 \quad (18)$$

Where, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The calculation of parameters is described below.

4.3 Quantitative analysis

The proposed method uses hybrid features by combining the CSP and CNN features into the MSVM classifier. The importance of the proposed method is shown by comparing the classifier MSVM with the existing methods such as Decision tree (DT), Random forest, (RF), K-Nearest Neighbor (KNN) is shown in Table 1. The proposed method validates the results by examining with respect to the DT classifier. The results showed that the values are unstable,

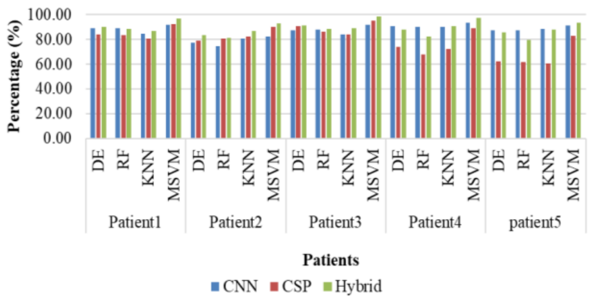

Figure. 5 Performance analysis for the proposed hybrid method in terms of specificity

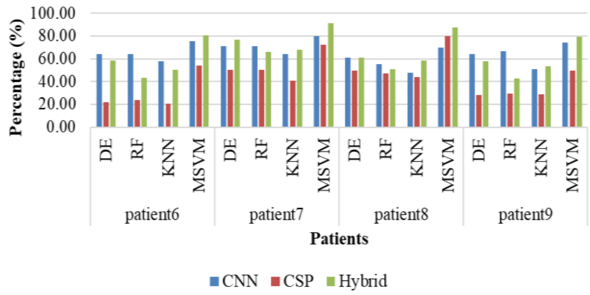

Figure. 6 Performance analysis for the proposed hybrid method in terms of F-measure

because of small change in the data showed a larger change in the optimal decision tree structure. The developed model relatively showed an accuracy of 73.13% and 62.97 % for other predictors performed better for the same data. The KNN model showed better accuracy based on the large quality of data because of the irrelevant features for data scaling. The accuracy of 78.28% and 80.16% were obtained using the multiple binary classifications. Table 1 shows the analysis of the performance in terms of accuracy and sensitivity using the hybrid model. Fig. 5 evaluates the performances in terms of specificity also. Fig. 6 will show the performance analysis for the proposed hybrid model in terms of F-measure.

4.4 Comparative analysis

Table 2 shows the values of average accuracy obtained for each of the methodologies using the dataset. The results showed that the proposed CSP-CNN has obtained features that obtained the accuracy of 89.68% better when compared with the existing models that obtained accuracy of 86.5 %, 52.173 %, 78.1 %. Similarly, Dual-Tree Complex Wavelet Neighbourhood Component Analysis 84.02 % and Ensemble RCSSP obtained accuracy of 82.64 %. The problem has occurred during the classification of EEG Motor imagery faced an overfitting issue because of the small training dataset. This operation will make the training dataset smaller, which may lead to a poorer training effect. The temporal features

Table 1. Performance analysis for the proposed hybrid method in terms of accuracy and sensitivity

		Accuracy			Sensitivity		
	Classifier	CNN	CSP	Hybrid	CNN	CSP	Hybrid
Patient1	DE	73.13	62.97	75.16	49.31	36.01	52.68
	RF	73.59	62.03	74.41	50.51	35.15	46.01
	KNN	63.28	54.69	65.63	37.33	26.27	38.50
	MSVM	78.28	80.16	90.63	57.99	58.07	77.69
Patient2	DE	53.91	55.00	62.19	28.99	28.50	35.68
	RF	50.63	57.66	58.28	26.83	31.05	32.01
	KNN	56.72	57.81	66.88	31.27	29.95	40.78
	MSVM	61.25	74.84	80.94	36.26	50.06	59.79
Patient3	DE	72.19	75.63	78.13	49.69	51.56	55.47
	RF	72.03	67.50	72.50	48.64	41.23	47.78
	KNN	61.72	62.66	72.34	35.76	35.47	47.74
	MSVM	80.00	85.78	95.47	60.77	67.86	88.66
Patient4	DE	77.34	48.13	78.19	56.04	23.37	49.51
	RF	76.56	41.41	61.09	55.90	18.98	35.30
	KNN	74.53	45.47	76.56	51.79	20.36	54.40
	MSVM	83.59	72.66	92.50	66.92	47.64	81.37
Patient5	DE	70.47	35.63	71.66	46.66	15.32	43.31
	RF	70.47	34.69	72.41	47.83	14.71	30.30
	KNN	71.25	32.66	71.41	47.23	12.48	48.27
	MSVM	78.13	61.25	82.03	58.13	34.65	62.61
Patient6	DE	77.50	36.88	79.50	56.27	15.88	49.66
	RF	77.34	38.91	81.00	56.16	17.21	34.20
	KNN	73.13	36.41	80.03	48.88	14.24	41.87
	MSVM	85.47	69.84	88.75	69.07	44.48	74.55
Patient7	DE	82.03	67.19	86.41	64.08	40.57	69.99
	RF	81.56	66.72	85.22	64.34	40.82	57.26
	KNN	77.19	58.44	80.47	56.82	31.64	60.56
	MSVM	87.66	84.22	95.47	74.34	64.63	88.49
Patient8	DE	74.84	66.56	75.31	52.56	40.45	51.96
	RF	69.53	64.53	70.81	46.79	37.75	41.22
	KNN	65.31	63.44	74.22	39.22	34.73	49.39
	MSVM	81.25	88.75	93.44	61.88	72.89	83.37
Patient9	DE	77.03	44.69	78.88	56.82	20.80	49.90
	RF	78.13	45.63	79.38	59.35	21.78	34.15
	KNN	66.41	47.03	69.38	41.84	21.31	44.47
	MSVM	83.44	66.09	87.97	68.52	39.79	73.88

Table 2. Comparative analysis

Authors	Dataset	Training and Testing	Methodology	Performance Measures (Average Accuracy %)
Zhao, X. [11]	BCI Competition IV 2a	10-fold cross-validation	3D Convolutional Neural Network	52.173
Rahman, M.K.M. and Joadder, M.A.M [14]		72 trials	Space-Frequency Localized Spatial Filtering	78.1
N.S. Malan and S. Sharma [15]		20 to160 trails	Dual-Tree Complex Wavelet and Neighbourhood Component Analysis	84.02
Mohammad Norizadeh Cherloo [16]		5-fold cross-validation	Ensemble RCSSP	82.64
Proposed		5-fold cross-validation	Hybrid CSP-CNN	89.68

in EEG are not fully considered to the classifier that gave rise to degraded results in the classification stage. The temporal features in EEG are not fully considered to the classifier that gave rise to degraded results in the classification stage. The crops increase the size of the training data and also increase the decoding performance. It also saves the models from overfitting on the limited training samples. The proposed model uses CSP and CNN features that manage the multi-source inputs for the extraction of features. The CNN features are fused into Multi SVM that classified only the relevant information from the combined feature vector. Thus, the proposed method showed better results in terms of accuracy when compared with the existing models.

5. Conclusion

Electroencephalography (EEG) motor imagery signals have gained lots of attention for physically challenged people. The motor imagery signals will help disabled people to control the devices like a wheelchair for autonomous driving. The neural networks used in the existing model utilized the MI BCI system for analyzing the movements. The existing CNN was employed for classifying the MI signals into right and left-hand movements, tongue or feet movements. The feature vectors showed alleviation due to heavy computation and over-fits the data having high dimensional space. The present research work uses hybrid features that combined diagonal and directional features that overcame the problem of overfitting. The obtained hybrid set of features are fed for the CNN model will automatically detect the significant features based on the convolution on patches to their adjacent pixels. The proposed Hybrid CSP-CNN Feature extraction model obtained 89.6% better accuracy when compared to existing models such as Sub-Band Common Spatial Patterns with Sequential Feature Selection obtained 86.50%, 3D Convolutional Neural Network of 52.173 %, Space-Frequency Localized Spatial Filtering of 78.1%, Non-dyadic wavelet decomposition of 85.6 %. The future work for the present research work can be carried out by investigating distinct channels by fusing or averaging or by setting a voting system for dimension reduction.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

References

[1] L. Yang, Y. Song, K. Ma, and L. Xie, "Motor imagery EEG decoding method based on a discriminative feature learning strategy", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 29, pp. 368-379, 2021.

[2] X. Deng, B. Zhang, N. Yu, K. Liu, and K. Sun, "Advanced TSGL-EEGNet for motor imagery EEG-based brain-computer interfaces", *IEEE Access*, Vol. 9, pp. 25118-25130, 2021.

[3] M. T. Sadiq, X. Yu, Z. Fan, A. U. Rehman, G. Li, and G. Xiao, "Motor imagery EEG signals classification based on mode amplitude and frequency components using empirical wavelet transform", *IEEE Access*, Vol. 7, pp. 127678-127692, 2019.

[4] Z. Huang, Y. Qiu, and W. Sun, "Recognition of motor imagery EEG patterns based on common feature analysis", *Brain-Computer Interfaces*, pp. 1-9, 2020.

[5] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. S. Hossain, "Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion", *Future Generation Computer Systems*, Vol. 101, pp. 542-554, 2019.

[6] M. Aljalal, R. Djemal, and S. Ibrahim, "Robot navigation using a brain computer interface based on motor imagery", *Journal of Medical and Biological Engineering*, Vol. 39, No. 4, pp. 508-522, 2019.

[7] N. Shajil, S. Mohan, P. Srinivasan, J. Arivudaiyanambi, and A. A. Murrugesan, "Multiclass Classification of Spatially Filtered Motor Imagery EEG Signals Using Convolutional Neural Network for BCI Based Applications", *Journal of Medical and Biological Engineering*, pp. 1-10, 2020.

[8] A. Jiang, J. Shang, X. Liu, Y. Tang, H. K. Kwan, and Y. Zhu, "Efficient CSP Algorithm With Spatio-Temporal Filtering for Motor Imagery Classification", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 28, No. 4, pp. 1006-1016, 2020.

[9] R. Fu, M. Han, Y. Tian, and P. Shi, "Improvement Motor Imagery EEG Classification based on sparse Common Spatial Pattern and Regularized Discriminant Analysis", *Journal of Neuroscience Methods*, p. 108833, 2020.

[10] J. Khan, M. H. Bhatti, U. G. Khan, and R. Iqbal, “Multiclass EEG motor-imagery classification with sub-band common spatial patterns”, *EURASIP Journal on Wireless Communications and Networking*, Vol. 2019, No. 1, p. 174, 2019.
[11] X. Zhao, H. Zhang, G. Zhu, F. You, S. Kuang, and L. Sun, “A multi-branch 3D convolutional neural network for EEG-based motor imagery classification”, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 27, No. 10, pp. 2164-2177, 2019.
[12] H. Alwasiti, M. Z, and K. Raza, “Motor Imagery Classification for Brain Computer Interface Using Deep Metric Learning”, *IEEE Access*, Vol. 8, pp. 109949-109963, 2020.
[13] V. P. Oikonomou, S. Nikolopoulos, and I. Kompatsiaris, “Robust motor imagery classification using sparse representations and grouping structures”, *IEEE Access*, Vol. 8, pp. 98572-98583, 2020.
[14] M. K. M. Rahman and M. A. M. Joadder, “A space-frequency localized approach of spatial filtering for motor imagery classification”, *Health Information Science and Systems*, Vol. 8, pp. 1-8, 2020.
[15] N. S. Malan and S. Sharma, “Motor imagery EEG spectral-spatial feature optimization using dual-tree complex wavelet and neighbourhood component analysis”, *IRBM, In Press*, 2021.
[16] M. N. Cherloo, H. K. Amiri, and M. R. Daliri, “Ensemble Regularized Common Spatio-Spectral Pattern (ensemble RCSSP) model for motor imagery-based EEG signal classification”, *Computers in Biology and Medicine*, Vol. 135, p. 104546, 2021.