ISSN: 2581-3404 (Online)
International Journal of Innovative Research in Technology and Management, Vol-5, Issue-6, 2021.

An Approach for Predicting ALS Problem with Machine Learning for BCI

Ankita Tripathi[1], Dr. Vikas Gupta[2]
Research Scholar, Department of ECE, TIT, Bhopal, M.P, India[1]
Prof. & Head, Department of ECE, TIT, Bhopal, M.P, India[2]

Abstract: *Currently, the Brain-Computer Interface (BCI) is an interesting research area whose goal is to create an interaction channel between the system and the person's brain. It provides a direct means of turning brainwaves into physical impacts that does not require the use of muscles. BCIs are customized devices that allow users to control computer programs with their brain waves. With the introduction of consumer-grade electroencephalography (EEG) equipment, brain-controlled systems began to find uses outside of the medical realm, opening up a plethora of research options in the field of Human-Computer Interface (HCI). In this paper discuss the application of BCI for finding more accurate results for the nerve diseases Amyotrophic Lateral Sclerosis (ALS). Here in this paper implement machine learning approach to finding the results with help of teaching learning based optimization techniques.*

Keywords: BCI, HCI, ALS, ERP, SSVEP, EEG, ITR, TPR, FPR, etc.

Introduction

Brain–Computer Interfaces (BCIs) are a type of user interface that allows people to interact with computing systems using solely electrical impulses generated in the brain, without the need for any bodily movement. This absence of direct physical touch with the system allows physically disabled users, such as those with ALS (Amyotrophic Lateral Sclerosis) and cerebral palsy, to do daily tasks like as walking (for those with limited limbs), accessing the Internet, playing games, and communicating.

BCIs are highly specialized systems that read, analyze, categories, and interpret brain waves, which are distinct physiological signals. The difference between a system that just reads a physiological signal and a BCI is that the latter allows the user to interact with a computer or any other machine1 by establishing a communication channel between the user's brain and the device on which he or she intends to work. Traditional BCI system applications are largely aimed towards improving interaction experiences for people with impairments; however, people without disabilities are also potential users of solutions that improve interaction between humans and computers using brain impulses.Because every control signal is derived from brain waves, they form the cornerstone of any BCI system. A BCI system may be characterized based on many characteristics, including the type of device used (invasive or noninvasive), the nature of the signal stimulus (exogenous or endogenous), the data processing modality (synchronous or asynchronous), and how the control signal is delivered (active, passive, or reactive).

An Electro-encephalography (EEG) method is typically employed since it is a non-invasive technology that does not require a brain implant to obtain data from the user. The downside of non-invasive technologies is that they have lesser spatial resolution than invasive devices. However, there are no hazards to the user because the equipment solely detects impulses from the scalp (i.e., the skin layer bordering the face and the neck). EEG has long been thought to be the best choice for creating BCI systems. Aside from the EEG, other modalities include Magneto-encephalography (MEG), Functional Magnetic Resonance Imaging (FMRI), and Near Infrared Spectroscopy (NIRS).

The brain is made up of two kinds of specialized cells: neurons and neuroglia. The neuroglia's role is to support neurons by maintaining them in place and supplying them with nutrition and oxygen. Neurons, on the other hand, are in charge of transmitting information via chemical and electrical impulses known as nerve impulses. This steady flow of electrical current in the brain, generated by synaptic activation of dendrites in neurons, creates electrical impulses known as brain waves, which travel from the encephalic mass to the scalp.

Brain waves may be monitored using electrodes inserted on the scalp in a relatively straightforward manner. Electroencephalography, or EEG, is the reading and measurement of brain waves. Because of its non-invasive (no implants or procedures required) and easy nature, EEG is the most often used method of measuring brain waves. The collected signals, however, are very weak and of low quality since they must pass through multiple layers of tissues, including the meninges (i.e., dura mater, arachnoid, and pia mater), the skull, and the scalp, before being captured by the electrodes. As a result, it is frequently required to employ many electrodes in order to get a better spatial resolution and a more accurate system.

Brain waves are a collection of impulses that may be grouped into five bands based on frequency, namely delta, theta, alpha, beta, and gamma waves. Each band is related with different mental states, and the value definition for each band varies depending on the study. Delta waves (frequency less than 4 Hz) are low-frequency waves linked with deep, dreamless sleep and intense meditation states. Their amplitude reduces as a newborn human grows older and is infrequent in awake adult people, where it is related with neurological illnesses.

Theta waves (from 4 to 7 Hz) are produced during sleep and deep meditation. They are often observed in young infants, and high levels while waking activity in adults, like delta waves, are connected with neurological illnesses. These waves are connected with cognitive processes, learning, memory, and dreaming. While the brain is at rest, alpha waves (from 8 to 12 Hz) are produced. They are present in the occipital and frontal regions, which are associated to visual processing and mental activity, respectively, and rise when the eyes are closed and the person is calm.Beta waves (from 12 to 30 Hz) are associated with motor activity. They are located largely in the frontal and parietal lobes, primarily in the pre-frontal cortex, and are further classified as low-beta or beta-1 (12 to 16 Hz), (mid-)beta or beta-2 (16 to 20 Hz), and high-beta or beta-3 (20 to 30 Hz), with range definitions varied between studies. When there are no motor activities in action, beta waves are known to be synchronized and have a symmetrical distribution, but they become desynchronized and lose symmetry when sight, imagination, or the performance of a motor activity. They are also linked to high levels of cognitive activity. Gamma waves (above 30 Hz) are associated with the simultaneous processing of information from many parts of the brain, such as auditory and visual stimuli perception and motor processes.

In this paper here discussed the various work done by the different authors in the field of BCI application to find out the basic problem of the biomedical field. Then in the other section here implement the new method for the optimized feature extraction of the ALS problem to resolve the better findings.

II. Background of BCI Work

A hybrid EEG/NIRS brain switch and compared its performance to single modality EEG- and NIRS-based brain switches (ITR) in terms of true positive rate (TPR), false positive rate (FPR), onset detection time (ODT), and information transfer rate is discussed on [1]. A systematic literature review is presented in [2]. In [3] shows that Brain-Computer Interface (BCI) connects signals created by human mind to a computer, which may then transform the signal into action. EEG is frequently used to assess BCI-processed brain activity.Three fusion approaches for the hybrid EEG and NIRS-based brain-computer interface system: linear fusion, tensor fusion, and path-order polynomial fusion is discussed in [4]. Several types of BCI systems as well as neuro imaging techniques for obtaining brain signals, fundamental brain activities, and a comprehensive evaluation of EEG–based BCI systems for human emotion identification is discussed in [5]. A system based on deep convolutional generative adversarial networks (DCGANs) for generating fake EEG to enrich the training set to improve the performance of a BCI classifier is developed in [6]. A new technique to operating drones using a P300-based brain-computer interface that can be employed in the military as assistive technology is given in [7]. Cortical EEG source signals in the motor cortex (evaluated in the 1-s window preceding movement initiation) are recovered in this manner by beam forming an inverse problem is given in [8]. Two types of series and parallel structures are produced by combining convolutional neural networks (CNN) with long short-term memory (LSTM) in [9].Deep learning has been to be beneficial in a wide range of disciplines [10]. Although just a modest amount of work has been done, deep learning has been used to evaluate electroencephalogram (EEG) information. An automated online artifact removal strategy based on a priori artifact knowledge to adapt to varied participants and EEG recording conditions is given in [11]. The robustness of the SRC technique against non-stationary EEG signal categorization is studied in [12-13]. A new tensor-based technique, UMNFLAfor the categorization of single-trial multidimensional EEG data during motor imagining is discussed in [14]. A unique approach for extracting discriminant patio-spectral EEG features in MI-BCIs dubbed separable common patio-spectral patterns (SCSSP). SCSSP, which assumes a binary classification issue, employs a heteroscedastic matrix-variant Gaussian model for multiband EEG rhythms and identifies patio-spectral characteristics whose variance is maximized for one brain job and minimized for the other [15].A processing paradigm for dealing with non-stationary as well as spectral, temporal, and spatial aspects related with motor task execution is proposed in [16]. The impact of several classification modalities on the classification of a two-class functional near-infrared spectroscopy-based brain-computer interface (BCI) according to a mental arithmetic task and rest experimental paradigm in this work [17]. A unique approach of EEG analysis for hybrid BCI that takes into account the interaction impact of concurrent activities and shows how it may aid enhance classification results for hybrid tasks in [18]. The training data and improve the performance of a BCI classifier, researchers proposed a system for generating fake EEG using deep convolutional generative adversarial networks (DCGANs) is proposed in [19].A hybrid EEG/NIRS brain switch and compared its performance to single modality EEG- and NIRS-based brain switches (ITR) is developed in [20].

III. Proposed Work

In this section, a feature optimization and feature selection approach for multi-level classification was suggested. The feature selection and feature optimization issues plagued the multi-level classification approach. During the classification process, the feature optimization method minimizes the undesired and underused features of data. The Teacher Learning Based Optimization approach was utilized to optimize the feature. The optimization approach known as Teacher Learning Based Optimization is a well-known optimization technique. The approach of Teacher Learning Based Optimization was based on the notion of biological ants.

A. Feature Extraction

The primary step of motor imagery categorization is feature extraction from EEG data. The wavelet transform function was used to extract features. The wavelet transform function is a set of functions that may be used to describe or approximate signals or processes [7, 15]. This function produced from the fundamental wavelet transform function is referred to as the mother wavelet transform function. The transform coefficient is close to the original signal. In both the temporal and frequency domains, the wavelet transform characterises the local nature of signals. The continuous wavelet transforms function of signal *x(t)* is defined as:

$$WTx(a,\tau)\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi\left(\frac{t-\tau}{a}\right) \qquad [1]$$

Where a represents the scale factor, τ is the time factor, and $\psi(t)$ is a wavelet basis function that includes the whole family of wavelet transform functions.

Because EEG data signals are non-stationary, discrete wavelets are a viable choice. The DWT function is defined as follows:

$$WT_{x(j,k)}=\int x(t)\psi_{j,k} \qquad [2]$$

The highest frequency of the signal, according to the sampling procedure, is fs/2. The whole frequency signal is divided into L+1 sub-band if the signal is decomposed by lower order. Figure1 shows a wavelet decomposition layer

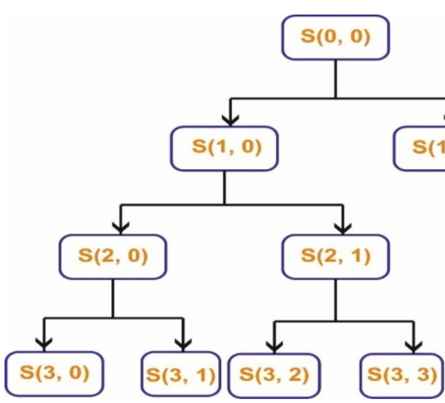

Fig. 1: Describe the process of 3 level decomposition of EEG signals data with DWT transform function.

B. Teacher Learning Algorithm

The retrieved characteristics of EEG data are optimised and redundant features of EEG signals data are removed using the Teacher learning algorithm (TLBO). The TLBO algorithm processing is described in detail in [14].The teacher learning-based optimization approach is used for noise reduction by populating and dynamically selecting constraints from EEG data. For data processing, the method involves three steps. The condition of maximum iteration defined by the algorithm process was stopped after the teacher phase, learner phase, and lastly the learner phase. The following terms are used to describe the algorithm process [14, 15].

N: define the population size.

D: number of features for the processing of optimization

MAXIT: condition for iteration.

The random distribution of population of extracted feature of DWT in terms search space of features and learner.

$$x^{0}_{(i,j)}=x_j^{min}+rand\times\left(x_j^{max}-x_j^{min}\right) \qquad [3]$$

The generation of new feature is

$$X^{g}_{(i)}=\left[x^{g}_{(i,1)},x^{g}_{(i,2)},\dots\dots\dots x^{g}_{(i,j)}\dots\dots x^{g}_{(i,D)}\right]$$

[4]

The mean parameter M^g of each subject of the learners in the class at generation g is given as

$$M^g=\left[m_1^g,m_2^g\dots\dots\dots m_j^g\dots\dots\right] \qquad [5]$$

The new feature set generation after the processing of mean.

$$Xnew^{g}_{(i)}=X^{g}_{(i)}+rand\times\left(X^{g}_{Teacher}-T \qquad [6]$$

TF stands for feature optimization function. Function has a value of 1 or 2.

If the learner characteristics are matched, the population of features is disrupted by the requirement of optimal value.

$$T_F=round[1+rand(0,1)\{2-\qquad [7]$$

New generation set of optimal features.

IJIRTM

$$Xnew^{g}_{(i)} = \begin{cases} x_i^g + rand \times (X_j^g - X_i^g) & if\ f(X_i^g) < f \\ x_i^g + rand \times (x_i^g - x_j^g) & otherwise \end{cases} \quad [8]$$

else

Terminate the condition

C. Deep Neural Network Algorithm

Through network function, a Deep Neural Network (DNN) establishes the nonlinear connection between two variables P and Pi+1. The function process is defined as

$$Pi + 1 = \delta(wpi + b) \quad [9]$$

Where δ is the activation function, and matrix W and b are the model parameters. Layers are represented by the variables P and Pi+1. Deep Neural Network is multilayer neural network argument with advanced learning. The network categorization is defined as y=f (u). The network function process is defined as

P1= δ1(w1u+b1)

P2= δ2(w2p1+b2)

….

………

Y= δL(wLpL-1+bL)

Where L is number of layers

Process for Training of DNN

The process of EEG data is defined by the relationship of neurons

$$F_k : R^{n_x} \rightarrow R^{n_x}, \text{where } x_k \in R^{n_x}$$

Be the collection of EGG data in neurons for processing.

1. E, Estimate the error hypothesis

$$E_j = H_j(x_j) + v_j, \quad \forall k \le j \le k + A$$

Where $H_j: R^{n_x} \rightarrow R^{n_y}$ is the relation of multilayer input?

2. Calculate the trained pattern

$$x_k - F_0 \rightarrow k(x_0) + \zeta k$$

3. Define learning factor as follows:

$$x_k^i = \underset{x}{\arg\min}\left\{ \|x - x_k\| B_k^{-1} + \sum_{j=k}^{k+A} \|H_j F_j(x) - y_j\| R_j^{-1} \right\}$$

Algorithm

Define $i = 0$

While $i < L$ do

M is the vector of convergence for the TLBO optimum data of EEG signals.

$$\{x_k^i \mid k \in [M.i, M.(i+1)]\}$$

$$x_k^i = \underset{x}{\arg\min}\left\{ \|x - x_k\| B_k^{-1} + \sum_{k}^{k+p} \|H_j M_{j,}(x)\| p_j^{-1} \right\}$$

Generates the channel of ALS $= \{Fs(x_{k-1}^i), x_k^i\}$ with $k \in [i.M, (i+1).M]$

Measure i for next step

end

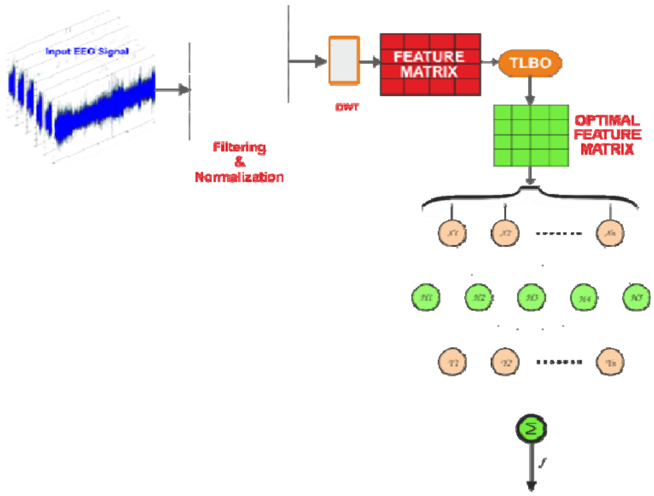

Fig 2: Process block diagram of EEG signal classification with Deep Neural Network.

IV. Simulation and Result

The method of collecting data from ALS patients is a time-consuming one. The bnci-horizon-2020 dataset of ALS patients with a sample size of 20 was utilised for the experimental task, using characteristics such as age, gender, location, and sample value [13, 21, 22]. MATLAB16Ra software was utilized in the simulation procedure. In addition, the following parameters [15, 20, 23] should be measured.

$$Accuracy = \frac{Total\ No.of\ Correctly\ Classified\ Instances}{Total\ No.of\ Instances} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

ISSN: 2581-3404 (Online)

International Journal of Innovative Research in Technology and Management, Vol-5, Issue-6, 2021.

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

Table I represent the dataset which is used in this proposed work.

Table I: Individual ALS patient demographic information for ALS patients.

ASL Subject	Age (Month)	Sex	ALSFRS-R	Motion
1	708	M	43	Hands
2	576	F	42	Right upper extremity
3	709	F	39	Left upper extremity
4	649	M	43	Hands
5	721	F	44	Right upper extremity
6	553	M	39	Right leg
7	780	F	29	Hands
8	721	M	46	Left foot
9	673	F	33	Left foot
10	708	M	39	Hands
11	600	M	43	Left foot
12	757	M	38	Hands
13	732	F	42	All four limbs
14	661	M	43	Right hand
15	780	F	33	Left leg
16	804	M	40	Legs
17	624	M	31	Left upper extremity
18	778	M	45	Right leg
19	699	M	46	Right Hand
20	765	M	33	Upper extremities

Three approaches were employed to analyse EEG data classification: BN [18, 19], EBL [16, 17], and DNN [3]. The classification approaches employed the optimal feature selection of distinct bands of data and raw signal as input for the classification procedure [24, 25]. Here discusses the categorization result description [26-30].

Table II: Comparative analysis of Accuracy using BN (Bayesian Networks).

Signal	**BN**		**EBL**		**DNN**	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	88.69	89.91	90.26	91.25	93.61	94.52
Delta	86.38	88.34	89.34	90.42	93.44	95.64
Theta	89.47	91.22	92.24	93.34	95.51	96.02
Alpha	85.24	88.65	89.35	90.05	92.36	93.24
Beta	86.24	89.36	91.50	92.89	94.25	95.61

EBL (Ensemble Machine Learning) and DNN (Deep Neural Network) are using 16- and 8-dimension features, respectively. Here we have all five signal bands of an electroencephalogram: raw signal, delta signal, theta signal, and beta single.

Table III: Comparative analysis of Precision using BN (Bayesian Networks)

Signal	**BN**		**EBL**		**DNN**	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)

Raw	75.56	78.67	79.64	82.65	85.45	88.48
Delta	76.44	79.24	80.55	81.34	84.45	90.35
Theta	78.41	83.12	84.08	86.25	87.47	92.47
Alpha	74.63	80.51	82.24	84.78	85.36	89.36
Beta	79.49	83.68	85.31	86.64	89.79	92.79

Table III: Comparative analysis of Sensitivity using BN(Bayesian Networks).

Signal	**BN**		**EBL**		**DNN**	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	85.26	88.49	89.55	92.64	95.37	98.48
Delta	86.41	89.26	90.34	91.47	94.61	96.45
Theta	88.26	93.26	94.62	96.62	97.34	98.47
Alpha	84.39	90.34	92.47	94.34	95.47	97.65
Beta	89.47	93.48	95.64	96.66	98.67	99.08

Table IV: Comparative analysis of Specificity using BN(Bayesian Networks).

Signal	**BN**		**EBL**		**DNN**	
	16DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	83.56	84.74	86.63	87.95	90.68	93.48
Delta	80.65	86.41	89.36	92.58	94.48	96.67
Theta	82.55	88.72	89.24	92.26	95.52	98.62
Alpha	80.13	89.61	89.59	93.75	94.75	95.34
Beta	84.64	86.69	88.41	90.61	91.28	98.65

V. Conclusion

This paper focuses on feature extraction approaches based on signal nature. In the future, hybrid optimization methods will be utilized to remove noise and increase the performance of EEG signal categorization. An approach for predicting Amyotrophic Lateral Sclerosis (ALS) problem with utilizing feature extraction method and a deep neural network for brain computer interface. The discrete wavelet transform function was utilized in the feature extraction procedure, and the wavelet transform function provides a superior feature coefficient for the selection process. The EEG signal is characterized by a combination of real and noise coefficients. TLOB decreases the value of noise and provides the ideal feature set of EEG data for noise reduction using the TLOB algorithm. DNN is fed the best characteristic of EEG data. The DNN design network predicts if the sample's proceeds data is ALS or not. DNN algorithms have an accuracy of 99.9% in specific categories of a data sample. The suggested technique has good compression using two algorithms, one of which is NB and the other is ELM, and both algorithms are machine learning-based for EEG data categorization. The increased precision boosts the effectiveness of the brain-computer interface system in biomedical engineering. Based on EEG signal categorization, the suggested method is trustworthy, cost-effective in terms of time complexity, and efficient for detecting ALS illness.

References

[1]. Han, Chang-Hee, Klaus-Robert Müller, and Han-Jeong Hwang. "Enhanced Performance of a Brain Switch by Simultaneous Use of EEG and NIRS Data for Asynchronous Brain-Computer Interface." IEEE Transactions on Neural Systems and Rehabilitation Engineering 28, no. 10 (2020): 2102-2112.

[2]. Vasiljevic, Gabriel Alves Mendes, and Leonardo Cunha de Miranda. "Brain–computer interface games based on consumer-grade EEG Devices: A systematic literature review." International Journal of Human–Computer Interaction 36, no. 2 (2020): 105-142.

[3]. Abdulwahab, Samaa S., Hussain K. Khleaf, Manal H. Jassim, and S. Abdulwahab. "A Systematic Review of Brain-Computer Interface Based EEG." Iraqi J. Electr. Electron. Eng 16, no. 2 (2020): 1-10.

[4]. Sun, Zhe, Zihao Huang, FengDuan, and Yu Liu. "A novel multimodal approach for hybrid brain–computer interface." IEEE Access 8 (2020): 89909-89918.

[5]. Bhise, Pratibha R., Sonali B. Kulkarni, and Talal A. Aldhaheri. "Brain computer interface-based EEG for emotion recognition system: A systematic review." In 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), pp. 327-334. IEEE, 2020.

[6]. Fahimi, Fatemeh, StrahinjaDosen, Kai KengAng, Natalie Mrachacz-Kersting, and Cuntai Guan. "Generative adversarial networks-based data augmentation for brain-computer interface." IEEE transactions on neural networks and learning systems (2020).

[7]. Al-Nuaimi, Fatima Ali, RaudaJasem Al-Nuaimi, Sara Saaed Al-Dhaheri, Sofia Ouhbi, and AbdelkaderNasreddineBelkacem. "Mind drone chasing using EEG-based Brain Computer Interface." In 2020 16th International Conference on Intelligent Environments (IE), pp. 74-79. IEEE, 2020.

[8]. Ieracitano, Cosimo, Nadia Mammone, Amir Hussain, and Francesco Carlo Morabito. "A novel explainable machine learning approach for EEG-based brain-computer interface systems." Neural Computing and Applications (2021): 1-14.

[9]. Wang, Li, Weijian Huang, Zhao Yang, and Chun Zhang. "Temporal-spatial-frequency depth extraction of brain-computer interface based on mental tasks." Biomedical Signal Processing and Control 58 (2020): 101845.

[10]. Kant, Piyush, ShahedulHaqueLaskar, JupitaraHazarika, and RupeshMahamune. "CWT Based transfer learning for motor imagery classification for brain computer interfaces." Journal of Neuroscience Methods 345 (2020): 108886.

[11]. Zhang, Shaorong, Zhibin Zhu, Benxin Zhang, BaoFeng, Tianyou Yu, and Zhi Li. "Fused Group Lasso: A New EEG Classification Model with Spatial Smooth Constraint for Motor Imagery-Based Brain–Computer Interface." IEEE Sensors Journal 21, no. 2 (2020): 1764-1778.

[12]. Liu, Ziming, Jeremy Shore, Miao Wang, Fengpei Yuan, Aaron Buss, and Xiaopeng Zhao. "A systematic review on hybrid EEG/fNIRS in brain-computer interface." Biomedical Signal Processing and Control 68 (2021): 102595.

[13]. Rashid, Mamunur, NorizamSulaiman, Mahfuzah Mustafa, SabiraKhatun, BiftaSama Bari, and MdJahidHasan. "Recent trends and open challenges in EEG based brain-computer interface systems." In InECCE2019, pp. 367-378. Springer, Singapore, 2020.

[14]. Alwasiti, Haider, MohdZukiYusoff, and Kamran Raza. "Motor imagery classification for

brain computer interface using deep metric learning." IEEE Access 8 (2020): 109949-109963.

[15]. Jin, Zhichao, Guoxu Zhou, DaqiGao, and Yu Zhang. "EEG classification using sparse Bayesian extreme learning machine for brain–computer interface." Neural Computing and Applications 32, no. 11 (2020): 6601-6609.

[16]. Taheri, Samaneh, Mehdi Ezoji, and Sayed Mahmoud Sakhaei. "Convolutional neural network-based features for motor imagery EEG signals classification in brain–computer interface system." SN Applied Sciences 2, no. 4 (2020): 1-12.

[17]. Chamola, Vinay, AnkurVineet, AnandNayyar, and EklasHossain. "Brain-computer interface-based humanoid control: A review." Sensors 20, no. 13 (2020): 3620.

[18]. Lian, Zhaoyang, LijuanDuan, YuanhuaQiao, Juncheng Chen, Jun Miao, and Mingai Li. "The Improved ELM Algorithms Optimized by Bionic WOA for EEG Classification of Brain Computer Interface." IEEE Access 9 (2021): 67405-67416.

[19]. Fahimi, Fatemeh, StrahinjaDosen, Kai KengAng, Natalie Mrachacz-Kersting, and Cuntai Guan. "Generative adversarial networks-based data augmentation for brain-computer interface." IEEE transactions on neural networks and learning systems (2020).

[20]. Han, Chang-Hee, Klaus-Robert Müller, and Han-Jeong Hwang. "Enhanced Performance of a Brain Switch by Simultaneous Use of EEG and NIRS Data for Asynchronous Brain-Computer Interface." IEEE Transactions on Neural Systems and Rehabilitation Engineering 28, no. 10 (2020): 2102-2112.