Controlling a Mini Game using a Brain-Computer Interface

Ryan Leo
Dept of Computer Science Engineering
Albertian Institute of Science and Technology, Kalamassery, Kochi
ryanleo345@gmail.com

Mathews P Jose
Dept of Computer Science Engineering
Albertian Institute of Science and Technology, Kalamassery, Kochi
josemathews1729@gmail.com

Eirene Nikky
Dept of Computer Science Engineering
Albertian Institute of Science and Technology, Kalamassery, Kochi
eirenenikky@gmail.com

Lloyd Micheal
Dept of Computer Science Engineering
Albertian Institute of Science and Technology, Kalamassery, Kochi
lloydmichael2002@gmail.com

Chinnu Edwin A
Assistant Professor
Dept of Computer Science Engineering
Albertian Institute of Science and Technology, Kalamassery, Kochi
chinnuedwina@aisat.ac.in

***Abstract*—The progress in Brain-Machine Interface technology has paved the way for innovative applications in various fields, including gaming. This investigation explores the growth and implementation of a novel BCI system for controlling a mini- game, showcasing the potential of direct brain-to-machine interaction in the gaming domain. The proposed system employs non-invasive electroencephalography (EEG) sensors to capture brain signals associated with specific mental commands. These signals are then processed using advanced signal processing techniques to extract meaningful features. Machine learning algorithms, such as classification models, are trained on these features to recognize and interpret user intent in real-time. To demonstrate the practicality of the BCI-controlled mini- game, a custom designed gaming environment is introduced. Users navigate and interact within the game solely through their mental commands, eliminating the need for traditional input devices. The mini-game serves as a platform to assess the accuracy, responsiveness, and user experience of the BCI system in a dynamic and engaging context. The study evaluates the BCI system's performance through user trials, analyzing factors such as accuracy, speed, and user satisfaction. Additionally, potential challenges and limitations of the BCI-controlled mini-game are discussed, and avenues for future research and improvement are explored. This research contributes to the growing body of knowledge in BCI technology by showcasing its applicability in the gaming realm. The findings not only provide insights into the feasibility of using BCIs for interactive entertainment but also contribute to the ongoing efforts to enhance the accessibility and inclusivity of gaming experiences through innovative technological solutions.**

Keywords—BCI; electroencephalography; mini-game; real-time; non-invasive;

I. INTRODUCTION

In the ever-evolving landscape of human-computer interaction, Brain-Computer Inter- face (BCI) technology stands at the forefront, offering a direct link between the human brain and machines. BCIs have transcended their initial medical applications and are now venturing into diverse domains, including gaming. This intersection of neuro- science and gaming presents a unique opportunity to redefine how we interact with virtual environments. This study delves into the realm of controlling a mini-game using BCI, exploring the possibilities and implications of harnessing the power of our cognitive processes for an immersive gaming experience. Traditional gaming interfaces, relying on keyboards, mice, and controllers, have long been the standard for user interaction. However, these interfaces may pose limitations, especially for individuals with physical disabilities or those seeking more intuitive and natural modes of interaction. BCI technology, which translates brain signals into actionable commands, offers a promising alternative. By tapping into the neural signals associated with specific mental activities, users can control aspects of a game merely through their thoughts, paving the way for a new frontier in gaming accessibility and engagement. The project constructs an EEG system which measures brain waves to establish whether the user is focused or at ease. EEG basically employs electrodes coupled on the scalp of a user to measure voltage differences between various areas of the brain. These differences in voltage oscillate and mean that neurons are active together in a network. Different placements of electrodes produce distinct types of brainwaves with different frequencies, magnitudes, and functions. In our endeavor, we calculate alpha waves which originate from occipital lobe because they are the most conspicuous among other EEG signals. Alpha waves have characteristic frequency ranging between 8-12 HZ. What you see there is what happens in your visual cortex: the magnitude of the activities increases when eyes are closed and you are relaxed, but decrease significantly when your eyes are open and you concentrate. We amplify the electrode signals coming from brain using a circuit during our project, and employ a range of high pass, low pass filters as well as notch filters to eliminate frequencies below 8-12 Hz. After that we take data with raspberry pi 4 and do post processing on it using digital filters then analyze it using statistical methods. In conclusion, we successfully detected alpha waves and noticed a substantial discrepancy in their value when someone is focused or not.

II. LITERATURE SURVEY

A. Brain-Computer Interface-Based Humanoid Control

The simplest definition of BCI is that it enables direct neural interaction with an external device via neural impulses [1]. In Passive BCI, it occurs without any reference to the nervous system. This has many advantages to people who suffer from severe motor disabilities. The earlier systems relied entirely on EEG recorded brain signals and used rule-based translation algorithms for generating control commands. How- ever, recent advances in algorithms that fuse data from different sources along with predictive modeling-based translation techniques have reduced errors in this kind of systems. This paper presents a few examples of BCI applications like grasping of objects, navigation, etc., employing various approaches such as multichannel recording and machine learning for controlling a humanoid robot to achieve given task(s). Additionally, overviews are given about methods and system design applied in these reviewed applications.

B. Shared Three-Dimensional Robotic Arm Control Based on Asynchronous BCI and Computer Vision

The main goal of this study [12] is to create and verify a new method for joint control of a 3D robotic arm with the use of an asynchronous Brain Computer Interface (BCI) and Computer Vision. The research is focused on improving collaboration between humans and robots by enabling users to easily and naturally control a robotic arm in a 3D environment using a combination of brain-computer interface (BCI) and computer vision technologies. To accomplish this, surface EEG sensors are employed to obtain brain signals associated with user intent, while computer vision algorithms process visual inputs for precise object recognition and localization. An asynchronous BCI paradigm is implemented to provide users with natural and real-time control over the robotic arm. The shared control framework emphasizes seamless collaboration between the user's cognitive commands and computer vision-based object tracking, ensuring precise and efficient robotic arm movements. The efficacy of the proposed system will be assessed through quantitative performance metrics and user feedback, validating its potential for intuitive and collaborative robotic arm control in shared environments.

C. Design and Measurement of a Minuscule-Sized Implantable Antenna for Brain–Machine Interfaces

This study [3] presents the optimization, design, and experimental validation of a minuscule implantable antenna tailored for Brain-Computer Interface applications operating at 916 Megahertz and 2.5 Gigahertz. The small antenna can easily be added to implantable devices, and its ability to work on two different frequencies means it uses power efficiently. Employing slitted ground and patch structures, along with shorting pins, enables miniaturization of the antenna and the BCI device to 9.8 millimeter and 420millimeter cube, respectively. Parametric analysis and optimization techniques are applied to maintain optimal performance despite miniaturization. In heterogeneous environments, a seven-layer brain model and realistic head model are utilized for performance analysis. Maximum Specific Absorption Rate (SAR) values are calculated and found to comply with safety standards defined by the IEEE, pro- vided maximum radiated powers remain under 10.1 and 8.1 Megawatts at 916 and 2450 Megahertz, respectively. To validate the simulated results, a prototype is fabricated and tested with cuts of pig muscle, demonstrating impedance bandwidths of 625 Megahertz and 165 Megahertz. This research contributes to the development of safe and efficient implantable antennas for BMI, opening avenues for enhanced neuro technology applications.

D. EEG Classification of Forearm Movement Imagery Using a Hierarchical Flow Convolutional Neural Network

Recent advancements in Brain-Computer Interface (BCI) technologies have significantly enhanced user-device interactions. However, accurately decoding kinematic information, especially related to forearm movements, remains a challenge in con- trolling human-like robots. This study [5] investigates how forearm movements can be classified based on detailed rotation angles using EEG signals. We introduce a new method that utilizes a Hierarchical Flow Convolutional Neural Network (HF-CNN) model for accurate classification. The effectiveness of the model is tested on both an experimental dataset and a public dataset (BNCI Horizon 2020). In the experimental dataset, the average classification accuracies for three rotation angles were found to be 0.64 (±0.09) for the motor imagery task and 0.74 (±0.05) for the motor execution task among ten participants. In the public dataset, the average classification accuracy was reported as 0.51 (±0.03) for ME and 0.52 (±0.04) for motor imagery tasks across fifteen participants. The results demonstrate the feasibility of decoding complex kinematic information using electroencephalogram signals. This study contributes to the advancement of brain-robotic arm systems capable of executing high-level tasks. The proposed HF-CNN model showcases its potential for accurate and robust classification of forearm movements, opening avenues for practical applications in neuro technology and robotics.

E. Brain-Computer-Spinal Interface Restores Upper Limb Function After Spinal Cord Injury

Brain-machine interfaces (BMIs) represent a promising avenue for intervention in spinal cord injuries (SCIs), with the potential to restore movement to paralyzed limbs. Traditionally, decoding movement intentions for controlling stimulation in BCIs involves spike-sorting methods, necessitating frequent calibration and computational complexity. Furthermore, closed-loop stimulation commonly targets peripheral nerves or muscles, resulting in quick muscular tiredness. In this study [5], we introduce a new method that utilizes a BMI based on local field potentials to manage spinal stimulation and improve forelimb performance in rats with cervical SCI. Frontal-limb motion is deciphered from multichannel field potentials that are local in the sensorimotor cortex using an algorithm that analyses correlation. The decoded signal is then utilized to trigger epidural spinal stimulation, facilitating the restoration of forelimb movement The closed-loop algorithm is implemented on a miniaturized onboard computing plat- form, creating a Brain Machine-Spinal Interface. This interface leverages recording and stimulation approaches already employed in separate human applications. The goal of this study is to show a possible neuro prosthetic way of improving function after upper extremity paralysis of the upper limbs. The findings offer insights into the development of BCIs as a viable blueprint for spinal cord injury mending, highlighting the use of local field potentials and closed-loop systems to enhance precision and reduce computational demands, ultimately paving the way for future advancements in neuro prosthetics.

F. A Comprehensive Review of Endogenous EEG- Based BCIs for Dynamic Device Control

The control of external devices by using a brain-machine interface that is based on electroencephalogram is an innovative approach. People who have very poor mobility can benefit from BCI technologies as they are important enabling technologies. Control of external devices through endogenous paradigms provides intuitive control. The paper [13] talks about BCIs for controlling different physical devices like robotic limbs, robots capable of motion, mobility chairs, and external robotic skeletons. Able to navigate the complex environment, these technologies must also be able to do precise motor movement. Neural control of such instruments is a complex fact-finding issue that combines prompt processing and classification procedures with control theory. Endogenous BCIs are hard to provide robust classification performance for, particularly the EEG decoder’s output signals are uncertain. There are many questions this paper explores in view of these problems. This review encompasses articles published through 2021 on BMI-controlled dynamic instruments. It covers controlled machines, shared control, stabilization of the EEG prompts, traditional deep learning and ML methods as well as user experience. Finally, there is an open question on how do we improve upon brain computer interfaces.

G. Building a Brain Computer Interface (BCI) Using Electroencephalogram (EEG) Signals’ Classification

The quick progression of Brain-Machine Interface (BMI) technologies since the mid1990s has spurred advancements in various domains. This paper [14] addresses the need for a BCI system meeting optimal criteria, specifically focusing on comfort, suit- able signal acquisition devices, diffusion and system confirmation, and dependability and prospective. Without existing BMI meeting all these requirements, the study is working on creating a new model that uses EEG signals to interpret neural patterns and turn them into directives. The main goal is to improve communication for people with neurological disorders so they can control devices and interact better with their environment.

The EMG dataset is used to build the model for classifying and extracting features. Feature selection makes use of Discrete Wavelet Transforms and Statistical features, with some categorizers. Outcomes demonstrate the success of the presupposed architecture, achieving a 98 percent accuracy for distinguishing between open eye and closed eye states. Additionally, a BMI system based on an electronic circuit is implemented after classification. As future work, the study emphasizes the need for further algorithm development and system evaluation, paving the way for continued enhancements in BCI technology for improved communication and interaction in individuals with neurological disorders.

III. Methodology

A. Requirement Analysis and Planning

The first phase of the methodology involves thorough requirement analysis and planning to establish the foundation for the BCI-controlled mini video game. Initial discussions with potential users and stakeholders help define the specific objectives and functionalities desired in the game. This includes identifying the game’s genre, the nature of interactions users wish to perform through the BCI, and any additional features for an engaging experience. Based on these requirements, a comprehensive project plan is developed, outlining the scope, milestones, and technical specifications. Hardware and software requirements for the BCI setup, such as EEG sensors and processing units, are determined during this phase. Additionally, the overall game design and story-line are conceptualized to align with both the gaming and BCI aspects, ensuring a cohesive and enjoyable user experience.

B. Libraries Used

To streamline the development process, various software libraries are employed for the BCI system. Popular EEG signal processing libraries such as MNE-Python or OpenBCI are utilized to handle data analysis and feature extraction. The selection of these libraries is guided by their compatibility, community support, and efficiency in meeting the specific requirements of the BCI-controlled gaming environment.

C. Key Features

1) Non-Invasive Procedure

The template is designed so that author affiliations are not repeated each time for multiple authors of the same affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization). This template was designed for two affiliations.

2) Cost Minimization

Focused on affordability, our system is designed with optimized components and streamlined processes, aiming to minimize costs without compromising functionality or performance.

3) Sophisticated Circuitry

Incorporating advanced circuitry, the system includes signal amplification mechanisms to ensure precise detection of alpha waves originating from the occipital lobe.

4) Frequency-Specific Filtering

Utilizes high pass, low pass, and notch filters to specifically isolate alpha wave frequencies (8-12 Hz), enhancing accuracy in identifying concentration and relaxation states

5) Raspberry Pi 4 Integration

Employing the Raspberry Pi 4 for data acquisition and processing, our system balances performance and affordability, providing a robust platform for comprehensive brainwave analysis.

6) Real-Time Data Processing

Enables swift digital filtering and statistical analysis post data collection, facilitating rapid insights into brainwave patterns for responsive user interfaces in diverse applications.

IV. WORKING

A. System Architecture

1) User Interaction Layer

- User Interface (A): This component serves as the interface through which the user interacts with the system. It collects user commands, preferences, and inputs necessary for game control and visual feedback.
- Game Control (B): Responsible for managing the game's control mechanisms. It interprets user inputs from the User Interface and initiates actions within the game environment accordingly.
- BCI Interaction (C): Facilitates the communication between the user's brain activity (captured through BCI hardware) and the system. It processes brain signals and translates them into commands or actions for the game.
- Game Feedback (D): Provides visual feedback or cues to the user based on game events, BCI signals, and interactions. It ensures the user is informed about the game's state and their interactions.

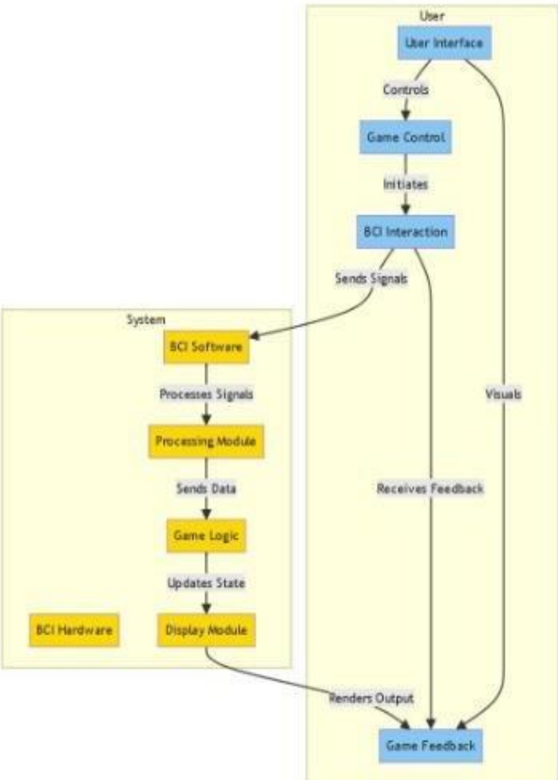

Fig. 1. System Architecture

2) *User Interaction Layer*

- BCI Hardware (E):Comprises physical components involved in measuring brain activity. It includes electrodes, sensors, or other devices necessary for capturing brain signals.
- BCI Software (F:)Software responsible for processing and interpreting the signals received from the BCI hardware. It translates raw brainwave data into action- able commands for the system.
- Processing Module(G):Manages the computational processing of signals received from the BCI software. It might involve signal filtering, amplification, or any necessary signal conditioning.
- Game Logic (H)Governs the underlying rules and mechanics of the game. It integrates inputs from the processing module to modify the game state and progress.
- Display Mo dule (I)Renders the visual elements of the game based on the updated game state. It presents the game environment, characters, and elements to the user for interaction.

3) *Interactions*

- User Interface sends commands or preferences to Game Control.
- Game Control initiates BCI Interaction to incorporate brain signals into the game.
- BCI Interaction processes brain signals and translates the into actionable data for the system.

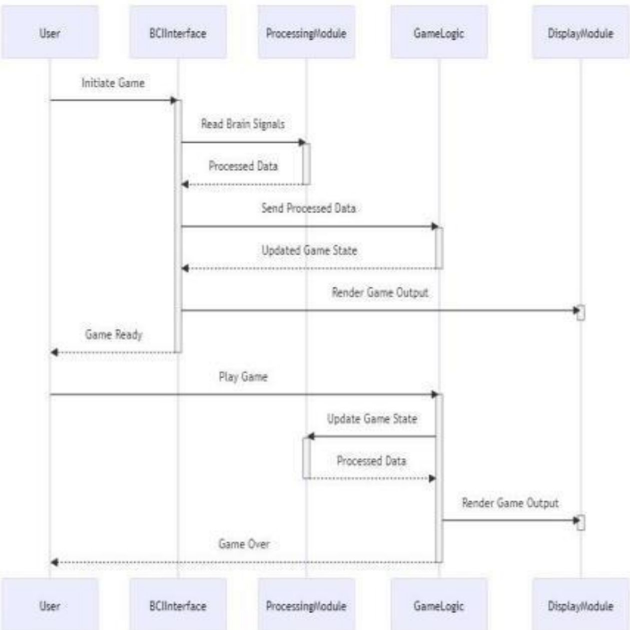

Fig. 2. Sequence Diagram

V. RESULT

In conclusion, this project redefines gaming by capturing brain signals via BCI Hard- ware and translating them into actionable commands. Users navigate game scenarios not just through traditional controls but also by utilizing their brain activity, elevating immersion and pioneering new gaming approaches. Simultaneously, pioneering an EEG device focusing on alpha wave measurement, this project precisely delineates focus and relaxation states. Alpha waves' distinct patterns (8-12 Hz) from the occipital lobe are captured using signal amplification, filtering, and Raspberry Pi 4 data acquisition. The project's architecture envisions a future where the fusion of BCI technology and gaming interfaces fundamentally transforms digital entertainment. By refining EEG-based analysis, the proposed system aims to enhance accuracy in discerning concentration and relaxation states, promising responsive user interfaces across diverse applications.

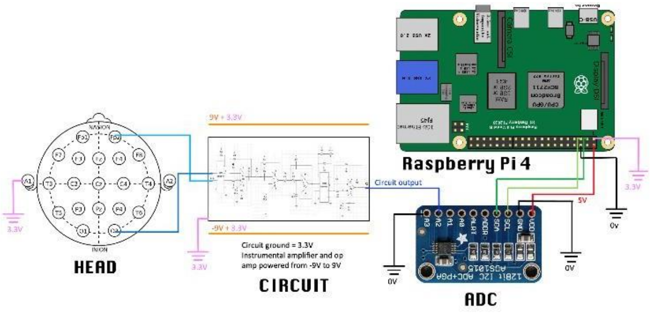

Fig. 3. Wiring

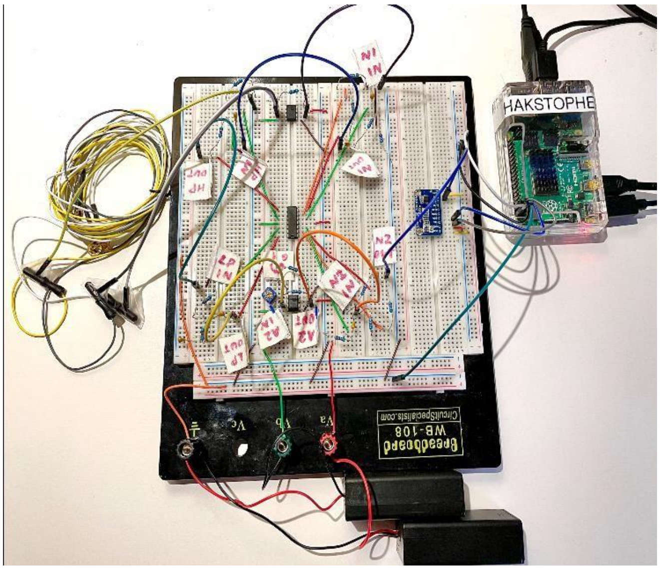

Fig. 4. Physical Setup

VI. CONCLUSION AND FUTURE SCOPE

Moving forward, the project's future scope lies in the continual evolution and refinement of gesture-based interfaces for enhanced user interaction. Expanding the system's capabilities beyond scrolling to encompass a wider array of gestures and commands could revolutionize how individuals engage with digital interfaces. Further advancements in machine learning algorithms and sensor technologies could augment the system's accuracy and responsiveness, enabling it to recognize and interpret more intricate head movements with greater precision. Integrating this technology into diverse domains such as virtual reality, gaming, healthcare, and assistive technologies holds immense potential, fostering a more inclusive and immersive user experience. Addition- ally, exploring the integration of multiple modalities for gesture recognition, including voice commands or hand gestures, could offer a comprehensive and seamless interaction paradigm. Collaboration with experts in accessibility and user experience design could refine the system's usability and cater to diverse user needs, ensuring its application across a broad spectrum of users. Ultimately, the future of this project converges on continual innovation, pushing the boundaries of gesture-based interfaces to create more intuitive, accessible, and adaptive digital interactions.

References

[1] Vinay Chamola, Ankur Vineet, Anand Nayyar and Eklas Hossain "Brain-Computer Interface-Based Humanoid Control: A Review" https://www.mdpi.com/1424-8220/20/13/3620

[2] A. Khorasani, R, Foodeh, V Shalchyan, and M. R. Daliri, "Brain Control of an External Device by Extracting the Highest Force-Related Contents of Local Field Potentials in Freely Moving Rats," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol.26, no.1, pp.18-25,Jan. 2018,doi:10.1109/TNSRE.2017.2751579.https://ieeexplore.ieee.org/document/8032482I.S. Jacobs and C.P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G.T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271-350.

[3] H. -I. Suk and S. -W. Lee, "A Novel Bayesian Framework for Discriminative Feature Extraction in Brain-Computer Interfaces," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 2, pp. 286-299, Feb. 2013, doi: 10.1109/TPAMI.2012.69..

[4] F. Lotte and C. Guan, "Regularizing Common Spatial Patterns to Improve BCI Designs: Unified Theory and New Algorithms," in *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 2, pp. 355-362, Feb. 2011, doi: 10.1109/TBME.2010.2082539

[5] S. Samejima *et al*., "Brain-Computer-Spinal Interface Restores Upper Limb Function After Spinal Cord Injury," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1233-1242, 2021, doi: 10.1109/TNSRE.2021.3090269..

[6] Carmena JM, Lebedev MA, Crist RE, O'Doherty JE, Santucci DM, Dimitrov DF, et al. (2003) "Learning to Control a Brain–Machine Interface for Reaching and Grasping by Primates". PLoS Biol 1(2): e42. https://doi.org/10.1371/journal.pbio.0000042R.

[7] J. -H. Jeong, K. -H. Shim, D. -J. Kim and S. -W. Lee, "Brain-Controlled Robotic Arm System Based on Multi-Directional CNN-BiLSTM Network Using EEG Signals," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 5, pp. 1226-1238, May 2020, doi: 10.1109/TNSRE.2020.2981659.

[8] Hout, Samnang & Chung, Jae-Young. (2019). "Design and Characterization of a Miniaturized Implantable Antenna in a Seven-Layer Brain Phantom". IEEE Access. 7. 162062-162069. 10.1109/ACCESS.2019.2951489..

[9] Zhang, Zhilu and Mert Rory Sabuncu. "Generalized Cross Entropy Loss for Training Deep Neural Networks with Noisy Labels." *ArXiv* abs/1805.07836 (2018): n. pag..

[10] Ganeshwaran, Nithyanandham & K J, Jegadish & Sathyanarayanan, Vidyashree. (2019). "Design of a Dual-Band Circular Implantable Antenna for Biomedical Applications". IEEE Antennas and Wireless Propagation Letters. PP. 1-1. 10.1109/LAWP.2019.2955140.

[11] Jeong JH, Yu BW, Lee DH, Lee SW. "Classification of Drowsiness Levels Based on a Deep Spatio-Temporal Convolutional Bidirectional LSTM Network Using Electroencephalography Signals". Brain Sci. 2019 Nov 29;9(12):348. doi: 10.3390/brainsci9120348. PMID: 31795445; PMCID: PMC6956039

[12] Y. Zhou *et al*., "Shared Three-Dimensional Robotic Arm Control Based on Asynchronous BCI and Computer Vision," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3163-3175, 2023, doi: 10.1109/TNSRE.2023.3299350

[13] Padfield, Natasha, Kenneth Camilleri, Tracey Camilleri, Simon Fabri, and Marvin Bugeja. 2022. "A Comprehensive Review of Endogenous EEG-Based BCIs for Dynamic Device Control" *Sensors* 22, no. 15: 5802. https://doi.org/10.3390/s22155802.

[14] M. N. Younis, S. H. Sleiman, S. Khadra, A. Zaylaa, A. Daher and M. Ayache, "Building a Brain Computer Interface (BCI) Using Electroencephalogram (EEG) Signals' Classification," *2023 Seventh International Conference on Advances in Biomedical Engineering (ICABME)*, Beirut, Lebanon, 2023, pp. 130-136, doi: 10.1109/ICABME59496.2023.10293031.