EEG Signals Based Motor Imagery and Movement Classification for BCI Applications

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***Abstract*—** The Brain-Computer Interface (BCI) is a system that uses the neural activity data of the brain to control the devices in the outside world, in other words, to communicate. BCI studies of wearable sensor EEG sensor technology have gained momentum. In this study, in order to enable the use of electroencephalogram (EEG) patterns in BCI applications, the extraction of statistical-based features, the selection of the most effective features with the NCA method, and the determination of the type of motion request with classification algorithms were carried out. The PhysioNet EEG Motor Movement/Imagery dataset was used. For six different types of motion and imaging, 30 statistical features were calculated (960 in total) for each channel of the EEG signals received from the 48-channel EEG sensor head, and the most effective 120 features were selected with NCA. The selected feature set is given as input to the LD, NB, SVM classification algorithms. The test accuracy success of the models is 91.18%, 95.41%, and 99.51%, respectively. These results show that the proposed method will give successful results in BCI applications.

Keywords*— *brain-computer interface, EEG signals, NCA feature selector, classification

I. INTRODUCTION (*HEADING 1*)

Electroencephalogram (EEG) is bioelectrical signals collected from the scalp with special sensors and information about brain activities [1]. EEG signals have been used for many years only in the diagnosis of neurological diseases (epileptic seizure detection, Alzheimer's, sleep disorders, etc.) [2], [3] in the medical field. [4]–[6]. However, the application area has expanded with the use of wearable sensor technology and surface electrodes. The use of EEG signals for brain-computer interface (BCI) identification studies enabled the use of EEG signals for communication with the outside world. In both cases, whether the movement is imagined or the action is performed, the corresponding EEG signals are produced in the brain [7]. By analyzing the EEG signals, the movement request and type of the person can be detected, and thus the BCI interface can be defined and the external devices can be controlled with the EEG signals.

BCI games in the entertainment industry, for example, have recently been discovered to have applications for healthy users. [8]. Because of its portable acquisition system and ease of use for scalp recording electroencephalography (EEG) is a practical way. When a person imagines moving different parts of his body or different control orders for an instrument, the resulting EEG signals fluctuate with different characteristics. By analyzing the EEG signals, the movement desire of the person can be recognized. Recently, BCI's studies have gained popularity and it is tried to be applied to real-world scenarios such as mind-controlled wheelchairs[9], [10], prosthetics[11], and exoskeletons[12]. BCI applications are increasing in many different application areas such as game technologies and smart home systems [13]–[16]. EEG-based BCI applications have some fundamental difficulties. Some of these are vibration-induced noises caused by recording device electrode connections, noises caused by physiological activities such as eye blinking, muscle activity, and heartbeat during the recording process, harming the healthy collection of EEG signals. In addition, it is quite challenging for the participants to concentrate on the action they will take during the recording. In addition, EEG recorders with 8 and 128 channels are generally used in BCI applications, and synchronous preprocessing, feature extraction, and interpretation of signals are required [8]. Although the wavelet transform (WT)[17], [18] and co-spatial model (CSP) [19], [20] methods are the most widely used feature extraction methods, many different feature extraction methods have been used by researchers [21]. As classification methods, Linear Discriminant Analysis (LDA) [22]–[24]and Support Vector Machine (SVM) are the two most popular methods in BCI research (SVM) [25]–[27]. It was stated that SVM performed better than LDA and K-NN, especially in two-class classification. [28]. Kottaimalai et al. also obtained good recognition results by combining an artificial neural network with principal component analysis to classify the EEG signal [29]. Because of its high prediction accuracy and capacity to process massive amounts of data, the support vector machine (SVM) is widely employed in the biomedical area. [30]. Unlike kernel-based techniques like SVM, which have great generalization and non-linear mapping capabilities, SVM is known to always have high processing costs.

In this study, classification of six different types of movement and imagery was performed using the PhysioNet EEG Motor Movement/Imagery dataset (108 subjects, 3.145.160 EEG recordings) [31]. Chapter 2 contains detailed information about feature extraction with statistical methods, feature selection with NCA, and classification algorithms. In Chapter 3, the results obtained with the proposed methods are evaluated with the performance table and confusion matrices. Chapter 4 includes the results section.

II. MATERIAL AND METHOD

A. Dataset Features

The Physionet dataset [31], [32] used in this study includes more than 1500 one- or two-minute EEG recordings from 109 healthy people. The EEG signal was recorded from 64 electrodes (64 channels) placed on the head at a sampling rate of 160 Hz. Subjects were asked to perform or imagine six different tasks. Figure 1 [31], [32] shows the locations of the electrodes on the subjects' scalp.

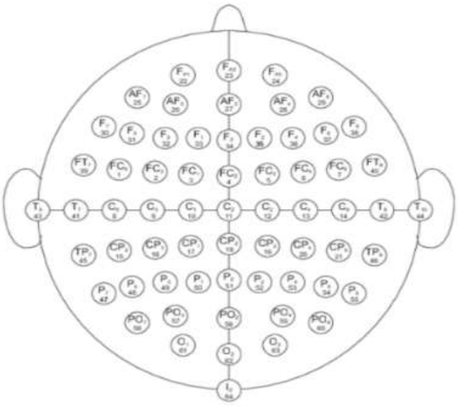

Fig.1. Layout of 64 EEG electrodes

When the data set was analyzed, it was determined that the data of some subjects were damaged (Subjects S59, S60, S61, S77, S95-S103, S106, S109 subjects were damaged). Therefore, these data were removed and EEG data obtained from the remaining 96 subjects were used in this study. The 6 tasks that were recorded within the scope of the study are summarized in Table 1.

TABLE I. MOVEMENT IMAGERY TASK DEFINITION

Task /Class	Definition	Task /Class	Definition
1	eyes open	4	imagine opening and closing left or right fist
2	eyes closed	5	open and close both fists or both feet
3	open and close left or right fist	6	imagine opening and closing both fists or both

B. Preprocessing and Feature Extraction

The vector size of the EEG signal data of each subject is 1x9600. The sampling rate per second of the EEG sensor head is given as 160. First, the segmentation process was applied to the EEG signals in the data set [31], [32]. The vector signal is segmented into one-second (60x160) segments. Then, 30 statistical features of each (1x160) dimensional signal were calculated. These statistical properties are given in Table 2.

TABLE II. STATISTICAL FEATURES

No	Feature	No	Feature
1	maximum(EEGvector)	16	maximum(abs(EEGvector))
2	mean(EEGvector)	17	mean(abs(EEGvector))
3	median(EEGvector)	18	median(abs(EEGvector))
4	variance(EEGvector)	19	variance(abs(EEGvector))
5	standard_deviation(EEGvector)	20	standard_deviation(abs(EEGvector))
6	minimum(EEGvector)	21	minimum(abs(EEGvector))
7	maximum(EEGvector) − minimum(EEGvector)	22	maximum(abs(EEGvector)) − minimum(abs(EEGvector))
8	root_mean_square(EEGvector)	23	root_mean_square(abs(EEGvector))
9	summation($EEGvector^2$)	24	summation(abs(EEGvector)^2)
10	wentropy(EEGvector, shannon)	25	wentropy(abs(EEGvector), shannon)
11	wentropy(EEGvector, sure, 1)	26	wentropy(abs(EEGvector), sure, 1)
12	wentropy(EEGvector, logenergy)	27	wentropy(abs(EEGvector), logenergy)
13	kurtosis(EEGvector)	28	kurtosis(EEGvector)
14	skewness(EEGvector)	29	skewness(EEGvector)
15	mean_absulute_deviation(EEGvector	30	mean_absulute_deviation(EEGvector)

C. Feature selection with NCA

Discriminative feature selection was carried out using NCA on the retrieved features. One of the most used features selection methods is NCA. These weights are used to describe the significance of each characteristic in NCA. An exponential kernel function and a Manhattan distance-based fitness function are used by NCA All feature weights are initially allocated a constant positive integer number (usually one). Weights are updated using stochastic gradient descent (SGD). NCA generates characteristics with a positive weighting. The NCA algorithm's most significant advantage is that it assigns each attribute a positive weight. In equations [33], the NCA algorithm is explained.

$$S = \{(x_1, y_1), \dots, (x_i, y_i), \dots, (x_N, y_N)\} \quad (1)$$

It's a multi-class system. There are N observations in the training set. The feature vectors are denoted by x_i. The class labels are y_i *{1, 2, 3,...,c}*. c stands for the number of classes. It's possible that all S elements might be used as a reference point in the NCA process, which uses random selection. The probability $P(Ref(x) = x_j \mid S)$ of choosing point x_j from S as the reference point for x is higher if x_j is closer to x as measured by the distance function d_w .d_w is explained in Equation 2.

$$d_w(x_i, x_j) = \sum_{r=1}^{p} w_r^2 \left|x_{ir} - x_{jr}\right| \quad (2)$$

In Equation 2 w_r are the feature weights. $P(Ref(x)$ is explained in Equation 3. A kernel or similarity function is represented by the variable k. It takes large values when $d_w(x_i, x_j)$ is small.

$$P(Ref(x) = x_j \mid S) = \frac{k(d_w(x, x_j))}{\sum_{j=1}^{n} k(d_w(x, x_j))} \quad (3)$$

Within the scope of this study, using the NCA method expressed mathematically above, the most important and effective 120 of the 1920 features calculated in the feature extraction method were selected to be used in the classification step.

D. Classification

The EEG signals from the dataset were segmented and features were produced, as mentioned in previous sections. The selected features are given as input to 3 different classification models, namely LD, NB, and SVM. the models are used.

Because it is fast, accurate, and simple to comprehend, Linear Discriminant (LD) analysis is a popular classification approach to test. Discriminant analysis works well with large datasets. According to discriminant analysis, distinct classes create data using different Gaussian distributions. In order to train a classifier, the fitting function calculates the parameters of a Gaussian distribution for each class [34].

The Bayes theorem underpins the naive Bayes algorithm, which assumes that predictors in a given class are conditionally independent. Each data point is assigned to the class that is closest to it using the Naive Bayes (NB) classifier. The distance from the mean is taken into account by NB, as well as how it relates to the class variance. The z-score is calculated for each dimension, which is the standard deviation divided by the distance from the mean. [34], [35].

The SVM classifier, in general, finds the best separation hyperplane between two or more classes. An SVM finds the best hyperplane for separating data points of one class from those of the other. The hyperplane with the biggest margin between the two classes is the optimum hyperplane for an SVM. The margin is the greatest width of the slab parallel to the hyperplane with no inside data points. The SVM optimizes the margin around the separation hyperplane, and the final classification decision is made using a subset of training samples known as support vector [36], [37]. The hyperparameter of classification ere summarized İn Table 3.

TABLE III. USED HYPER PARAMETERS OF CLASSIFIER

Classifier	Parameters
LD	Model :Linear Discriminant, Covariance structure: Full
NB	Kernel: Gaussian, Distribution name for Predictor: Kernel, Distribution name of categorical prediction: MVMN
SVM	Type: Linear, Kernel: Polynomial, Polynomial Order: 3, Kernel Scale: Auto, Box Constraint Level : 1

E. Performance Evaluation

A range of performance criteria was used to compare the performance of machine learning techniques. Accuracy, Error, Sensitivity, Specificity, Precision, F1 Score, MCC, Kappa performance criteria values are calculated with the formulas in Table 4 [33], [38] and presented in the results section .

TABLE IV. PERFORMANCE METRICS

Performance Metric	Equation	Performance Metric	Equation
Precision	$\frac{TP}{TP+FP}$	Accuracy ACC	$\frac{TP+TN}{TP+TN+FP+FN}$
Negative Prediction	$\frac{TN}{TN+FN}$	F-Score	$\frac{2\times precision\times recall}{precision+recall}$
Sensitivity – Recall	$\frac{TP}{TP+FN}$	MCC-Matthews correlation coefficient	$\max([(TP*TN)-FP*FN)/((TP+FP)*P*N*(TN+FN))\hat{}0.5],\ [((TP+FP)*P*N*(TN+FN))\hat{}0.5])$
Specificity	$\frac{TN}{TN+FP}$	Cohen's Kappa	$\mathrm{po}=\mathrm{ACC}$ $\mathrm{pe}=((\mathrm{P}*(\mathrm{TP}+\mathrm{FP})+(\mathrm{FN}+\mathrm{TN}))/(\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN})\hat{}2$ $\mathrm{kappa}=\max(\left[\frac{\mathrm{po}-\mathrm{pe}}{1-\mathrm{pe}};\frac{\mathrm{pe}-\mathrm{po}}{1-\mathrm{po}}\right])$

in Table, true positives (TP) is a number of cases that were accurately predicted. False negatives (FN) refer to the number of cases that were incorrectly predicted. The amount of correctly anticipated negative cases is known as true negatives (TN), while the number of incorrectly predicted negative cases is known as false positives (FP).

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental setup

A workstation with a 2.60 GHz Intel i7-6700HQ CPU, 16 GB RAM, and a 64-bit Windows 10 operating system was used to test the proposed method. The classification learner toolbox in MATLAB was used as a result.

B. Experimental Results and Discussion

Table 5 shows the EEG based movement/imagery prediction successes of LD, NB and SVM classifiers based on EEG signals with the proposed method. The highest accuracy was obtained with the SVM method with 99.51% and the lowest accuracy with the LD method with 91.18%. The success of the NB classifier remained at 95.41%. The same performance ranking is valid for F1, MCC, Kappa criteria. For all methods, sensitivity is greater than 0.90, specificity greater than 0.98, and precision greater than 0.93. The confusion matrix provides a class-specific summary of the estimation results in classification problems. Confusion matrices for the three machine learning methods used are presented in Table 6. It is seen that the highest classification success among the three methods is obtained for tasks 3,4 and 5. The lowest success was obtained in the estimation of class 1. The lowest success was obtained in the estimation of class 1. Although 3rd and 5th grades belong to movement 4th and 6th grades imagery EEG data, the average success for both groups seems to be quite close. Table 7 contains the results of motion classification studies for EEG-based BCI made using machine learning techniques in the last five years. It is seen that statistical feature extraction, NCA-based feature selection and SVM classification algorithm proposed in this study achieve a much higher performance than similar studies in the literature.

TABLE V. CONFUSION MATRIX FOR EACH METHODS

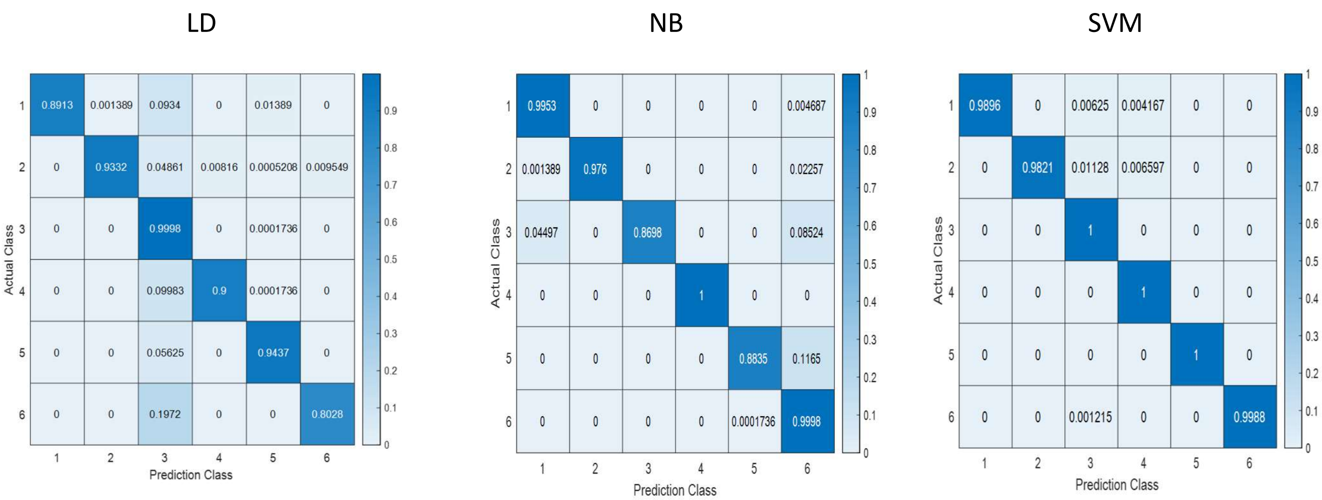

TABLE VI. HUMAN IDENTIFICATION PERFORMANCE RESULTS

	Accuracy	Error	Sensitivity	Specificity	Precision	F1 Score	MCC	Kappa
LD	0.9118	0.0882	0.9118	0.9824	0.9385	0.9169	0.9054	0.6825
NB	0.9541	0.0459	0.9541	0.9908	0.9615	0.9547	0.9478	0.8347
SVM	0.9951	0.0049	0.9951	0.9990	0.9952	0.9951	0.9941	0.9823

TABLE VII. EEG SIGNALS CLASSIFICATION PERFORMANCE FOR BCI

Reference	Feature Extraction and Classification Method	Accuracy
[39]	Linear regression	95
[25]	PCA +SVM	92.5
[26]	WT + SVM	90
[19]	CSP + Fuzzy	91.43
[27]	WT , PCA, FFT + SVM ANN	84
[40]	NB, RF, SVM	87
[20]	CSP + MLP	97.812
In this study	Statistic Features + LD	91.18
	Statistic Features + NB	95.41
	Statistic Features + SVM	**99.51**

IV. CONCLUSIONS

A method for identifying brain-computer interfaces using electroencephalography (EEG) data was developed in this study. First, the statistical properties of the EEG data collected from 64 channels for six different tasks of 96 people in the PhysioNet dataset were calculated. The NCA approach was used to identify the 120 most essential features in the feature vector. In the last step, the selected feature vector is given as input to the LD, NB, and Support Vector Machine (SVM) classifiers, and the classification successes are tested. The average accuracy of LD, NB, and SVM classifiers were calculated as 91.18%, 95.41%, and 99.51%, respectively. These results clearly confirmed the suggested method's success in categorizing multi-class motion and imagery with EEG signals for BCI.

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