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EEG based brain-computer interface control applications: A comprehensive review

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ABSTRACT

Brain computer interfaces (BCI) is a tool that can make user requests to computerized systems by directly processing brain signals. In order to perform the procedures to be performed, brain signals must be classified. For this purpose, many classification algorithms have been tried with machine learning. The purpose of this study is to talk about both the type of brain signals used in the brain computer interface and the machine learning techniques used in the classification of these signals. In addition, summary information about the classification methods used in brain computer interface control applications in recent years are given in a table.

Key words: Brain computer interfaces, EEG, machine learning, classification, mental control signals.

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Introduction

The brain computer interface (BCI) is the system that transforms, develops a system that measures central nervous system (CNS) activity into an artificial output and replaces the ongoing interactions between CNS and the external or internal environment. More simply, a BCI can be defined as a system that converts brain signals into new types of output [1]. The aim is to help people with serious disabilities to live their lives as regularly as possible. Some of these disabilities are classified as neurological neuromuscular disorders [2]. BCI helps neurological patients in daily life, but is generally used for purposes such as: medical, neuro-economic and smart environment, neuromarketing and advertising, education and self-regulation, games and entertainment, and security and authentication [3].

Many operations need to be performed to perform a command with the brain computer interface system. These processes will be mentioned below as articles. But in summary, the working principle of a brain computer interface is as follows in the block diagram in Figure 1: The signals received from the cortex by invasive or non-invasive methods are passed through pretreatments such as amplification and filtering. The signals are then subjected to feature extraction in order to reduce and convert them to data sufficient for classification. The data obtained from here are directed to the classifier according to the classification method whether it is trained or uneducated. In order to realize control in brain computer interfaces, the most accurate classification with the most accurate data is done by classification methods within the scope of machine learning. The purpose of this study is to examine the machine learning methods used to classify the EEG signal types used in brain computer interface control applications in the last 5 years.

between neurons via electrodes over the scalp [5,6]. EEG is a type of biopotential amplifier that transfers the signal received through the

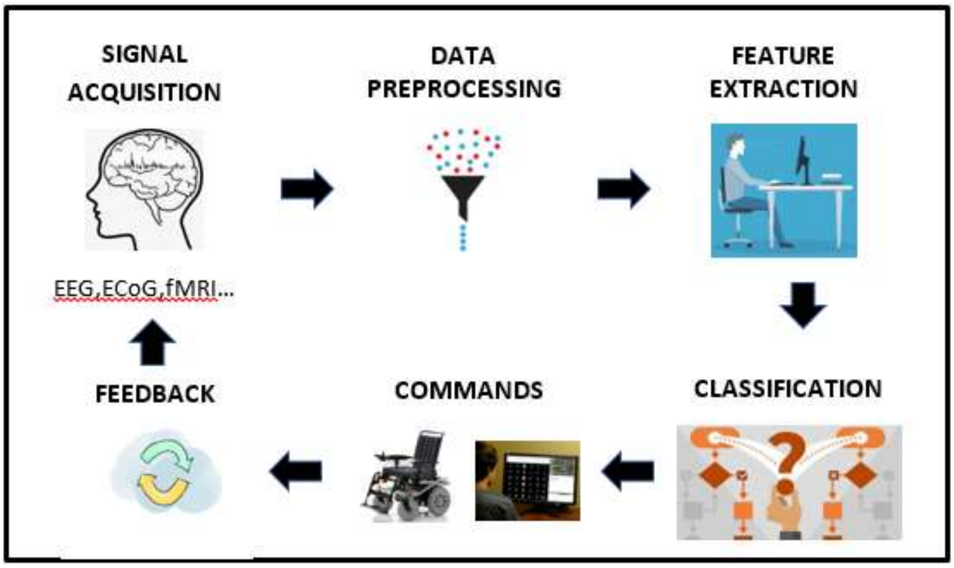

Figure 1. Brain computer interface block diagram.

Signal acquisition

The first thing to do in brain computer interfaces is to obtain brain signals. Many methods are used for this. These methods can be divided into two groups as generally invasive and non-invasive. Examples of invasive methods are ECoG, microelectrode arrays, while non-invasive methods are EEG, fMRI, fNIRS, MEG. In Table 1, there are signal acquisition methods used in brain computer interface technologies [2], [4].

EEG, which is one of the signal acquisition methods, is the most used method in brain computer interfaces due to its features such that it contains the least risks and difficulties during application due to its non-invasiveness, being more economical and portable than other methods. Therefore, this study focuses only on EEG. A graphic is cited from the work cited in Figure 2 [5].

Electroencephalography is the process of measuring and recording the postsynaptic potentials resulting from ionic activities electrodes to the system output by subjecting it to amplification and filtering [7]. To perform these operations, as shown in the EEG block diagram in Figure 3, the signals received through the electrodes are amplified with the operational amplifier and filtered on the frequency axis, passed through the last amplifier, converted to digital and displayed for analysis according to the new function or directed to the new function.

Electrodes are placed on the scalp according to certain standards. The most common and traditional of these standards is the 10-20 electrode placement system designed by Jasper in 1958. In this form of settlement, the head is marked by four standard points. "Nasion", nose; "inion", the back of the head; left and right "Preauricular" means ear, dividing between "Nasion" and "inion" to be 10-20-20-20 and 10%, electrodes placed. Other electrodes are placed with these electrodes to form a circle [8]. Figure 4 shows the location points of the 10-20 electrode system.

Table 1. Signal acquisition methods used in brain computer interface technologies.

Signal Acquisation Method	Signal Source Type	Invasive/Non-Invasive	Spatial Resolution	Temporal Resolution	Portability
Electroencephalography (EEG)	Electrical	Non-invasive	~10 mm	~0.001 s	Portable
Electrocorticography (ECoG)	Electrical	Semi-invasive	~1 mm	~0.003 s	Portable
Magnetoencephalography (MEG)	Magnetic	Non-invasive	~5 mm	~0.05 s	Non-portable
Positron emission tomography (PET)	Metabolic	Non-invasive	~1 mm	~0.2 s	Non-portable
single photon emission computed tomography (SPECT or SPET)	Metabolic	Non-invasive	~1 cm	~10 s–30 min	Non-portable
Functional magnetic resonance imaging (fMRI),	Metabolic	Non-invasive	~1 mm	~1 s	Non-portable
Optical imaging (functional Near InfraRed (fNIR))	Metabolic	Non-invasive	~2 cm	~1 s	Portable
Intracortical Neuron Recording	Electrical	invasive	~0.1 mm	~0.003 s	Portable

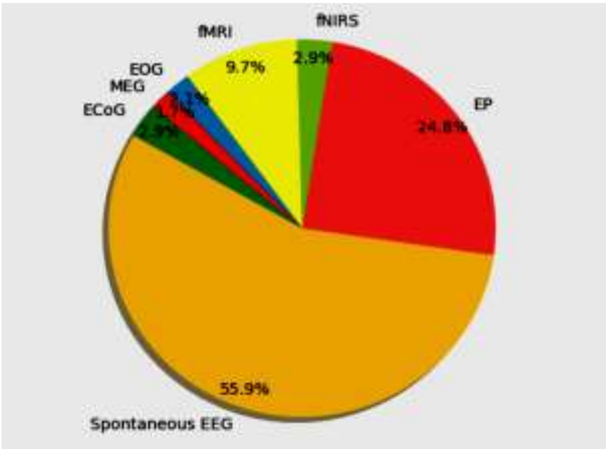

Figure 1. Usage rates of signal acquisition methods in the literature.

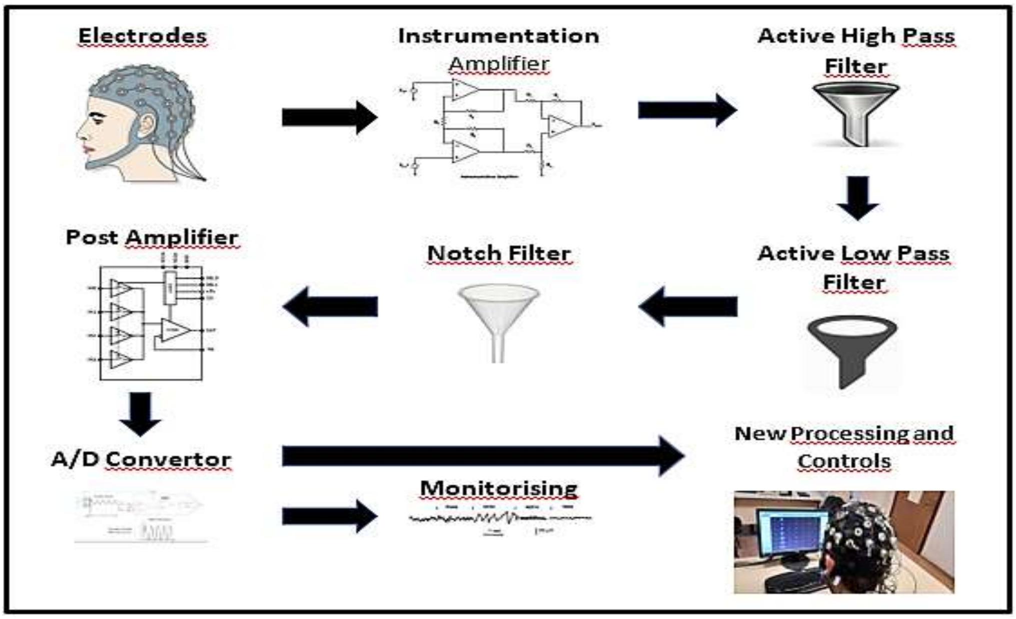

Figure 2. EEG block diagram.

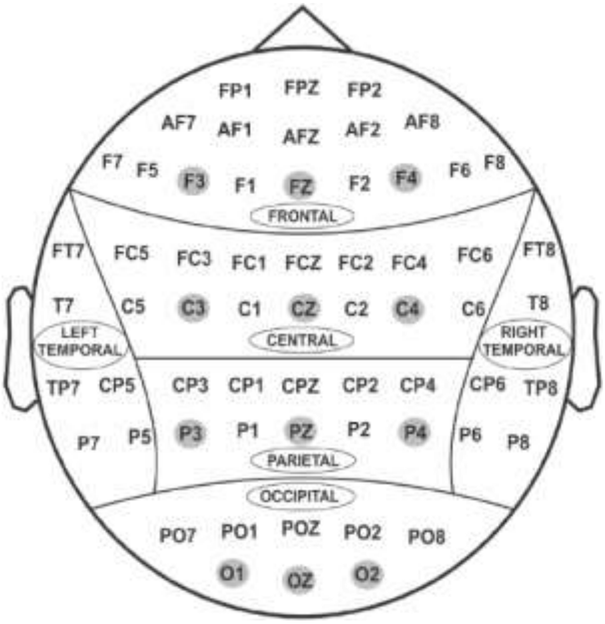

Figure 3. 10-20 elektrot sisteminin yerleşim noktaları [9].

In the use of EEG systems, a conductive gel or paste should be applied to bridge the gap between the scalp and the electrode and reduce the electrode impedance. However, with the development of dry electrodes, it eliminates the need for conductive gel or paste application, thereby reducing the electrode application time, allowing users to record EEGs for wired and wet electrode systems in impractical situations [10]. It has even been argued that EEG data recorded from a wireless dry electrode system can replace EEG data recorded with gel electrodes from a conventional system [11].

An EEG system should display a maximum of 6 µVpp input noise to detect µV level EEG signals. This nominal peak-to-peak noise can be converted to average square root (rms) noise, resulting in an integrated noise of 0.91 µVrms. As a result, state-of-the-art bioamplifiers target a <1 µVrms noise for the input, usually 0.5-100 Hz bandwidth. Also, 1 / f noises are typically reduced by dynamic circuit techniques [12]. Signals are filtered and amplified between these limits.

Signal processing

Since the ionic current is formed inside the brain, it is measured in the scalp, and layers between the cortex and the electrodes, such as the skull, reduce the Signal-to-Noise Ratio (SNR) by approximately 5%, which represents the relationship of the original brain signals to the measured EEG signals [13]. EEG recordings are often negatively affected by noise with different artifacts. Artifacts in the EEG recording are various species from different sources. Artifacts in EEG can originate from internal and external sources and mix noise into recordings in both temporal and spectral areas with broad frequency bands. Internal artifacts result from the patient's physiological activities (eg ECG, EMG / muscle artifacts, EOG) and movement. External artifacts are environmental interference, recording devices, electrode pop-up and cable motion.

In addition, some artifacts appear as regular periodic events, such as ECG or pulse (regular / periodic), while others may be extremely irregular. In order to increase the Signal-to-Noise Ratio (SNR), operations that will clear the signal from artifacts should be done. Cleaning the artifact involves canceling or correcting the artifacts without disrupting the corresponding signal. This is done primarily in two ways: filtering and regression, or separation / separation of EEG data into other fields. With regression analysis, Independent Component Analysis (ICA), Principal Component Analysis (PCA) or Morphological Component Analysis (MCA), Blind Source Separation, Wavelet Transform, Empirical Mode Separation, Adaptive Filtering or their hybrid use are used to clear the signal from artifacts [14].

Feature extraction

Feature extraction in brain computer interfaces means identifying information in domains other than brain signals that are free from noise. These properties can be signal amplitude, signal mean, kurtosis, variance in the time domain as well as Fourier transform and mean frequency in the frequency domain. Also, a feature that can be valid for both domains is the information extracted from the wavelet transform [15].

The result appears to vary significantly from feature to feature. Feature selection provides less data and hence the classification system becomes less complex and increases the calculation of machine learning algorithms [16]. That is, it is important in terms of cost, working time and performance of the system whether or not to use which features for classification in feature selection [17].

Feature selection is used not only to achieve the smaller size of the feature matrix for classification, but also to select a corresponding subset of all available features that throw out irrelevant features from the matrix, which can reduce noise. Some of the feature selection methods used for this feature reduction are: Principal Component Analysis, Linear Discriminant Analysis, Factor Analysis, Multi Dimensional Scaling, Isometric Feature Mapping, Complex Band Power, Common Spatial Patterns [18].

Classification

A classification is made according to the control application using the feature matrix obtained from the appropriate feature selection methods. Classification techniques are used to identify different brain signals produced by the user. These identified signals are then converted into control commands for application interface purposes [19]. Classification methods can be divided into two as supervised and unsupervised. Supervised classification is a traditional classifier where weights of optimum values are applied to the predictive states as supervised labels.

It is clear that the classification techniques based on supervised learning are largely preferred in the literature compared to those based on unsupervised learning. Unattended techniques are mainly used for feature selection. However, unsupervised techniques such as Gaussian mix models have been used for EEG classification problems other than MI EEG processing, and may possibly be applied to MI EEG in future studies [20]. Various machine learning algorithms have been used as emotion classifiers such as support vector machine (SVM), K-nearest neighbors (K-NN), linear separation analysis (LDA), random forest, Naïve Bayes (NB) and Artificial Neural Network (NB). Therefore, in general, the choice of which classification algorithm can be used when designing a BCI largely depends on both the type of encoded brain signal and the type of application being controlled [21]. Figure 5 shows a diagram describing the estimates made by supervised classification method.

The unsupervised classification is the classifier where an estimate is added to the system to determine possible target characters and train the classifier. For example, Kindermans et al. They proposed a method that uses expectation maximization (EM) to train the system during an unattended free writing session. During use, the subject selects characters for a target word or phrase as in the traditional system. After each election, the classifier tries to retrain himself using an iterative process. First, EEG signals are classified according to a random initial system configuration. Then, looking at these classifications as real tags, system parameters are optimized as in a training session. Using

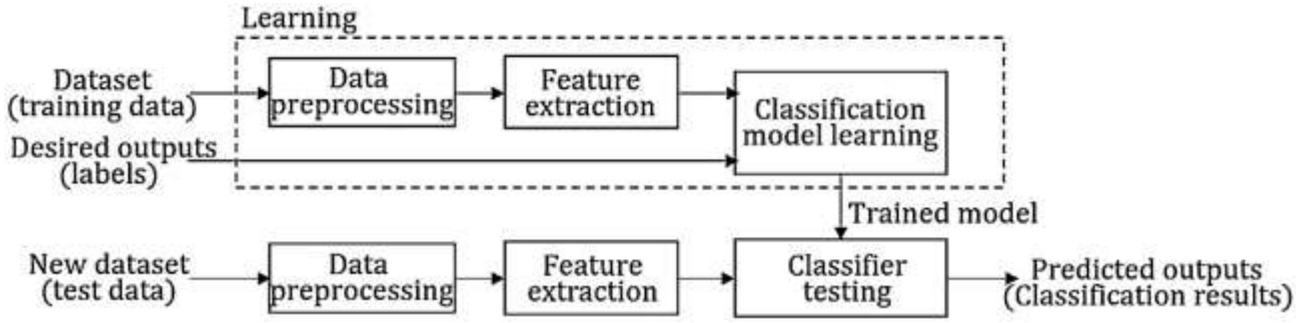

Figure 4. A diagram describing the estimates made by supervised classification method [22].

these parameters, EEG signals are reclassified and change alternately until the process gets close to a single configuration. This method depends on the initial configuration and may result in local optima that does not classify the signals correctly. In this study, the problem was solved by creating multiple initial configurations and running EM separately for each. The result with higher log probability will be selected as the true classifier [23],[24].

In recent years, classifiers have focused on identifying and designing classification methods that are compatible with the characteristics of EEG-based BCIs. In particular, topics such as low signal / noise ratio of EEG signals, which are the main challenges faced by classification methods for BCI, not being stationary over time, calibrating the classifiers with available training data of users' EEG signals, and eliminating overall low reliability and performance of existing BCIs. Adaptive classifiers have been developed in online applications to track changes in EEG features whose parameters are incrementally updated over time, i.e. to cope with EEG stability. Adaptive classifiers are also used to deal with limited training data by learning online, so less offline training data is required. Transfer learning techniques aim to transfer properties or classifiers from a single area. For this reason, they aim to address the non-stationary and limited educational data within the subjects by completing a small number of educational data that can be obtained with the data transferred from other fields. Finally, to compensate for the low EEG signal-to-noise ratio and poor reliability of existing BCIs, new methods for processing and classifying signals in one step were combined, combining feature extraction, feature selection, and classification. This was accomplished using matrix (especially Riemann methods) and tensor classifiers, as well as deep learning. The additional methods explored specifically aimed at learning with limited amounts of data and dealing with multiple class problems [25].

The types of EEG signal classified used in BCI

The purpose of this study is to investigate which classification method is widely preferred in EEG signal types used practically in brain computer interfaces. For this purpose, this section describes what type of EEG signals are used in BCI in practice.

In brain computer interface systems, control application is done by solving the meaning of thought. For this, it is necessary to detect and classify a brain signal pattern or the response expected from the brain for a specific task. EEG based BBA systems that can be used in practice are named according to the type of EEG signal used. The brain signals related to the event used in the brain computer interfaces in practice are: P300 signals resulting from the acquisition of potentials, steady state visual evoked potentials and slow cortical potentials. The mental strategy that needs to be developed for these potentials to arise is to be focused on a certain stimulus. Cortical oscillations, on the other hand, are sensorimotor rhythms obtained from the sensory motor cortex of the brain, for example, with the imagination of a limb movement. For this reason, his mental strategy has been named as an engine dream [26].

BCI is based on control signals received directly from the brain. Some of these signals are relatively easy to remove and some are difficult and require some extra pretreatment. These control signals can be divided into three categories: Excited signals, Spontaneous signals and Hybrid signals [2]. It is showed in Table 2. We concentrated on the 4 most commonly used EEG signal types in practice among the 3 categories mentioned in this study: A Sensori Motor Rhythms (μ and β rhythms) based BBA systems. K Slow Cortical Potential (YKP) based BBA systems. 300 P300 Signal based BBA systems. Steady State Visual Evoked Potential based BBA systems. Table 3 contains summary information compiled from studies related to this subject.

Table 2. Mental control signals [2].

MENTAL CONTROL SIGNALS					
EVOKED		**SPONTANEUS**			**HYBRID**
SSEP signals are brain signals that are generated when the subject perceives periodic stimulus such as flickering image, modulated sound, and even when the subject feel some vibrations	**P300** It is an EEG signal that appears after almost 300 ms when the subject is exposed to infrequent or surprising task.	**Motor and Sensorymotor Rhythms** are those rhythms related to motor actions such as moving arms. These rhythms are coming from over the motor cortex with frequency bands located at μ (≃8–13 Hz) and β (≃13–30 Hz). The amplitude of these rhythms could be controlled by the subject.	**SCP (Slow Cortical Potentials)** is an EEG signal that belongs to a frequency below 1 Hz. It is a low frequency potential detected in the frontal and central parts of the cortex; it is also the results of the depolarization level shifts in the upper cortical dendrites.	**Non Motor Cognitive Tasks** Non-motor cognitive tasks mean that cognitive tasks are used to drive the BCI. Many of the tasks could be performed such as music imagination, visual counting, mental rotation, and mathematical computation	Hybrid signals mean that a combination of brain generated signals are used for control. Therefore, instead of only one type of signals is measured and used in the BCI system, a hybrid of signals are utilized. The main purpose behind using two or more types of brain signals as input to a BCI system is the reliability and to avoid the disadvantages of each type of signals.

Table 3. Information from some studies on brain computer interface in recent years

Source	**EEG Signal Types**	**Classification Methods**	**Application**	**Accuracy**	**Subject Type**	**Preprocessing**	**Feature Extraction Method**
[27]	P300	PCA	P300-based text editor for Android-based devices	97.19	Healthy	Common average reference spatial filte	PCA
[28]	P300	LDA eSVM CNN-1 MCNN1 EFLD SRDA STDA HODA+LDA SWLDA	Defining tensor-based feature reduction technique Higher Order Spectral Regression Discriminant Analysis (HOSRDA)	LDA 96.5 eSVM 96.5 CNN-1 94.5 MCNN1 95.5 EFLD 95 SRDA 95 STDA 95 HODA+LDA 94 SWLDA 92.5 Reg. + HODA+LDA 92	Healthy (Data of BCI competition III)	Bandpass filtered in the band 0.1–60 Hz Each trial was bandpass filtered between 0.1 and 10 Hz with 8-order Chebyshev type I filter and then decimated to 20 Hz	HOSRDA
[29]	P300	LDA	Impact of fatigue brain behavior on P300 signals and developing wavelet multiple solution complex network to analyze P300 EEG signals	95.42	Healthy 10	The signals are filtered with a bandpass of 1–40 Hz. The Independent Component Analysis (ICA) method is applied to remove eye movement and blink artifacts.	-
[30]	P300	Naïve-Bayes	Designing an interface for social attention disorders such as autism spectrum disorder using Virtual Reality	Between 85-90	13 Healthy 4 autism spectrum disorder	Notch: 50 Hz; 2Hz–30 Hz, 8th order Butterworth band-pass filter	FC filter model Max-SNR filter model spatial filtering
[22]	P300	SVM	In P300 spells, based on the distance of each row and column according to the targeted character, separating the training data into groups at the same distance, measuring the accuracy rate in the eSVM classifier, examining its effect on the classifier diversity.	97	Healthy (Data of BCI competition III)	Bandpass frequency filtering between 0.1 and 10 Hz	eSVM

[31]	P300	SVM	An approach based on multipurpose dual differential evolution (MOBDE) algorithm to optimize system accuracy and number of EEG channels used for classification	92.8 (averaged)	Healthy	A band-pass filter of cut-off frequencies between 1 and 10 Hz	down sampling
[32]	P300	SWLDA, FLDA	To apply the vibration movement with piezo activators to the fingers in the Oddball paradigm method, to ensure the formation of P300 and to use for the classification of 2 and 4	2 class. 85 4 class. 60	Healthy	band-pass filtered from 0.53 to 120 Hz	moving average and down sampling
[33]	P300	SVM	Classification of schizophrenia patients and healthy individuals using both sensor level and source level features extracted from EEG signals recorded during an auditory oddball task	88.24	34 Schizophrenia 34 Healthy	band-pass filtered at 1 to 30 Hz	sensor-level features Source level features the combined features
[34]	P300	SVM	Three distinctive feature-based multi-core learning (MKL) is recommended to learn an efficient P300 classifier to improve character recognition accuracy in a P300 speller BCI.	98	Healthy	4th-order bandpass Chebyshev Type I between 0.1 Hz and 20 Hz.	the three discriminant features: Raw samples Amplitude Negative area
[35]	P300	BN (Type of CNN)	Develop a new CNN called BN (Batch Normalization) to detect P300 signals	84	Healthy	8th-order bandpass Butterworth filter 0.1 and 20 Hz.	CNN
[36]	P300	SVM	To design a new lie detection system and apply 2 new feature extraction methods in the system	88.7	Healthy	band pass at 0.01 Hz to 100 Hz ocular artifact reduction	Wavelet packet transform Nonlinear interdependences
[37]	P300	Unsupervised	Collection of matching filter and context analysis for P300 detection, use of unsupervised learning systems	91.66	Healthy (physionet.org)	Band-Pass Filtering 0.15 Hz and 5 Hz cancel the saccadic spike poten- tial (SP) ICA Wiener filtering	-
[38]	P300	LDA	To evaluate the somatosensory discrimination and command after using the vibrotactile P300-based Brain-Computer Interface (BCI) in Unresponsive Vigilance Syndrome (UWS) and to investigate the predictive role of this cognitive process on clinical outcomes.	97	Thirteen UWS patients and six healthy	The data were notch-filtered at 50 Hz and bandpass-filtered within 0.1–30 Hz. Trials with an amplitude above 100 mV were automati- cally rejected.	-

[39]	P300	LDA	The auditory paradigm, also known as the drip-stimulating hearing BCI paradigm, the audio paradigm (BP), called drip paradigm (BP), was compared with the difficulty and difficulty scores to demonstrate the advantages of online accuracy and DP.	80.87 (averaged)	Healthy	filtered with a third-order Butter-worth band-pass filter between 0.1 and 30 Hz.	
[40]	P300	LDA	The effect of the translucent face model (STF-P) (the subject could see the target character when flashing) and the traditional face model (FP) (the subject could not see the target character when flashing) Performance comparison in terms of transparency in terms of transparency	95.2	Healthy	Band-pass filtered 0.5-30 Hz	Downsampli ng Winsorizing
[41]	MI	SVM	Examination of EEG signals of 4 different states Turning hands on or off with the audio video command Open and close hands with silent video Pressing the piano with the same two ways command	87.5	Healthy	band-pass filtered from 0.5 to 40 Hz common average reference visual in- spection	Common Spatial Pattern (CSP) filter
[42]	MI	Naive Bayes	A correlation analysis was performed between various quantitative evaluation metrics of motor imageries. For this, the actions to be done by the subjects were taught in the first step, the most effective image strategy was determined in the 2 and 3 steps.	87 (ortalama)	Healthy	bandpass filtered in 4– 40 Hz range with a 4th-order Butterworth filter,	Common Spatial Pattern (CSP) filter
[43]	MI	Linear Regression	Design a system to modulate activity in the default mode network (DMN) without involving sensorimotor paths by instructing to activate their reference memories or focus on a process without reminder content.	ALS 60.8 Healthy 62.5	11 Healthy and 5 ALS	ICA	computed the trial-wise log-bandpower of the averaged, combined y- and a-range at every channel location using the Fourier transform.
[44]	MI	LDA	30 healthy SMR-BCI participants were trained to control right hand movement and SMR-based BCI on separate days for five days with traditional bar feedback (CB) or visual funnel feedback (UF) or multimodal (visual and auditory) funnel feedback (MF).	63	30 healthy		power spectral density (PSD)

[45]	Hybrid P300-SSVEP	SSVEP-> canonical correlation analysis (CCA) P300 -> SWLDA	The hybrid spelling consists of nine panels that vibrate at different frequencies. Each panel contains four different characters that appear in a random order. The vibrating panel and the periodically updated character evoke the dual-frequency SSVEP, while the strange stimulus of the target character evokes the P300.	SSVEP 89 P300 90 Hybrid 93	Healthy 10	band-pass-filtered at [2 50] Hz	
[46]	mVEP	SVM	A red line sliding to the left in random order appears in each of the 6 stimuli placed in a rectangular visual interface. Contribution of using deep learning to the classification in the selection of objective features	Compressed sensing and deep learning features 87.5 Conventional mVEP features 84.0	Healthy 11	50 Hz notch filter bandpass filtered within 0.5–10 Hz	Deep learning
[47]	SCP	MLP	Each signal is first divided into wavelet sub-marks, and then features such as Logenergy entropy are extracted from these sub-marks. These features are fed to an MLP for classification. Finally, it was compared with SVM and KNN.	MLP 92.83 KNN 89.76 SVM 86.01	BCI Comp. 2003 datasets		Wavelet packet decomposition (WPD) Log energy entropy

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