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MOTOR-IMAGERY EEG SIGNAL CLASSIFICATION USING OPTIMIZED SUPPORT VECTOR MACHINE BY DIFFERENTIAL EVOLUTION ALGORITHM

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Abstract

Background: *Motor-Imagery (MI) is a mental or cognitive stimulation without actual sensory input that enables the mind to represent perceptual information. This study aims to use the optimized support vector machine (OSVM) by differential evolution algorithm for motor-Imagery EEG signal classification.*

Methods: *A total of three filters were applied to each signal during the preprocessing phase. The bandstop filter was used to remove urban noise and signal recorders, the median filter to remove random sudden peaks in the signal, and finally, the signal was normalized using the mapminmax filter. The most valuable features were extracted including mean signal intensity, minimum signal value, signal peak value, signal median, signal standard deviation, energy, corticoids, entropy, and signal skewness.*

Results: *The accuracy of the SVM for linear, Gaussian, polynomial, and radial base kernels was 67.3%, 55.1%, 63.6%, and 55.1%, respectively, which was optimized after the classification model by differential evolution algorithm; however, the accuracy for OSVM was increased to 99.6%.*

Conclusion: *Examination of the brain signal appearance for uniform motor-Imagery of both hands showed a significant difference between the signal of motor-Imagery mode with OSVM algorithm (99.6% accuracy), which gave promising results for classification motor imagery EEG signal.*

Keywords: *Brain-Computer Interfaces, Electroencephalogram, Machine Learning, Support Vector Machine, Motor Imagery.*

Introduction

Motor-Imagery (MI) is a mental or cognitive stimulation without actual sensory input that enables the mind to represent perceptual information. These processes are used in many sports and psychological situations [*Cheng S et al. 2020*]. In recent years, signal processing techniques, and machine learning (ML) has progressed, enabling the analysis of cerebral Electroencephalography (EEG) signals [*Sousa T et al. 2017; Garcia-Moreno FM et al. 2020*].

The Brain-Computer Interface (BCI) or brain-machine interface (BMI) provides a new way of communicating and controlling the brain's signal and output device [*Chamola V et al. 2020*]. Most BCI systems are based on EEG signals [*Abiri R et al. 2019*]. The MI EEG signal is autonomous and

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independent of output stimuli. This signal is emitted when imagining an operation in the brain [*Tang X et al. 2019*]. Nevertheless, accessing EEG data longer than the visual evoked potential, and the testing process is slow, making the person feel tired [*Abiri R et al. 2019; Tang X et al. 2019; Cheng S et al. 2020*]. Therefore, how to reduce the training time of BCI based on MI in the context of labeled samples has become a vital issue that should be addressed. Regulatory classification methods have been used in most BCI studies. On the other hand, labeled samples are used in supervisory learning to construct models to estimate the class label of unlabeled samples. However, obtaining labeled samples takes a long time, high costs, and enormous effort [*Tang X et al. 2019*].

EEG signals must be accurately recognized or classified for proper control or communication in BCI systems. Therefore, ML methods have been one of the main parts [*Cheng S et al. 2020*].

Among the ML methods, the support vector machine (SVM) algorithm has always been more popular due to its higher accuracy in many issues compared with other methods [*Quitadamo LR et al. 2017*]. This method is both accurate and fast due to finding the maximum boundary between the samples of two classes and using a limited number of samples as support vectors. Unlike methods deep learning (DL)-based methods, large data sets are not required since the parameters are much less configurable than other methods, such as neural networks [*Güler I, Ubeyli ED 2007; Ma Y et al. 2016; Arora A et al. 2018*].

One of the problems with this method is the parameters is most MLs that directly affect the accuracy of the classification, but their optimal value is not easily calculated. Therefore, ML algorithms are used in many studies without considering these parameters [*Qin AK et al. 2008*]. Recent results have shown that if basic and straightforward algorithms, even lazy methods, such as the nearest neighbors, are optimized well, in some cases, the results will be even superior to DL-based methods [*Dacrema MF et al. 2019*].

Some parameters must be set in SVM as other methods; the maximum SVM capacity will be achieved if these values are chosen optimally [*Jrad N et al. 2011*]. Therefore, a population-based evolutionary optimization algorithm, namely the differential evolution algorithm, is used in the present study to find the global optimal points [*Jo SY, Jeong JW. 2021*]. In the proposed method, first, with a limited set of EEG signals, the motor-Imagery of the SVM algorithm is learned several times. Each time, different parameters are tested by differential evolution to finally obtain the best settings for input parameters by differential evolution [*Guerrero MC et al. 2021*]. The SVM is then trained, and optimized SVM (OSVM) performance is evaluated using the entire training data set and optimal settings.

Materials and Methods

Database

In this study, brain signals related to two types of motion perception were extracted from the PhysioNet database. This database is available for free in the reference [*Schalk G et al. 2004*]. The data used in this study included 64-channel EEG signals using the BCI2000 system (http://www.bci2000.org) in the time domain for two types of MI. The experiments were performed in three sessions for each person. Seven hundred fifty signals were available for uniform MI mode and 6192 signals for the MI method of both hands; 750 data were used for both classes. The recording signals' sampling frequency was 250 Hz, and each signal sample was 1 minute long. Sixty-four electrodes were used to record the EEGs using the worldwide 10-10 system (excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10). Noting that signals in the records are numbered from 0 to 63, while the numbers in the figure vary from 1 to 64, the numbers beneath each electrode name reflect the sequence in which they appear.

Signal preprocessing

Three filters were applied to each signal during the preprocessing phase (band-stop, median, and mapminmax filters). A band-stop filter is a filter that passes most frequencies unchanged but reduces frequencies within a specific range to deficient levels. Usually, the width of the band-stop is about 10 to 100%. Typically, the band-stop width is about 10 to 100%. The bandwidth frequencies are 100 Hz and 200 Hz. The primary filtering of EEG signals aims to eliminate the frequencies caused by the signal recording devices, noise, and utility power [*Mohan A et al. 2020*].

Since during data collection, there is a possibility that out-of-set signaling will be recorded by the device unintentionally due to environmental conditions, therefore, a median filter was used to remove the effect of this phenomenon. Each point of the signal in this filter is compared with its neighboring points, and if its intensity is much higher than the average of several points around it, the filter will correct its value [*Ahmed A, Hussein SE 2020*].

The last step in the preprocessing section was data normalization with the mapminmax filter. Normalization by a min-max method is the easiest method to change a set's numerical range of values to [1, 0] or [1, -1]. In simpler terms, normalization organizes data to reduce data redundancy and resolve structural and anomaly problems. The purpose of normalization is to remove data redundancy and preserve the dependence between related data [*Bashar SK et al. 201*].

Wavelet transforms

All the recorded signals show changes in signal amplitude per unit of time, indicating an ensemble's overall behavior. A time signal contains in-depth information that must be extracted from inside the signal, and to access more detailed information, a signal must be decomposed into more useful components during the signal processing operation. Signal processing in the time-frequency domain simultaneously provides the user with all the time and frequency information of a signal. One of the practical and powerful methods in processing EEG signals is the signal decomposition method by wavelet transform, which has been proven in research [*Chai R et al. 2012; Kim HS et al. 2013; Chatterjee R, Bandyopadhyay T, 2016*].

Wavelet transform is designed to overcome the shortcomings of the Fourier transform. The Fourier transform reflects the frequency characteristics of the signal but cannot display the features of the signal over a period. Wavelet analysis of excellent frequency separation at low-frequency values and its frequency resolution at high-frequency values is inferior, which only compensates for the shortcomings of Fourier. In much research, researchers have used different signal processing methods to extract information from the EEG signal; in this research, the raw signals were processed by the wavelet transform method. In this method, wavelet transform was used in three levels of analysis. Finally, after applying the wavelet transform, each signal was decomposed into three detail signal levels and one approximate signal level [*Mebarkia K, Reffad A 2019*].

Feature extraction

A review of the research background and records related to extracting features from EEG signals in diagnosing neurological diseases showed that nine features were introduced as the most valuable features [*Narayan Y 2021*]. These characteristics included mean signal intensity, minimum signal value, signal peak value, signal median, signal standard deviation, energy, corticoids, entropy, and signal skewness. **Table 1** shows these characteristics and their relationships.

Recognize and classify the type of motion perception

The differential evolution algorithm is a population-based chance search strategy that K Price et

Table 1.

Features extracted from EEG signals.

Features	Formula
Average signal strength	$\frac{\sum_{n=1}^{N} x(n)}{N}$
Minimum signal value	$\mathbf{Min}\,(\sum_{n=1}^{N} x(n))$
The peak value of the signal	$\mathbf{Max}\,(\sum_{n=1}^{N} x(n))$
The middle of the signal	$\frac{\sum_{n=1}^{N}(x(n) - Mean)^2}{N}$
Signal standard deviation	$\frac{\sum_{n=1}^{N}\lvert x(n) - Mean\rvert}{N}$
Energy	$\sum_{b=0}^{L-1} x(n)^2$
Cortosis	$\frac{(N-1)\times(N+1)}{(N-3)\times(N-2)\times N\times Mean^2}\times\sum_{n=1}^{N}(x(n) - Mean)^4 - \frac{3\times(N-1)^2}{(N-2)(N-3)}$
Entropy	$\sum_{i=1}^{n}\frac{x(n)}{Mean}$
Skewness	$\sqrt{\frac{N-1}{N}}\times\frac{1}{(N-2).mean^{1.5}}\times\sum_{n=1}^{N}(x(n) - Mean)^3$

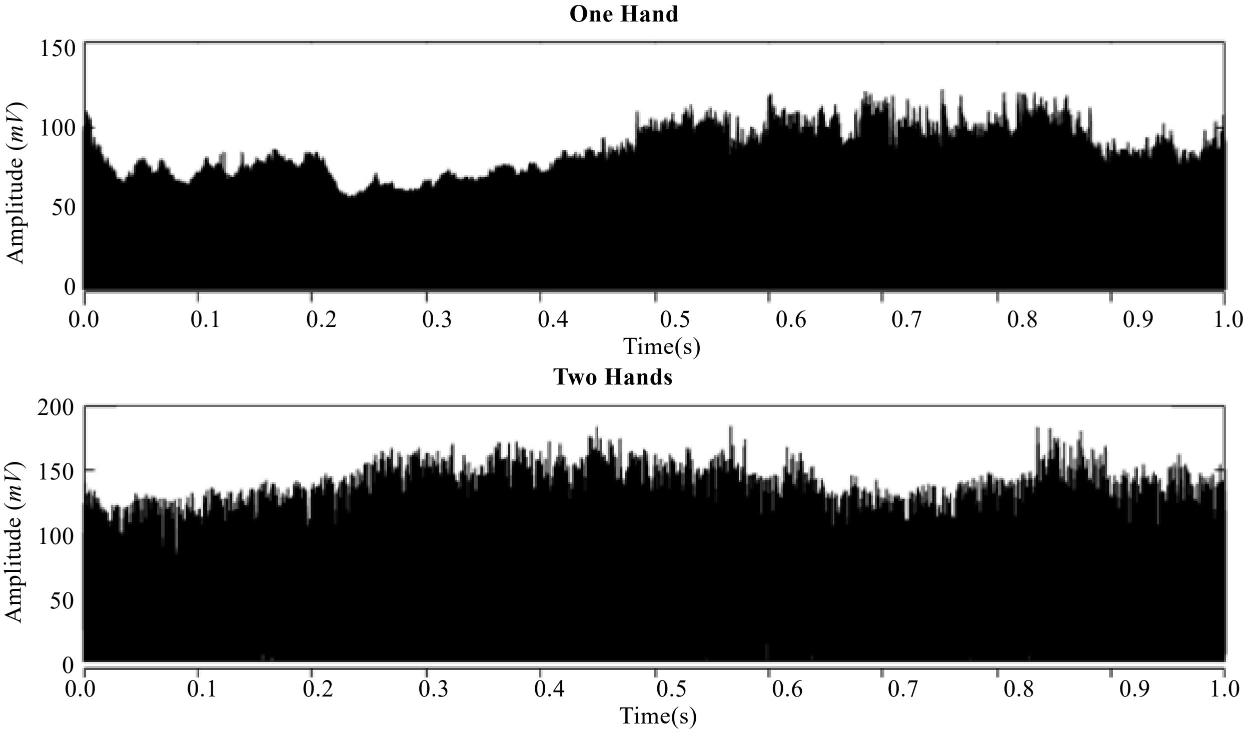

***FIGURE** 1. Cerebral imagery signal Imaging movement when moving one hand (up) and both hands (down) from C3 (Channel 5)*

al., 2006 presented. This algorithm uses a simple mutation operator based on the difference between a pair of vectors. It also uses a constant replacement mechanism in which the newly born offspring competes only with its respective parent [*Temiyasathit C 2014*].

The OSVM method is used to classify many types of Motor-Imagery. OSVM is a supervised classification method. The primary purpose of this classifier is to find a level of decision-making as an optimal meta-page to maximize the margin between the two categories. To separate nonlinear data, it uses different kernels, including linear, Gaussian, polynomial, and sigmoid kernels. The data can be mapped to a higher-dimension space by changing the kernel type. The features and the OSVM model were optimized by the differential evolution algorithm in this study. OSVM is carried out by MATLAB (ver. 9.5, R2018b) with Radial Basis Function (RBF) kernel [*Wang F et al. 2020*]. Among the main influencing parameters on classification accuracy are features extracted from brain signals in different classes. In this research, a differential evolution algorithm optimized the features and the support vector machine model. Notably, 70% of the data was used for training and 30% for testing.

Evaluation of the model of recognizing the type of motor perception

The perturbation matrix was used to evaluate the proposed method and determine the motion perception type. Statistical indicators such as overall accuracy, sensitivity, and accuracy evaluated the proposed classification system. The objective function that should be optimized in this research is the model's overall accuracy in classifying the type of motion perception.

RESULTS

Brain signals of motor perception

Examination of the appearance of these two states of the brain signal shows a significant difference between the signal of the state of uniform motor-Imagery with both hands (Figure 1). An increase in the oscillation amplitude was observed in the MI mode of both hands compared to the MI method of one hand (Figures 2, 3).

Signal processing

In general, the study of the signal decomposed by wavelet transform showed that the appearance of the time signal is different for both MI modes for uniform and two hands, but the decomposed signals are entirely different.

Feature extraction

The mean of the F_2 attribute for the two different classes of motion perception is significantly different. Still, the value of the F_6 attribute is al-

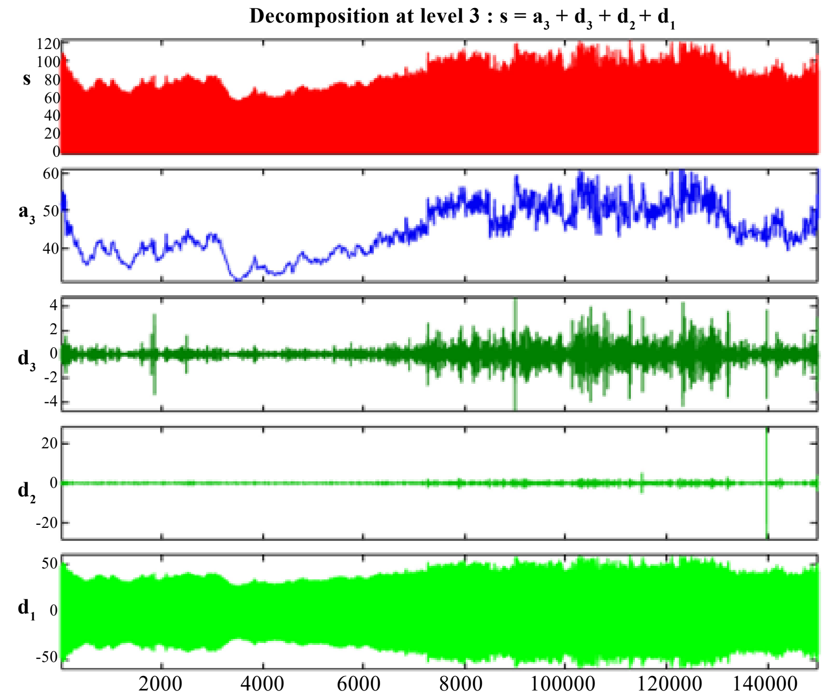

FIGURE 2. Decomposed brain signal for motion-imaging mode for a hand. The a_3 approximation signal is the general behavior of a signal that contains low-frequency components. Still, the detail signal one or d_1 has high-frequency components that typically include the noise frequencies of signal signaling and power meters.

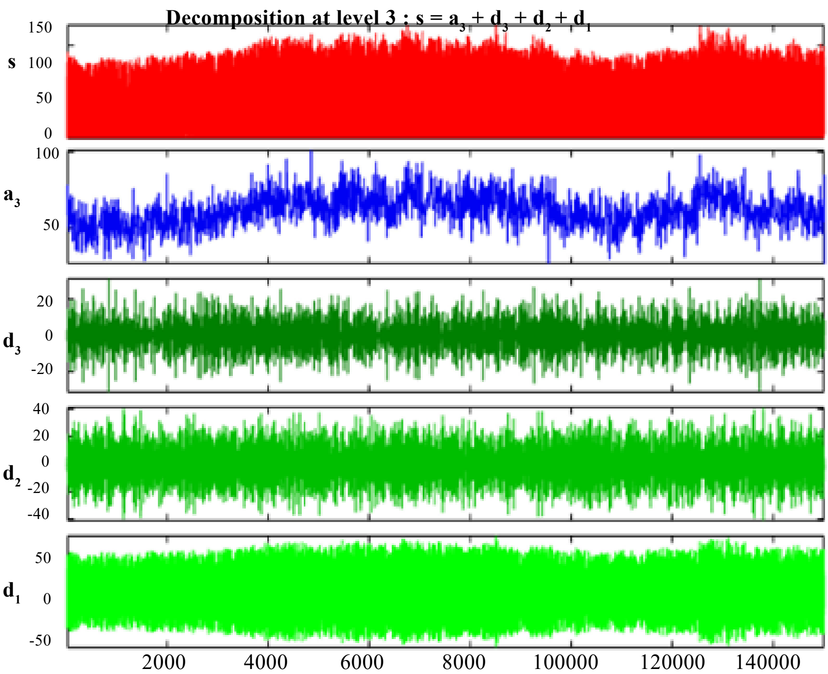

FIGURE 3. Decomposed brain signal for motion-imaging mode for both hands. The a_3 approximation signal is the general behavior of a signal that contains low-frequency components. Still, the detail signal one or d_1 has high-frequency components that typically include the noise frequencies of signal signaling and power meters.

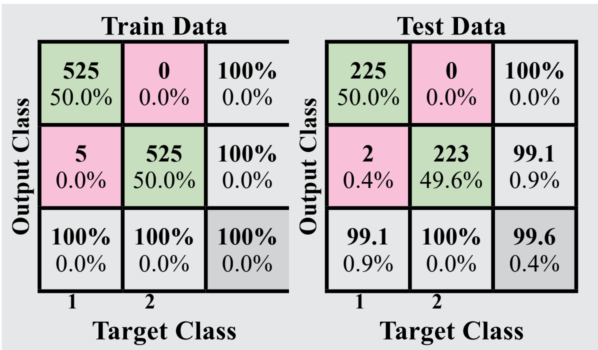

FIGURE 4. The output perturbation matrix of the optimized support vector machine with the differential evolution algorithm.

most the same for both types showing no significant differences. However, the study of all extracted properties from the signals of detail and approximation also showed that some of the extracted properties are significantly different between the two different classes of MI (Figure 4).

Recognize and classify the type of motor-Imagery signal

The OSVM model was implemented to detect and classify the motor-Imagery signal. All 45 extractive features were used as input to the AI model. The OSVM was trained for four different kernels, including linear, Gaussian, radial base, and polynomial kernels. The following are the results of the MI signal classification for four different models.

Using the linear kernel, OSVM training accuracy was 92.8%. Then, the accuracy of the SVM model with linear kernel was 67.3% in the detection of MI signal. The overall accuracy of the OSVM with Gaussian kernel for detecting the type of motion perception werer 100% and 55.1% for training and test data, respectively. The use of the polynomial kernel for OSVM training increased the accuracy of training and modeling reaching an accuracy of 100% and 63.6% for OSVM with the polynomial kernel, respectively. Finally, by changing the kernel to the radial base, the accuracy of the OSVM model for training data remained constant (100%). Still, the test accuracy of the model was 55.1%, which was exactly the same as the OSVM with a Gaussian kernel. The OSVM training accuracy was 100%, similar to the previous methods. Still, the accuracy of classifying the type of motion signal with the optimized support vector machine was 6.99%, which is at least 30% lower compared to the previous methods. The sensitivity of the optimized OSVM for signal recognition was 100% for one-handed motion and 99.1% for two-handed motion.

Discussion

This study presented an optimized model for detecting the type of EEG signal for uniform and two-handed motor-Imagery. Four OSVM models were implemented for the initial review, and finally, another model was implemented which was optimized by the differential evolution algorithm. In this study, a total of 45 features were extracted from each MI signal. Examination of the features extracted from the detail and approximation signals showed significant differences in terms of some of the extracted features from the two different classes of MI. The accuracy of the SVM for linear, Gaussian, polynomial, and radial base kernels was 67.3%, 55.1%, 63.6%, and 55.1%, respectively. Out of 225 test-related signals, the optimized SVM could detect 223 signals correctly. The general review of the results showed that OSVM parameters and creating new data from the features by the differential evolution algorithm increased the problem-solving accuracy by up to 33%.

The wavelet transform method was used to process EEG signals to present a model for recognizing the type of MI based on brain signals,. The SVM method was used to classify the type of MI. To increase the accuracy of the MI type recognition model, the structure of the classification model was optimized using the differential evolution algorithm. Table 2 compares the results of the proposed study with similar studies in recent years. The results showed that the OSVM had increased the accuracy of this model in detecting and classifying the type of MI by the differential evolution algorithm, thereby the accuracy of this method has increased compared to similar methods [*Bashar SK et al. 2015; Chai R et al. 2012; Kim HS et al. 2013; Temiyasathit C 2014; Chatterjee R, Bandyopadhyay T, 2016; Mebarkia K, Reffad A 2019; Wang F et al. 2020; Narayan Y 2021*]. Y Narayan (2021) showed that the SVM algorithm followed by the multi-layer perceptron (MLP) classifier had a high accuracy (98.8%) [*Narayan Y 2021*]. These results were close-knit, similar to our OSVM algorithm (F. Wang et al. (2020) [*Wang F et al. 2020*], and Mebarkia K, Reffad A (2019) [*Mebarkia K, Reffad A 2019*] studies with 99.6%, 93.13%, and 94.11% accuracy, respectively). However, this accuracy in the R. Chatterjee et al. (2016) study that evaluated SVM for classification EEG Based Motor Imagery was 85% [*Chatterjee R, Bandyopadhyay T, 2016*]. Signal decomposition by wavelet transform provides new signals differed for both uniform and two hands MI modes. The wavelet transform of the brain signal is decomposed into new signals that contain more information about the type of motion perception. By extracting features from these decomposed components, a model can be extracted to identify the type of motion perception. Four different models were created for the OSVM with an accuracy of 100% for training in all kernels except the linear kernel. Still, the accuracy of the OSVM in classifying the

TABLE 2.

Summary characteristics of literature review.

ID/year	Subject	Imagery Movement	Dataset	Feature	Classifier	Accuracy
Chai R et al., 2012	5	The arithmetic calculation, Letter composing, Rubik's cube is rolling, Visual counting, Ringtone, and Spatial navigation.	Prepared by Researchers	PSD	GA based NN	76%-85%
Kim HS et al., 2013	99	Left, right hand, both hands, and both feet	Physio net	Common Spatial Patterns	LDA	81.96% (Right hand/both Feet)
Thang L Q, & Temiyasathit C 2014	9	Left, right hand, foot, tongue	BCI Comp. IV	Common Spatial Patterns	LDA	Training: 70.18% Testing: 58.48%
Bashar SK et al. 2015	1	Left/right hand	BCI Comp. II	MEMD+STFT	kNN	90%
Chatterjee R et al. 2016	1	Left/right hand	BCI Comp II	Statistical, WT, Average Power, Average Band Power	MLP SVM (Polynomial, Linear)	85.7143% 85%
Mebarkia K, Reffad A 2019	3	Left/right hand	BCI Competition IIIb	Multi optimized SVM (3)	PSD Kurtosis Continuous wavelets transform	94.11%.
Wang F, Xu Z, et al 2020	5	Right hand or Foot	BCI Competition III Dataset IV	-Riemannian Geometry(R) -Common Spatial Pattern (CSP) -RCSP -Geodesic Filtering CSP (GFCSP)	SVM	93.13%
Narayan Y 2021	20	Left/right hand	BCI Comp II	AAR, Barlow, Hjorth, Temporal Furthermore, Spatial Complexity (TSC), Running Fractal Dimension (RFD), minimum energy, band power, and variance.	SVM, MLP, LDA	98.8%

MI type for the test data in linear kernel mode was higher than the other three kernels. These results showed that the most sutiable model can be reported with certainty.

CONCLUSION

Examination of the brain signal appearance for uniform motor-Imagery of both hands was shown a significant difference between the signal of motor-Imagery mode with OSVM algorithm (99.6% accuracy), which gave promising results for classification motor-imagery EEG signal. A very sharp fluctuation in the signal amplitude was observed in uniform motor-Imagery mode. Also, the signal decomposed by wavelet transform showed that the signal time's appearance for both motor-Imagery methods for uniform and two hands are different, but the decomposed signals are entirely different.

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