Brain-Driven Robotic Arm: Prototype Design and Initial Experiments

Fatma Abdelhedi[1,2][a], Lama Aljedaani[1][b], Amal Abdallah Batheeb and Renad Abdullah Aldahasi[2][c]
[1]*Department of Electrical and Computer Engineering, King Abdulaziz University, Jeddah, Saudi Arabia*
[2]*Control and Energy Management Lab, National Engineering School of Sfax, Sfax University, Tunisia*

Keywords: Assistive Device, Robotic Arms, Brain-Computer Interface Technology (BCI), Electroencephalogram (EEG).

Abstract: Advances in robotic control have revolutionized assistive technologies for individuals with upper limb amputations. Daily tasks, which are often complex or time-consuming, can be challenging without assistance. Traditional assistive devices often demand significant physical effort and lack versatility, limiting user independence. In response, the Brain-Driven Robotic Arm project aims to develop an advanced assistive device that allows individuals with disabilities to control a robotic arm using their brain signals. Utilizing brain-computer interface (BCI) technology with electroencephalogram (EEG) signals, the system processes brain activity to generate commands for the robotic arm, offering a more intuitive and efficient assistive solution. The experimental setup integrates the 6-DOF Yahboom DOFBOT Robotic Arm Kit with the 14-Channel EPOC X EEG Headset, where the system control is managed via Python software, using the Latent Dirichlet Allocation (LDA) algorithm for AI-driven tasks.

1 INTRODUCTION

In recent years, significant progress has been made in developing methods to control robotic systems for individuals with paralysis or limb amputations. According to the World Health Organization (WHO) and the World Bank, an estimated 35-40 million people worldwide require prosthetic or orthotic services, yet only one in ten has access to them (Lemaire, 2018). By 2050, this figure is expected to rise to over two billion. Additionally, diabetes leads to a major limb amputation every 30 seconds globally, resulting in over 2,500 limbs lost daily (Bharara, M.). To address these challenges, researchers have focused on non-invasive approaches like brain-computer interface (BCI) technology, which uses EEG signals to create a communication and control link between the brain and external devices (Shedeed, 2013). The Brain-Driven Robotic Arm is a BCI-based solution designed to assist individuals with disabilities by interpreting their brain signals to control robotic systems.

Advances in BCI and robotics have significantly enhanced the precision and control of robotic arms. However, many existing assistive devices remain limited, often demanding considerable physical effort and providing only basic functionality, which compromises user independence and versatility. There is a growing need for a more advanced and cost-effective solution that improves control and usability. A brain-driven robotic arm offers a promising alternative, empowering individuals with severe motor disabilities, such as limb loss, to regain mobility and independence. By integrating principles from neuroscience, computer science, and robotics, this system establishes a direct interface between the brain and the robotic arm, allowing users to control the arm's movements through their brain signals (Mu, 2024), (Yurova, 2022).

1.1 Robotic Arm

Robotic systems have evolved from their early industrial automation to becoming versatile tools across a multitude of industries. In particular, robotic arms have undergone significant advancements, becoming increasingly flexible and adept at executing complex tasks with precision. The general representation of a dynamic model of a robotic arm is presented as follows:

$$M(q)\,\ddot{q} + C\,(q,\dot{q})\,\dot{q} + G(q) = \tau$$

[a] https://orcid.org/0000-0003-1658-8067

Abdelhedi, F., Aljedaani, L., Batheeb, A. A. and Aldahasi, R. A.
Brain-Driven Robotic Arm: Prototype Design and Initial Experiments.
DOI: 10.5220/0013146700003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 3*, pages 427-434
ISBN: 978-989-758-737-5; ISSN: 2184-433X

where vectors q, $\dot{q}$, $\ddot{q} \in \mathbb{R}^n$ denote the measured position, velocity, and the articulatory acceleration vectors, respectively. Besides:

- $M(q) \in \mathbb{R}^{nxn}$ is a uniformly bounded-symmetric-positive-definite inertia matrix,
- $C(q, \dot{q}) \in \mathbb{R}^n$ is the centrifugal and Coriolis forces' vector,
- $G(q) \in \mathbb{R}^n$ presents the vector of gravitational forces,
- $u = \tau \in \mathbb{R}^n$ presents the vector of external control torques and forces applied to the robot's joints,

For the considered robot we have $n=3$, where the open-loop manipulator comprises three revolute joints as demonstrated in Figure 1.

Equipped with sensors, robotic arms can perceive and react to its surroundings, enhancing its adaptability across diverse environments (Aljedaani, 2024). The integration of various types of end effectors, such as grippers or specialized tools, enables these arms to interact effectively with their surroundings, extending applications across manufacturing, healthcare, and various other sectors. Ongoing progress in robotics, sensing technologies, Artificial intelligence (AI), including collaborative robotics, is propelling the robot's evolution to learn and adapt their actions, further amplifying their capabilities and expanding their potential applications .

1.2 Brain-Computer Interface (BCI)

Brain-Computer Interface (BCI) enables interaction between the human brain and machines, employing advanced algorithms to analyze brain signals and recognize user commands. BCI is classified into three types based on signal acquisition: invasive (inserting an electrode into the brain), semi-invasive (positioning electrodes on the brain's surface), and non-invasive (using scalp sensors) (Ramadan, 2017). This study focuses on EEG technology, a non-invasive method, to record brain activity. The combination of EEG, signal processing, and machine learning enables direct and intuitive interaction with a robotic arm, enhancing the independence of individuals with disabilities in their environment.

1.3 Electroencephalogram (EEG)

The human brain is composed of billions of cells that control various bodily functions. It consists of different regions responsible for functions like movement, vision, hearing, and intelligence. Brainwaves, which are small electrical signals, are generated by these brain cells. To record these brainwaves, electrodes are connected to the scalp, and this technique is called an electroencephalogram (EEG) (Zhou, 2023). EEG has been extensively used in clinical applications and research, including Brain-Computer Interfaces (BCI) (Biasiucci, 2019). One significant application of EEG is the brain-driven robotic arm, which enables direct communication between the brain and a machine, benefiting paralyzed or amputated individuals. EEG sensors capture numerous snapshots of brain activity, which are then transmitted for analysis and storage in various formats like computer files, mobile devices, or cloud databases.

2 PRELIMINARIES AND PREVIOUS WORKS

Significant progress has been achieved in BCI in recent years, allowing a direct connection between the human brain and external technology. This literature review aims to offer a thorough overview of the present status of research on brain-driven robotic arms.

2.1 The Generation and Detection of EEG Signals

Electroencephalography (EEG) is a method that involves placing metal electrodes on the scalp to measure and record the brain's electrical activity. This activity is generated by the communication between neurons and produces continuous and persistent electrical currents. Hans Berger, the scientist credited with introducing the term "electroencephalogram" (EEG), observed that these brain signals exhibit regular patterns rather than random activity. This discovery paved the way for various applications that rely on EEG signals to infer different brain functions. The detection of electric fields in the brain is made possible by the coordinated activity of pyramidal neurons located in the cortical regions (Khosla, 2020). These specialized neurons are critical in generating and synchronizing the electrical signals captured by EEG. The EEG technique records changes in electrical potentials that result from synaptic transmissions. When an action potential reaches the axon terminal, neurotransmitters are released, leading to the formation of excitatory potentials and the flow of ionic currents in the extracellular space. The cumulative effect of these potentials from groups of neurons amplifies the overall electric field, making EEG signals valuable for measurement and analysis. Different regions of the cerebral cortex are responsible for processing distinct types of information (Yip, 2023). For instance, the motor cortex, located in the frontal lobe, is central to controlling body movement and consists of three main areas: the primary motor cortex (Brodmann Area 4), the premotor cortex, and the supplementary motor area (Brodmann Area 6).The primary motor cortex is responsible for transmitting the majority of electrical impulses from the motor cortex, while the premotor cortex is essential for movement preparation, particularly for proximal muscle groups. The supplementary motor area aids in stabilizing body posture and coordinating movements. Notably, research indicates that sensory input to one hemisphere of the brain can evoke electrical signals that result in movement on the opposite side of the body, highlighting the cross-wiring of motor functions between the two hemispheres (Rolander, 2023).

2.2 EEG Rhythms

To provide a complete understanding of Electroencephalography (EEG) and the different mental states of the brain, previous literature reviews were consulted. According to (Huang, 2021) (Orban, 2022), EEG signals exhibit distinct frequency ranges corresponding to different types of brain waves. Delta (δ) waves, with a frequency range of 0.5-4 Hz, are observed during deep sleep. Theta (θ) waves, ranging from 4-8 Hz, are associated with emotions and mental states. Alpha (α) waves, in the frequency range of 8-14 Hz, are typically detected in the frontal and parietal regions of the scalp during awake or resting states. Beta (β) waves, ranging from 14-30 Hz, are prominent during movements and can be observed in the central and frontal scalp areas. Finally, gamma (δ) waves have a frequency higher than 30 Hz and are linked to processes such as idea formation, language processing, and learning.

2.3 Electrode Placement and EEG Recording

As The placement of metal electrodes over the scalp is crucial for measuring and recording EEG signals. To capture arm movement, the electrodes need to be positioned strategically. Research indicates that the primary region responsible for controlling body movement is the motor cortex in the brain's frontal lobe. Several electrode placement systems exist, but one of the most promising is the (10-20) system, as mentioned in reference (Orban, 2022). As seen in Figure 2, this system uses a combination of letters and numbers to denote specific brain regions and electrode locations. The letters "F," "T," "P," and "O" represent Frontal, Temporal, Parietal, and Occipital regions, respectively. Odd numbers (1, 3, 5, 7) are assigned to electrodes on the left hemisphere, while even numbers (2, 4, 6, 8) represent the right hemisphere. The letter "z" indicates an electrode along the midline (CAO, 2021). This standardized system ensures consistent and precise electrode placement for EEG recordings.

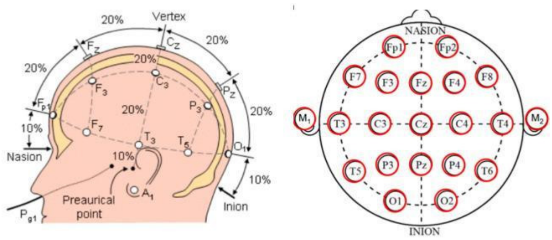

Figure 1: The 10-20 System of Electrode Placement.

In reference (Bousseta, 2018), a study used a 14-channel EEG sensor and identified that electrodes AF3, AF4, F3, and F4 were associated with moving a robot's arm right, left, up, down.

The frequency band utilized is 8 Hz to 22 Hz.

A study referenced in (HAYTA, 2022) utilized a 64-channel EEG sensor to control a robot's arm movement along multiple axes (x, y, and z). For this purpose, twenty EEG were selected within the frequency range of 8 Hz to 30 Hz. In another study (Arshad, 2022), researchers developed an intelligent robotic arm controller including a BCI integrated with AI to aid individuals with physical disabilities. This study employed EEG to capture brain activity and proposed a method for controlling the robotic arm using various AI-based classification algorithms. Algorithms such as Random Forest, K-Nearest Neighbors (KNN), Gradient Boosting, Logistic Regression, Support Vector Machine (SVM), and Decision Tree were tested, with Random Forest achieving the highest accuracy of 76%. The paper also highlighted the influence of individual variations in dominant frequencies and activation bandwidths, which can affect the EEG dataset. The research provides insights into effective electrode placement for detecting different arm movements and demonstrates the feasibility of intelligently controlling a robotic arm through BCI and AI methods. The proposed technique offers a reliable and non-invasive approach to assist individuals with physical disabilities, and the results highlight the effectiveness of Random Forest compared to other classification algorithms.

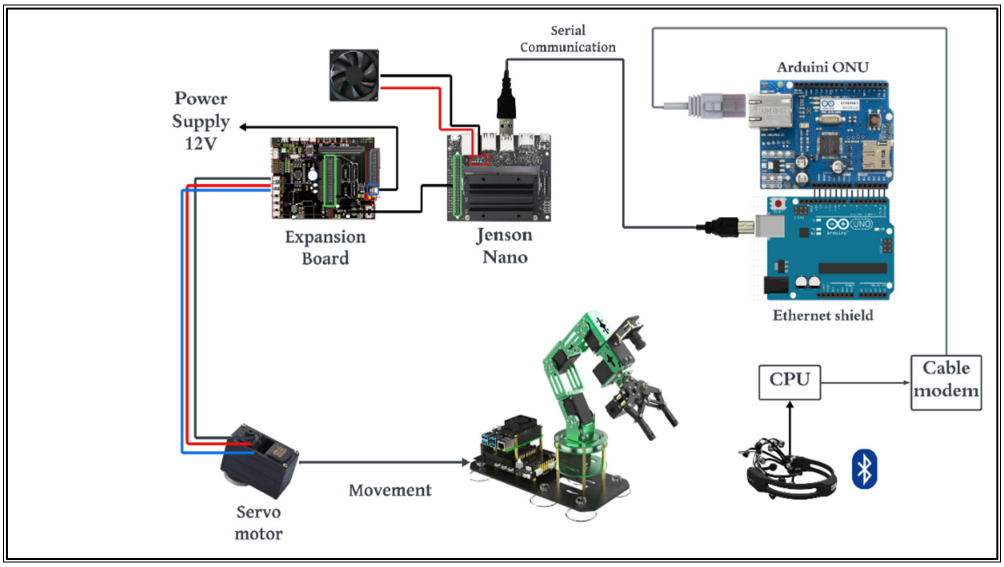

Figure 2: Brain Driven Robotic Arm Circuit Diagram.

3 PROPOSED BRAIN DRIVEN ROBOTIC SYSTEM

This paper introduces the design of a robotic system aimed at empowering individuals with severe motor disabilities by providing functional robotic limb movements and enhancing their independence. The brain-driven robotic arm achieves this by precisely interpreting the user's brain signals and converting them into commands that control and manipulate a robotic arm's movement.

3.1 Proposed Design Solution

The proposed system integrates cutting-edge hardware components, a versatile programming platform, and advanced machine learning techniques. This combination creates a highly interactive and sophisticated system that can efficiently interpret brain signals to effectively control the robotic arm.

The proposed robotic system design involves the following important steps:

1- EEG wave reading.
2- Transmission of the EEG waves to a processing unit.
3- Analysis of the waves/signals.
4- Activation of the Robotic Arm for movement.

Using the LucidChart website, we demonstrate the circuit diagram of the Brain Control Robotic Arm, illustrating the visual representation of the circuit diagram as presented in Figure 3. A 12V DC voltage supply is used to power the system, which includes a Jetson Nano microcontroller and a Yahboom Dofbot expansion board for controlling a robotic arm. The EEG sensor is connected to the CPU (Laptop) via a Bluetooth module, enabling wireless communication. The CPU undergoes a machine learning phase, and the data is then sent to Arduino UNO through an Ethernet cable. A serial communication between Arduino and Jetson Nano transmits real-time data. In expansion board, each port can accommodate up to 6 cascade motors, and in this configuration, 6 motors

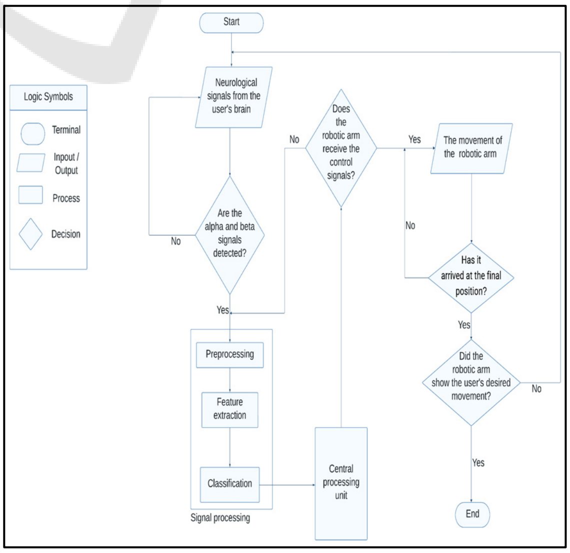

Figure 3: Flow Chart of Process Flow of the Design.

are connected in series into one port. These connections ensure efficient power distribution, machine learning capabilities, robotic arm control, EEG data acquisition, and temperature regulation within the system.

3.2 Flowchart

The flowchart in Figure 4 outlines the sequence of actions and conditions necessary to achieve a specific task or outcome in the robotic system. The process starts with the acquisition of neurological signals from the user's brain using EEG. The system then verifies whether these signals contain specific frequency patterns, such as alpha and beta waves. If these frequencies are detected, the signals proceed to the signal processing block. Next, the system checks if the robotic arm is successfully receiving the categorized control signals generated from the previous step. If the signals are received, they are processed to control the movement of the robotic arm.

The system subsequently verifies whether the robotic arm has reached its target position and executed the intended movement as per the user's commands. Once the movement aligns with the intended commands, the flowchart indicates the successful completion of the process.

In this work, machine learning plays a significant role in the project by enabling users to control the arm using their brain signals. The machine learning model has several stages. The first stage is preprocessing the data, then feature extraction, and lastly choosing an appropriate classification model. In this project, a large data set is used to reduce the dimensionality of the dataset, a feature selection technique was employed, also a filter between 8 and 30 Hz is used to keep the required frequencies. The Fast Fourier Transform (FFT) is used as a feature extraction method. Lastly, the Latent Dirichlet Allocation (LDA) method is used as a classification method.

4 EXPERIMENTAL RESULTS

4.1 Test Bench Description

The proposed design involves utilizing Yahboom DOFBOT Robotic Arm Kit, in combination with the 14-Channel EPOC X EEG Headset shown in Figures 5 and 6, respectively.

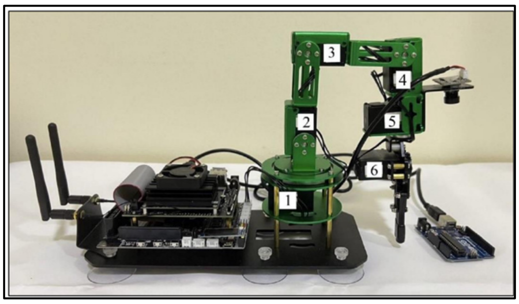

Figure 4: 6-DOF Yahboom DOFBOT Robotic Arm.

The system is controlled by Jetson Nano and programmed using Python. Regarding machine learning, the project employs a Latent Dirichlet Allocation (LDA) method. Yahboom DOFBOT Robotic Arm Kit provides a versatile and precise robotic arm mechanism capable of performing complex tasks.

Figure 5: The 14-Channel EEG Headset 'EPOC X'.

In addition, EPOC X enables the system to capture brain signals and interpret them as commands or inputs for controlling the robotic arm. The Jetson Nano and Arduino Uno act as the controller, coordinating the communication and interaction between the two main parts of our system: EEG brain signal extraction and robotic arm movement control.

4.2 EEG Data Extraction Testing and Results

The EmotivBCI application is designed to capture and interpret brain signals. Detecting facial expressions presents the first testing task using EEG Headset 'EPOC X', that has many practical applications serving accessibility technology, neuromarketing, psychological research...etc. By training the system to recognize specific facial expressions, it becomes possible to map those expressions to corresponding neural patterns. This enables the creation of a responsive system that could, for instance, help individuals with mobility impairments communicate more effectively or provide insights into a user's emotional response to stimuli for biomedical research.

In this context, advanced brain-computer interface (BCI) technology requires a high-quality connection with the EEG sensor headset worn by the user. The first brain signal extraction yields real-time feedback on signal strength across multiple EEG channels, ensuring the device is properly connected and signals are accurately captured.

The EEG quality for each position is measured and visually represented in the sensor map, as illustrated in Figure 7. However, in order to enhance the EEG quality, it is necessary to allow for a period of relaxation. Table 1 provides a comprehensive representation of various signals' colors.

Table 1: Colors and their Corresponding Status.

Color	Status
Black	No contact detected
Red	Poor contact quality
Light Green	Average contact quality
Green	Good contact quality

Figure 6: Contact quality 25%.

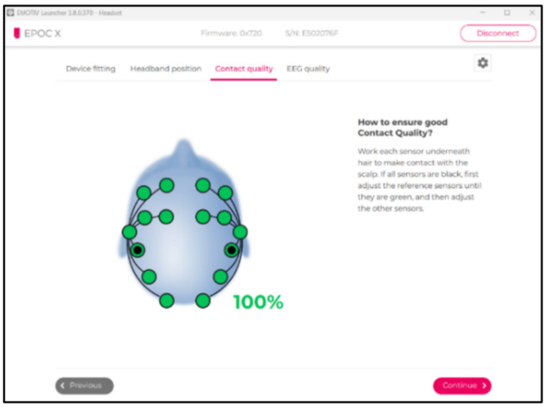

Figure 7: Contact quality 100%.

This calibration ensures that the BCI system can distinguish between various states and respond appropriately. The collected data underwent processing, as depicted in Figure 9.

In this figure, a multichannel EEG signal readout with varying amplitudes and frequencies across different electrodes placed on the scalp. These electrodes are labeled according to standard EEG placement nomenclature such as AF3, F7, F3, etc. The signals exhibit the brain's electrical activity, with each line representing a different sensor position on the EEG headset.

The application's interface allows the user to adjust settings such as channel spacing and amplitude to optimize the visualization of these brain waves.

4.2.1 Extract Brain Signals (Alpha, Beta, Theta)

To analyze the signals, the EMOTV PRO software was utilized. This software offers the capability to visualize real-time signals while utilizing the EEG headset sensor. Initially, an attempt was made to detect the signal in a normal state using two electrodes, which are AF3 and AF4. However, the signals exhibited variability and did not demonstrate a specific pattern, as illustrated in Figure 10.

To analyze the signals extracted from the "Right" command, four electrodes were utilized: AF3, AF4, FC5, and FC6. The signals displayed almost similar patterns for alpha and beta waves, which are associated with the mental state. However, the theta waves vary since they are influenced by the emotional state, as depicted in Figures 11 and 12.

Figure 8: Collected data.

To gather the data, each movement was tested ten times, and the response time was recorded. The response time varied across trials, due to various factors, including user relaxation and other parameters.

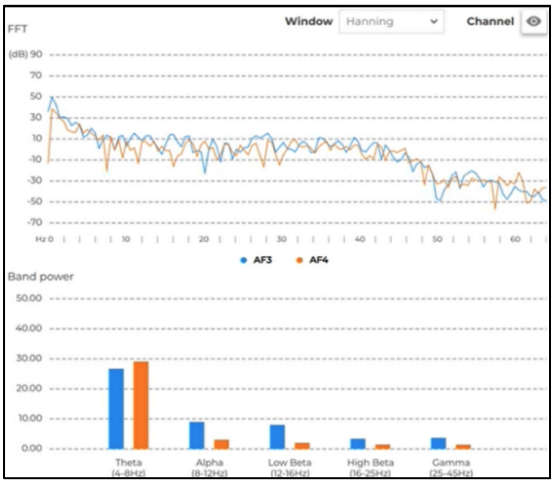

Figure 9: Obtained AF3 and AF4 signals in Normal States.

4.2.2 Translate the Brain Signals to Commands:

The objective is to verify the accuracy of converting the collected signal into commands using an Arduino. The process involves a five-second duration to gather the signal. The testing focuses on three movements: Right, Drop, and Left. The signal is collected during these movements, and the most common signal pattern is identified. By repeating this process ten times for each movement, an average signal pattern for movement is derived. The aim is to achieve an accuracy level of 70% in accurately translating the signals into corresponding commands. Using the following equation:

$$\text{Accuracy} = \frac{\textit{Achieved commands}}{\textit{number of trials}} \times 100$$

the accuracy for the overall device has been calculated when testing all movements, to obtain the accuracy percentage of 76.67%.

It is important to note that the processing stage involves filtering out noise, identifying characteristic features of the EEG signals associated with each expression, and using machine learning algorithms to improve the recognition of these patterns over time. Analysing these waves requires filtering the raw EEG data to focus on the frequencies of interest. The software might apply band-pass filters to isolate the frequency range associated with each type of brain wave. For example, to analyze alpha waves, the software would use a band-pass filter to isolate frequencies between 8-12 Hz.

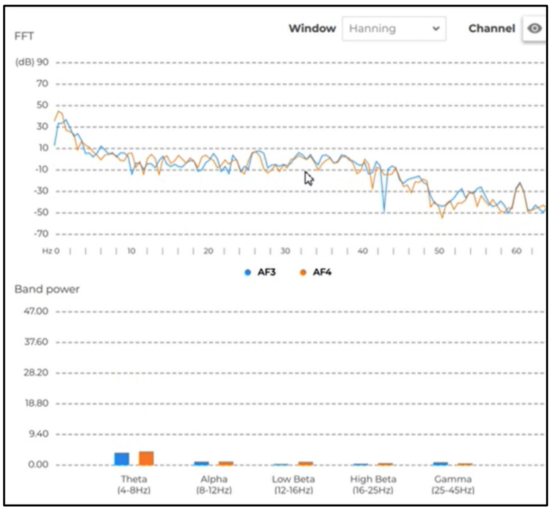

Figure 10: Obtained AF3 and AF4 signals for Right movements.

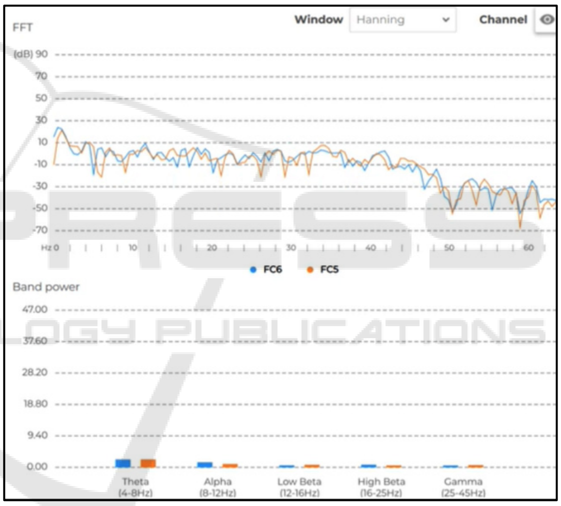

Figure 11: Obtained FC5 and FC6 signals for Right direction move.

4.2.3 Movement of the Robotic Arm

To ensure the reliability of the results, after the training phase and obtaining brain commands, the participant was instructed to continuously generate the mental command of moving the arm to the right. The data was collected every 5 seconds, and the command with the highest occurrence was considered the chosen command.

```
111
Right
Before ReadServo1Angle: 90
After ReadServo1Angle: 55
Moving to Right*************************************************
```

Figure 12: Output of Serial Communication After Detecting Right Movement.

As illustrated in Figure 13, a specific code such as "111" is transmitted during serial communication, which corresponds to the "right" mental command. As a result, the arm will move to the right at a 35-degree angle. The same procedure was applied for “drop” mental command.

5 CONCLUSION

This paper highlights the development of a new design for a Brain-driven Robotic Arm as an advanced assistive device for individuals with upper limb amputations. In fact, the convergence of advancements in brain-computer interfaces (BCI) and robotics has created a new era of enhanced precision and control for robotic arms, addressing the pressing need for assistive devices that offer greater independence and functionality for individuals with disabilities. The project aims to provide greater control and functionality to enhance amputees' independence, by utilizing brain-computer interface (BCI) technology and electroencephalogram (EEG) signals. The proposed experimental design involves utilizing the 6 DOF-Yahboom DOFBOT Robotic Arm Kit, in combination with the 14-Channel EPOC X EEG Headset. The system is controlled by Jetson Nano and programmed using Python, employing a Latent Dirichlet Allocation (LDA) method for Artificial intelligence task. Finally, as traditional devices, often limited by their demand for substantial physical effort and lack of versatility, fall short of meeting the daily needs of these individuals, the development of the proposed robotic arm emerges as a vital solution, promising to revolutionize the support available to individuals with severe motor disabilities, including limb loss. Future work will focus on advancements in feature extraction techniques for EEG signals to enhance control accuracy. Specifically, exploring advanced methods such as time-frequency analysis and deep learning-based feature extraction holds significant potential for improving the discrimination of relevant brain activity patterns.

REFERENCES

Lemaire, E. D., Supan, T. J., & Ortiz, M. (2018). Global standards for prosthetics and orthotics. In *Canadian Prosthetics & Orthotics Journal*, 1(2).

Bharara, M., Mills, J. L., Suresh, K., Rilo, H. L., & Armstrong, D. G. (2009). Diabetes and landmine-related amputations: a call to arms to save limbs. In *International Wound Journal*, 6(1), 2.

Shedeed, H. A., Issa, M. F., & El-sayed, S. M. (2013). Brain EEG signal processing for controlling a robotic arm. In *8th International Conference on Computer Engineering & Systems (ICCES)*, pp. 152–157.

Aljedaani, L. T., Abdelhedi, F., Aldahasi, R. A., & Batheeb, A. A. (2024, April). Design of a Brain Controlled Robotic Arm: Initial Experimental Testing. In *2024 21st International Multi-Conference on Systems, Signals & Devices (SSD)* (pp. 209-215). IEEE.

Ramadan, R. A., & Vasilakos, A. V. (2017). Brain computer interface: control signals review. In *Neurocomputing*, vol. 223, pp. 26–44.

ZHOU, Y., et al. (2023). Shared three-dimensional robotic arm control based on asynchronous BCI and computer vision. In *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.

Biasiucci, A., Franceschiello, B., & Murray, M. M. (2019). Electroencephalography. In *Curr. Biol.*, vol. 29, no. 3, pp. R80–R85.

Khosla, A., Khandnor, P., & Chand, T. (2020). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. In *Biocybern. Biomed. Eng.*, vol. 40, no. 2, pp. 649–690.

Yip, D. W., & Lui, F. (2023). Physiology, Motor Cortical.

Rolander, A. (2023). Analyzing the Effects of Non-Generative Augmentation on Automated Classification of Brain Tumors.

Huang, Z., & Wang, M. (2021). A review of electroencephalogram signal processing methods for brain-controlled robots. In *Cognitive Robotics*, vol. 1, pp. 111–124.

Orban, M., Elsamanty, M., Guo, K., Zhang, S., & Yang, H. (2022). A review of brain activity and EEG-based brain–computer interfaces for rehabilitation application. In *Bioengineering (Basel)*, vol. 9, no. 12, p. 768.

CAO, L., et al. (2021). A brain-actuated robotic arm system using non-invasive hybrid brain–computer interface and shared control strategy. In *Journal of Neural Engineering*, 18(4), 046045.

Bousseta, R., El Ouakouak, I., Gharbi, M., & Regragui, F. (2018). EEG based brain computer interface for controlling a robot arm movement through thought. In *IRBM*, vol. 39, no. 2, pp. 129–135.

HAYTA, Ü., et al. (2022). Optimizing Motor Imagery Parameters for Robotic Arm Control by Brain-Computer Interface. In *Brain Sciences*, 12(7), 833.

Arshad, J., Qaisar, A., Rehman, A. U., Shakir, M., Nazir, M. K., Rehman, A. U., & Hamam, H. (2022). Intelligent Control of Robotic Arm Using Brain Computer Interface and Artificial Intelligence. In *Applied Sciences*, 12(21), 10813.

Mu, Y., Zhang, Q., Hu, M., Wang, W., Ding, M., Jin, J., & Luo, P. (2024). Embodiedgpt: Vision-language pre-training via embodied chain of thought. In *Advances in Neural Information Processing Systems*, 36.

Yurova, V. A., Velikoborets, G., & Vladyko, A. (2022). Design and implementation of an anthropomorphic robotic arm prosthesis. In *Technologies*, 10(5), 103.