E3S Web of Conferences **351**, 01026 (2022) https://doi.org/10.1051/e3sconf/202235101026
ICIES'22

An enhanced EEG prediction system for motor cortex-imagery tasks using SVM

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Abstract. After the emergence of many new technologies, it is possible to search on the development of new devices that can be predicting what is happening in human thought based on EEG signals, such as the method used this paper contains a novel classification of the EEG signals acquired for multiple motor cortex-imagery tasks, where this method was based on the use of the Extra Tree algorithm to well select the best channels that were used for the acquisition of EEG signals, then the use of support vector machine (SVM) algorithm for data classification, moreover this work uses grey wolf optimizer (GWO) algorithm to improve all SVM parameters quickly and to converge the accuracy of the system towards the highest possible values. As a result, this work shows that the accuracy of prediction of motor cortex-imagery based EEG signals can be increased more than 99%. Also, this paper contains a comparison with other methods of the literature.

Keywords: Brain-computer interface (BCI), Electroencephalogram (EEG), Data analysis, Machine learning, Parameters optimization.

1 Introduction

The brain-computer interface (BCI) is a rapidly growing technology that establishes direct contact between the brain and output devices. It accomplishes this by attempting to identify the brain activities generated by a typical motor neuron pathway [6, 7]. Because there are differences in brain signals that correlate to different activities from each trial of each session, as well as test data, efficient signal processing algorithms are required for this distinction [1, 16]. EEG technology is a simple and low-cost solution for BCI systems from many methods to monitor brain activity, and it is employed in several non-invasive BCI investigations [5]. EEG is a useful tool for assessing and managing PWE, and it has a long and illustrious history as a clinical neurophysiological technique used in hospital and outpatient community settings [4, 15]. These signals are then converted into control commands for a variety of applications, such as virtual reality (VR) navigation, computer cursor movement, wheelchair motion, robot control, and prosthesiology [1, 5, 9, 12, 14]. The GWO algorithm [2] was utilized to establish an appropriate combination of SVM parameters as illustrated in Figure 1, and acquisition signals were classified to found the best ten electrodes with accuracy values remaining 99% in this current work. The following is a breakdown of the rest of the article. The proposed classification and optimization techniques for the system are presented in section 2. Section 3 contains the results and discussion, while section 4 contains the conclusions and a look ahead to future projects.

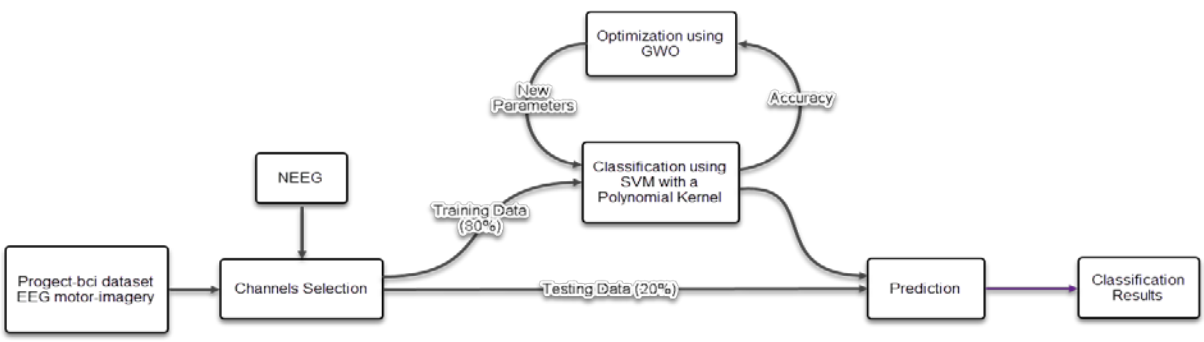

Fig. 1. Illustrate EEG data pre-processing and classification.

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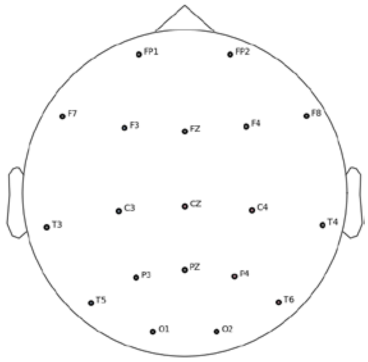
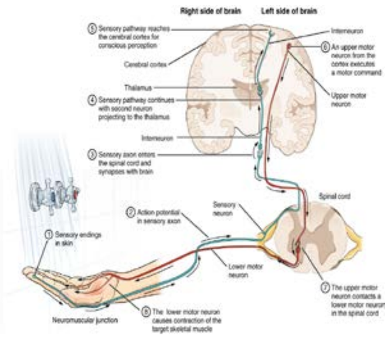


a) Electrodes position



b) Nerve system between left hand and brain central lobe

Fig. 2. (a) Positioning of all acquisition electrodes (Hands and legs), **(b)** Nervous system of the left hand.

2 Methods

2.1 Dataset

Dataset 'Projectbci 2D': The subject is a 21-year-old right-handed man with no known medical conditions. EEG monitors the true random movement of the left and right hands when the eyes are closed. The electrodes are positioned in the sequence listed below as illustrated in Figure 2.a: (FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, FZ, CZ, and PZ), where Figure 2.b shows the level of the nerve system that ties the left hand with a right part of the brain or what is called the motor cortex of the left hand. At 500Hz, an integrated EEG NeuroFax system with daisy chain attachment was employed for recording. This data is exported using the 'eemagine EEG' as illustrated in the reference [8]. The country's electrical wires have a 50 Hz frequency The labels that were used in this project are as follows:

- 'LF': Left-hand forward movement trials;
- 'LB': Left-hand backward movement trials;
- 'RF': Right-hand forward movement trials;
- 'RB': Right-hand backward movement trials;
- 'LFI': Imaginary left-hand forward movement;
- 'LBI': Imaginary left-hand backward movement;
- 'RFI': Imaginary right-hand forward movement trials;
- 'RBI': Imaginary right-hand rearward movement;
- 'LL': Left-leg movement trials;
- 'RL': Right-leg movement trials.
- 'L': Left-hand movement trials;
- 'R': Right-hand movement trials.

2.2 Channel selection

This work used the feature selection step to determine the best channels that have acquired the changes in brain activity during each class with good precision, to properly select these channels, this work uses the Extra Trees algorithm which is one of the best EEG data classifiers [3], knowing that this algorithm allows building a classification tree based on training data and then calculate the degree of importance D of each channel i in using the following relationship:

$$D_i = \sum_{j=1}^{n_f} n_j * \sum_{l=1}^{L} f_l * (1 - f_l) \qquad (1)$$

With f_l is the frequency of the label l in the tree, L is the number of labels, n_j is the number of samples used in each node, and n_f is the number of channels.

2.3 Support vector machine (SVM)

In 1963, Vapnik and Chervonakis came up with the SVM machine learning method. Traditional artificial neural networks that are based on the lowest empirical risk outperform the SVM since it is based on the smallest structural risk. This classifier's purpose is to find the best hyperplane for distinguishing each mode class [1, 2, 3]. The SVM chooses hyperplanes that group the most points of the same class together while keeping the gap between each class and those hyperplanes as little as possible. The support vector is created using the hyperplane's nearest point. The shortest path between them and class points is the distance from the class to the hyperplane [1, 2, 3]. This is how far something is measured.

2.4 Grey wolf optimizer (GWO)

GWO is a collective intelligence program that imitates the predatory behaviour of grey wolves (Tripathi et al., 2018). GWO uses a population-based natural-inspired method, which was created by Mirjalili et al. [2, 13]. Grey wolves are assigned varying levels of prey and hunting behaviours such as fencing, hunting, and attack based on their social rank, resulting in a global optimization process. Long et al. [11] have apparent advantages in terms of functional optimization, such as straightforward operation, fewer tuning parameters, and easy programming, as compared to other sets of intelligent algorithms.

3 Results

3.1 Channel selection results

Figure 3 illustrates some of the EEG signals acquired by different electrodes using the NeuroFax device, saying that all signals are noisy and incomprehensible in real-time. Figure 4 shows a classification of the degree of electrode importance for selecting the best electrodes at the classification and prediction stage of the motor cortex-imagery EEG signals in this work, such that the two best electrodes are FP1 and CZ, where the bad electrodes used are PZ and T6.

Table 1. Symbol and description

Symbol	Description
DG	degree
C0	coef0
TL	tol
CS	Cache-size
NEEG	Electrodes number
k	Kappa-score
MC	Matthews correlation
JS	Jaccard-score
ZOL	Zero One Loss
Tc	Classification time
Tp	Prediction time
To	Optimization time

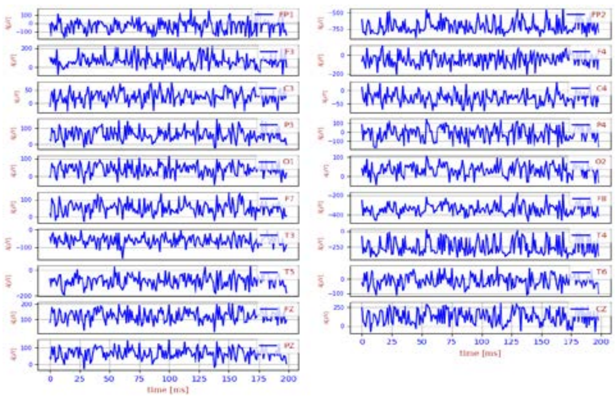


Fig. 3. A part of EEG signals acquired using Neurofax device.

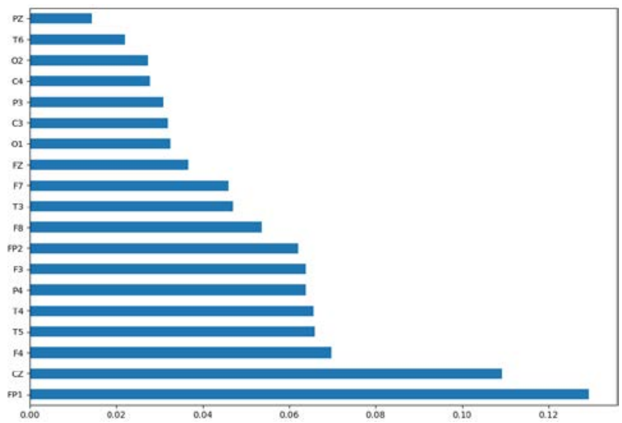


Fig. 4. Channels selection of all acquisition electrodes used for EEG motor cortex-imagery

3.2 Evaluation metrics

The performance of detection and prediction is measured using the metrics as illustrated in Table 1: The most widely used method for comparing algorithm performance in classification without class concentration. As a result, prediction accuracy (AC) is the most frequent means of experiencing to avoid separating the number of excellent labels between distinct tasks [2, 3]:

$$AC = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Sensitivity (SE) and precision (PR) are commonly used to assess the classification performance of biological and complicated data.

$$SE = \frac{TP}{TP+FN} \tag{3}$$

$$PR = \frac{TP}{TP+FP} \tag{4}$$

Another metric for evaluating performance is the F1 score, which is as follows:

$$F1 = \frac{2*PR*SE}{PR+SE} = \frac{2*TP}{2*TP+FP+FN} \tag{5}$$

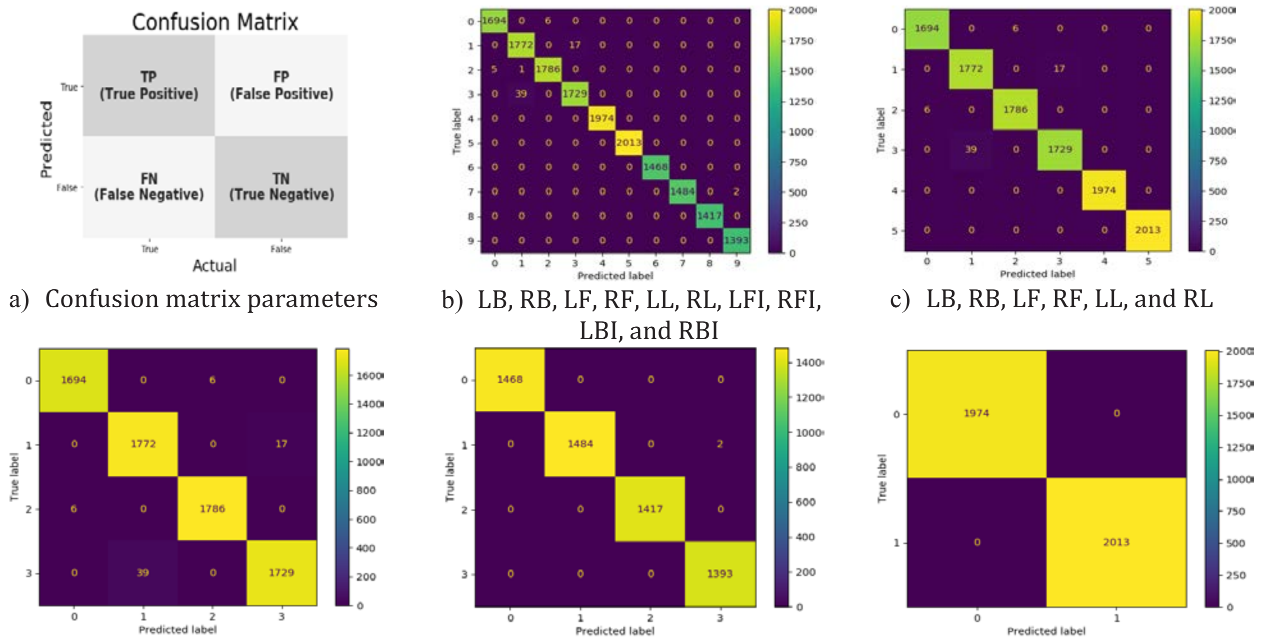
$$ZOL = FP + FN \tag{6}$$

$$MC = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{7}$$

The diagonal values in the confusion matrix parameters in Figure 5.a, reflect the number of times the predictor correctly answers for each task, while the other values indicate the predictor's wrong response. The predictor finds 70 false answers in Figure 5.b for the classification of 9 tasks; the predictor falsely answers 56 times between the two RF and RB tasks due to a large identity between these two classes, and the same exhausts in Figure 5.c also shows that there are 12 errors during testing between the two LF and LB classes.

Table 2. SVM-poly parameters optimization results using GWO for EEG classification

SVM parameters					Optimization results		
DG	***C***	***C0***	***TL***	***CS***	AC (%)	ZOL	To (s)
113	0.368	0.723	0.276	319	24.10	3448	2.89
2	1.769	0.060	0.661	455	99.96	2	3.05
1	1.027	0.811	0.255	227	99.96	2	45.15



a) Confusion matrix parameters b) LB, RB, LF, RF, LL, RL, LFI, RFI, LBI, and RBI c) LB, RB, LF, RF, LL, and RL d) LB, RB, LF, and RF e) LFI, RFI, LBI, and RBI f) LL and RL

Fig. 5. Example of the confusion matrix for each classification task using SVM-poly

Table 3. Classification results of all EEG motor cortex-imagery when estimate the number of the electrodes using SVM-poly

Tasks	NEEG	Classification results									
		AC(%)	SE(%)	PR(%)	F1 (%)	k (%)	MC(%)	JS(%)	ZOL	Tc(s)	Tp(s)
LB, RB, LF, RF, LL, RL, LFI, RFI, LBI, RBI	19	99.58	99.60	99.60	99.60	99.54	99.54	99.22	70	26.59	0.70
LB, RB, LF, RF, LL, RL	19	99.38	99.36	99.36	99.36	99.26	99.26	98.74	68	25.20	0.31
LFI, RFI, LBI, RBI	19	99.97	99.97	99.96	99.97	99.95	99.95	99.93	2	0.25	0.01
	14	99.95	99.95	99.95	99.95	99.93	99.93	99.90	3	0.23	0.01
	10	99.97	99.97	99.97	99.97	99.95	99.95	99.93	2	0.18	0.01
	7	99.90	99.90	99.90	99.90	99.86	99.86	99.79	6	0.24	0.01
LB, RB, LF, RF	19	99.04	99.04	99.05	99.04	98.71	98.71	98.11	68	24.96	0.17
L, R	19	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.10	0.01
	10	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.11	0.01
	7	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.7	0.01
LL, RL	19	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.07	0.00
	14	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.19	0.00
	10	100.0	100.0	100.0	100.0	100.0	100.0	100.0	0	0.23	0.00
	7	99.85	99.85	99.85	99.85	99.70	99.70	99.70	6	1.66	0.01

Table 4. Comparative results with related work

Work	Tasks	Method	AC (%)	PR (%)	SE (%)	F1 (%)
Lerga et al. (2021)	LFI, RFI, LBI, RBI	TFD-LSSVM	92.4	92.5	92.2	92.4
Hossain et al. (2015)	L, R	PNN	99.1	nan	nan	nan
		BP	88.9	nan	nan	nan
This Work	LFI, RFI, LBI, RBI	SVM-GWO	99.97	99.97	99.97	99.97
	L, R	SVM-GWO	100.0	100.0	100.0	100.0

3.3 Classification results

The classification in Table 2 shows the results of optimizing the SVM (kernel-poly) algorithm parameters using GWO optimizer, knowing that the prediction value increases from 24.1% to 99.96% in a 3-second optimization time, which implies the high effect of optimization algorithms during the classification of EEG signals. Table 3 shows the results of classification of the signals of the different tasks when the number of electrodes is reduced, such that in the case of 9 classes the accuracy valuer remains 99% higher with classification and prediction speeds higher than 3700 and 42000 samples per second, respectively. Similarly, the classification of EEG motor cortex signals of the movement of hands and legacies shows higher accuracy values of 99.3%. In this table it is noted that during the imagination of the movements of the hands, the precision value remains at 99.95%, this value indicates the possibility of practised neuroheadset device for control of the external devices using imagination alone. The results of actual movements of the hands and bequests show that the accuracy is in the order of 100% during testing, which shows the efficiency of the parameters of the SVM-poly algorithm for a prediction of EEG motor cortex-imagery signals with more than ten electrodes. Table 4 shows a comparison between the results of this work with related work, such as in the work of Hossain et al [8] the classification of raw EEG for hand movement using the probabilistic neural network (PNN) algorithm finds a precision value of 99.1%, also an accuracy value of 88.9% using BP algorithm which shows that the use of GWO in our work improves the quality of prediction, likewise also when classifying the tasks of motor imagery using least-squares SVM (LS-SVM) in the work of Lerga et al. [10], the accuracy value remains at the level of 92.4% which is a low value compared to the results illustrated in Table 3.

4 Conclusion

In conclusion, this work shows that there is a possibility to predicting the tasks of the imagination easily using new technologies, such as the application of the Extra Tree algorithm for the selection of features which shows that the number of channels can decrease up to the minimum possible and that the use of the SVM algorithm with a polynomial kernel shows that the EEG data acquired using NeuroFax device are non-linearly separable, moreover than this work has been well shown the effectiveness of the GWO algorithm to improve the internal parameters of classifying SVM and as results, this work shows that the prediction of EEG data of motor cortex-imagery tasks remains higher of 99% in binary cases and multiple tasks. We hoped that this work can help and give a good initiative to other researchers to develop and find better results. Our future research is focused on real-time application control by thought and helped humanity.

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