Advanced Signal Processing and Classification of EEG Patterns in Neurointerface Systems

Serhii Lupenko [1,2], Roman Butsiy [2], Oleksandr Volyanyk [2] and Nataliia Stadnyk [3]

[1] *Faculty of Electrical Engineering, Automatic Control and Informatics, Opole University of Technology, 45-758 Opole, Poland*
[2] *Institute of Telecommunications and Global Information Space, National Academy of Sciences of Ukraine, 02000 Kyiv, Ukraine*
[3] *Ternopil Ivan Puluj National Technical University, 46001 Ternopil, Ukraine*

Abstract

This study provides a comprehensive assessment of an extended set of modern classifiers designed for electroencephalography signal analysis in brain-computer interface systems. Using the modern model of the vector of cyclic rhythmically connected random processes for estimating signal characteristics, the classifiers compared encompass k-NN, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, AdaBoost, and Naive Bayes. By decomposing signals into Fourier series, the optimal number of coefficients is investigated to both reduce computational complexity and increase accuracy. To facilitate a transparent and decisive comparison among the classifiers, the Confusion Matrix methodology is used. Results suggest that among the diverse range evaluated, Linear SVM, Naive Bayes, and Multilayer Perceptron classifiers showcased superior accuracy.

Keywords

BCI-systems; EEG signals; brain-computer interface; vector of cyclic rhythmically connected random processes; classifiers; Confusion Matrix;

1. Introduction

Brain-computer interface (BCI) systems [1, 2, 3] based on the processing and interpretation of electroencephalography (EEG) signals play an important role in neuroscience and technology. EEG, which captures the electrical activity of the brain, is a crucial component of the effective functioning of BCI systems. Being a non-invasive and relatively cost-effective [4, 5] method, EEG provides real-time information on brain activity, making it invaluable for BCI. The ability to accurately interpret these EEG signals is vital, especially for people with movement disorders [6], as it facilitates direct communication between their brain and external devices, giving them regained independence. In addition to therapeutic applications, advances in EEG processing are improving human-machine interaction in sectors such as gaming [7], virtual reality [8, 9], and robotics control [10]. Moreover, the ontological frameworks, as discussed by authors in the study [11], can be pivotal in enhancing BCI systems by integrating diverse data sources, which is essential for expanding the applications of BCI into fields like Chinese Image Medicine, offering new modalities for diagnosis and treatment planning.

In a previous study [12], several classifiers were investigated and compared for classifying EEG-recorded signals. However, this work did not delve deeply into each stage of signal processing. This study provides a more detailed description of each processing step. Additional filtering methods will be applied, and a new model, called a vector of cyclic rhythmically connected random processes, will

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EMAIL: s.lupenko@po.edu.pl (A. 1); romanbutsiy@gmail.com (A. 2); wonderage2018@gmail.com (A. 3); natalya.stadnik15@gmail.com (A. 4)
ORCID: 0000-0002-6559-0721 (A. 1); 0000-0002-8415-8635 (A. 2); 0000-0001-9137-7580 (A. 3); 0000-0002-7781-7663 (A. 4)

be applied during the evaluation of the EEG signal characteristics. A Confusion Matrix will be used to test the classifiers, which will increase the reliability of an experimentally based choice of the most effective decision-making technologies in BCI systems.

2. Methodology

2.1. Signal registration

The processing of EEG signals in the BCI-system is commonly recognized to involve five [13, 14] primary stages (Fig. 1), namely, signal registration, pre-processing of signals, estimation of signal characteristics, classification (recognition) of signals and computer interaction.

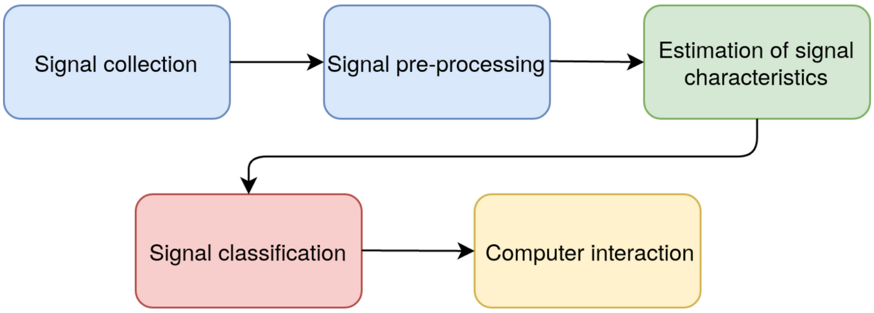

Figure 1: Main stages of signal processing by the BCI-system

Signal collection (registration) as the first stage of signal processing by the neurointerface system in terms of accuracy and cost is significantly determined by hardware and software of BCI system. Although the market for affordable and accessible neurointerfaces is relatively limited, there are some cost-effective solutions [16] available that can facilitate experiments with satisfactory levels of accuracy and reliability. The choice of the Open Source Brain-Computer Interfaces (OpenBCI) [17] platform was justified and experimentally tested in the works [12, 13, 14]. This platform is an affordable, straightforward, and open-source solution that can be easily assembled in the your own home.

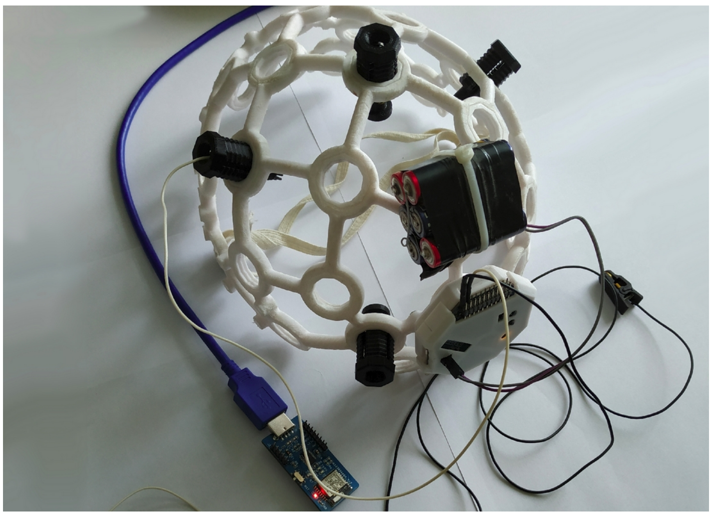

Figure 2: The Ultracortex Mark IV headset is produced using a 3D printer

A non-invasive method of electroencephalography was chosen to register the electrical activity of the scalp surface. The 8-channel version of the OpenBCI platform was utilized to record the signals. It should be noted that the 8-channel version can easily be expanded to 16 channels by using the additional Daisy module. However, in this research, an 8-channel version was used, since only one channel was enough for the experiment. C3 electrode and A2 reference electrode were used to record the signals. The data sampling frequency for each channel is set to 250 Hz. Ultracortex "Mark IV" was employed to securely attach the electrodes, with the device being made using a 3D printer at home (see Fig. 2). To manage the recording of EEG signals, the OpenBCI GUI utility is utilized. The measurement outcomes are saved on a microSD memory card directly integrated into the board. For processing the acquired results, custom scripts were developed in Python, leveraging various auxiliary libraries including Sklearn, Numpy, Scipy, Matplotlib, and others.

2.2. Pre-processing of signals

The subsequent step involves the pre-processing of the analyzed EEG signals, which involves the utilization of Butterworth filters. In the initial stage, a 3rd order rejection filter is employed to eliminate noise originating from the power grid at a frequency of 50 Hz (60 Hz). The signals prior to and following the initial filtering stage are depicted in Figure 3 ((a) and (b), respectively).

In the second stage, a 5th order bandpass filter is employed. For this experiment, the filter's bandwidth is set to 1-17 Hz, effectively removing low-frequency and high-frequency noise. The filtered signals, which are prepared for subsequent processing stages, are illustrated in Figure 3 *c*.

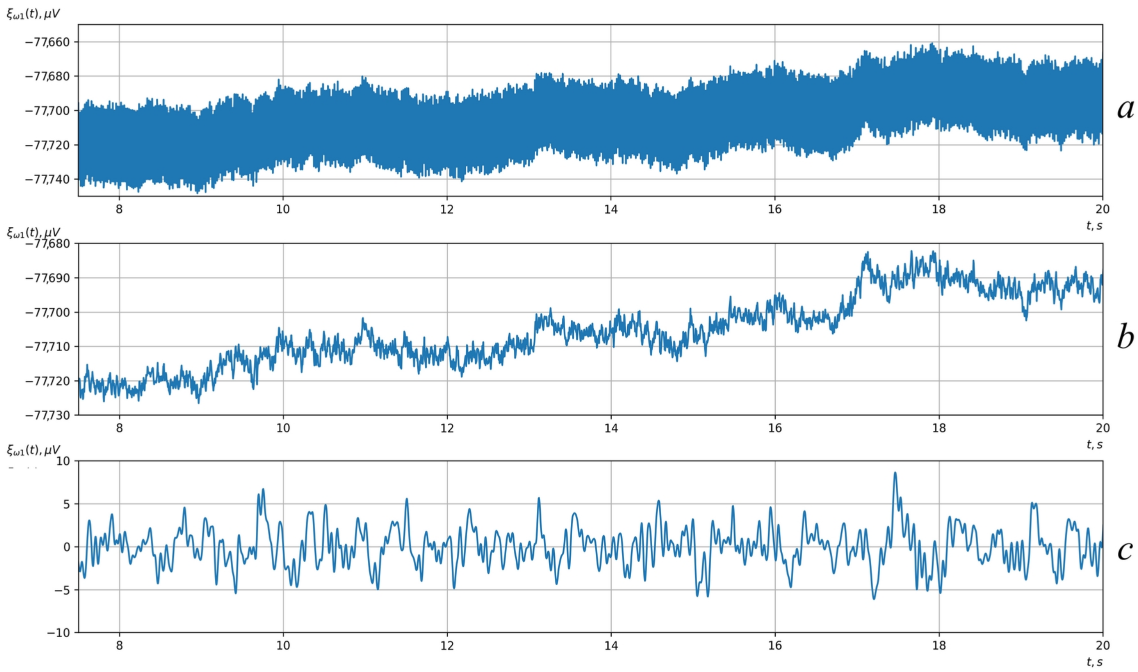

Figure 3: EEG signals filtering. Recorded signal (a), after 3rd order rejection filter (b), after 5th order bandpass filter (c) [13]

2.3. Estimation of signal characteristics

In this study [14], a new mathematical model of vector EEG was proposed and substantiated in the form of a vector of cyclic rhythmically connected random processes. By considering the stochasticity, cyclicality, variability of the rhythm of multidimensional distribution functions, initial, central, and mixed moment functions of the signals under investigation, it provides efficient statistical tools for studying a wide range of characteristics of vector EEG.

The vector EEG mathematical model introduced in this study [14] aligns with methodologies used in [15], where a similar vector approach is applied to the statistical processing and modeling of synchronously registered cardio signals of various physical natures, demonstrating the versatility and applicability of such models across different domains of biomedical signal analysis

Using the estimated rhythm function [14], the pre-processed vector of signals will be segmented into cycles. These cycles can further be divided (see Fig. 4) into active zones (when the operator performs a mental controlling action) and passive zones (when the operator's mental controlling action is absent).

The obtained vectors of activity and passivity zones will be decomposed into Fourier series. This decomposition allows us to form a vector of informative features for the classifiers using the Fourier coefficients (see Fig. 4 (b) and (c)). In addition, these coefficients, when considered alongside Bessel's inequality, provide a comprehensive framework for feature extraction. The resulting coefficients will be used for training the classifiers to achieve optimal performance.

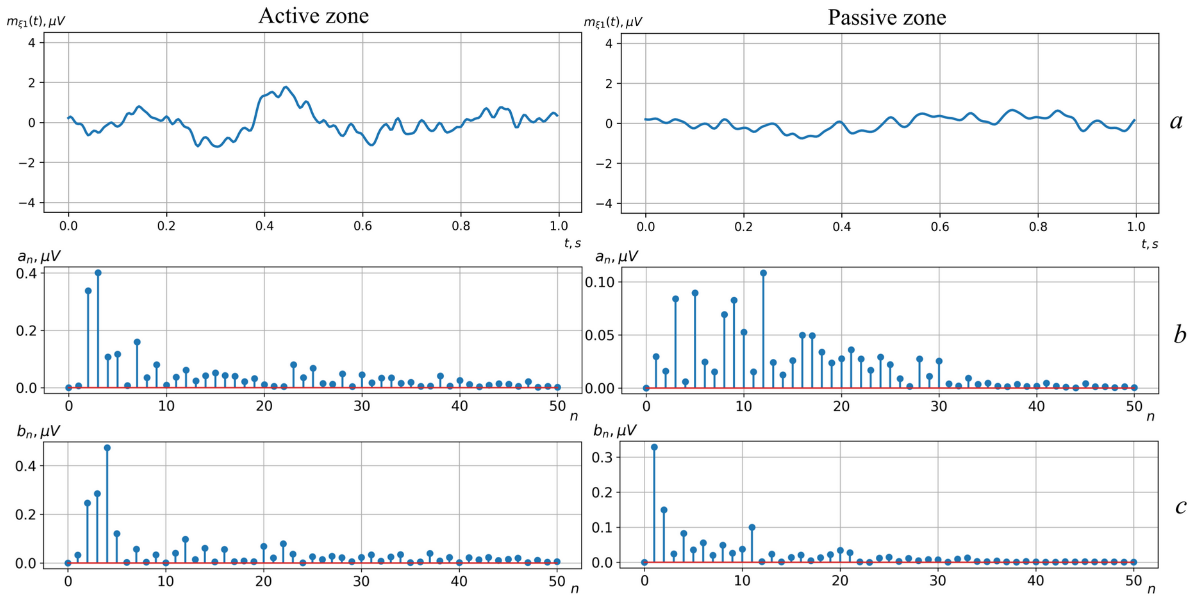

Figure 4: Visualization of EEG signal characteristics across two zones. On the left, three plots represent to the activity zone, and on the right, three plots represent the passivity zone. Horizontally, plots (a) display mathematical expectations, (b) display cosine coefficients from the Fourier series, and (c) display sine coefficients from the Fourier series

The Figure 4 shows the characteristics of the EEG signal in the zones of activity and passivity using mathematical expectations and Fourier series coefficients. It can be seen from the graphs that the primary information is concentrated in the first 30 coefficients, while the following coefficients demonstrate noise-like properties.

2.4. Classification

The selection of a classifier plays a vital role in the development of neurointerface systems. This study aims to assess the accuracy of well-known classifiers including k-Nearest Neighbors (k-NN), Linear Support Vector Machine (Linear SVM), Decision Tree, Random Forest, Multilayer Perceptron (MLP), Adaptive Boosting (AdaBoost), and Naive Bayes. This classifiers are common [18] in machine learning due to their versatility, efficacy, and scalability. Their popularity stems from several strengths: k-NN's simplicity and adaptability [18], SVM's robustness in high-dimensional spaces [19], decision trees' interpretability [20], Random Forest's ensemble-based accuracy [21], MLP's capability to capture non-linearities [22], AdaBoost's iterative refinement [23], and Naive Bayes' speedy predictions and efficiency with large datasets [24]. Their combined theoretical soundness and proven real-world applicability make them first-choice tools for many practitioners.

The choice of these classifiers is justified by the following considerations.

The k-Nearest Neighbors algorithm (k-NN) is one of the simplest machine learning methods and falls under the category of supervised learning [18]. Its fundamental principle is that an object is classified based on the "votes" of its nearest neighbors in the feature space. The size of "k" denotes the number of neighbors participating in the "voting". The k-NN algorithm does not require any predictive model, but instead utilizes all available training information during classification.

The Support Vector Machines (SVM) method is a powerful and flexible machine learning technique used for classification and regression tasks. A Linear SVM is a specific instance of SVM, where the decision boundary or hyperplane is linear [19].

The main idea behind Linear SVM [22] is to find a hyperplane that best separates the data into two classes, maximizing the margin (distance) between the closest data points (support vectors) from both classes. These points, which lie closest to the hyperplane and determine its position, are called support vectors. Thanks to this strategy, Linear SVM exhibits good resistance to overfitting.

The Linear SVM algorithm implements a linear decision boundary, but to implement nonlinear boundaries, a kernel SVM can be used, applying different kernel functions. In this case, the input data is transformed into a higher-dimensional space where it can be linearly separated. Despite this, Linear SVMs are used when data can be linearly separated, or when the feature space far exceeds the number of training examples, which allows for high computational speed and simplicity of interpreting results.

A Decision Tree is a common machine learning algorithm that is employed for both classification and regression tasks. The principle of a Decision Tree involves dividing the input feature space into segments, with each corresponding to a specific class or a predicted value [20]. Essentially, a Decision Tree is a binary tree in which each internal node signifies a test on one of the features, while each leaf represents the predicted class or value.

Random Forest is an machine learning algorithm that constructs multiple decision trees and combines their predictions [21]. Using decision trees and their individual decisions, it effectively handles the overfitting issue often seen in a single decision tree, providing more generalized predictions. It works well with both classification and regression tasks, can handle large datasets with high dimensionality, and provides measures of feature importance, making it a versatile and widely used algorithm in machine learning.

MLP is a type of artificial neural network widely used for classification and regression tasks. MLP uses a supervised learning technique called backpropagation for training. It should be noted that the inclusion of one or more non-linear hidden layers allows MLPs to solve problems that are not linearly separable, adding to its versatility as a machine learning classifier.

AdaBoost is a powerful machine learning algorithm that works by combining several weak learners, typically decision trees, to create a robust classifier that improves prediction accuracy. The AdaBoost algorithm iteratively adjusts the weights of training instances by increasing the weights of incorrectly classified instances and decreasing the weights of correctly classified instances. Thus, it "adapts" by focusing more on difficult cases in subsequent iterations. The final prediction is made by weighted voting, taking into account the accuracy of each weak learner, making AdaBoost effective for both binary and multi-class classification problems [23].

The Naive Bayes classifier is a probabilistic machine learning algorithm based on applying Bayes' theorem with strong independence assumptions between the features [24]. Despite its oversimplified assumptions, Naive Bayes classifiers often perform remarkably well in many complex real-time situations. The model is also favored for its efficiency and scalability, handling large datasets with high dimensionality effectively.

2.5. Experiment Procedure

During EEG signal capture, there are multiple technical challenges, largely attributed to the diminished amplitude of the signal. As it travels through the brain's protective layers, cerebrospinal fluid, and the skull to reach the scalp, the signal's amplitude ranges merely between 1-100 microvolts, with frequencies spanning from 0.1-100 Hz. The choice of electrode material and the tightness of contacts also impact the quality of the recording.

To obtain an artifact-free EEG recording, it's crucial that the research participant remains relaxed during the experiment, seated in a specialized comfortable chair. External light and sound stimuli should be minimized. Proper electrode placement is vital, with the electrode-skin resistance maintained below 5 kOhms.

In this experiment, the participant performed a mental action of either extending or flexing the arm for approximately one second, followed by a state of relaxation for the next second. This "mental action-relaxation" cycle was repeated 100 times consecutively.

3. Results

The results of the study of the effectiveness of various classifiers for the analysis of EEG signals are presented below. The Confusion Matrix was used to quantify the classification results. The main calculations and analyzes were carried out for two operators, which helps to take into account possible individual characteristics in the results. Figures 5-8 shows graphs of the dependences of some accuracy characteristics of the Confusion Matrix on the number of Fourier coefficients, which enables the selection of both a classifier and a vector of informative features in BCI systems.

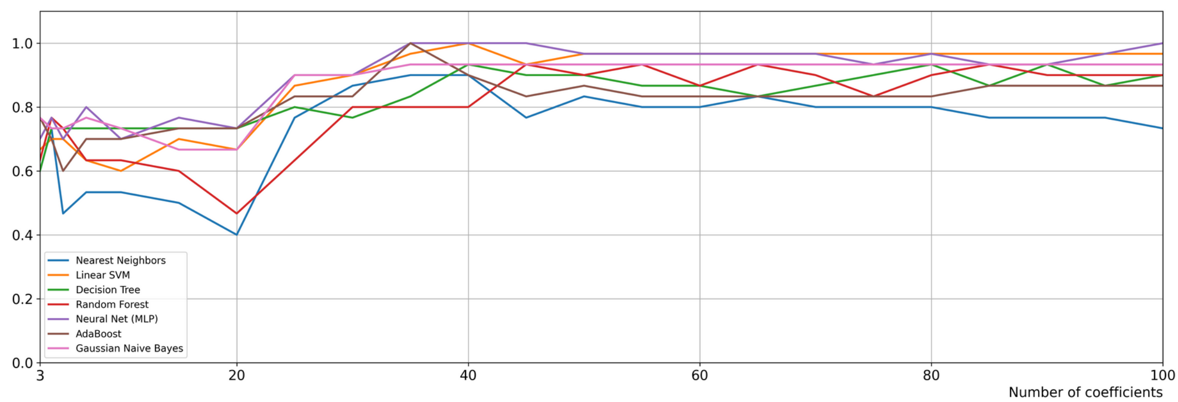

Figure 5. Accuracy (ACC)

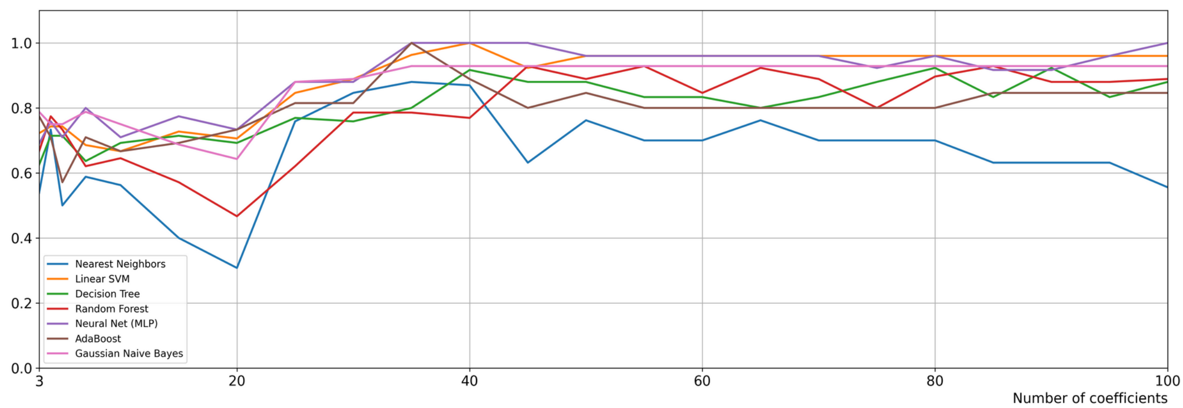

Figure 6. The harmonic mean of precision and sensitivity (F1 score)

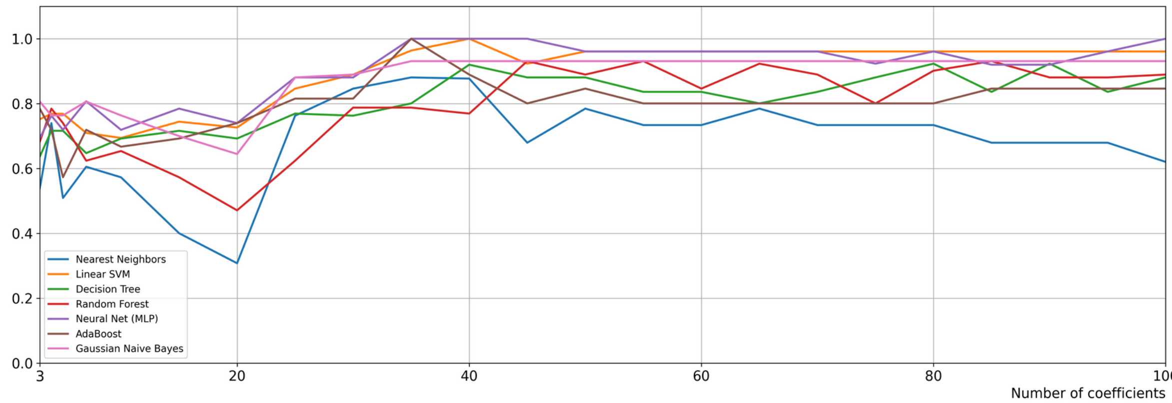

Figure 7. Fowlkes–Mallows Index (FM)

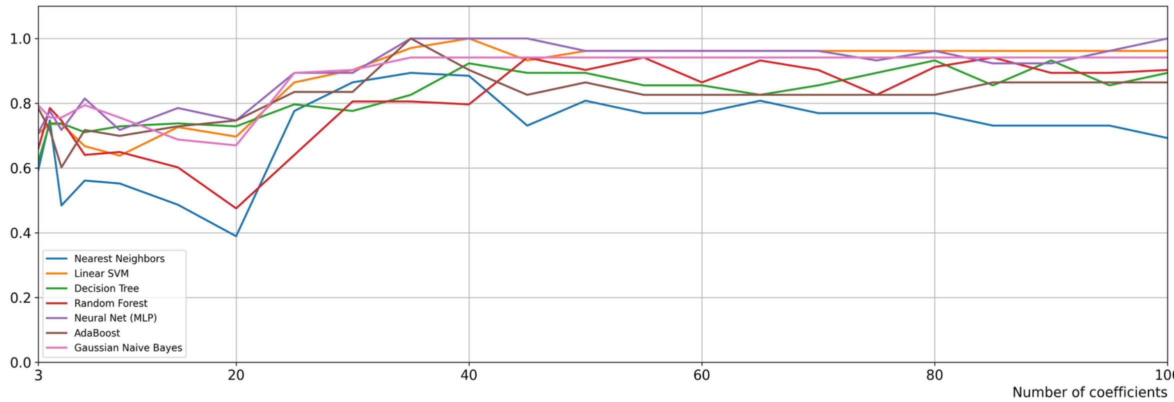

Figure 8. Balanced Accuracy (BA)

As can be seen from the figures 5-8, the classifiers were trained using the coefficients from the Fourier series, and most of them showed similar behavior. Optimal performance was observed at 20-40 coefficients; as the number of coefficients increases, there is an obvious tendency towards overfitting, especially noticeable with the k-NN classifier, which can be explained by the noisy nature of the subsequent coefficients, which have no informative value.

4. Conclusion

In this study presents an in-depth evaluation of several modern classifiers for EEG signal analysis in the realm of brain-computer interface systems. Using an innovative model vector of cyclic rhythmically connected random processes, it was possible to provide a reliable estimation of EEG signal characteristics. The use of the Confusion Matrix further augmented the clarity of classifiers comparison in BCI systems. Among the evaluated classifiers, which included k-NN, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, AdaBoost, and Naive Bayes, the most accuracy was observed from Linear SVM, Naive Bayes, and Multilayer Perceptron. Based on the analysis of the dependence of the main accuracy characteristics of the Confusion Matrix on the number of spectral components, the approach to the optimal selection of the vector of informative features in BCI systems is substantiated.

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