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A Comprehensive Survey of Brain–Computer Interface (BCI): Definitions, Applications, Techniques, Challenges, and Future Work

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ABSTRACT

Brain-computer interfacing is one of the significant outcomes of rapid developments in information and communication technology along with the advances of bio-sciences. Sensing and data acquisition technologies have provided the capability of capturing the brain bio-signals that represents the brain status and behavior. Further, efficient signal processing and features extraction methods have been developed and implemented considering the contribution of computation for more accurate findings. Therefore, the applicability of brain-computer interfacing based systems has become more attractive for future trends. Among this very rich and complex context, an intensive investigation and exploration could be helpful for researchers interested in this area. This paper aimed to sum up a milestone of the great contributions and outcomes in the brain-computer interfacing scope for researchers and promote several promising indicators for future efforts. It provides a well underlying background, explores the most advanced data acquisition technologies, and investigates and estimates recent contributions to signal processing. The paper also features extraction methods and classifiers, and highlights the significance of the applications considering the most common challenges such as anatomical and bio-signal characteristics, performance, efficiency, accuracy and ethics. Then, it proposes some further promising concepts, methods and ideas to be investigated, and innovative objectives to be achieved.

1. INTRODUCTION

Brain-computer interfaces (BCIs) are being developed to assist disabled people with communication by using their brain activity to control a computer without any muscle activity (E. Salari, 2019). BCI is a neural interface based on electroencephalography (EEG), which is able to make the central nervous system (CNS) communicate with an external peripheral through appropriate electrodes. In the biomedical field, the application of the BCI ranges from joint prosthetic systems to the remote control of powered wheelchairs and devices capable of processing virtual words and images (Hitesh Yadav, 2025). BCIs are devices that can allow communication or control without movement. The BCI detects specific patterns of the user's brain activity that reflects different messages or commands that the user wants to send, such as spelling or changing a television channel. Signal processing tools then decode this brain activity to diagnose the desired message or command and then send this message to an output device. BCIs are closed-loop systems, so that the BCI must provide the user with some information in real-time that hopefully reflects the intended message or command (Guger, C.,2014). Most advanced BCIs depend on one of the following four methods: **electroencephalography** (EEG), **electrocorticography** (ECoG), **depth electrode recording** and **functional magnetic resonance imaging** (fMRI)**.**

Over the last several years, BCI research has developed in many different ways. BCI publications are becoming increasingly common in journals and books. The first journal devoted only to BCIs, called the BCI Journal, was launched in late 2013. BCI conferences and workshops are becoming more common and drawing more attendees. Videos and media articles about BCIs are increasingly popular online. New BCI systems are being tested with a broader range of patient groups, allowing new options for communication and rehabilitation. This increase in BCI activity has encouraged some exceptional projects that merit additional attention (Guger, C.,2014). BCI technology is a powerful communication tool between users and systems. It does not require any external devices or muscle intervention to issue commands and complete the interaction (Sarah N. Abdulkader,2015). The primary motivation for conducting this survey stems from the rapid, fragmented expansion of BCI methodologies over recent years. Previous review papers frequently suffer from structural fragmentations, over-indexing on descriptive narratives rather than critical analytical taxonomy. Recent advancements in optimization heuristics, generative artificial intelligence, and non-hair-bearing wearable channels necessitate a consolidated, structured survey framework to evaluate the operational pipeline of modern BCIs and establish a comprehensive performance assessment architecture. The objectives of this survey are the following:

1. To sum up a milestone of the great contributions and outcomes in the Brain Computer Interfacing scope for researchers and promote several promising indicators for future efforts.
2. To explore the most advanced data acquisition technologies.
3. To investigate and estimate recent contributions in signal processing, features extraction methodsand classifiers.
4. To highlight the significance of the applications considering the most common challenges such as anatomical and bio-signal characteristics, performance, efficiency, accuracy and ethics.
5. .To propose some further promising concept, methods and ideas to be investigated and innovated objectives to be achieved.

2. METHODS AND MATERIALS

In this survey, the literature search strategy involved searching the following databases: IEEE Xplore, PubMed, Scopus and Google scholar. This survey search covered the period from 2014 to 2024. The keywords used are the following: *BCI, EEG, signal processing, classification, neurorehabilitation, assistive technology.*

3. BCI TECHNIQUES

The standard operational pipeline of an engineering-grade BCI system contains four critical sequential steps: signal acquisition, preprocessing/artifact rejection, feature extraction/dimensionality reduction, and classification instruction translation. Figure 1 illustrates the sequential progression from raw neural signal generation to control signal for peripheral device actuation.

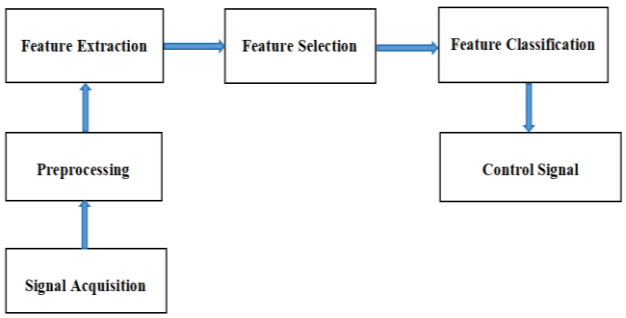


Figure 1: Diagram of BCI system

3.1 Brain Signal Acquisition Modalities and Wearable Hardware

Neuroimaging approaches vary based on invasiveness, spatial granularity, and temporal tracking precision. Non-invasive electroencephalography (EEG) remains the most widely adopted modality for practical BCI systems, capturing post-synaptic dendritic potentials via scalp

electrodes. To overcome the limitations of classic multi-channel scalp caps that require conductive wet gels, modern wearable innovations focus on non-hair-bearing anatomical spaces like the forehead and ear canal zones (ear-EEG), which offer highly comfortable configurations suitable for ambulatory clinical monitoring and daily assistive platforms.

EEG signals are classified into different rhythm frequencies ranging from 0.5 Hz to 30 Hz. The EEG waves are Delta, Theta, Alpha, Beta and Gamma waves (K. Saranya, 2018). The gamma wave band is a good indication of event-related synchronization (ERS) of the brain.

3.2 Signal Preprocessing and Artifact Handling

Raw captured neural signals are heavily corrupted by physiological artifacts such as electrooculographic (EOG) ocular blinks, electrocardiographic (ECG) cardiac cycles, and electromyographic (EMG) myogenic movements alongside external 50/60 Hz power-line interference. Because these artifacts can possess amplitudes similar to or greater than native EEG signals, software-based noise attenuation is critical to obtain an artifact-free signal before feature extraction. The artifacts could have similar amplitudes to those of the EEG signal so it is difficult to identify them. The objective of the signal preprocessing is to eliminate or to attenuate the noise in order to obtain a free-artifact EEG signal to extract reliable features. The EEG acquisition systems can be set to filter by hardware the majority of the artifacts. These filters must be designed in a way not to introduce any change or distortion to the signals. EEG acquisition systems can filter a majority of these artifacts via specialized hardware configurations designed to prevent signal distortion. High-pass filters with a cut-off frequency of usually less than 0.5 Hz remove very low-frequency components such as breathing artifacts. Conversely, high-frequency thermal noise is mitigated using low-pass filters with a cut-off frequency of approximately 50–70 Hz. Notch filters with a null frequency of 50 Hz are strictly necessary to eliminate power supply noise. Spatial signal enhancement is optimized via the **common average reference** (CAR) framework, determined by subtracting the mean of all active EEG channels from each individual channel. While CAR minimizes the influence of far-field sources, it can introduce minor spatial smearing across adjacent electrodes. The processing of data is done with a specific algorithm allowing the extraction of useful information from the EEG. Therefore, it is important that the data at this stage have the best signal-to noise ratio. Some features extracted from EEG and used in BCI are, for example, amplitude values, bands power (BP), power spectral density (PSD) values, autoregressive (AR) and adaptive autoregressive parameters, time- frequency (TF) features, and inverse model-based features. Each of these parameters implies different processing techniques. The properties that the features will have are dependent on the technique used and this influences the classifier selection (M. Agustina Garcés, 2018).

3.3 Feature Extraction Paradigms

Feature extraction is a general term for methods of deriving values (features) intended to be informative, from an initial set of measured data. The set of extracted features is called **feature vector**. Feature extraction is related to dimensionality reduction. There are many feature extraction methods for example **fourier** transform, **principal component analysis, linear discriminant analysis, wavelet transform**, and **content based image retrieval**. Most of the information in a signal is carried by its transient phenomena and its irregular structures. In such cases it is preferable to decompose the signal into elementary building blocks that are well localized in both time and frequency. This alternative can be done by using the **short time fourier transform** (STFT) and the **wavelet transform** (WT) (Bo Li, 2024). The core extraction methodologies are structured as follows:

- **Time-Domain Analysis:** directly estimates features as a function of time. Key parameters include amplitude (instantaneous energy, maximum/minimum values, mean, and standard deviation), regularity (measured via autocorrelation functions), and synchronicity. Time-domain analysis is rarely employed as a standalone technique due to its lack of frequency information and is typically combined with other spectral metrics (M. Agustina Garcés, 2018).
- **Spectral (Frequency-Domain) Analysis:** decomposes temporal traces into their constituent spectral components using the **fast fourier transform** (FFT). **Power spectral density** (PSD) is calculated to isolate maximum power, frequency of maximum power, mean/peak frequencies, and relative power, serving as one of the most reliable approaches to recognize mental tasks (M. Agustina Garcés, 2018).
- **Time-Frequency Analysis:** combines temporal and spectral resolution simultaneously using representations like the **short-time fourier transform** (STFT) or **wavelet transform** (WT). The **wavelet transform** is by far the most popular approach for non-stationary EEG processing, decomposing the signal into detail and approximation coefficients through a specialized filter bank. Choosing an appropriate mother wavelet based on prior knowledge of the target EEG pattern is a crucial factor for optimal performance (M. Agustina Garcés, 2018).

After the features are extracted the optimal features should be selected, one of the popular approaches of **artificial intelligence** (AI) is a **computational intelligence** (CI). CI has become one of the most useful and successful tools for dealing with uncertainties and

complex problems in many fields, such as neural networks, genetic algorithms, and swarm intelligence, artificial intelligence, risk management, financial monitoring, etc. With the development of CI, abundant publications have arisen related to many research directions and hotspots (Bo Li, 2024).

3.4 Feature Selection via Condensed Metaheuristic Optimization

Following extraction, identifying an optimal feature subset is essential to prevent the curse of dimensionality. computational intelligence (CI) tools, specifically population-based metaheuristic optimization algorithms, are widely implemented for feature selection because they are easy to implement, bypass local optima, and do not demand gradient information. These stochastic algorithms balance two main phases: **exploration** (discovering new promising areas in the search space using random movements) and **exploitation** (investigating localized areas in fine detail). These nature-inspired metaheuristic algorithms are broadly categorized into three classes (Raja Masadeh, 2019):

1. Evolution-Based Methods: Inspired by natural evolution laws, these methods iteratively improving a random population using selection, crossing, and mutation laws (e.g., **genetic algorithms** [GA], **evolution strategies, genetic programming**).
2. Physics-Based Methods: they mimic the physical principles in the world. Some of the most common techniques are **ray optimization** (RO), **black hole** (BH), **small-world optimization algorithm** (SWOA), **simulated annealing** (SA), **big-bang big-crunch** (BBBC), **gravitational search algorithm** (GSA), **charged system search** (CSS) and **curved space optimization** (CSO) (Bo Li, 2024).
3. Swarm-Based Methods: imitate the collective social behavior of animals in nature. This includes **particle swarm optimization** (PSO, mimicking bird flocking behavior), **ant colony optimization** (ACO, tracking optimal foraging routes), the **vocalization of humpback whale optimization** Algorithm (VWOA, modeling whale pods), and the **sea lion optimization** (SLnO, mathematically modeling coordinated sea lion hunting behavior).

3.5 Classification Frameworks

The objective of classification within a **brain-computer interface** (BCI) framework is to recognize user intentions by mapping multidimensional feature vectors to explicit control commands. This optimization process establishes geometric boundaries or separating hyperplanes between classes, ranging from simple predefined feature thresholds to advanced machine learning algorithms. Over the past 50 years, several clustering and classification techniques have been applied to BCI systems, including association rules, hidden Markov modeling, k-Means clustering, fuzzy logic, **linear discriminant analysis** (LDA), **artificial neural networks** (ANNs), and **Support Vector Machines** (SVM) (M. Agustina Garcés, 2018).

4. BCI APPLICATIONS

BCI technology represents a highly growing field of research with application systems. It participates in medical fields range from prevention to neuronal rehabilitation for serious injuries. Mind reading and remote communication have their unique fingerprint in numerous fields such as educational, self-regulation, production, marketing, security as well as games and entertainment. Applications of BCI base its functionality on either observing the user state or allowing the user to deliver his\ her ideas. A variety application in healthcare field could take advantage of brain signals in all associated phases including prevention, detection, diagnosis rehabilitation and restoration (Sarah N. Abdulkader,2015). Numerous applications exist for BCIs, and the design of a BCI depends on the intended application.

There are two main branches of BCI applications:

1. Control applications are oriented towards manipulating an external device using brain signals.

2. Monitor applications are oriented towards identifying the mental and emotional state of the user in order to control the environment (Natasha Padfield,2019).

A. Application of BCI as Assistive Device and in Rehabilitation Medicine

In recent years, EEG signals have come to be used not only for service communication aid systems and devices such as wheelchairs, but also as a brain- controlled rehabilitation and controlling assistive devices. Assistive BCI technology can significantly help many people with their everyday live and enhance overall quality of life irrespective of their disability degree. Unlike BCIs used as assistive devices, BCI oriented for neurorehabilitation have to be rather efficient than present perfect performance, which means they should at least increase the effects of rehabilitation achieved by traditional methods. EEG-based BCIs are said to be able to restore neuromuscular bypass. Motor and somatosensory BCI technology can help rehabilitate those injured by amputation or neurologic injuries such as stroke, spinal cord injury and motor neuron disease. Restoration and replacement of affected neurologic functions are key roles of BCI in rehabilitation. In addition, it has been noticed that long-term use of BCI-controlled exoskeleton

improves gait of those with spinal cord injury (Wiktoria Fr,2021).

B. Application of BCI in Mental Health

In diagnosis, BCI is used to predict and detect health issues such as abnormal brain structure in brain tumor and epilepsy with the mental state monitoring function of BCI systems. BCI systems can be used as therapeutical means for assisting people in relearning and regaining effective motor function after having got their neuromuscular function reduced due to trauma or disease. Mobility rehabilitation is a type of physical therapy that can help people with mobility problems restore their abilities to a level or adapt to their new disability (Zahrah Alwi Alkaff1 ,2023).

5. BCI CHALLENGES

Nowadays, smart home devices developed from BCI have started to take part in everything in our life. Applications of BCIs are being explored in applications as diverse as security, lie detection, alertness monitoring, gaming, education, art, and human cognition augmentation. The present researches aim to survey the principal features and challenges of BCIs (such as reliable acquisition of brain signals, filtering and processing of acquired brainwaves, ethical and legal issues related to BCI, data privacy, and performance assessment) with special focus on biomedical engineering and automation engineering applications. BCI research poses ethical and legal issues related to the question of mind-reading as well as mind-conditioning. BCI research and its translation to therapeutic intervention has given rise to significant ethical, legal, and social concerns, especially about person-hood, stigma, autonomy, privacy, safety, responsibility, and justice. One of the challenges aims to assess BCI users' experiences, self-observations, and attitudes in their own right and looked for social and ethical implications. BCI users sense themselves as active operators of a technology that offers them social participation and impacts their self-definition. Users understand that BCIs can contribute to retaining or regaining human capabilities and that BCI use contains elements that challenge common experiences, for example, when the technology proves to be in conflict with their affective side. The majority of users feel that the potential benefits of BCIs exceed the risks because BCI technology is considered to promote valuable qualities and capabilities. BCI users appreciate the opportunity to restore lost capabilities as well as to gain new ones. Several general limitations of BCI technology may be recognized, such as inaccuracy in terms of classifying neural activity, limited ability to read brain signals for BCIs placed outside of the skull, and, in limited cases, the requirement for pretty drastic surgery. In addition, the limitations include the amount of ethical issues due to reading people's inner thoughts, the bulky nature of the system leading to possibly uncomfortable user experience, the security of personal data not being guaranteed against attackers or intruders, and other limitation related to the methods used to record brain activity (Bonci; 2021). Implanting devices inside humanity brain gives permission and high ability to these systems in some cases to share brain thinking, activity processing and/or, perhaps, decision making. That raises the question "Which would be responsible for errors when they happen, the human being or the machine?; and which violates public rules or leads to an unintended accident?!" (Bonci, 2021). The ethical challenges of smart home systems that use BCI for personal monitoring have been reviewed, analyzed and discussed regarding the fundamental principles in the 'Statement of Ethical Principles for the Engineering Profession' of the UK. Consequently, there are a number of ethical issues to be taken into account when such devices are used in any application, such as health care or even in entertainment systems. There are four different areas of ethics concern, which are privacy, agency, identity, and bias as well. In recent months, Neuralink BCI (1024-Electode) has been approved to be used by Food and Drug Administration (FDA) in the USA. Neuralink BCI (1024-Electode) can help disabled people to communicate better and control devices by their brain thinking activity. That makes the ethical related studies have more attention to apply these devices and technologies in our daily life with more security. According to the ethics challenges BCI Neuralink's devices have six groups of ethics challenges. The first one is the device has to be lawful and justified for work, which means that the device has to be approved before its ethics issues will be considered. The second challenge is to clarify the hazards and research ethics officially from the producer and the organizations. The third issue is the physical safety. As a result, for that, the BCI device has to be clear, and not hidden from society, by setting rules for that. To ensure equal access and reduce societal inequality, BCI devices have to be available to all people who need them. This can be accomplished by enacting laws that mandate accessibility for the manufacturing companies (Akram Jassim Jawad, 2021). Brain signals contain valuable information about the mental state and brain activity of the examined subject. However, due to their non-stationarity and susceptibility to various types of

interference, their processing, analysis and interpretation are challenging. For these reasons, the research in the field of BCIs focuses on the implementation of artificial intelligence, especially in five main areas: calibration, noise suppression, communication, mental condition estimation, and motor imagery. The use of algorithms based on artificial intelligence and machine learning has proven to be very promising in these application domains, especially due to their ability to predict and learn from previous experience. Therefore, their implementation within medical technologies can contribute to more accurate information about the mental state of subjects, relieve the consequences of serious diseases or improve the quality of life of disabled patients (Katerina Barnova, 2023). **Generative artificial intelligence** (GAI) has recently appeared as an artificial intelligence domain in which trained models can be used to generate new data with properties resembling that of available data. Given the enhancements observed in other domains that possess similar challenges to BCI development, GAI has been recently employed in a plenty of BCI development applications to generate synthetic brain activity, thereby, augmenting the recorded brain activity (Eldawlatly S., 2024).

6. FUTURE TRENDS FOR BCI

Wearable BCIs signify a critical evolution in human machine communication, driven by the convergence of neuroscience, engineering, and information technology. Global trends toward digitization and overall computing environments have concentrated the need for wearable technologies that integrate seamlessly with daily life. Consequently, the incorporation of neural interfacing with wearable devices has become an attractive research area, significantly advancing fields such as rehabilitation, communication, and entertainment (Zhao, 2023). A new approach to create a more reliable BCI that takes advantage of each system is to combine two or more BCI systems with different brain activity patterns or different input signal sources. This type of BCI, called hybrid BCI, may reduce disadvantages of each conventional BCI system. In addition, hybrid BCIs may create more applications and possibly increase accuracy and the information transfer rate. The main purpose of combining different systems to form a "hybrid" BCI is to improve accuracy, reduce errors, and overcome disadvantages of each conventional BCI system. Different types of hybrid BCI systems can be defined according to the types of systems which are combined, how systems are joined, and what types of inputs are considered. In non-hybrid BCIs, based on the property of EEG signals used as the input of BCI system, four major EEG-based BCIs are considered: SSVEP, P300, SCP, and ERD/ERS. A hybrid BCI is composed of two BCIs, or at least one BCI and another system. A hybrid BCI, like any BCI, must fulfill the following four criteria: (i) the device must rely on signals recorded directly from the brain; (ii) there must be at least one recordable brain signal that the user can intentionally modulate to affect goal-directed behaviour; (iii) there should be real time processing; and (iv) the user must obtain feedback. Hybrid BCIs can also use one brain signal and a different type of input. This additional input can be an electrophysiological signal such as the heart rate, or a signal from an external device such as an eye tracking system. The key to EEG-based BCI lies in neural decoding, and its accuracy can be improved by using hybrid BCI paradigms, that is, fusing multiple paradigms. However, hybrid BCIs usually require separate processing processes for EEG signals in each paradigm, which greatly reduces the efficiency of EEG feature extraction and the generalizability of the model (Luo, 2023). One of the promising fields of research is computer-to-brain interface, (CBI) which aims to use the computer to produce electrical signals. These signals carry the same useful information and features that mimic the bioelectrical signals extracted from the brain activity. This will help in the rehabilitation of the patient who lost the sensory part of the brain by inserting the computer signal into the concerned parts of the human brain. CBI will create a breakthrough in modern nanoscience with the possibility of the intervention in the treatment of electrical problems in the brain and the possibility of controlling humanity brain ability. According to this new technology a lot of problems will be solved, but several medical and ethical issues need to be considered.

7. CONCLUSION

This study provides a comprehensive and organized review of the standard brain-computer interface (BCI) architecture. It summarizes recent research in advanced data acquisition methods and evaluates the latest contributions in digital signal preprocessing, feature extraction, metaheuristic optimization algorithms, and machine learning classifiers. Additionally, the paper highlights the practical importance of these applications while discussing key technical challenges, such as anatomical constraints, non-stationary bio-signal characteristics, operational efficiency, accuracy, and bioethical concerns. Finally, this work outlines the emerging future trends of this technology to open new perspectives and research horizons within the field of neural engineering.

8. References

[1]***Akram Jassim Jawad1***,2*" Bioethics of Medical Devices Based on Brain Computer Interfaces (BCI)", Journal of Clinical Research & Bioethics, Vol.12 Iss.S8 No:1000003, February 2021.

[2]***Bo Li, Zeshui Xu***, Xinxin Wang," Computational intelligence and its dynamic development: statistical exploration, comprehensive evaluation and prospect expansion", July 2024, Soft Computing. 1-16. 10.1007/s00500-024-09789-7.

[3]***Bonci, A.; Fiori***, S.; Higashi, H.; Tanaka, T.; Verdini, F. An "Introductory Tutorial on Brain– Computer Interfaces and Their Applications". Electronics February 2021, 10, 560. https://doi.org/10.3390/electronics 10050560.

[4]***Eldawlatly S.*** On the role of generative artificial intelligence in the development of brain-computer interfaces. BMC Biomed Eng. 2024 May 2;6(1):4. doi: 10.1186/s42490-024-00080-2. PMID: 38698495; PMCID: PMC11064240.

[5]***E.Salari*** , Z. V. Freudenburg , M. P. Branco , E. J. Aarnoutse , M. J. Vansteensel & N. F. Ramsey, ''Classifcation of ArticulatorMovements and Movement Direction from Sensorimotor Cortex Activity'', Scientific RepoRtS | (2019) 9:14165 |https://doi.org/10.1038/s41598-019-50834-5 ,*Received: 9 May 2019 Accepted: 11 September 2019 Published online: 2 October 2019.*

[11]***Guger, C.***, Vaughan, T., & Allison, B. (Eds.). (2014). Brain-computer interface research: A state-of-the-art summary 3. Springer Cham. https://doi.org/10.1007/978-3-319-09979-8

[12]***Hitesh Yadav, Surita Maini,*** Decoding brain signals: A comprehensive review of EEG-Based BCI paradigms, signal processing and applications, Computers in Biology and Medicine, Volume 196, Part C, 2025, 110937, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2025.110937.

[13]***Katerina Barnova***, Martina Mikolasova, Radana Vilimkova Kahankova, Rene Jaros, Aleksandra Kawala-Sterniuk, Vaclav Snasel, Seyedali Mirjalili, Mariusz Pelc, Radek Martinek, Implementation of artificial intelligence and machine learning-based methods in brain–computer interaction, Computers in Biology and Medicine, Volume 163, 2023, 107135, ISSN 0010-4825.

[14]***K.Saranya,*** S. Jayanthy,'' BCI based EEG Signals for Emotion Classification'', International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-4S, November 2018.

[15]***Luo***, W., Yin, W., Liu, Q., & Qu, Y. (2023). A hybrid brain-computer interface using motor imagery and SSVEP Based on convolutional neural network. Brain-Apparatus Communication: A Journal of Bacomics, 2(1).

[6]***M. Agustina Garcés***, Lorena L. Orosco,'' EEG signal processing in brain– computer interface'', National Scientifc and Technical Research Council (CONICET), Buenos Aires, Argentina, 8 June 2018.

[7]***Natasha Padfield***, Jaime Zabalza, Huimin Zhao, Valentin Masero and Jinchang Ren, "EEG-Based Brain-Computer Interfaces Using Motor- Imagery: Techniques and Challenges", *Sensors MDPI Received: 30 January 2019; Accepted: 19 March 2019; Published: 22 March 2019.*

[8]***Raja Masadeh***, Basel A. Mahafzah, Ahmad Sharieh "Sea Lion Optimization Algorithm",(IJACSA) International Journal of Advanced Computer Science and Applications,Vol. 10, No. 5, 2019.

[9]***Sarah N. Abdulkader*** , Ayman Atia, Mostafa-Sami M. Mostafa ,"Brain computer interfacing: Applications and challenges", *Egyptian Informatics Journal Received 20 December 2014; accepted 4 June 2015 Available online 6 July 2015.*

[10]***Wiktoria*** Fr˛ acz," Techniques, Challenges and Use in Rehabilitation Medicine of EEG-Based Brain-Computer Interfaces Systems", Springer Nature Switzerland AG 2021 S. Paszkiel (Ed.): ICBCI 2021, AISC 1362, pp.72-78,2021.

[16]***Zahrah Alwi Alkaff1*** , Nurul Hashimah Ahamed Hassain Malim2 *, Putra Sumari2 and Jafri Malin Abdullah3,4,5, Applications of Brain Computer Interface in Present Healthcare, Setting DOI:

http://dx.doi.org/10.5772/intechopen.112353, 2023

[17]***Zhang J***, Li J, Huang Z, Huang D, Yu H, Li Z. Recent Progress in Wearable Brain–Computer Interface (BCI) Devices Based on Electroencephalogram (EEG) for Medical Applications: A Review. Health Data Sci. 2023;3: Article 0096.

[18]***Zhao***, Yingzhen. (2023). Wearable brain-computer interface technology and its application. Theoretical and Natural Science. 15. 137-145. 10.54254/2753-8818/15/20240468.