ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

DOCTORAL (PhD) THESIS FOR HOME DEFENSE

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Innovative Brain-Computer Interface Systems: Robotics Control through EEG Signals

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DOCTORAL SCHOOL ON SAFETY AND SECURITY SCIENCES

Date 26- Feb -2025

DECLARATION

I am **IHAB SATAM** a student of *Bánki Donát faculty of the Doctoral School on Safety and Security Sciences, Óbuda University*, I hereby declare that this Ph.D. dissertation entitled "***Innovative Brain Computer Interface Systems: Robotic Control Through EEG signals***" was written by myself, except where it is cited in the references or the appendixes. I also certify that this dissertation is an original report of my work, and it has not been submitted anywhere for other qualifications or professional certifications.

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Budapest, …….. 20

ACKNOWLEDGEMENTS

I would like to thank the people who supported me during this research, and my special thanks and appreciation to my supervisor **Prof. Dr. habil. Róbert Szabolcsi** for his valuable help in guiding me during this research, without his support and guidance this research would not have been possible.

Also, I would like to thank **the staff of Óbuda University**, especially the Doctoral School on Safety and Security Sciences and my colleagues who worked with me and co-authored some of the published papers on the topic, as well as **my family** for their continuous encouragement and support.

Special thanks to **the Hungarian people** and the **Stipendium Hungaricum Scholarship program**, for their amazing hospitality and cooperation. In addition, a special thanks to my friends: **Michal Ludwinek** and **Julius Máté** for their support during this journey. I have many people to thank for being part of this research and I want to pay my respect and gratitude to everyone who made this process possible.

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1. Introduction

The brain is our most valuable and enigmatic organ. It comprises around 100 billion neurons, each generally possessing 10,000 connections that can reach up to one meter. Consequently, it constitutes a complex network that allows us to see the environment. The brain has approximately an equal number of glial cells as neurons, over 700 kilometers of blood vessels, the extracellular matrix, and is encased in clear cerebrospinal fluid, all of which collaboratively sustain the delicate environment of the neurons in a healthy condition. At the whole-organ level, this is already exceedingly intricate; yet this is but a portion of the narrative. At each moment, several processes occur in the brain, including electrical impulses between neurons and the intricate chemical communication that facilitates homeostasis. Given the inherent micro-scale complexity of the brain, a natural methodology for comprehending its physiology and function is provided by homogenized, continuum-based modeling, which emphasizes the large-scale behavior resulting from the aggregation of small-scale contributions[1].

Notwithstanding the remarkable advancements in neuroscience study in recent decades, our comprehension of how the brain facilitates object and action recognition, learning, planning, and language utilization remains incomplete. An enhanced comprehension of cerebral function and cognition will facilitate the management of neurological and psychiatric disorders, while also enabling the creation of novel systems, gadgets, or robots that interact with people in a natural and cognitively compatible manner.

This PhD thesis aims to explore the applications of brain signals in robotics applications, such as prosthetics or Robotic arm, Mobile Robots, and home system Automation. The research plan focuses on designing a Brain computer interface (BCI) that enhances the efficiency, cost effective and reliable control of actuators. The proposed BCI system contains several steps starting from EEG signal recordings, preprocessing, feature extractions and classification. And, at the end transform these signals into commands to control actuators.

1.1. Background

Brain-computer interface (BCI) is a communication method designed for identifying a subject's brain intentions and converting them into machine commands to regulate the functions of electromechanical devices[2]. Electroencephalography (EEG) may be the most prevalent noninvasive imaging technology in brain-computer interfaces (BCI). Due to the non-stationary character of EEG, typically resulting from variations in electrode impedance or positioning, as well as factors such as individuals' concentration, tiredness, eye movements, or muscle activity, EEG data demonstrate significant intra- and inter-subject variability. Therefore, a recorded EEG pattern from a subject may not be reproducible from the same person later or from several individuals undertaking the exact same task.

1.2. Basis of Brain Computer interface.

The reason for Brain-Computer Interface (BCI) technology is based on the necessity to establish direct communication channels between the human brain and external technologies[3]. Brain-Computer Interfaces

(BCIs) seek to circumvent conventional neuromuscular routes, enabling users to engage with computers only via cerebral impulses. This approach is especially beneficial for those with motor impairments, including those affected by paralysis, ALS, or other physical disabilities, who cannot utilize traditional input devices such as keyboards, mice, or touchscreens. The scientific reasoning is utilizing the brain's electrical activity, predominantly recorded by Electroencephalography (EEG), to understand and decode cognitive states, intents, or directives. Through the analysis and categorization of brain signals, BCIs facilitate the operation of assistive devices, prosthetic limbs, communication systems, or robotic arms, therefore improving the quality of life and autonomy for those with significant physical disabilities[4]. Furthermore, BCIs serve as an experimental framework for enhancing neuroscience and comprehending cerebral functioning, since they investigate the brain's encoding of movement goals, attention, and decision-making processes. The advancement of BCI technology serves not only to enhance human-machine connection but also to elucidate the intricacies of brain processing[5], promote advances in neural rehabilitation, and progress neurofeedback treatments.

1.3. Research Objectives and scope

This PhD thesis aims to contribute to the field of BCI technology. In this work we investigate the implementation of BCI in robotic applications. The research objectives are to design a BCI system that collects the signals non-invasively from the brain, then apply different algorithms for preprocessing, feature extractions and classifications to convert the modified signals into commands to control actuators such as robotic and prosthetic arms, and wheeled robots.

1.4. Hypotheses

Hypothesis 1: Due to their simplicity and fewer health hazards, non-invasive BCIs are better for real-world robotic applications than invasive or semi-invasive technologies, notably in assistive robots for disabled users.

Hypothesis 2: The utilization of wavelet transforms for feature extraction, in conjunction with Adaptive Neuro-Fuzzy Inference System (ANFIS) for classification, enhances the level of accuracy of EEG data analysis. The same can imply if Supervised Machine learning algorithms are used for classification.

Hypothesis 3: Employing a Brain-Computer Interface (BCI) for controlling a 6 Degrees of Freedom (DOF) robotic arm that closely replicates human arm movements facilitates more intuitive and precise robotic control.

Hypothesis 4: An innovative technique to control higher degrees of freedom in a robotic arm with less cognitive commands from the brain can improve usability and efficiency. This method enables the users to control a higher degree of freedom robotic arm using 4 mental commands only.

Hypothesis 5: Using Brain-Computer Interface (BCI) technology for the control of mobile robots will facilitate efficient and effective robotic control.

1.5.Overview.

In this research, a BCI system was designed in order to use mental commands from the brain in different Human-Robot applications. This proposal is expected to facilitate the complexity of controlling Robots using brain activities. The Human-Machine application has been used for a long time. However, there is always a new method of implementing control that is developed every time.

We have investigated how the BCI system worked and how it can be developed to be more efficient and have higher accuracy. This thesis is organized into 7 main chapters. Each chapter contributes to the understanding of the applications of BCI in human robot interaction applications. Chapter 2 offers a preliminary study that provides insights into the existing knowledge of BCI system and identify the research gap. Chapter 3 presents the methodology and the conceptual design of the BCI system. Chapter 4 contains the experimental work of each hypothesis. Chapter 5 presents the safety and security aspects of the BCI and why the chosen method of the signal recorded was selected. Chapter 6 identifies the results of each hypothesis. Chapter 7 discusses the results and what new scientific contributions have been made in this work.

2. Literature Review

The application of brain signals in robotics is a swiftly evolving domain that investigates the utilization of brain-computer interfaces (BCIs) to provide direct communication between the human brain and robotic systems [6]. Researchers are exploring advanced techniques to convert mental directions into actionable inputs for robotic systems by using electrical brain activity through sensors such as electroencephalograms (EEGs). This method creates new opportunities in areas including assistive robotics, neuro-prosthetics, and human-robot interaction, presenting possible advancements in improving mobility and autonomy for those with motor disabilities [7]. Applications of brain signals concentrate on deciphering diverse mental states such as intention, concentration, or imagined movement utilizing machine learning algorithms that translate these signals into orders for the operation of robotic arms, mobile robots, or exoskeletons [8]. This integration of neurology and robotics seeks to develop intuitive and adaptable systems that can respond to human intents instantaneously. To comprehend the breadth and possibilities of these breakthroughs, it is crucial to analyze fundamental research that explores the principal methodologies of signal gathering, feature extraction, classification methods, and integration with robotic platforms. These first experiments establish the foundation for creating resilient and adaptive brain-controlled robotic systems.

2.1.EEG Signal recording.

Electroencephalography (EEG) is an essential tool in brain-computer interface (BCI) research and several therapeutic applications [9], offering insights into cerebral activity by capturing electrical impulses produced by the brain. There are three main EEG recording techniques: invasive, semi-invasive, and non-invasive [10], each presenting distinct advantages, drawbacks, and uses.

2.1.1. Invasive Method

Invasive EEG, often known as intracranial EEG, is a technique in which electrodes are directly inserted into brain tissue or positioned on the brain's surface, behind the dura mater [11]. This method yields superior recordings, accurately capturing intricate brain activity with exceptional spatial and temporal resolution. Invasive EEG includes Depth electrodes implanted in targeted regions of the brain, specifically inside deep brain structures like the hippocampus. They are often used to observe regions that are less accessible to non-invasive techniques and are essential in the management of disorders like epilepsy [12]. Depth electrodes are particularly advantageous in pre-surgical planning, since accurate localization of brain activity is crucial for focused intervention.

2.1.1.1. Advantages and Limitations

Invasive EEG offers the most precise depiction of cerebral activity. The operation is significantly invasive, presenting hazards such as infection, inflammation, and possible long-term damage to cerebral tissue [13]. Thus, invasive EEG is often confined to clinical environments, where the advantages – such as seizure localization for epilepsy management – exceed the surgical hazards.

2.1.2. Semi Invasive Method

Semi-invasive EEG holds an intermediary position between invasive and non-invasive techniques. The electrodes are positioned inside the skull, external to the dura mater, enhancing signal quality compared to non-invasive methods while preventing direct contact with the brain [14]. Illustrations comprise:

1- The subdural grid and strip electrodes are positioned between the skull and dura mater, providing mild invasiveness and superior signal quality relative to non-invasive methods. They are often used in pre-surgical assessments, especially for epilepsy patients, to identify brain areas associated with seizure activity.

2- Epidural electrodes are situated above the dura mater and under the skull, making them somewhat less invasive than subdural electrodes. They provide sufficient spatial resolution while mitigating some dangers linked to direct brain contact. This strategy is sometimes used in research and is beneficial for prolonged observation in certain clinical scenarios.

2.1.2.1. Advantages and Limitations of Semi-Invasive Method

Semi-invasive EEG offers a suitable balance between invasiveness and signal fidelity. The electrodes, while not in direct touch with the brain, are positioned inside the skull, yielding sharper data than non-invasive methods. Semi-invasive techniques need surgical intervention, albeit they have a reduced risk compared to fully invasive procedures. This restricted use is often limited to situations, when accuracy is crucial, but a completely intrusive method is considered too hazardous.

2.1.3. Non-Invasive

Non-invasive EEG is the predominant and extensively used technique owing to its safety, simplicity, and cost-effectiveness [15]. This method involves placing electrodes on the scalp to assess electrical activity across the skull. The prevalent configuration consists of a cap equipped with several electrodes (from 16 to 256), enabling multi-channel recording across various brain areas [16]. Non-invasive electroencephalography techniques encompass:

1- Scalp EEG: Conventional EEG entails the placement of electrodes at defined sites on the scalp, according to protocols such as the 10-20 system, which standardizes electrode positioning for uniform data acquisition. This approach is favored in clinical and research environments due to its accessibility and low danger.

2- Dry and Wet Electrodes: Wet electrodes need conductive gel to enhance signal transmission, guaranteeing intimate contact between the skin and the electrode. Dry electrodes, which eliminate the need for gel, have gained popularity due to their ease and mobility, especially in consumer applications. Despite generating more noise, new advancements have enhanced the reliability of dry electrodes[17].

2.1.3.1. Advantages and limitations of non-invasive methods

The advantages of non-invasive EEG include its great accessibility and safety, with applications in brain-computer interfaces, neuro-feedback, and consumer-grade devices for monitoring and relaxing. However, it also has limitations. Its principal restriction is diminished signal quality resulting from skull attenuation, which reduces spatial resolution and complicates the accurate localization of brain activity. Moreover, non-invasive EEG is susceptible to aberrations caused by ocular movements, muscular activity, and external electrical interference, which might compromise recordings [17].

2.1.4. Comparison of EEG recording methods

Table (1) below compares each EEG recording method according to Application and other different aspects.

Table (1) Methods of EEG recording

Method	Level of Invasiveness	Electrode location	Quality of the signals	Application Scope	Risks
Invasive	High	Brain Tissue	High	Clinical Epilepsy treatment	Infection, Inflammation
Semi-Invasive	Moderate	Between skull and dura mater	High to moderate	Epilepsy Localization, Clinical Research	Mild surgical risks
Non-Invasive	Non	Scalp Surface	Moderate	BCI neurofeedback, Consumer Devices	Minimal

Every EEG recording technique has unique benefits and drawbacks, depending upon the intended use and permissible risk thresholds. Invasive and semi-invasive procedures provide superior precision and are crucial in clinical environments where accuracy is vital, such as in the treatment of epilepsy. In contrast, non-invasive EEG is extensively used in research and consumer applications because of its safety and user-friendliness, however this comes at the expense of diminished signal quality. The advancement of sophisticated signal processing and electrode technology is enhancing the capabilities of non-invasive EEG, rendering it more applicable for intricate uses, such as real-time brain-computer interfaces and neuro-feedback systems.

2.2.BCI applications.

The integration of Brain-Computer Interface (BCI) technology with robotics and medical applications is an expanding focus within neuro-engineering, control systems, and biomedical engineering. This chapter examines the existing research environment, fundamental ideas, and technical advancements in BCI applications within robotics and illness diagnosis and treatment [18]. This review analyzes the main approaches, problems, and findings of current investigations, emphasizing the potential of BCI to transform assistive devices, robotic control, and diagnostic systems in healthcare.

2.2.1. BCI in Robotics

2.2.1.1. BCI and Assistive Robotic Devices

The use of BCI in assistive robots has increased in response to the requirements of people with impairments. Brain-computer interfaces (BCIs) enable people to use robotic equipment, such as prosthetic limbs and exoskeletons [19], via the interpretation of neurological signals, presenting exciting opportunities for enhanced mobility and autonomy. Research demonstrates that BCI-controlled prosthetic arms, often using EEG-based non-invasive BCIs, may attain functionality that closely resembles natural limb motions. Significant advancements encompass:

- Neuro-prosthetic Arms: These devices convert EEG-derived brain signals into accurate motor functions. Advanced systems use machine learning to enhance categorization precision and control dependability. Exoskeleton is a type of assistive robot that can be controlled by Brain signals. They proved to be a great help in assisting disabled people or in rehabilitation for people suffered from strokes, as the work of the teams in[20], [21], [22], [23], [24] show.
- Six Degrees of Freedom (DOF) Robotic Arms: High-degree-of-freedom arms may be manipulated using a restricted array of cognitive instructions, facilitating streamlined but efficient control [25]. Innovative techniques have arisen to enhance command mapping for high degrees of freedom with less cognitive exertion [26].

2.2.1.2. Brain Controlled Wheeled Robots

Brain-controlled wheeled robots represent a distinct category of assistive equipment[27], specifically designed for those with mobility impairments. Utilizing BCIs for these applications necessitates advanced signal processing and real-time control techniques. Recent research illustrates the efficacy of wavelet transform-based feature extraction and adaptive neuro-fuzzy inference system (ANFIS) classification in attaining accurate robot control. Investigations in this domain concentrate on:

- Advanced preprocessing and feature extraction approaches, including wavelet transformations, increase signal quality and improve classification accuracy [28].
- Classification using Machine Learning Models: Techniques such as Support Vector Machines (SVM) and neural networks have been used in conjunction with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to enhance command accuracy, achieving performance levels of up to 90% accuracy.

2.2.2. BCI in disease inspection and treatment

2.2.2.1. BCI for Diagnostic Applications

BCI has shown promises in illness detection and diagnosis, especially in neurological conditions where non-invasive EEG offers insights into cerebral activity. BCI-based diagnostic systems have been used in the detection of epileptic seizures, the monitoring of neurodegenerative disorders, and the evaluation of cognitive deficits.

- Seizure Detection Systems: EEG-based Brain-Computer Interfaces may be used for real-time seizure detection [29], facilitating early management for individuals with epilepsy [30]. Machine learning methodologies, including neural networks and deep learning, improve detection precision.
- Assessment of Cognitive Impairment: BCI applications in evaluating cognitive functioning may assist in identifying illnesses such as Alzheimer's disease and dementia [31], [32]. Non-invasive EEG equipment, when integrated with cognitive task assessments, has shown their efficacy as significant diagnostic indicators.

2.2.2.2. BCI in neurological Rehabilitation

Besides diagnostics, BCI is progressively used in the therapy and rehabilitation of people recuperating from stroke, spinal cord injuries [33], and other neuromuscular disabilities. Rehabilitation robotics, in conjunction with brain-computer interfaces (BCIs), enable patients to manipulate exoskeletons or functional electrical stimulation (FES) devices using their neural signals, therefore facilitating motor rehabilitation.

- Stroke therapy: BCI-driven robots in stroke therapy enable patients to engage in regulated motor motions [34], therefore promoting neuroplasticity and facilitating motor recovery [35].
- Spinal Cord Injury Therapy: Brain-Computer Interface systems integrated with robotic exoskeletons provide paraplegic patients an assistance equipment for mobility training, improving their capacity to regain fundamental motor abilities [36].

2.2.2.3. BCI for Mental Health Applications

Brain-computer interfaces are being investigated as instruments for the monitoring and treatment of mental health conditions. Neuro-feedback-based brain-computer interfaces (BCIs) are used to address anxiety, depression, and other mental health disorders by instructing users to modulate certain brainwave patterns linked to stress and relaxation. Research indicates that this method may provide enduring improvements in mental health.

2.2.3. Challenges, Limitations and future Work in BCI Application

Notwithstanding its prospective uses, BCI technology encounters several technological and ethical hurdles [37]. Constraints in signal capture, processing, and interpretation provide considerable challenges, particularly in real-time applications. Factors such as auditory interference, user weariness, and the variability of cerebral signals among people might influence the reliability of BCI performance [38]. Moreover, ethical problems about data privacy and the autonomy of BCI users persist in influencing the development and implementation of these systems. Progress in machine learning, hardware downsizing, and signal processing has the capacity to substantially improve BCI applications in robotics and medical treatment [39]. Innovative technologies, including deep learning for signal analysis, tiny and wearable brain-computer interface systems, and connection with Internet of Things devices, have the potential to revolutionize the use of BCIs in healthcare and assistive technology.

2.3.Conclusion

The use of Brain-Computer Interface (BCI) technology in robotics and medical treatment represents a significant advancement towards individualized, responsive, and user-focused healthcare and assistive solutions. In robotics, brain-computer interfaces (BCIs) have empowered humans, particularly those with significant physical limitations, to operate robotic arms, exoskeletons, and wheeled robots using neural impulses [40]. This advancement has allowed the creation of assistive devices that provide improved mobility, autonomy, and quality of life, along with the possibility of personalized prostheses and highly articulated robotic limbs that closely mimic human motor capabilities. Researchers have enhanced the accuracy and dependability of brain-computer interfaces (BCIs) using sophisticated signal processing methods and machine learning algorithms, hence increasing their accessibility and efficacy for practical applications. In the field of illness diagnosis and treatment, BCIs have shown significant potential in diagnostics, rehabilitation, and mental health therapy. By enabling real-time observation of brain activity, BCIs facilitate the early identification of disorders such as epilepsy and cognitive decline, hence assisting in prompt treatments. For patients in rehabilitation for stroke, spinal cord injuries, or other neuromuscular disorders, BCI-driven robotic devices facilitate neuronal regeneration via regulated motor exercises and functional electrical stimulation. Moreover, BCI neuro-feedback systems are shown efficacy in mental health interventions, assisting people in managing illnesses like anxiety and depression by self-regulation of brainwave patterns.

Despite these encouraging developments, BCI technology continues to encounter several hurdles, including signal unpredictability, processing constraints, and ethical issues pertaining to privacy and autonomy. Non-invasive brain-computer interfaces (BCIs) provide a practical, safe, and efficient method for capturing electroencephalogram (EEG) data, making them an optimal selection for both research and application contexts. In contrast to invasive and semi-invasive techniques that need surgical implantation of electrodes, non-invasive BCIs use sensors positioned on the scalp, therefore mitigating the dangers associated with surgery, including infection and tissue damage. This accessibility facilitates wider and more adaptable applications, making them particularly appropriate for the development of assistive technology, neuro-rehabilitation tools, and diverse human-computer interactions. Non-invasive brain-computer interfaces have evolved significantly, with improvements in signal processing and machine learning facilitating precise capture and interpretation of cerebral activity [41]. Furthermore, non-invasive techniques provide prolonged and repeated use without health hazards, which is crucial for applications in routine contexts such as prosthesis operation, wheelchair maneuvering, and robotic assistance devices. This method integrates safety, user-friendliness, and technical compatibility, making it the favored technique for capturing EEG data in several BCI applications. The literature reviews in the above the sections support **Hypothesis 1**: Due to their simplicity and fewer health hazards, non-invasive BCIs are better for real-world robotic applications than invasive or semi-invasive technologies, notably in assistive robots for disabled users.

3. EEG classification algorithms for better accuracy

There are several different components that make up the human brain. These structures include the major cerebrum, the cerebellum, which is smaller, and the brain stem. From magnetic resonance (MR) imaging of the brain, these structures may be identified with relative ease (Figure 1). The cerebrum is made up of two hemispheres: the left and the right. These hemispheres are connected to one another by bundles of nerve fibers known as the corpus callosum connections.

Glial cells and neurons, often known as nerve cells, are the two primary categories of cells that make up the brain. In most cases, a neuron is made up of a cell body, also known as the soma, a long nerve fiber, also known as the axon, and further branching extensions, known as dendrites. White matter and gray matter are the two basic forms of brain tissue matter that manifest themselves as a consequence of the spatial distribution of brain cells. Gray matter is characterized by the presence of neuronal cell bodies and glial cells, whereas white matter is mostly made up of bundles of axons that have been myelinated.

Figure 1 (B) illustrates the distribution of white matter and gray matter in the cerebrum. It shows the white matter as well as the gray matter that is found in the cortical and subcortical regions of the nervous system. The sub-cortical gray matter is comprised of a number of significant structures or areas that are situated deep inside the brain. These include the thalamus, basal ganglia, and the hippocampus [1].

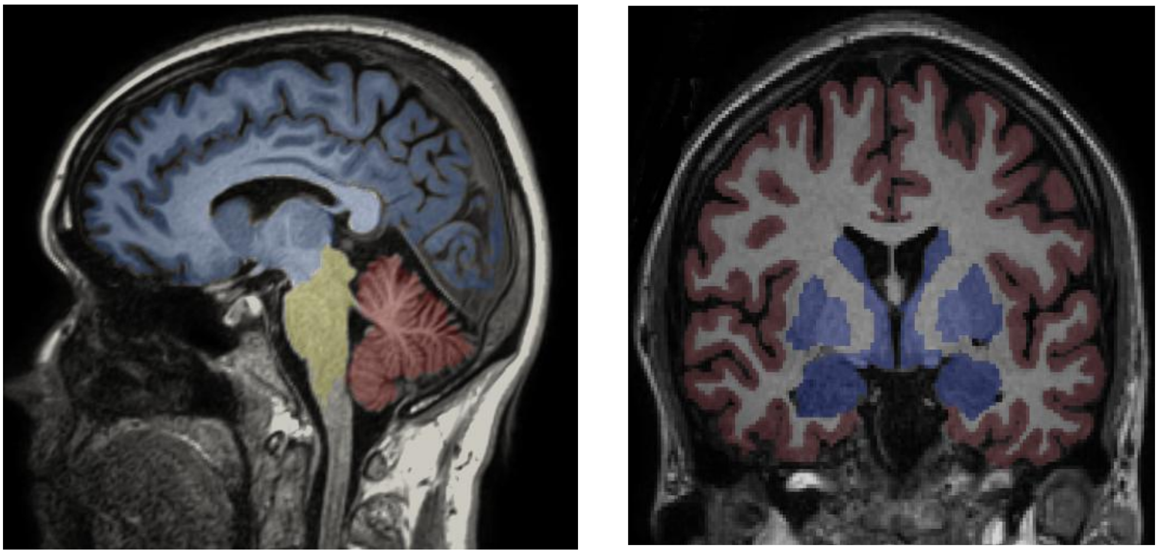

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Figure (1) MR images of human Brain

The brain is enclosed and shielded by three layers underneath the skull. Arachnoid mater, Dura mater, and pia mater. Based on how it functions, the human brain may be divided into three primary sections. The limbic system oversees emotions, the stem, or cerebellum, is in charge of essential bodily functions, and the cortex is in charge of processing and evaluating critical thought. The frontal, parietal, occipital, and temporal lobes are the four areas that make up the cortex. Major processes including critical thinking, memory storage, visual data processing, sensation, and movement are all controlled by these lobes. The neurophysiology theory states that synapses allow nerve cells to interact with one another. In terms of its functioning, the nervous system is divided into two parts: the peripheral nervous system (PNS) and the central nervous system (CNS). The PNS is made up of sensory neurons that link the body's many sensory receptors to the central nervous system (CNS), whereas the CNS is made up of the brain and spinal cords [1].

In addition, there are two types of cells in the nervous system: neurons, which may send electrical signals, and supportive glial cells, which carry out essential tasks. One particular kind of cell that differs from other types of cells is a neuron. Axons, cell body, and dendrites make up its three components. Cytoskeletal protein and ribosomes, which help in information processing and reception, are abundant in the dendrites. The postsynaptic specialization and the presynaptic terminal make up the synapse. The synaptic cleft, an extracellular gap between these two sections, is where neurotransmitter-mediated communication between neurons takes place. Following its passage through the cell body, the axon is in charge of interpreting the combined signals [42].

In the spinal cord, which is in charge of sending impulses to distant regions parts of the body, the axon length varies from a few microns to up to one meter [43]. As a result, in summary, the body processes signals, the axon transfers signals, and the dendrites receive information. The glial cells' primary job is to keep the neurons connected [44]. Nonetheless, they carry out crucial tasks such maintaining the brain's ionic equilibrium, promoting the healing process following a damage, and regulating the neurotransmitters in the synaptic clef. There are four different kinds of glial cells in the central nervous system: astrocytes, oligodendrocytes, microglia, and ependymal cells. Every one of these kinds serves a crucial purpose [45]. The chemical environment must be balanced by astrocytes in order to improve neuronal signaling. To facilitate quicker signal transport, oligodendrocytes in the central nervous system perform the same role as axons. Microglia helps clear damaged sites of cellular debris. The ependymal cells create cerebrospinal fluid. The action potential (AP) is the name given to the electrochemical signaling that occurs inside neurons [46].

Ion exchange across the neuron membrane is the cause of AP, which is a transient alteration in the membrane potential along the axon. Beginning in the cell body, the AP moves only in one direction. The definition of EEG signal is that it is the measurement of the flowing current during synaptic excitations of the dendrites of neurons in the cerebral cortex. The electrical dipoles between the body of the neuron and the dendrites create electrical potentials. The pumping of positive ions of Sodium Na^{+}, Potassium K^{+}, calcium $Ca^{+}$and the negative of chlorine Cl^{-} causes the current in the brain, and this current generate a magnetic field over the scalp that is measurable by EEG system. There are five types of brain signals regarding the frequency ranges

[47]. These types are Gamma (>35Hz), Beta (12-35 Hz), Alpha (8-12Hz), Theta (4-8Hz) and Delta (0.5-4Hz). Each type of these signals is related to a specific Brain state as shown in Table 2.

Table (2) Brain signal bands

No.	Brain Waves	Frequency Hz	Brain Location	Brain State
1	Delta	0.5-4	Frontal Lobe	Deep Sleep
2	Theta	4-8	Various depends on the state	Light sleep, Meditation
3	Alpha	8-12	Occipital lobe	Relaxation
4	Beta	13-35	Distributed symmetrically	Active thinking
5	Gamma	>35	Somatosensory cortex	High level cognitive function

From Table 2, like sleeping or dreaming each band of EEG is generated in a specific state of the mind. Such as sleeping or relaxing etc. as it explained below:

1. Delta Waves: These signals are generated in deep sleep, and they are usually very slow waves.
2. Theta Waves: These signals are dreamy state, they are generated in sleep and Meditation.
3. Alpha Waves: These signals are generated in the rest state of the mind. The waves are noticeable when the eyes are closed.
4. Beta Waves: These are generated when the person is active and conscious. The waves can be detected during tasks that require significant attention.
5. Gamma Waves: The waves are used for advanced cognitive processing.

The brain signals collected using the Emotive insight have noises and errors [48]. Therefore, the signals need to be preprocessed in order to prepare them for feature extraction that helps with the classification. From Table 2 the Delta and Theta bands are more likely dominant during the unconscious state of the mind, while the Gamma band is dominant in the hyperactive state. For this reason, this work deals with Alpha and Beta for robotic applications.

3.1. Brain Signal Generation

Neurons are building blocks of the neurons system [49]. It consists of the nucleus, axon and axon terminal (Figure 2). The human brain is made up of approximately 60 billion neurons. In a resting state the inside of the neuron is relatively more negative on the outside and this concept is important to realize.

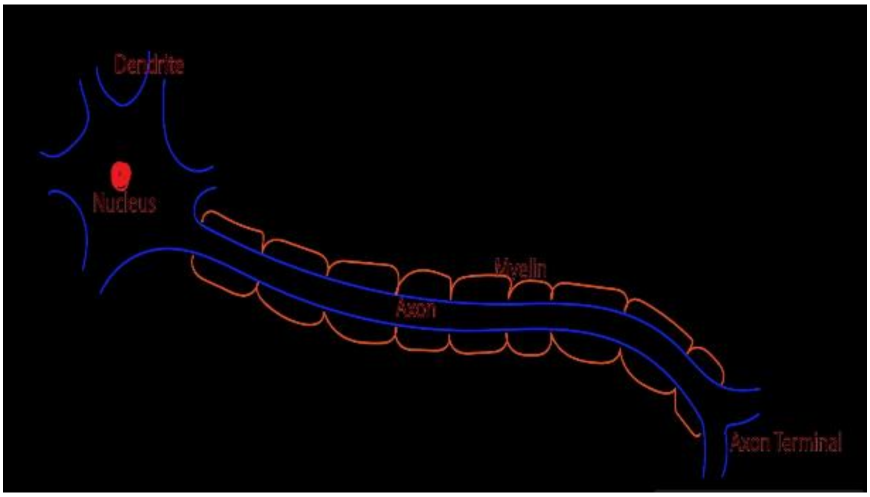


Figure (2) Neuron

The neurons communicate with each other through an electrochemical signal. Figure (3) shows the synapse. Synapse is the place where the neurons connect and communicate with each other. From Figure (3) the part before the synapse is called the presynaptic terminal or presynaptic neuron and the part after the synapse called the postsynaptic neuron [50]. The presynaptic neuron sends releases the neurotransmitters and they can create potentials on the postsynaptic neurons. This potential is excitatory signaling that leads to an increase in positive charges inside the postsynaptic neurons. It is called excitatory post synaptic potential EPSP. If the presynaptic neurons cause the postsynaptic neurons to become more negative from the inside. It is called Inhibitory Postsynaptic Potential IPSP. Beneath the surface of the scalp, lies the pyramidal neurons. These neurons arranged

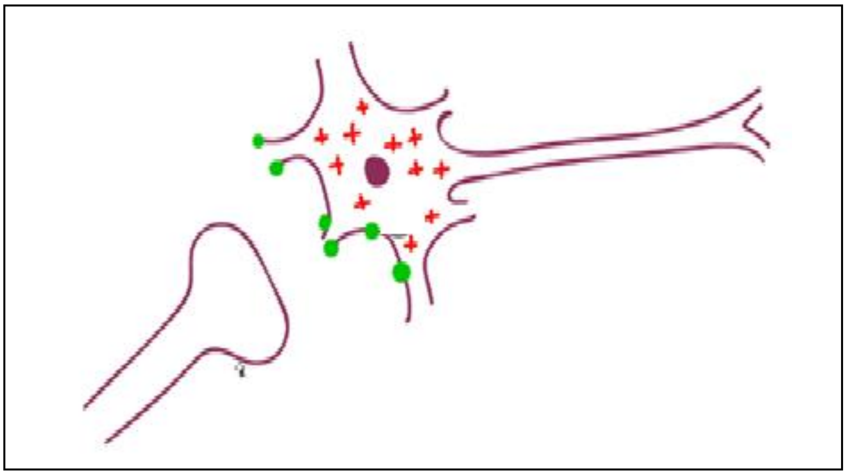


Figure (3) Synapse

perpendicular to cortical surface with the apical dendrites closer to the cortical surface. When there is an excitatory postsynaptic potential, there will be an increased positivity inside the cell. The intracellular positivity leads to a relative increase of the negativity on the outside of the cell which is called the extracellular negativity [51]. The extracellular negativity on one end of the neuron leads to extracellular positivity on the other end of the neuron (the one that is close to the surface). In simple words the negative charge on one end leads to positive charge on the other end. The distant space between the end of the neuron the have the difference in charges between the positive and negative end is called the Dipole. The current flows from the positive end to the negative end (figure (4)).

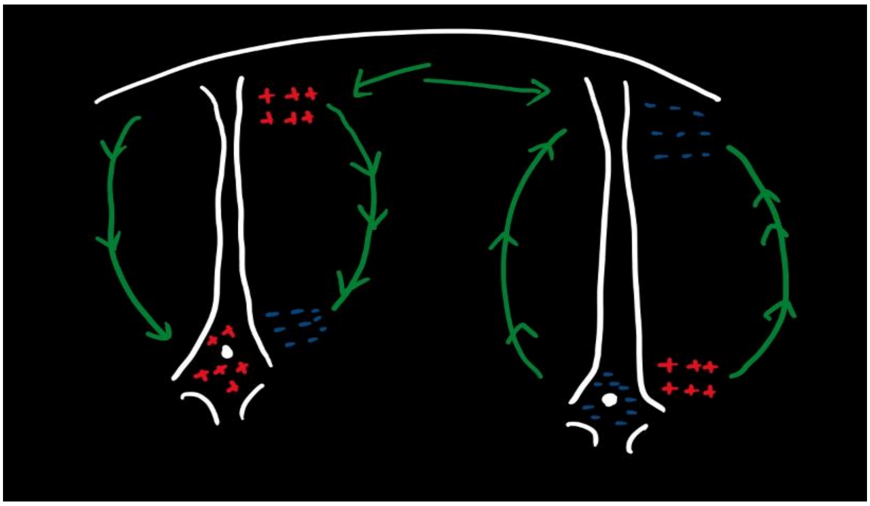


Figure (4) Neuron Potential

If there is an IPSP inside the neurons (negative charge), this will cause a positive charge on the outside space of the cell. Positive charge on one end leads to negative charge on the other end, and the current will flow from positive side to the negative side. The continuous excitation and inhabitation of these neurons leads to change in the potential at the end of the neurons. This difference in potential for the neurons that are close to the surface of the scalp can be detected using the electrodes [52]as shown in figure (5).

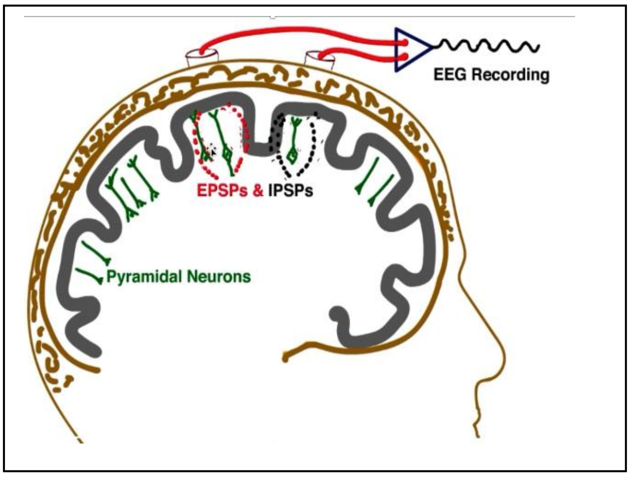


Figure (5) Brain Signals

Electroencephalography (EEG) classification has become a fundamental technique in brain-computer interfaces (BCIs), revealing substantial promise across several domains, including neuroscience, medicine, and assistive robots. EEG signals, produced by cerebral neuronal activity, are intricate, high-dimensional, and susceptible to noise due to their vulnerability to artifacts from muscle movement, external disturbances, and intrinsic non-stationary properties [53]. This unpredictability is a significant difficulty for precise signal classification, as nuanced patterns in the EEG data must be consistently recovered to distinguish mental states, motor images, or cognitive directives. In light of these problems, the development of effective EEG classification algorithms that attain high accuracy has emerged as a primary priority in BCI research, since even little advances in classification accuracy can result in significant improvements in system efficiency and user experience. Recent improvements in signal processing and machine learning have facilitated the development of novel EEG classification methods that enhance accuracy [54]. A principal method is pre-processing techniques, including band-pass filtering and artifact elimination, to enhance signal quality prior to classification. Feature extraction techniques such as Wavelet Transform, which encapsulate both temporal and spectral attributes of EEG data, have demonstrated potential in improving feature clarity and discriminability. Machine learning approaches, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), neural networks (NN), and support vector machines (SVM), are utilized for effective categorization, each offering distinct advantages for the task. ANFIS utilizes fuzzy logic concepts to manage uncertainty and unpredictability in EEG data, whereas neural networks, particularly deep learning models, are proficient in recognizing intricate, non-linear patterns. Support Vector Machines (SVM), recognized for their effectiveness in high-dimensional environments, are a favored option for EEG classification, frequently achieving high accuracy with little overfitting. These strategies, utilized either independently or in conjunction, have shown remarkable enhancements in EEG classification accuracy, with current research indicating success rates over 90%, a considerable advancement from earlier methods that frequently failed to surpass 65%. These developments have significant significance, especially in BCI applications designed to aid people with impairments via neuro-prosthetics or in the operation of assistive robotic equipment, where accurate and dependable signal interpretation is essential.

3.2. DataSet

In order to prove the second hypothesis, I used a dataset from a previous study. The data was made by [55] and the ethics board at the Chinese Academy of Science's Institute of Automation approved each trial.

Twenty-five healthy, right-handed people (19 men and 6 women) participated in the poll. The participants lacked knowledge of Mi-Based BCI. To completely comprehend the scenario, it is essential to discuss the technique used to record the signals. The individuals looked at the screen from a distance of one meter while sitting comfortably in a chair with their hands resting naturally on their knees. (Figure 6a). Each trial lasted eight seconds and started with a white circle in the center of the screen for two seconds, as seen in Figure 7. A red circle then flashed for a single second as a signal to assist people focus on the approaching goal. Before the desired reaction was needed, the "Hand" or "Elbow" cue was shown for four seconds. The participants were instructed to visualize carrying out the necessary action with their entire body, not just their eyes, during this time. The participants were told to think about anything they wished while relaxing their limbs.The subjects' right forearms and hands were used to record their EMGs. (Fig 6. 2b) to ensure they weren't operating independently (the EMG signals were eliminated during the EEG preprocessing). The 8s experiment and the fantasy were ultimately stopped by a "break" of 1s. During the interval, the patients were instructed to relax and reduce their muscle and eye movements.

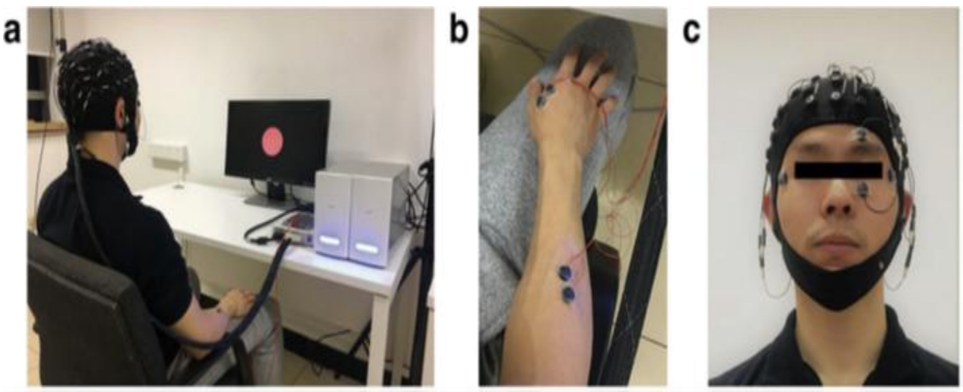


Figure (6) Data Recording

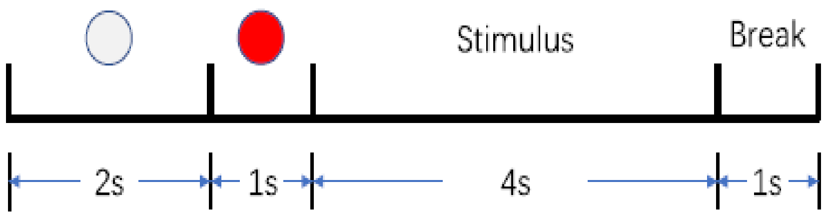


Figure (7) Time for one Trial

Event-related synchronization and desynchronization (ERS/ERD) are associated with alpha (8-13 Hz) and beta (14-30 Hz) motor-related activities. When the action is executed or envisioned, ERD manifests as a decrease in a certain frequency component associated with an increase in brain activity. An increase in a particular frequency component result in increased frequency sensitivity, or ERS. Occasionally, it can be seen even in the absence of tangible action or intention, as it is associated with the suppression of brain activity. Recent study has identified a robust correlation between a particular brain area associated with sensory perception and the capacity to visualize the movement of certain body parts (as seen in Figure 8). The central dark blue region of the brain, as seen in the figure, governs limb motion. The pale cyan area is crucial for guiding hand movement. The region above the ears is responsible for the movement of the cheekbones and the lips. Motor imagery may induce event-related desynchronization (ERD) in the dominant hemisphere and event-related synchronization (ERS) in the non-dominant hemisphere. Figure 9 illustrates the intensity of brain frequency bands, shown in red.

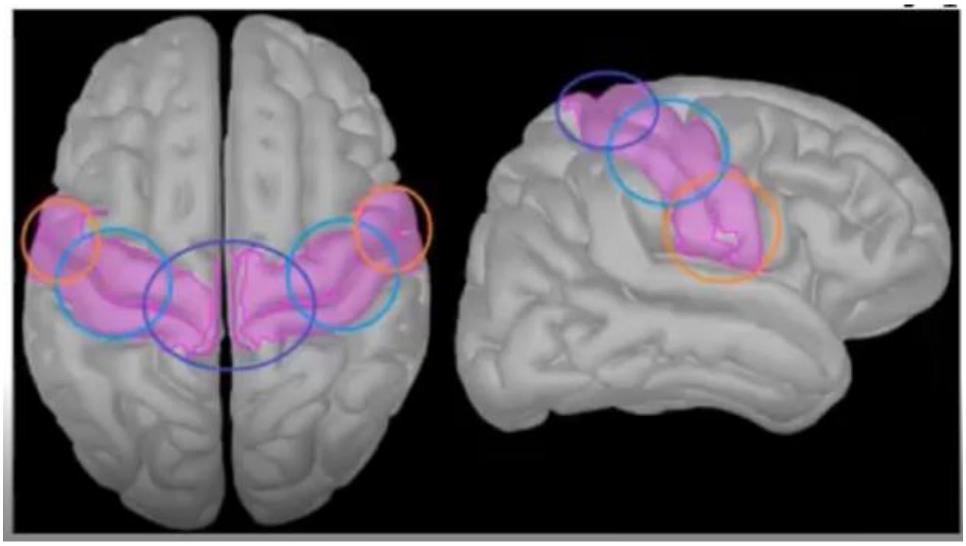


Figure (8) Region of motor imagery

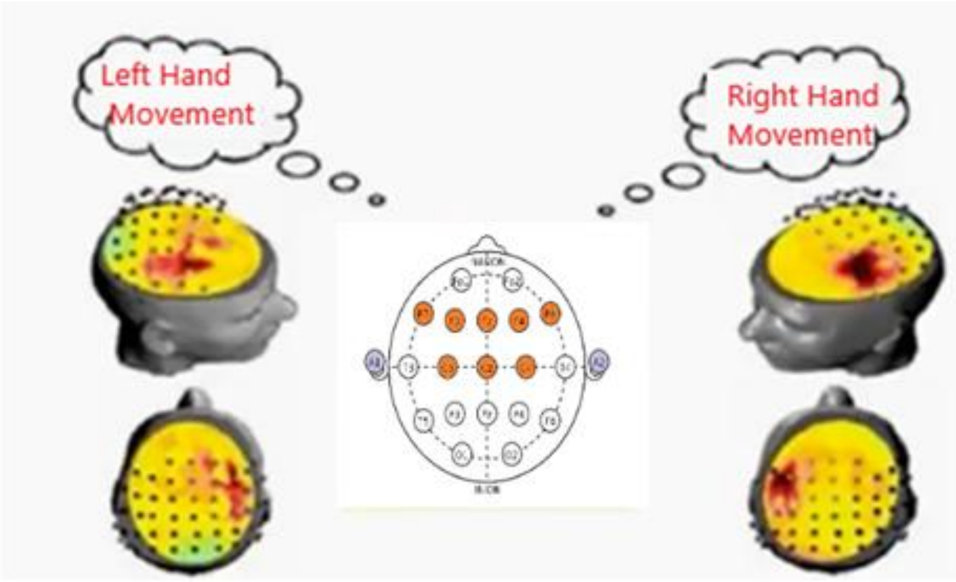


Figure (9) ERD/ERS

The conventional 10/20 System was employed to acquire EEG data at a sampling rate of 1000 Hz with a Neuroscan SynAmps2 amplifier and a 64-channel electrode cap. The left mastoid served as the reference point for the electroencephalogram (EEG) recordings. Electrode impedances were maintained below 10 kΩ during the testing.

3.3. Problem Statement

In the field of brain-computer interfaces (BCIs), precise classification of electroencephalogram (EEG) data is essential for efficient command of extraneous devices like mobile robots or robotic arms. The complicated and chaotic nature of EEG data makes it difficult for conventional approaches to achieve high classification accuracy. The practical uses of EEG-based control systems have been severely hampered by previous studies' low classification accuracies. The dataset has a low score of classification accuracy. The goal of the work is to use state-of-the-art machine learning and signal processing methods to improve the EEG signals' classification accuracy. In addition to proving the usefulness of new approaches, this enhancement would make EEG-based control systems more practical and dependable for use in autonomous robotic systems and prosthetics.

3.4. Proposed Work

The data collected was processed using the EEGLAB toolbox (v14.1.1_b) within MATLAB (R2015a). During the preliminary phases of processing, we utilized a common average reference (CAR). A 40-hertz low-pass filter and a 0.1-hertz high-pass filter were implemented. The input was down sampled to 200Hz to minimize processing expenses. Automatic artifact removal (AAR) was employed to eliminate anomalies associated with ocular and muscular activity in the EEG. The dataset has already undergone preprocessing in [55] and was prepared for feature extraction. For feature extraction, the wavelet transform was used to accomplish it.

3.5. Signal analysis

The signals collected from the brain are subjected to noise and artifacts due to muscle movements or blinking. For that reason, they need to preprocess to get rid of those deformities. The process starts with a signal preparation phase. This stage is essential since it involves removing a lot of noise and abnormalities from the data. It is necessary to extract the best features from the data and use feature selection to reduce the Dimension. The actual classification process is the final step. The steps in this investigation are shown in Figure 10.

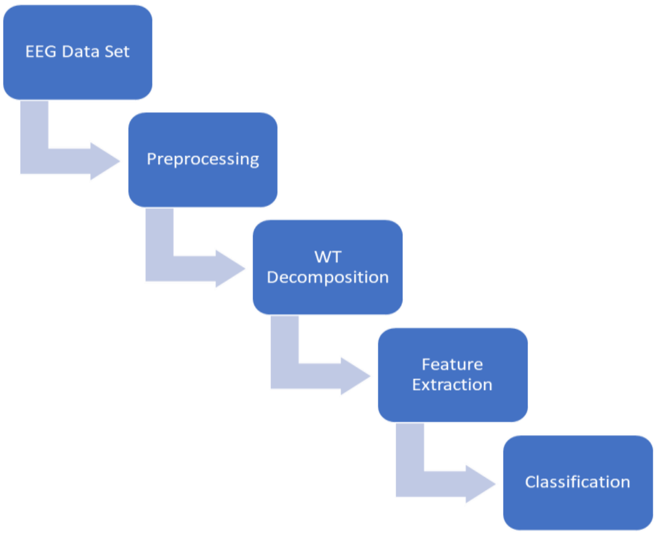


Figure (10) Signal analysis stages

3.5.1. Preprocessing

Preprocessing is an essential first phase in the analysis of electroencephalography (EEG) signals, aimed at augmenting signal quality and enhancing the precision of subsequent tasks such as feature extraction and classification [56]. EEG signals, which record brain activity via electrical impulses on the scalp, are inherently intricate and susceptible to interference from several sources. Sources of noise, including ocular movements, muscular activity, and power line interference, can substantially impair the quality of recorded EEG data, complicating the analysis and interpretation of the underlying brain signals. To precisely interpret brain activity, efficient preprocessing techniques must be employed to eliminate or reduce artifacts, guaranteeing that the signals analyzed are both pristine and reflective of authentic brain activity [57]. EEG preprocessing often encompasses many phases, each targeting distinct facets of signal quality. Standard procedures encompass filtering, wherein band-pass filters delineate pertinent frequency ranges, and artifact removal, utilizing techniques such as Independent Component Analysis (ICA) to segregate and eradicate extraneous signal sources. Baseline correction, signal normalization, and methods such as notch filtering enhance the data by diminishing the impact of extraneous noise, hence rendering the signals more appropriate for comprehensive analysis. These strategies together seek to reduce variability induced by environmental or physiological causes, hence improving the dependability of the processed signals. Preprocessing is crucial in brain-computer interfaces (BCI), cognitive neuroscience, and clinical diagnostics, as high-quality EEG data are vital for precise interpretation and decision-making. Recent improvements in preprocessing techniques, such as adaptive filtering and machine learning-based artifact rejection, provide novel solutions for addressing ongoing issues in EEG data quality.

3.5.2. Feature Extraction

Feature extraction in EEG signals denotes the identification and isolation of significant patterns or qualities within recorded brainwave data that are pertinent to a given task or study. EEG signals are intrinsically complex, comprising substantial raw data accompanied by noise and superfluous information [58]. The primary aim of feature extraction is to diminish complexity by pinpointing the most useful elements of EEG data applicable for classification, grouping, or control tasks.In the area of EEG signals, feature extraction approaches seek to emphasize particular attributes of the signals, including:

1- Time-domain features: These characteristics are extracted directly from the EEG signal in the time domain, including mean, variance, skewness, kurtosis, peak amplitude, zero-crossing rate, and more metrics[59]. Time-domain features are valuable when the temporal characteristics of signals are important [60].

2- Frequency-domain features: These characteristics encapsulate the signal's frequency components using methodologies such as Fast Fourier Transform (FFT) or Power Spectral Density (PSD) analysis [59]. Frequency characteristics may represent power in designated frequency bands (such as delta, theta, alpha, beta, and gamma) or the peak frequencies within those bands.

3- Time-frequency features integrate both temporal and spectral information, often derived using techniques such as Short-Time Fourier Transform (STFT) or Wavelet Transform (WT). The Wavelet Transform is particularly favored for EEG feature extraction due to its capability to capture the non-stationary characteristics of EEG data [61].

4- Spatial characteristics: These pertain to patterns seen across several EEG channels. Techniques such as Common Spatial Patterns (CSP) are employed to identify spatial filters that optimize the variation across classes [62].
5- Nonlinear features: These encompass metrics that reflect the complexity of EEG signals, including fractal dimensions, entropy (such as approximation entropy or sample entropy), Lyapunov exponents, and the Hurst exponent [63].
The extracted features serve as input for classification algorithms (such as neural networks, SVM, ANFIS, etc.) to discern various mental states, cognitive activities, or control commands derived from EEG data. Efficient feature extraction is essential since it dictates the efficacy of future analyses and control applications.

3.5.2.1. Wavelet Transforms

The wavelet transform is a method for analyzing non-stationary time-scale data, applicable to EEG recordings [64]. The ability to examine non-stationary signals and decompose them into discrete frequency components over many timeframes is highly advantageous. Utilizing WT, researchers may condense complex biological signals composed of several time-varying data sets into a digestible array of diagnostic criteria [65]. The continuous and discrete Wavelet transform formula are both given in equations (1) and (2).

$WT_x(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi * \frac{(t-\tau)}{a} dt$ ------(1) Continuous Wavelet transform

Where a represents scale displacement, τ represents time displacement, and ψ is a wavelet basis function, including Hear, db.Series, Coiflet and so on.

$WT_x(j,k) = \int x(t)\psi_{j,k}^{*}(t)dt$ -------(2) Discrete Wavelet transform

The Discrete Wavelet Transform (DWT) restricts the parameters a and τ of the wavelet basis function ψ(a,τ) to discrete values, representing the discretization of scale and translation [66]. Figure 11 illustrates the decomposition of the discrete wavelet transform (DWT) of the EEG signal $x(n)$. The convolution, utilizing low-pass or high-pass filter coefficients, is a multiplication procedure involving two functions, which is then executed through its own sampling. To down-sample, one must halve the sample signal (reduction). Wavelet signals manifest in two forms: approximation and detail signals. A signal obtained from the convolution of the original signal with a low-pass filter serves as an approximation, whereas a signal derived from the convolution with a high-pass filter represents a detail. In Figure 11, each output generates a detailed signal D and an approximation signal A, with the latter functioning as the input for the subsequent phase. The major frequency component of the EEG signal dictates the number of levels in the wavelet decomposition.

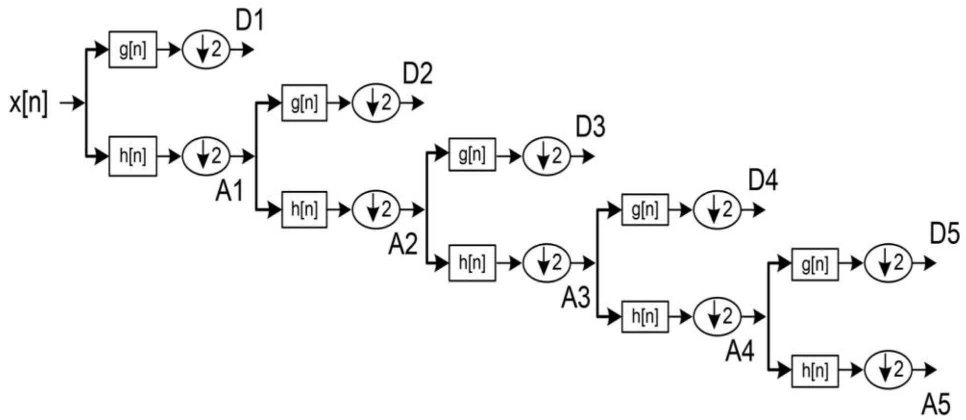


Figure (11) Wavelet Decomposition

Formula of WT and filter h, is a low pass, can be formulated in the formulation as follows

$H(z) H(z\text{-}1) + H(\text{-}z) H(\text{-}z\text{-}1) = 1$ (3)

In the above formula, $H(z)$ is used to represent the h, z-transform filter and the complement transformation of this high-pass filter is expressed as:

$G(z) = zH(\text{-}z\text{-}1)$. (4)

According to Section above, DWT is used to evaluate the spectrum components of EEG data. EEG signal analysis relies heavily on WT, specifically the careful selection of a wavelet and the optimal number of breakdown stages. The number of thresholds is calculated based on the primary frequency component of the EEG data. In order to classify signals, the levels are chosen such that the wavelet coefficients maintain a strong connection between the various parts of the signals and the requisite frequencies. The analysis was performed using five distinct degrees of decomposition. Therefore, the EEG data is segmented into D1-D5 details and a final method, A5. Multiple wavelet varieties are typically tested to find the most effective combination for a particular application. As a result of its Daubechies wavelet feature, second order (db2) filtering is more adept at detecting variations in the input signal. Therefore, wavelet coefficients were generated using db2 for this study [67]. For the Daubechies wavelet of the second order (db2), the band frequencies are as follows, with a sampling frequency of 256 Hz: D1 (64-128 Hz); D2 (32-64 Hz); D3 (16-32 Hz); D4 (8-16 Hz); D5 (4-8 Hz); and A5 (2-4 Hz). (0 - 4 Hz). To determine discrete wavelet values, MATLAB is used. Because even the most effective classifier will fail with a badly selected input feature, this is a crucial factor in the design of artificial neural networks based on pattern categorization. Determining the wavelet discontinuous coefficient provides a representation of the signal's energy across time and frequency. For this reason, the discontinuous wavelet coefficient calculated from the EEG signal of each record serves as the feature vector used to characterize the signal. The size of the recovered feature vector is reduced by using statistics on top of the collection of wavelet coefficients. The temporal frequency distribution of the signals under study is represented by the statistical characteristic listed below:

- Means and standard deviation value.
- Variance.
- Skewness.
- Kurtosis.
- Root Mean Square.

The data needed for the right arm is collected from C3 channel. In order to retrieve the features for the EEG data prior to classification, code is developed in MATLAB for this wavelet.

a) Means and Standard Deviation Value

The definition of the mean is very simple as it is the sum of all the signals divided by the number of the signals [68].

$$\mu = \frac{1}{N}\sum_{i=0}^{N-1} X_i \text{ ------- (5)}$$

The expression $|X_i - \mu|$ indicates the difference between the deviation of the sample and their mean. The average deviation can be found by the sum of all the derivatives of the sample signals and dividing by the total number of samples. The standard deviation is similar, but the average is done by power instead of amplitude as shown in equation (6).

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu)^2} \text{------- (6)}$$

b) Variance

It is the variability measure. In order to determine the variance, the average cubed departure from the mean is used as the denominator. The extent of dispersion in a data collection can be better understood by examining its variance. Variance from the mean increases as data spreads out[69].

$$\sigma^2 = \frac{1}{N-1}\sum_{i=0}^{N-1}(X(i) - \mu)^2 \text{-------(7)}$$

c) Skewness

Skewness is a statistical measure of the degree to which a signal deviates from its mean value. To compute it, divide the cubed standard deviation by the cubed mean variation [70].

$$\gamma = \frac{1}{(N-1)\sigma^3}\sum_{n=0}^{N-1}(x_n - \mu)^3 \text{--------- (8)}$$

d) Kurtosis.

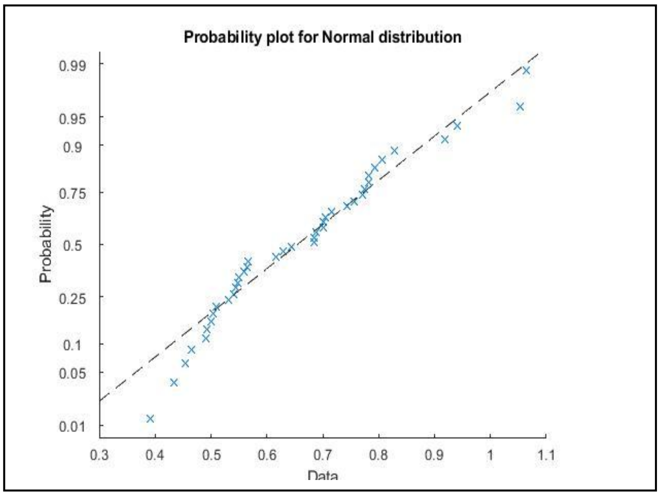
It is the Kurtosis of the signal that determines its Peakedness. More peaks in the waveform correspond to a greater kurtosis number [70].

$$K = \frac{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i^4)}{(\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i^2))^2} \text{ ------ (9)}$$

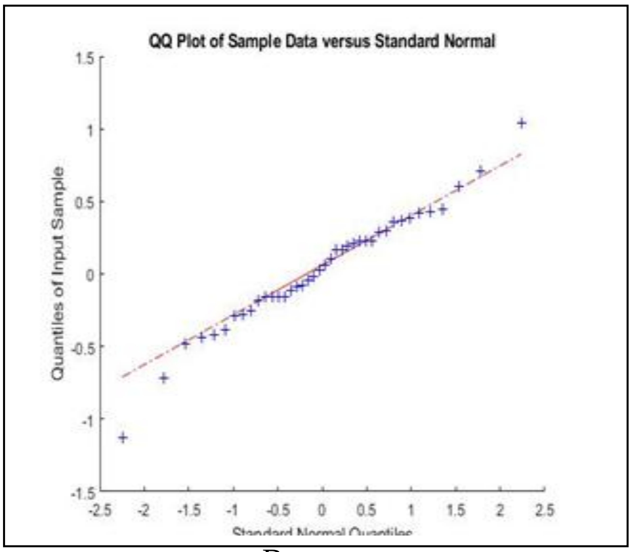
e) Root Mean Square.
It is a quantitative representation of the signal's intensity. The signal's magnitude is determined using the root-mean-square formula. The strength is represented by the range [71]. The root-mean-square deviation provides a measure of the variability in the system's response to external factors.

$$R.M.S = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1} x_i^2} \text{ ------ (10)}$$

Once the data had been cleaned up, the wavelet transform technique was used to pull out the most useful information. Subject one's characteristics are displayed in a, likelihood, quantile-quantile and histogram figure (a, b, and c, respectively, in Figure 12). The QQ diagram demonstrates that the feature data is normally distributed.



A



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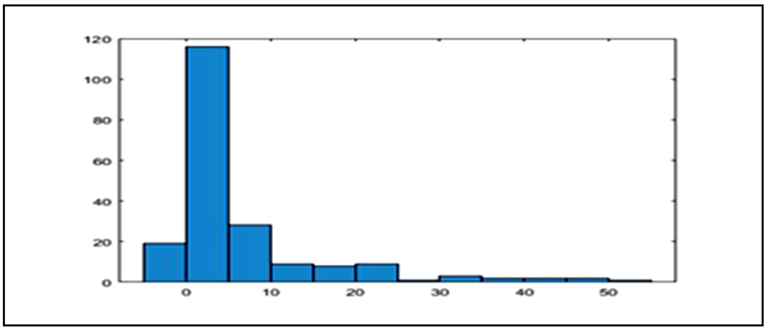

C

Figure (12 A,B,C) Probability, QQ plot and Histogram

3.5.3. Classification

The classification of EEG signals entails the categorization or labeling of various EEG data segments according to distinct mental states, cognitive processes, or environmental stimuli. The objective is to convert intricate brainwave patterns into significant classifications for diverse applications such as medical diagnosis, Brain-Computer Interfaces (BCIs), cognitive state assessment, or robotic control [72]. In this thesis, different algorithm used for the classification of EEG signals.

3.5.3.1. ANFIS (Adaptive Neuro Fuzzy Inference System).

The names "adaptive neuro-fuzzy inference system" (ANFIS) and "adaptive network-based fuzzy inference system" denote artificial neural networks based on the Takagi-Sugeno fuzzy inference system [73]. This method emerged in the early 1990s. By integrating components of neural networks with fuzzy logic, it may harness the advantages of both within a cohesive framework. It can learn and approximate nonlinear functions by a reasoning process akin to a series of IF-THEN fuzzy rules. Consequently, ANFIS is regarded as a global predictor. The ANFIS may be utilized more efficiently and effectively with the ideal configurations identified by a genetic algorithm. Potential applications encompass intelligent energy management systems with contextual awareness. The network architecture has two primary components: the foundation and the outcome [74]. The structure has five increasingly deeper levels. The first layer utilizes the input integers to select the appropriate membership functions. It is frequently termed the "fuzzyfication layer“. The membership degrees of each function are calculated using the parameter set {a, b, c}. The second level is responsible for generating the rule-based discharge rates. The second layer is tasked with generating the regulated discharge intensities. The second layer is referred to as the "rule layer" due to the regulations it encompasses. Fuzzyfication introduces an additional layer of complexity. Layer 4 seeks to normalize the projected firing strengths by dividing each value by the overall firing strength. The fifth layer receives the normalized data and the parameter set {p, q, r} as input. The output is sent utilizing the defuzzyfied values provided by this component. Figure 13.

Following feature extraction from the EEG data, ANFIS was implemented using MATLAB code for this research. Subsequent to the incorporation of registration functionalities. The results for each subject were obtained utilizing the previously established FIS procedure.

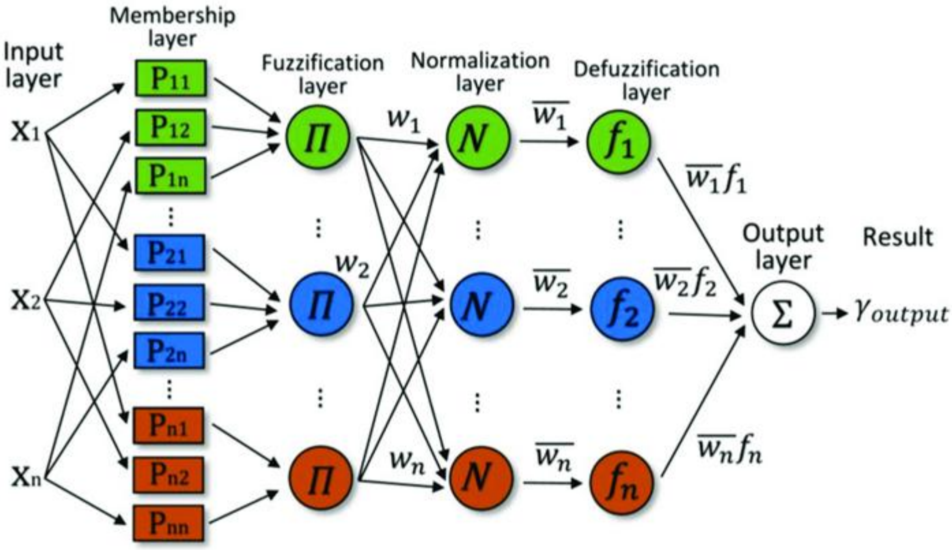

Figure (13) ANFIS

Figure 14 shows the Fuzzy inference system for the first subject and how the rules are based in order to collect the output.

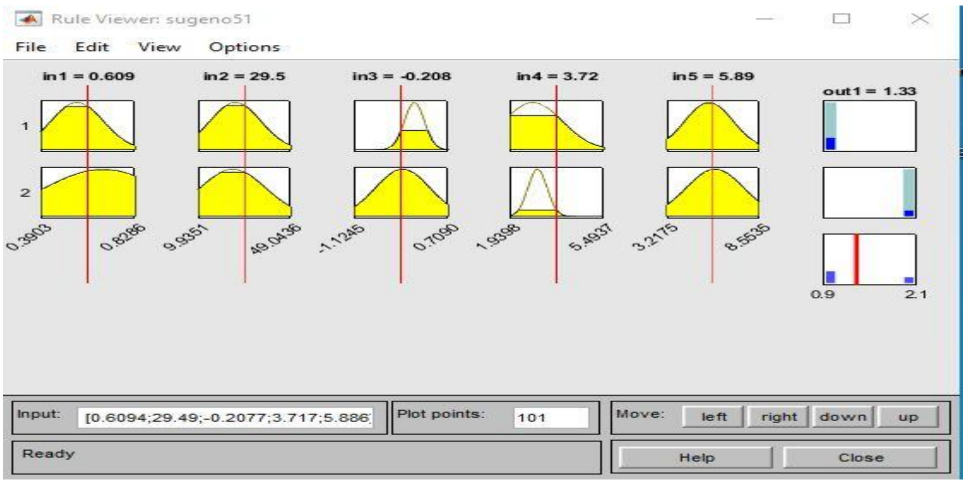

Figure (14) Fuzzy set for subject 1.

Figure 15 depicts the real result of the fuzzy system, which is the application of fuzzy principles to all the samples within each topic. The outcome changes with the characteristics chosen by WT transform, as demonstrated by the findings. Figure 16 displays the discrepancy between the real and ideal outputs. The

ANFIS algorithm produces results that are within a tolerable margin of error in comparison to the intended results.

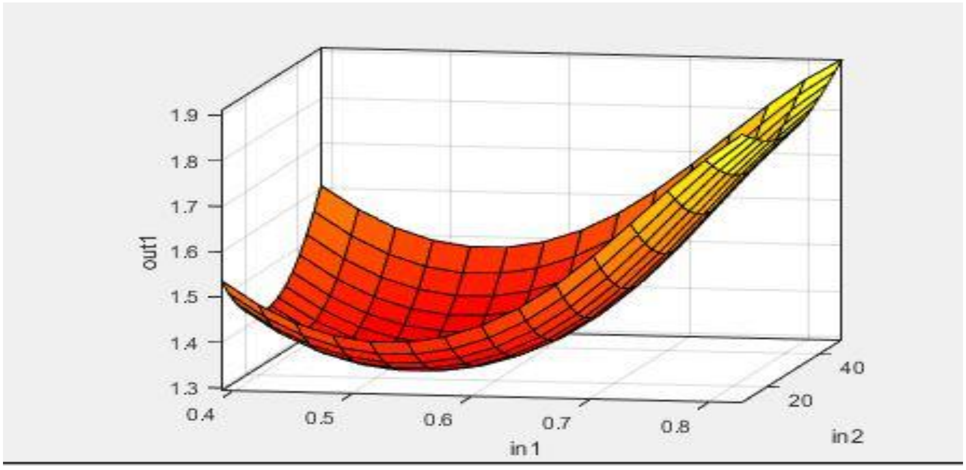

Figure (15) Fuzzy output

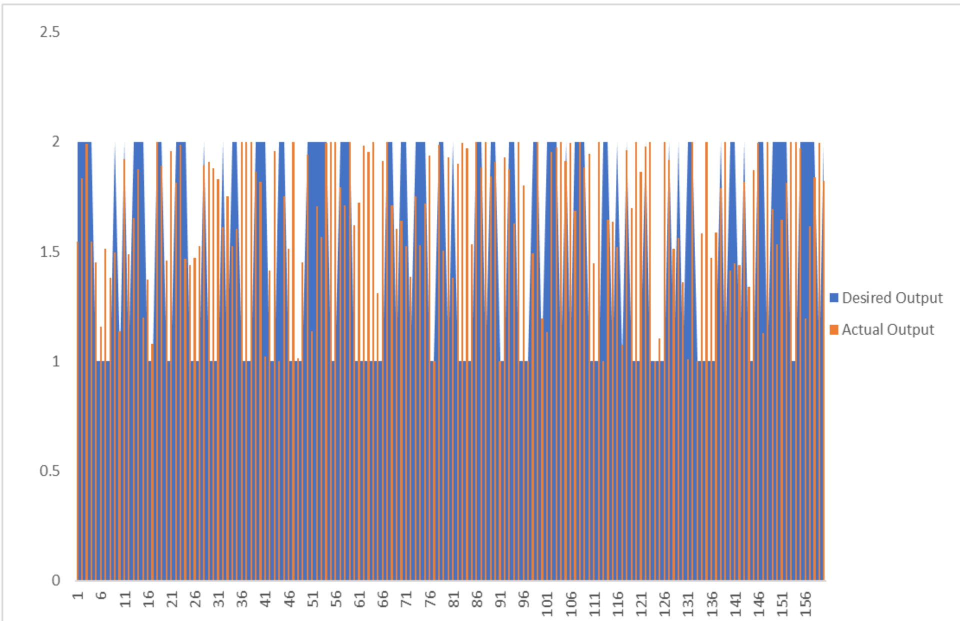

Figure (16) sub 1 Output

Table (3) Accuracy of ANFIS

No	Accuracy of ANFIS classification algorithm		
1	85.00%	14	91%
2	95.30%	15	85%
3	86.06%	16	93%
4	96.40%	17	90%
5	99%	18	87%
6	80%	19	95%
7	91%	20	80%
8	88.10%	21	92%
9	88%	22	95%
10	80%	23	96%
11	85%	24	95,00%
12	90.30%	25	96%
13	94%		

Figure 17 given below shows the accuracy achieved in this study compared to the results in[55]. Due to its superior performance compared to its predecessors, the algorithm is heavily relied upon for signal classification.

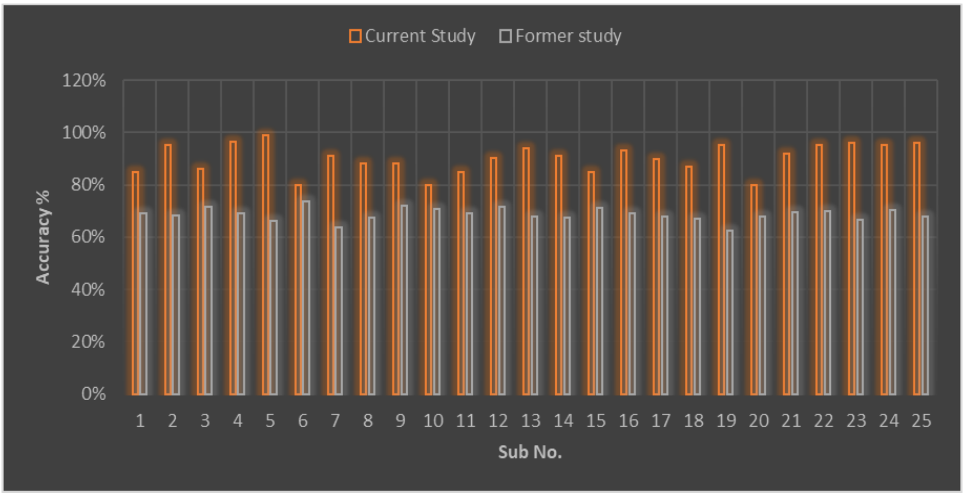

Figure (17) - Accuracy for Both Studies

3.5.4. Supervised Machine Learning

Machine Learning (ML) algorithms are systems that can discern latent patterns in data, forecast outcomes, and enhance performance [75]. Various methods utilized in MI are illustrated in Figure 18. The picture illustrates three categories of algorithms: Supervised, Unsupervised, and Reinforcement Learning.

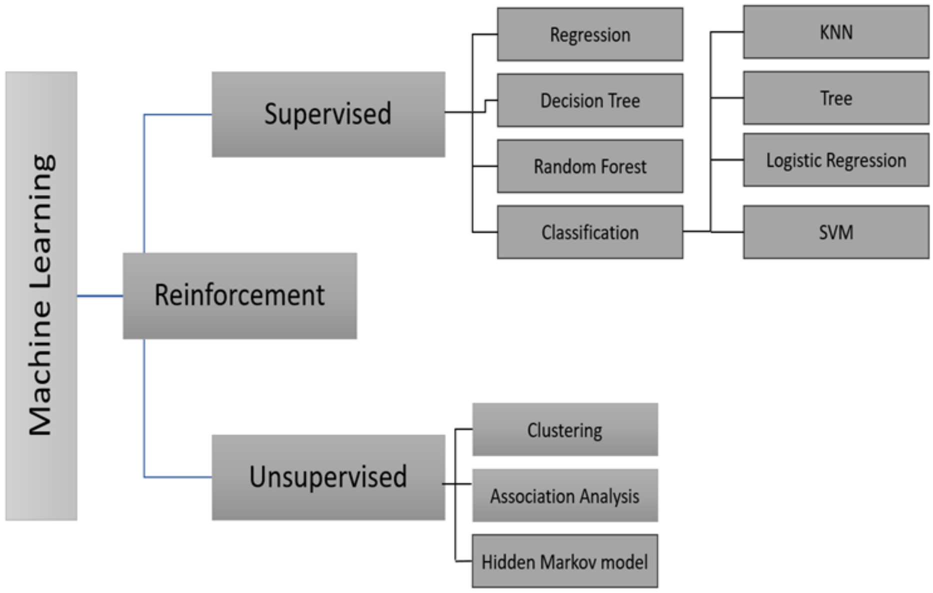

Figure (18) Machine Learning Types

Supervised Learning, as the term suggests, requires external supervision for the machine to acquire knowledge. Supervised learning models are taught using labeled datasets. Upon completion of training and processing, the model undergoes testing by supplying sample test data to evaluate its predictive accuracy. Supervised learning is categorized into classification and regression. Unsupervised learning is a method in which the computer learns from data without requiring external supervision [76]. The unsupervised model may be derived from an unlabeled dataset that is neither classed nor categorized, requiring the algorithm to operate on this data without supervision. The categories of unsupervised algorithms include Clustering and Association [77]. Reinforcement learning is a paradigm in which the agent engages with the environment through actions and acquires knowledge via feedback [78]. The primary concept of Supervised Machine Learning is the correlation between input and output data. To do this task, the algorithm is provided with training data. The training data comprises input-output pairs. Inputs are multidimensional vectors that encapsulate pertinent information on the signal states, specifically the brain signal states, or activities to be decoded. Raw data is often utilized to generate features, which are subsequently refined through feature engineering to discern the most promising or pertinent ones. Training encompasses the acquisition of the relationship between attributes and intended results. The response variable, or dependent variable, denotes the output of interest associated with these characteristics, such as brain state or behavior. In the training phase, the model learns to correlate input features with target variables by optimizing its parameters, which is accomplished by minimizing a cost function [79]. The model's performance is represented by the loss or error assessed by the cost function. Numerous techniques exist that can reduce the cost function, with gradient descent being the most prevalent. An appropriate machine learning algorithm model comprises training and testing datasets. The testing set must not be assessed by the algorithm during the training phase. It must precisely represent the model's true environment. The outcomes of the testing sets should be comparable to those of the training sets. Figure 19 illustrates the machine learning architecture.

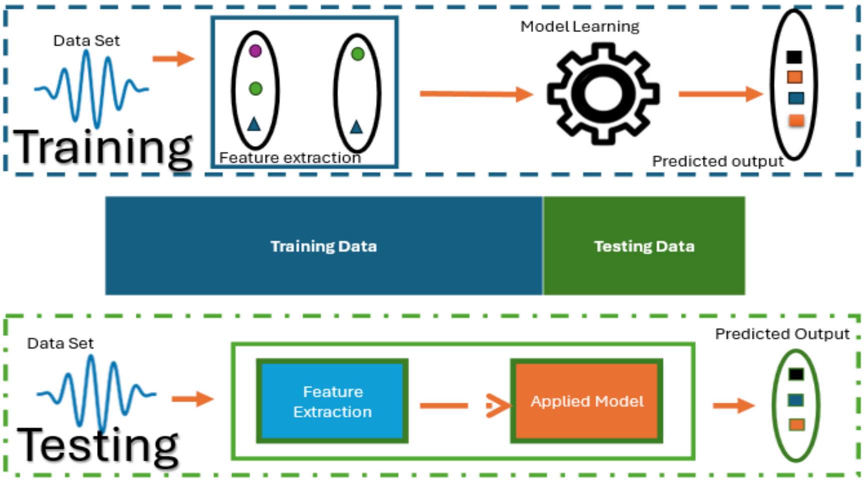

Figure (19) Architecture of Supervised Machine Learning

There are several types of supervised machine learning. In this thesis, the Support vector machine and neural network were used.

3.5.4.1.Support Vector machine (SVM).

Support Vector Machine (SVM) is a robust and versatile supervised machine learning method mostly employed for classification tasks, while it may also be applied to regression. Its capability to manage both linear and non-linear data significantly enhances the performance of several challenging classification jobs [80]. Support Vector Machines (SVM) often identify the most suitable separating border, whether linear or hyperplane. Support Vector Machine (SVM) identifies the hyperplane that maximizes the margin for a binary classification problem, signifying that it is the furthest distant from the nearest data points of each class. Support vectors, the nearest points, are crucial for defining the hyperplane [81].

3.5.4.2. Neural Network (N.N).

A neural network designed for optimization or enhancement over time is termed a "optimizable neural network." The optimization of a neural network often aims to improve its efficacy in certain tasks, such as predictive modeling, language processing, or picture recognition [82]. The following are essential principles pertaining to optimizable neural networks:

1- The learning algorithm of an optimizable neural network is its most critical component. This method, often a variant of gradient descent, adjusts the network's weights based on input. The aim is to minimize the discrepancy, sometimes termed as the cost or loss, between the network's projected and actual outcomes.
2- Backpropagation is a prevalent optimization method utilized in neural networks, especially within deep learning architectures. It is a method for rapidly computing the gradients of the loss function with respect to the network weights. The weights are subsequently adjusted utilizing this information to minimize the loss.
3- Hyperparameters: These are the configurations or settings that govern the neural network's overall behavior but remain unchanged during the learning process. Examples include learning rate, batch size, and the number of network layers. Fine-tuning hyperparameters is a crucial step in optimizing neural networks.
4- Overfitting occurs when a network becomes overly specialized to the training set, resulting in worse performance on new, untested data. Regularization techniques like dropout, weight decay, and early stopping mitigate overfitting, hence enhancing the network's generalizability and performance in real-world applications.
5- Data Preprocessing: The efficacy of the network can be significantly influenced by the method of data preparation and presentation. Normalization, standardization, and augmentation are strategies that enhance the efficacy and efficiency of network training.
6- Transfer Learning: Employing a pre-trained model on a substantial dataset and subsequently fine-tuning it for a specific task is a prevalent technique utilized to improve neural networks. This method can yield significant performance improvements, especially when there is a scarcity of data for the specific task.
7- Evolutionary Algorithms: Advanced approaches such as evolutionary algorithms are employed to optimize neural networks. These strategies iteratively improve network performance by generating a population of networks, selecting the highest-performing ones, and utilizing them to create a new generation of networks.
8- Hardware Optimization: Finally, utilizing GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units) for accelerated processing – a vital component in the efficient training of large networks – can also improve the performance of neural networks at the hardware level.

The featured extracted in section 3.5.2.1 helps the classification algorithms to train in order to find a pattern that can predict the outcome for each trial. The data was labeled as 1 and 2 which represent if the subject imagined moving his elbow or wrist. Figures 20 and (21-22) show the SVM and NN algorithms respectively for the classifications.

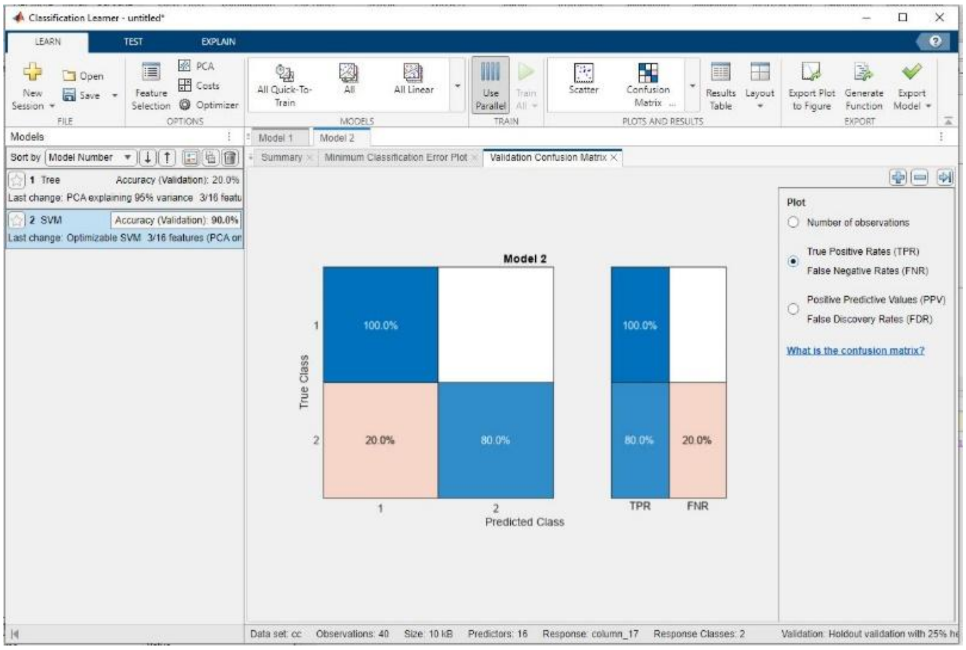

Figure (20) SVM

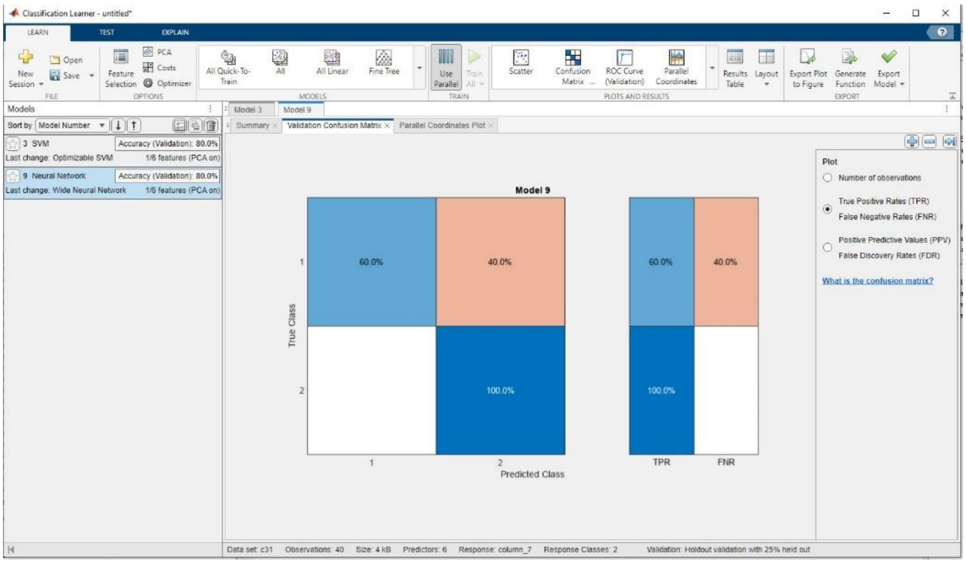

Figure (21) Neural network 1

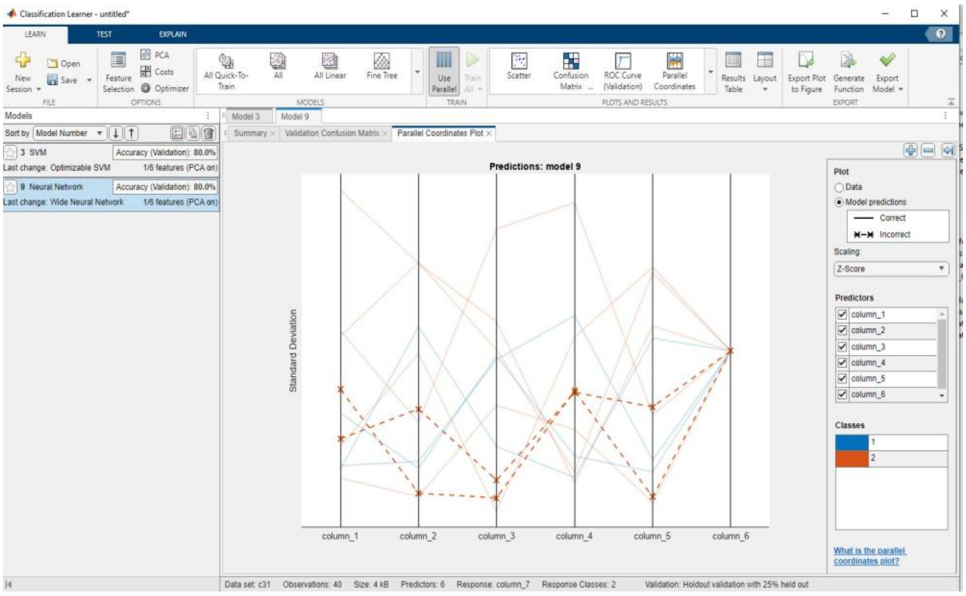

Figure (22) Neural Network 2

The figure shows the results for only one subject. Table 4 present all subjects results after applying the same signal processing, feature extraction and classifications.

Table (4) Classification Accuracy

Subject No.	Accuracy		Subject No.	Accuracy	
	SVM	NN		SVM	NN
1	90.00%	80.00%	14	85.00%	81.00%
2	85.00%	84.00%	15	73.00%	86.00%
3	85.00%	82.00%	16	78.00%	90.00%
4	80.00%	80.00%	17	88.00%	85.00%
5	84.00%	81.00%	18	84.00%	81.00%
6	82.00%	82.50%	19	86.00%	83.00%
7	75.00%	84.00%	20	91.00%	81.00%
8	80.00%	83.00%	21	96.00%	81.00%

9	79.00%	84.00%	22	98.00%	81.00%
10	76.00%	87.00%	23	85.00%	85.00%
11	85.00%	80.00%	24	96.00%	82.00%
12	80.00%	80.00%	25	82.00%	81.00%
13	77.00%	80.00%			

Figure 23 shows the difference between the SVM, and NN results compared to the results shown in[83]. The improvement made in this study shows a good step up in classifying the signals.

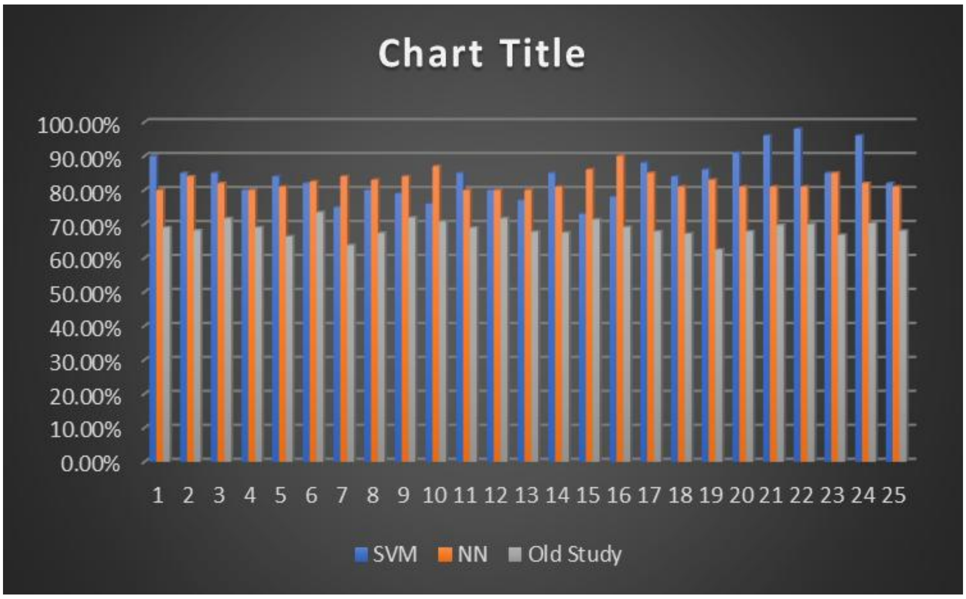

Figure (23) Comparison of Results

3.6. Conclusion

The focus of this chapter is to identify a new method for EEG signal analysis to achieve higher accuracy. In this work, the study from [55]was chosen for the investigation. The following points were noted.

1- Daubechies wavelet feature, 2nd order (db2) filtering is more adept at detecting variations in the input signal. Therefore, wavelet coefficients were generated using db2 for this study.
2- fuzzy set theory is useful for addressing ambiguity and making choices. With the help of fuzzy logic, we were able to incorporate doubt into the classifier's architecture. The categorization of EEG data. When the wavelet coefficients of the EEG signals were used as inputs, the ANFIS algorithms were able to distinguish between two groups of EEG signals. Although it will take a long time to process, this can be overcome by using a computer with a high CPU process, the more characteristics pulled

from the data, the more efficient the program can be. When using the algorithm to control the motion of a mechanical arm, the varying results increase the likelihood that the arm will be moved by varying the pace at which the elbow and the wrist rotate. The ANFIS was assessed based on the classification outcomes and data metrics. The overall precision of the ANFIS model's classification was 90.13%. Indicating the algorithm's dependability and potential for further uses, the suggested ANFIS model can be used to classify EEG data.

3- The identical approach was demonstrated using the Supervised Machine Learning algorithm for the classification accuracy of brain signals. The results illustrate that the algorithms enhanced the categorization accuracy of the previous study, suggesting that the research was progressing appropriately. Attaining this level of accuracy facilitates the formulation of novel strategies for future enhancements in precision. Various methods exist for categorization; however, in our investigation, we utilized only two, as they yielded the most favorable outcomes. The results were derived from the characteristics retrieved. The findings of the two methods of classifications support **Hypothesis 2** that indicates " The utilization of wavelet transforms for feature extraction, in conjunction with Adaptive Neuro-Fuzzy Inference System (ANFIS) for classification, enhances the level of accuracy of EEG data analysis. The same can imply if Supervised Machine learning algorithms used for classification".

4. Using BCI for Controlling Higher Degree of Freedom Robotic Arm

The amputation of limbs significantly impacts the individual's everyday activities. Individuals with upper limb loss encounter difficulties in tasks such as tossing a ball, operating a vehicle, and engaging in handshakes. The concept of regulating actuators, including robotic and prosthetic limbs, mobile robots, automobiles, and bicycles [84]. The use of brain signals has advanced significantly during the past few decades. Nevertheless, more investigation remains to be conducted. The procedure has many stages. The initial step is to non-invasively record signals from the subject's brain. Secondly, it is necessary to preprocess these signals by eliminating any artifacts and noise to prepare them for the subsequent classification phase. Subsequently, we may utilize these signals to translate them into commands for actuators, contingent upon the specific applications in which they are employed. The Brain-Computer Interface (BCI) facilitates communication between the brain and computers by capturing electrical activity and connecting external devices. A Brain-Computer Interface (BCI) is a device that detects and collects electroencephalogram (EEG) signals generated by the brain and translates them into orders to execute a specific action for an externally linked device. The non-invasive technology is economically viable and possesses significant promise for many human-robot applications, including wheelchairs and prosthetics [85]. The concept of BCI involves gathering signals from the scalp, which are then transformed into a functional output. The microcontroller is controlled by this active function. The microprocessor assesses the incoming signals to ascertain the degrees of freedom, prompting the robotic arm to respond accordingly. The robot kinematic model pertains to the robot's mobility independent of the forces that generate it. As mentioned in chapter 3, the bands of EEG signals are classified in 5 types. For motor imagery, the Alpha and beta bands were used for robotic application. The system component can be seen in Figure 24. The figure shows the system component and bifunctional feature of each part of the system.

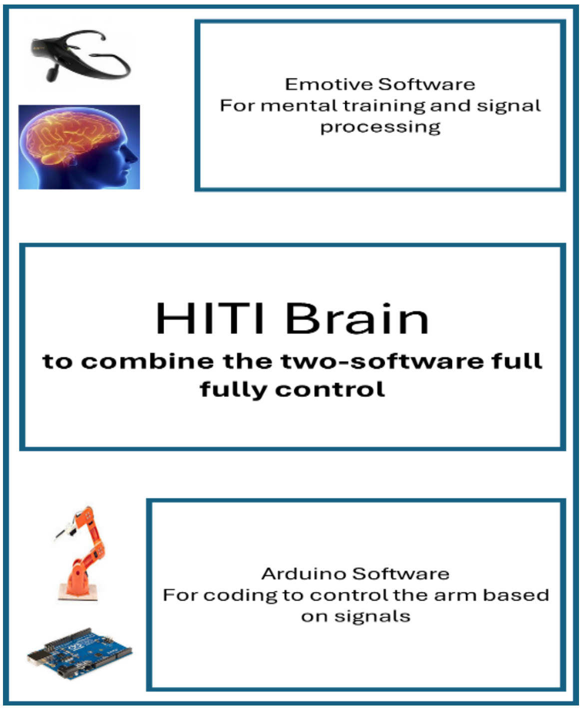

Figure (24) system architecture.

4.1. Brain Computer Interface.

BCI is a device that makes direct connections between electrical activity from the brain and an external device [86]. For recording the signals, there are typically three methods. The invasive, semi-invasive and non-invasive method as explained in chapter two. Due to the easement of installations and it does not require any incisions or stiches, the non-invasive method is used in this work. The device used in this work is Emotive Insight 2.0 with 5 channels. The device has 5 EEG sensors to detect brain activities and two reference (CML/DRL) sensors. One of the reference sensors is an active electrode (CML: Common Mode Sense) and the other is Passive electrode (DRL: Driven Right Leg).

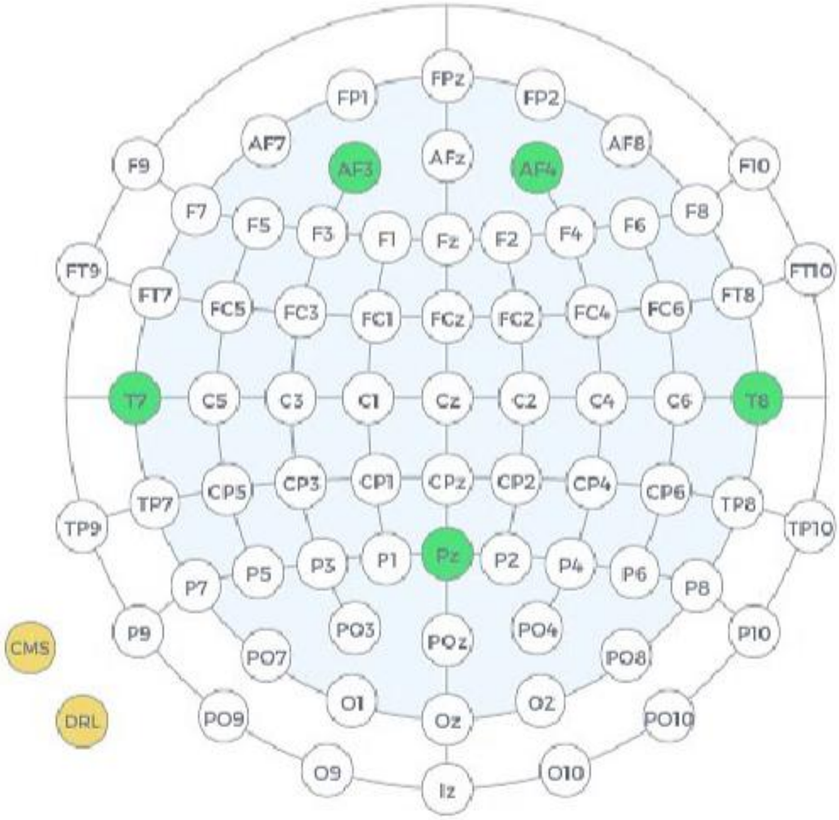

Figure (25) Electrode distribution of BCI on the scalp

As shown in Figure 25 the yellow circles represent the location of the reference sensors, and the green circle represents the sensor locations, which are the frontal, temporal and parietal part of the head. Emotive insight provides a non-invasive solution for detecting brain signals. The device (as shown in Figure 26) detects a wide range of brain signals from three different parts of the brain, the Frontal lobe specifically from points (AF3) and (AF4), the Temporal lobe by points (T8) on the right and (T7) on the left and last the Parietal lobe from point (Pz). The device`s measurements are based on six keys: focus, Stress, Excitement, Relaxation, interest, and engagement [87]. The Emotive Insight software is an open-source software that can be downloaded from the Emotive website. There are several versions of the software, each one is used for different applications. Emotive BCI is the one that is used in this work. The Emotive BCI is a desktop application. It can be used in both Mac and Windows. The Emotive BCI allows the user to view and train the brain. The data streams for the Emotive BCI are classified in four categories: Mental Commands, Performance Metrics, Facial Commands and Motion sensors.

- **Mental Commands:** the software allows the user to train the brain based on commands such as Push, Pull, move right, Move left…. etc.

- **Facial Expression:** the software can trigger events based on facial expression. It records the brain signals based on smile, blink, wink …. etc.

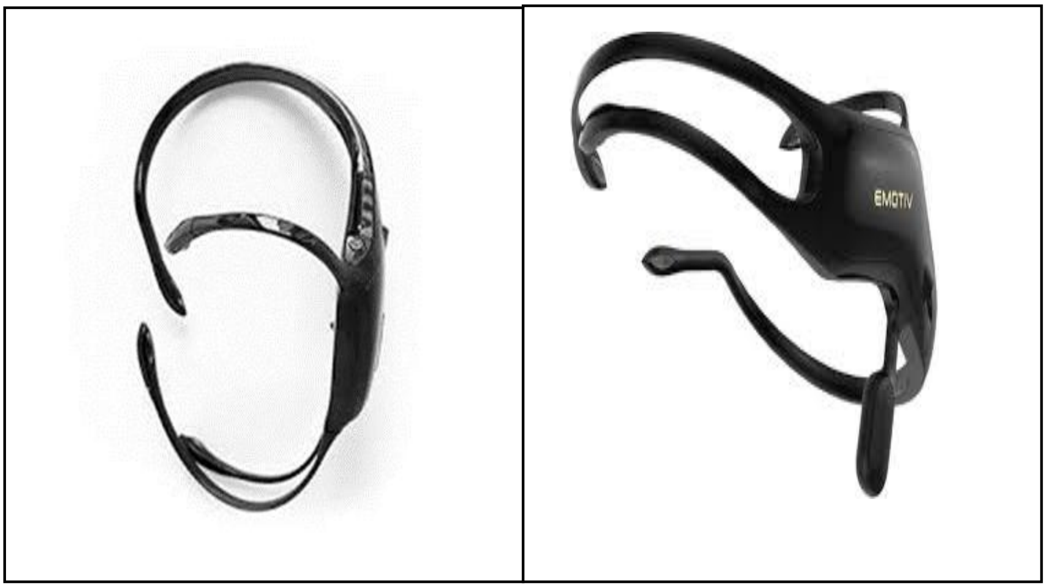

Figure 26 Emotive Insight BCI.

The EEG signals are passing through a few stages of preprocessing. Firstly, the data is processed to remove sharp spikes. And then passed to a high pass filter to remove the DC offset and slow drift. The Emotive insight uses 2-second epochs and applies a Hanning-filter before performing the FFT. The POWER is calculated from the square of the amplitude in each frequency bin and output as uV^2/ Hz.

The emotive software has the option of displaying all the signals detected from the brain. The brain data is recorded from five points (as the device used is emotive insight 5 channels). Figure 27 shows the Emotive software.

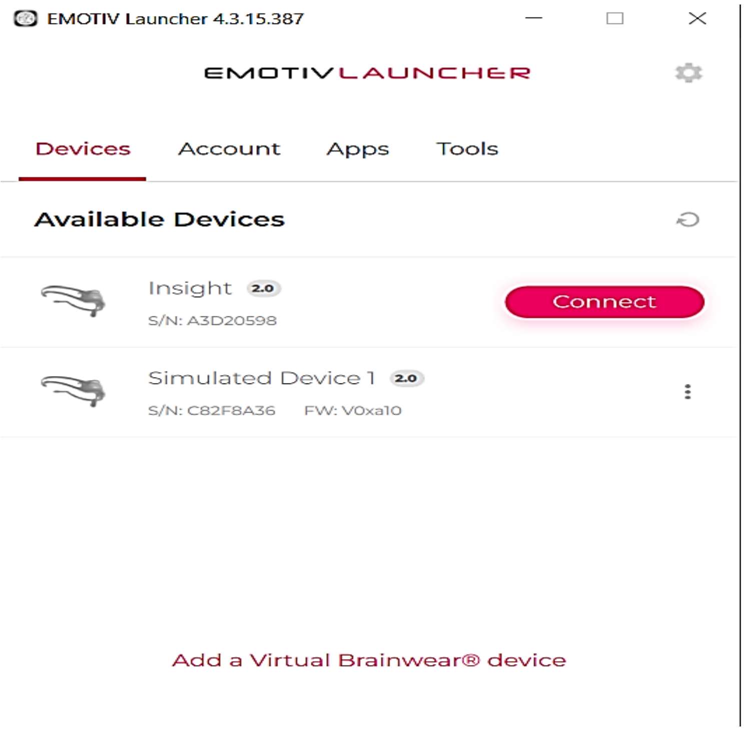

Figure (27) Emotive Software.

The data sampling of Emotive Insight is 128 HZ with 16-bit resolution. The value of these data is affected by the different thoughts of the person. The emotive software also has the ability to train the brain to do some mental commands like: Push, Pull, move left, right etc. as shown in Figure 28.

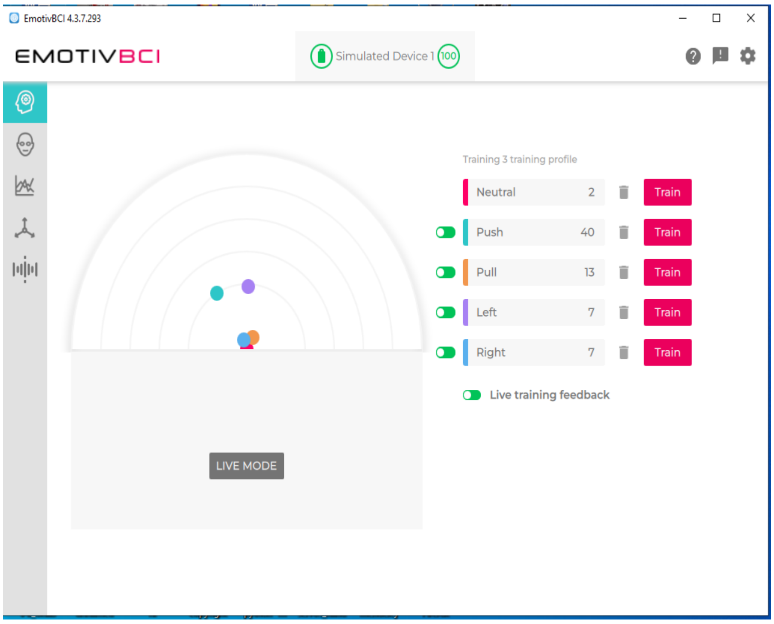

Figure (28) Mental Command

It also can record the signals of the brain due to facial expressions such as: smile, Blink, Wink left and right etc. (Figure 29). These records are useful to use for further applications in moving mobile robots or controlling multi degree of freedom robotic arms.

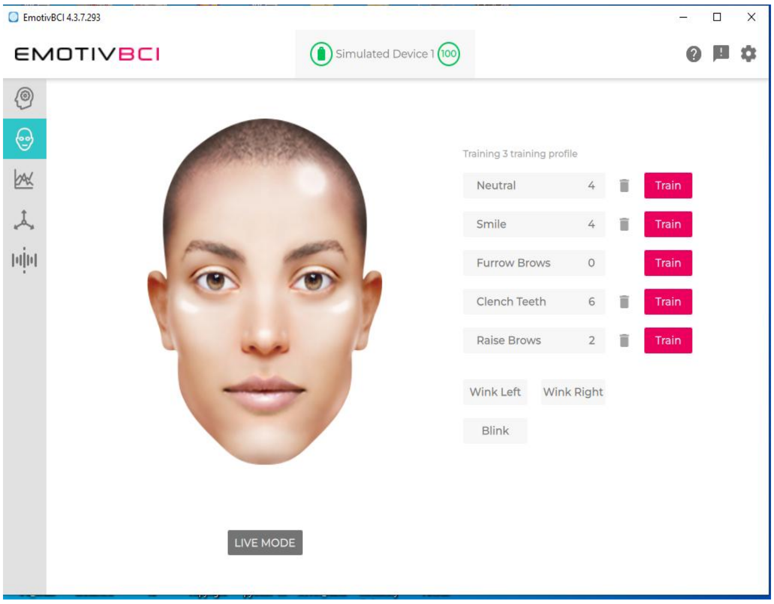

Figure (29) Facial Expressions

4.2. Robotic Arm

The 6 DOF robotic arm has a wide range of applications in industry or for personal use as it is the closest to the human arm. The Degree of Freedom (DOF) refers to the number of independent movements the robot arm can make [88]. A 3DOF robot arm can move up, down, right, left, in and out. The more Degree of freedom the arm has the wider range of motions it can perform. The 6 DOF robotic arm can perform three linear motions (forward/back, right/left, up and down) and three rotational movements (tilting, twisting and rotating the arm itself) [89].

This allows for a great precise and complex manipulation, mimicking the flexibility of the human arm. One of the most important steps for controlling robot manipulator is to implement the complete and accurate system`s mathematical model. The arm basically is a series of manipulators with revolute joints. The geometric configuration of the arm is made up of base, shoulder, elbow, and wrist. Figure (30) shows the robotic arm in correspondence to human arm model. Each joint except the wrist has a 1 DOF. The wrist has 2 DOF as it can move vertically and rotationally. Each DOF in the arm is actuated by a servomotor. The end-effector is a two-finger gripper. Each joint is connected to a servo motor that allows the joint to perform two movements. 6 servo motors lead to 12 movements for the arm. The combination of brain thoughts enables the arm to perform complex motions such as Pick and Place.

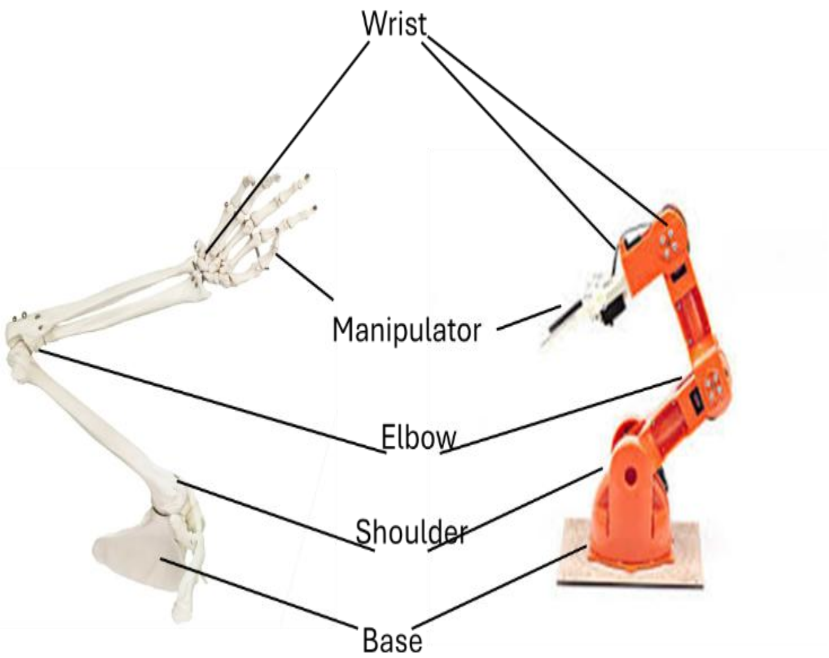

Figure (30) Robotic/Human Arm Model

4.2.1. Forward Kinematic Model.

The kinematic model in this work is achieved using Denavit-Hartenberg (DH) parameter. Figure 31 presents the kinematic model of the robotic arm in L position. The Base, shoulder and elbow are moving the tool point to its desired position, the orientation of the end-effector is implemented by the wrist joints. DH works with twist angle α_{i-1}, link length a_{i-1}, link offset d_i and joint angle θ_i $\{\alpha_{i-1}, a_{i-1}, d_i, \theta_i\}$[90].

As shown in Figure 31 a coordinate system is attached to each link of the manipulator. Table 5 lists the DH parameter of the robotic arm. The derivation of the links (joint expressed as i in its previous neighboring joint $i-1$ was derived and presented in Equation (1) which represents the overall matrix of the end-effector to the base of the robotic arm.

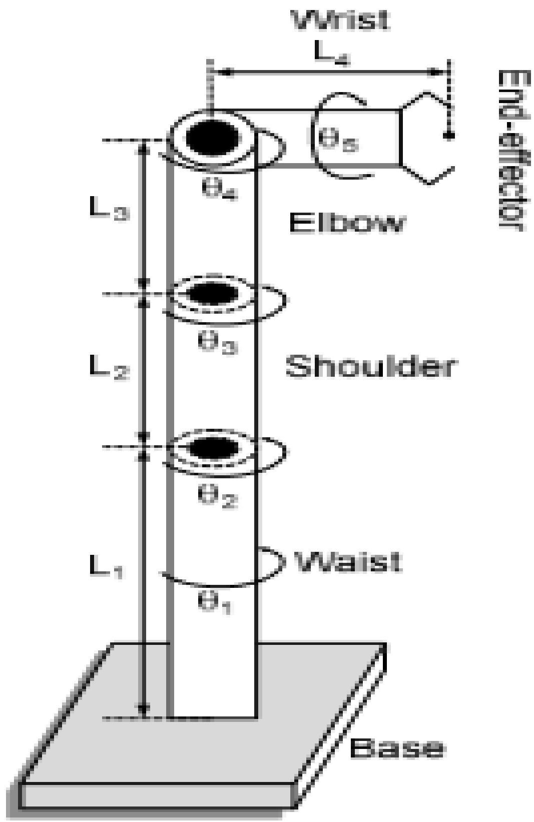

Figure (32) Kinematic Model

Table (5) DH parameter of Robotic arm

Symbols	Joints					
	1	2	3	4	5	6
$\boldsymbol{\alpha_{i-1}}$	0	-90	0	0	-90	0
$\boldsymbol{a_{i-1}}$	0	0	$\boldsymbol{L_2}$	$\boldsymbol{L_3}$	0	0
$\boldsymbol{d_i}$	$\boldsymbol{L_1}$	0	0	0	0	$\boldsymbol{L_4}$
$\boldsymbol{\theta_i}$	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2} - 90$	$\boldsymbol{\theta_3}$	$\boldsymbol{\theta_4}$	$\boldsymbol{\theta_5}$	0

$$ {}^{0}_{6}T = \begin{bmatrix} C_1C_5S_{234} + S_1S_5 & -C_1S_{234}S_5 + C_1C_{234} & C_1C_{234} & C_1A \\ -S_1C_5C_{234} - C_1S_5 & S_1C_{234}C_5 + C_1C_5 & S_1C_{234} & S_1A \\ C_{234}C_5 & -C_{234}S_5 & -S_{234}\,B & S_1A \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (1) $$

where

$$ A = L_2S_2 + L_3S_{23} + L_4C_{234} $$
$$ B = L_1 + L_2C_2 + L_3C_{23} - L_4S_{234} $$

From equation (1), the 3*3 matrix (the first three rows and first three columns) is the rotation matrix. The last column represents the position (x, y, z) of the end-effector with respect to the base.

4.1.1. Inverse kinematic Model.

In practical robotic systems, inverse kinematics have more potential applications. With inverse kinematics, the computation of the joint angle required for achieving the required position and orientation can be calculated [90]. In inverse kinematic, the joint angles $(\theta_1, \theta_2, \theta_3, \theta_4)$ must be calculated, while θ_5 is directly given by the desired orientation for object manipulation.

The transformation matrix from the tool to base is given by:

$$ {}^{Base}_{Tool}T = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix}. \qquad (2) $$

The first 3*3 matrix represents the rotation, and the last column represents the translation of the end-effector with respect to the base.

$$ \theta_1 = Atan2(p_x, p_y) \qquad (3) $$

$$ s_{234} = c_1a_x + s_1a_y \qquad (4) $$

$$ c_{234} = a_z \qquad (5) $$

$$\theta_{234} = Atan2(s_{234}, c_{234}) \quad (6)$$

$$c_3 = \frac{(c_1 p_x + s_1 p_y + l_4 s_{234})^2 + (p_z - l_1 + l_4 c_{234}) \quad - {l_2}^2 - {l_3}^2}{2 l_2 l_3} \quad (7)$$

$$s_3 = \mp\sqrt{1 - {c_3}^2} \quad (8)$$

$$\theta_3 = Atan2(s_3, c_3) \quad (9)$$

$$c_2 = \frac{(c_1 p_x + s_1 p_y + l_4 s_{234})(c_3 l_3 + l_2) - (p_z - l_1 + l_4 c_{234}) s_3 l_3}{(c_3 l_3 + l_2)^2 + {s_3}^2 \, {l_3}^2} \quad (10)$$

$$s_2 = \frac{(c_1 p_x + s_1 p_y + l_4 s_{234})(s_3 l_3) - (p_z - l_1 + l_4 c_{234})(c_3 l_3 + l_2)}{(c_3 l_3 + l_2)^2 + {s_3}^2 \, {l_3}^2} \quad (11)$$

$$\theta_3 = Atan2(s_2, c_2) \quad (12)$$

$$\theta_4 = \theta_{234} - \theta_2 - \theta_3 \quad (13)$$

4.2. Experimental work (controlling the robotic arm).

The experiment implemented in two conditions, the first one is quiet environment and the second is noisy environment (such as two people were talking next to the subject). The system consists of three different software working together. The Emotive software (for Emotive BCI), the Arduino UNO software and the HITI brain software that combines the two previous software together. The HITI brain is software that can make communication between Arduino board and Emotive EEG headset very easy. It allows the Arduino to receive mental commands from Emotive insight headset. Figure 33 shows the system block diagram.

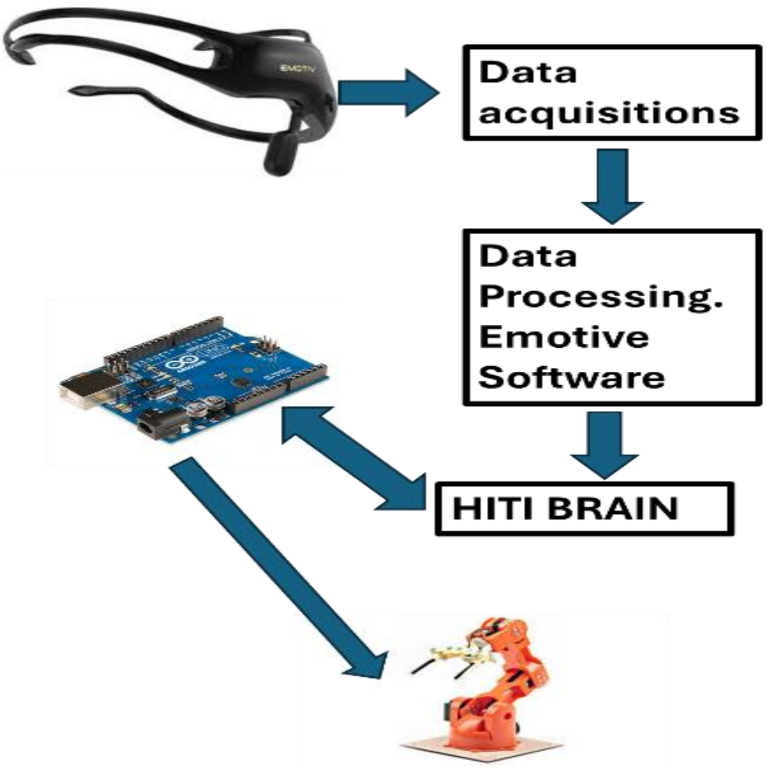

Figure (33) The System Block Diagram

The target movement in this work is as follows:

1- Test all the movement using the mental commands separately.
2- Make the full pick and place by combining different mental commands.

As mentioned earlier, the 6 DOF robotic arm is very close to the human arm. The work of the robotic arm is more important than the outside shape of the robotic arm. Therefore, the main aim in this work is the actuators that move the robot links together (aka. The servo motors). The Arduino code defines the motors work and posterization of which motor work is defined in the code according to the mental commands. Figure 34 shows the flowchart of the system working. The actuators' movement is based on the predicted category. The three-software cooperating between each other in order to make a language that the robots understand. The BCI read the signals using the electrodes connected to the cortex, then transfer the signal to the Emotive software for recording and further process for noise reduction and classification. The Arduino UNO has the codes for controlling the actuator and implementing the path in the robotic arm workspace. The HITI brain software connects the Arduino code and the Emotive software, executes the code with the database from the emotive software, and transforms it into actual motion to the connected arm. The software working principle is building a GUI to control the actuators according to the code written in Arduino IDE. It's important to mention that the subject needs to be trained before the final test. The emotive software has a training feature through a designed experiment. The subject sits in a relaxed position in front of the screen. A cube in the center of the screen appears and the subject needs to imagine moving it forward, backward, right, left, up and down. This experiment is important for two reasons. First, is to sharpen the brain to produce the same pattern of signals for each movement. Secondly, store these signals for referencing and compare them with the real time signals in the final test, so the HITI brain can command the Robot arm to move according to the mental command with the help of the Arduino code.

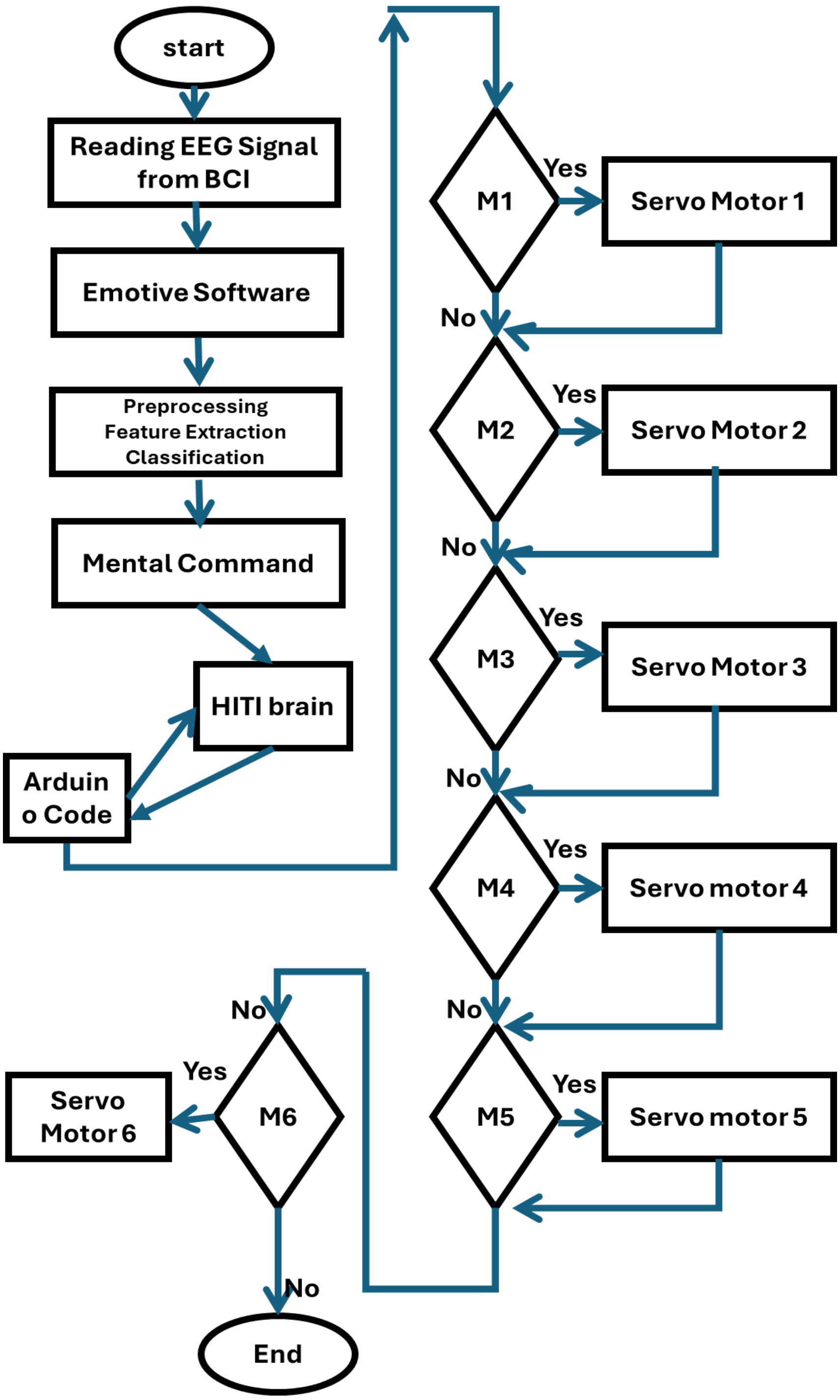

Figure (34) The System Flowchart

The servo motor is controlled by a pulse width modulated signal [91]. The Arduino sends a pulse of 1mS and 2mS long every 20ms to the servo motor. Figure 35 shows the servo signal.

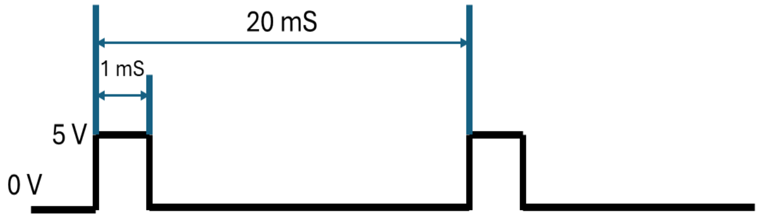

Figure (35) Servo Signal

The servo motor rotates the shafts to the central position during the 1ms pulse. Several pulses rotate the motor enough to move the links to the desired location. The servo library in Arduino generates the necessary PWM signals to send it to the servo. During Motor imagery (imagining movement without actual physical motion), a distinct pattern is shown in the EEG signals in the Alpha and Beta bands. These patterns play a great role in decoding mental commands to control the robotic arm or other devices. In the state of motor imagery task, the Alpha power tends to decrease in the sensorimotor cortex. This is called Event-Related Desynchronization (ERD). The Brain tends to reduce the Alpha-band to prepare for motor actions. On the contrary, during motor imagery, the Beta wave is increasing [92]. This increase is called Event-Relate Synchronization (ERS). The ERS occurs as a response to imagining moving a part of the body [93]. Before the controlling of the robotic arm, the Emotive EEG signals have to be passed through several steps, preprocessing, Feature Extraction and classification.

A- Preprocessing

As mentioned before, the EEG signals contain noises and artifacts that are caused by Eye blinking, moving the face muscles. Using band pass filter is essential to remove all other bands and focus only on Alpha (8-12 Hz) and Beta (13-30 Hz). As for the artifacts, the Emotive insight automatically removes them.

B- Feature Extraction

In this work, Wavelet transform, the same method in was used for feature extraction. To capture the Alpha and Beta band waves, 4-level decomposition of the EEG signals must be executed. The common features captured were as follows:

- Energy of wavelet coefficient: the energy is extracted using the equation

$$E = \sum_{i-1}^{N} |D_i|^2 \text{ ----(14)}$$

Where D_i is the detailed coefficient corresponding to Level N.

- Mean: the average of signals in the band.

$$\mu = \frac{1}{N} \sum_{i=1}^{N} (D_i - \mu)^2 \text{-----(15)}$$

- Other features such as variance, skewness, kurtosis, max and min.

C- Classification

This stage comes after the extractions of features of the EEG signals that accomplished in the previous step. For each segment of the EEG, the feature vector needs to be labeled for mental commands (i.e. Push=1, Pull=2, etc.) to train the classifier to detect them and use it to control the robotic arm. The main aim of this is to make the subject brain get used to the device and second to make the brain produce the same patterns of signals for a specific action. For example, the first training is for pushing.

motor imagery, when the subject is imagining pushing an object. After several trials the brain will produce the same pattern of signals for such action. The Emotive software comes with experiment features for subject training as shown in Figure 36. From the figure we can see the subject sitting in-front of the screen where there is a cube in the middle.

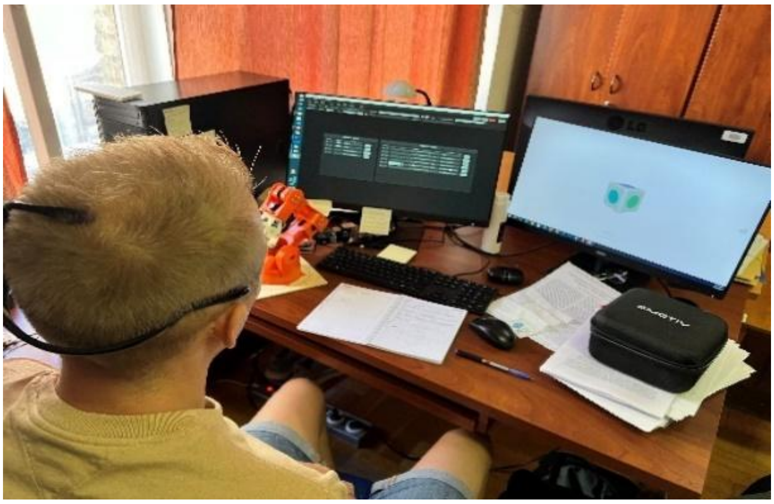

Figure (36) Subject Training

The subject has to relax and focus on the cube to perform several actions, such as Push, Pull, Lift, Drop, move right and move left. All the signals from the different trainings will be stored and preprocessed for artifact removal, feature extractions and classifications. Figure 37 shows the features (Energy and mean) extracted from Beta and Alpha waves for four mental commands.

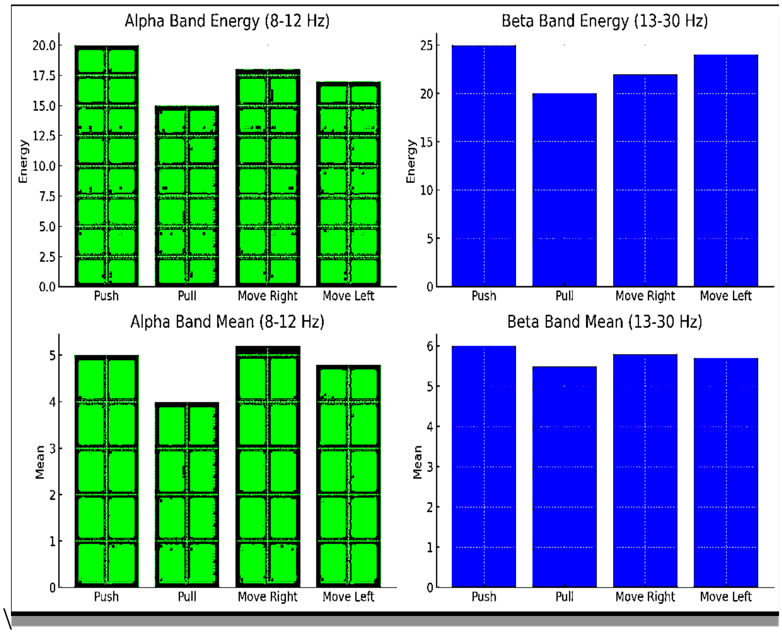

Figure (37) Mean and Energy for EEG signal

The Arduino code uses the stored signals as a reference to convert them to commands to control the robotic arm. The result of this work is divided into two parts:

1. Separate movement.
2. Full pick and place movement.

Both of the parts were executed in two conditions, the Quiet mode, where there is no extra noise in the environment. The second condition is where there is noise in the environment, as people talking or playing music next to the subject.

1- Separate movements (Mental Command)

Each joint in the robotic arm is connected to a servomotor. The servomotor moves in two directions. That means each movement needs 1 mental command. For example, mental command move right will result in rotating the servo 90 degrees CW. And the mental command move left will force the motor to rotate 90 degrees CCW as shown in Figure 38 below. The movement of the Base joint was chosen for this section which also is shown in Figure 39 a, b, c.

Figure (38) Mental Command

As it shown in Figure 39, the initial position of the robot arm was in figure b at 0 degree the figure a is moving right CW and figure c is rotating Left CCW. Beta waves are related with active thinking, problem solving, concentration, and increased attentiveness

A B C

Figure (39) Robot Arm (Base) Movement

In an agitated environment, beta waves rise. This is a method of being attentive in the face of imagined threats from ambient noise. Figures 40 and 41 show the beta waves amplitude changing as Figure 40 represents the beta waves in a quiet environment and the low beta waves are increasing.

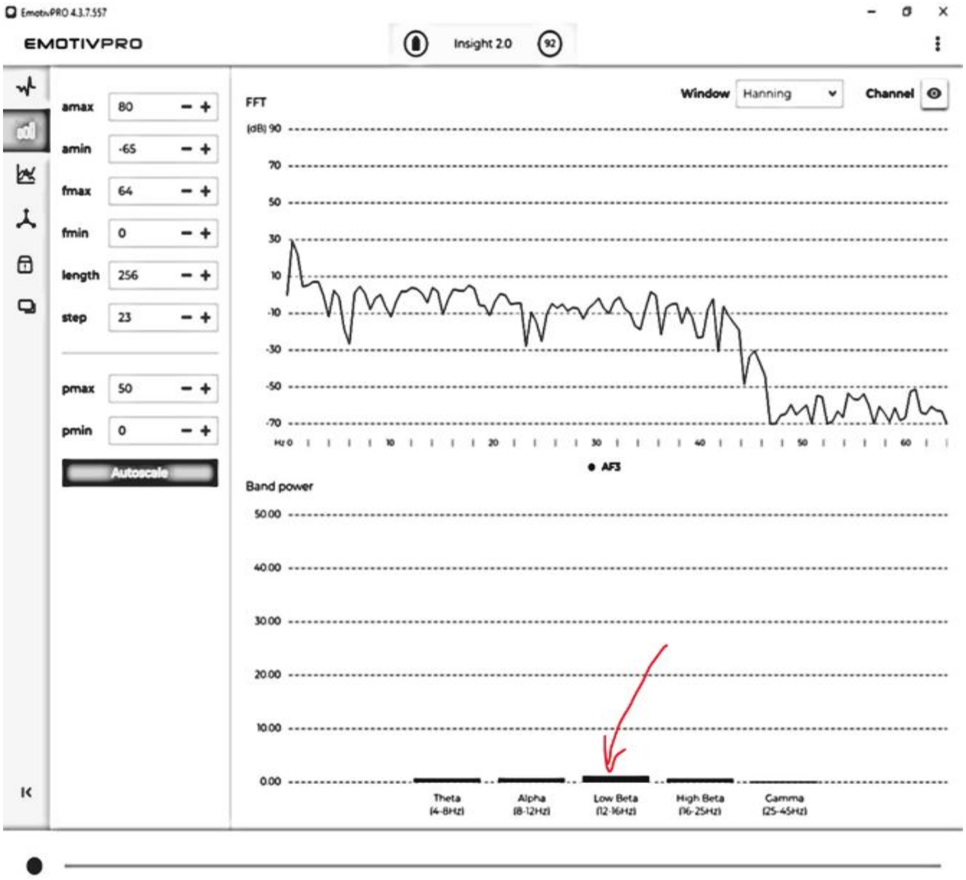

Figure (40) Low Beta Waves in A Quiet Environment

Figure 41 shows the High beta waves in a noisy environment a music was playing next to the subject. From Figure 41, high beta waves were arising as the subject was in a high focus as the noise environment affected the training. The same results were achieved for the Robotic arm movement.

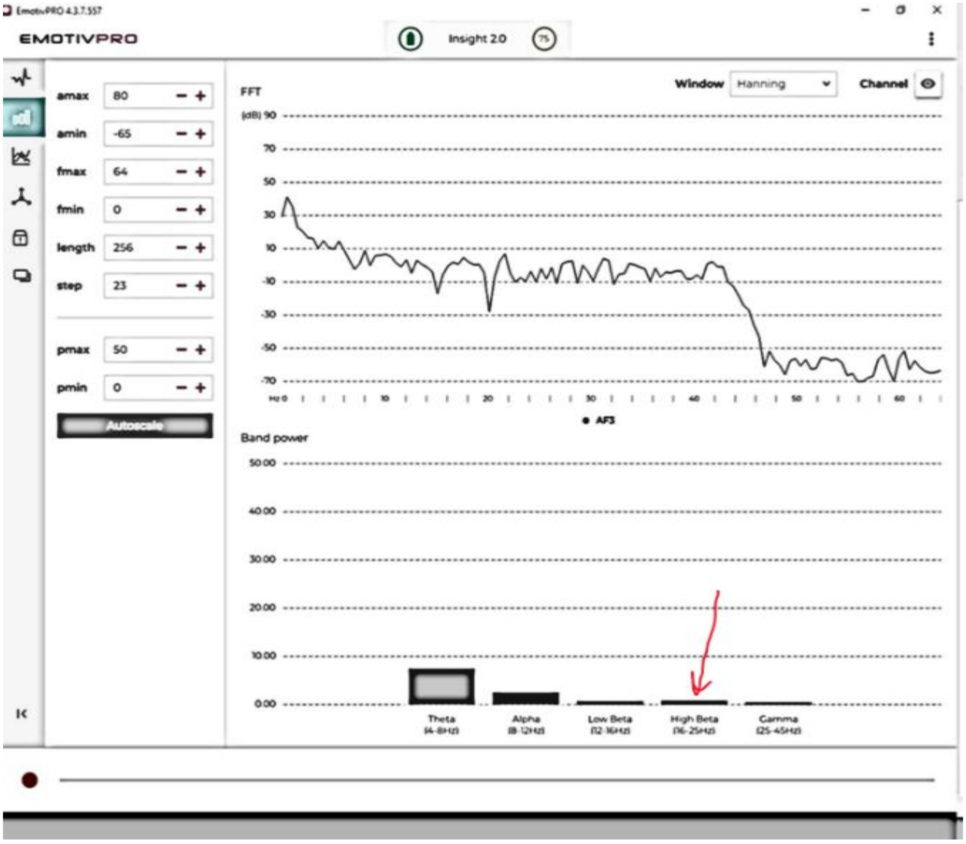

Figure (41) High Beta Waves in A Noisy Environment.

The execution accuracy is calculated regarding each joint. The number of correctly executed actions to the total number of actions attempted as shown in equation 16. Table 6 shows the execution accuracy for each joint of the robotic arm using mental commands.

$$Execusion\ Accuracy = \frac{No.of\ correctly\ excuted}{Total\ No\ of\ action\ attempt} * 100\text{---------(16)}$$

Table (6) Execution Accuracy for Robotic Arm using HITI brain Software

Joint	Command	Quiet Environment			Noisy Environment		
		Total Number of trials	Number of Correctly Executed Trial	Accuracy	Total Number of trials	Number of Correctly Executed Trial	Accuracy
Base	Push (C.W)	10	10	100	10	9	90
	Pull (C.C.W)	10	10	100	10	8	80

Shoulder	**Lift (Up)**	10	9	90	10	9	90
	Drop (Down)	10	10	100	10	9	90
Elbow	**Lift (Up)**	10	9	90	10	7	70
	Drop (Down)	10	9	90	10	7	70
Wrist Vertical	**Right (UP)**	10	10	100	10	7	70
	Left (Down)	10	10	100	10	7	70
Wrist Rotational	**Left (C.W)**	10	9	90	10	8	80
	Right (C.C.W)	10	10	100	10	8	80
Manipulator	**Push (Open)**	10	10	100	10	9	90
	Pull (Close)	10	10	100	10	9	90

From the table above, some of the joints have the same mental commands that is due to the limitations of the Emotive software for the subscriptions this research could afford. And since the testing was for each joint separately, the testing can be performed with the same mental command. Figure 42 shows the difference of the execution accuracy in both conditions.

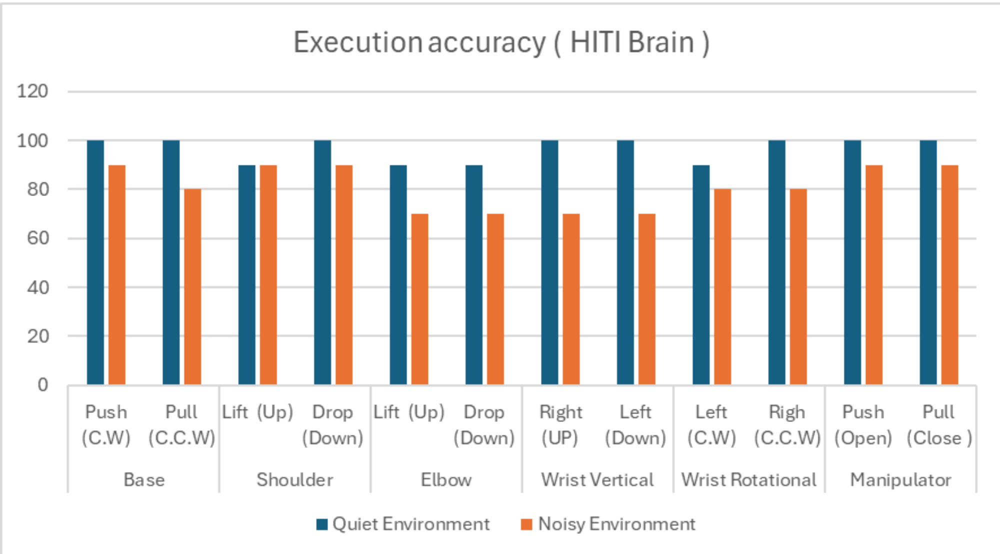

Figure (42) Execution Accuracy (HITI Brain)

2- Separate movement (Facial Expression).

The BCI records the signals of the brain based on special facial actions. Every time a person winks, blinks, smiles or does special action in the face, the brain produces different type of signals. Moreover, since the servomotor rotates in two directions, each direction requires one facial action. For example, a smile will force the motor to rotate CW. In addition, the raised eyebrows facial action leads to rotating the motor CCW. Figure

43 a, b shows the facial expression. In this section, the accuracy calculated was for the command recognition accuracy which can be calculated using Equation 17. Table 7 shows the command recognition accuracy for the facial recognition.

A B

Figure (43) Facial Expression

$$Command\ Recognition\ Accuracy = \frac{No.of\ correctly\ identified}{Total\ No\ of\ command\ sent} * 100 \text{-----------} (17)$$

Table (7) Command Recognition Accuracy

Command	Quiet Environment			Noisy Environment		
	Total Number of trials	Number of Correctly Executed Trial	Accuracy	Total Number of trials	Number of Correctly Executed Trial	Accuracy
Smile	10	10	100	10	9	90
Blink	10	10	100	10	10	100
raise eyebrow	10	8	80	10	9	90
wink left	10	10	100	10	8	80
wink right	10	10	100	10	8	80

clench teeth	10	10	100	10	9	90
furrow eyebrows	10	7	70	10	7	70

The accuracy of facial recognition (as shown in figure 44) in both conditions (Quiet and Noisy Environment) was high as this depends on reading the signals from the brain based on physical actions, there was no motor imagery in this test. Figure 45 a, b, c shows movement of the elbow joint that was chosen for this section.

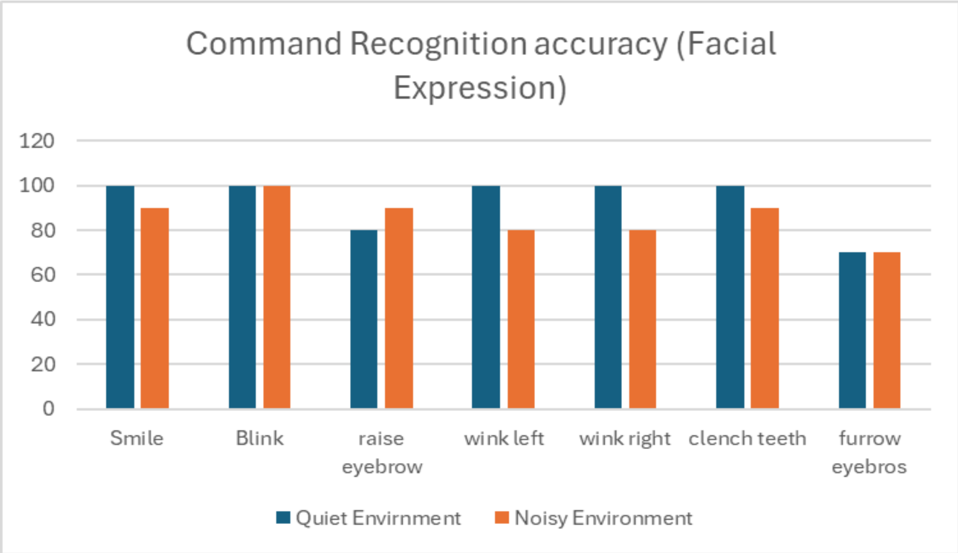

Figure (44) Command Recognition Accuracy (Facial Expression)

A B C

Figure (45) Elbow Movement.

From the Figures above, Figure ‘b’ represents the zero position, Figure ‘a’ is for CCW shoulder joint and Figure ‘c’ shows the CW rotation of the shoulder joint.

3- Full Pick and Place movement.

This is a little hard to perform since the work is limited by the actions available in the emotive software. The robotic arm has 6 joints and each joint moves in two directions. So, the total brain actions needed for the full arm are 12 actions. Therefore, in order to perform this complex movement with the limited resources in hands, the combinations of mental commands and facial expression were implemented in this section. Table 8 presents each joint with their movement and which action is connected to it. Table 9 and figure 46 present the execution accuracy for combined movement of different joints at the same time. It is crucial to mention that the test was performed in a quiet environmental condition only.

Table (8) Joints and Brain Actions.

<table>
<tr><th colspan="2">Joint</th><th>CW rotation</th><th>CCW rotation</th><th>Mental Command</th><th>Facial Expression</th></tr>
<tr><td colspan="2">Base</td><td>Move Right</td><td>Move Left</td><td>Yes</td><td>No</td></tr>
<tr><td colspan="2">Shoulder</td><td>Push</td><td>Pull</td><td>Yes</td><td>No</td></tr>
<tr><td colspan="2">Elbow</td><td>Lift</td><td>Drop</td><td>Yes</td><td>No</td></tr>
<tr><td rowspan="2">Wrist</td><td>Rotational</td><td>Raise brows</td><td>Furrow brows</td><td>No</td><td>Yes</td></tr>
<tr><td>Transitional</td><td>Wink left</td><td>Wink Right</td><td>No</td><td>Yes</td></tr>
<tr><td colspan="2">Manipulator</td><td>Smile (Open)</td><td>Clench Teeth (Close)</td><td>No</td><td>Yes</td></tr>
</table>

Table (9) Execution Accuracy for Combined Joint Movement

<table>
<tr><th rowspan="2">Joint</th><th colspan="4">Quiet Environment</th></tr>
<tr><th>Commands</th><th>Total Number of trials</th><th>Number of Correctly Executed Trial</th><th>Accuracy</th></tr>
<tr><td>Base (CCW)-shoulder(Up)-Elbow(Down)</td><td>Left-Push-Drop</td><td>10</td><td>8</td><td>80</td></tr>
<tr><td>Elbow(Up)-shoulder(Down)-Base(CW)</td><td>Lift-Pull-Right</td><td>10</td><td>8</td><td>80</td></tr>
</table>

Shoulder(Up)-Wrist V(Up)-Manipulator (Open)	**Push-Raise Brows-Smile**	10	7	70

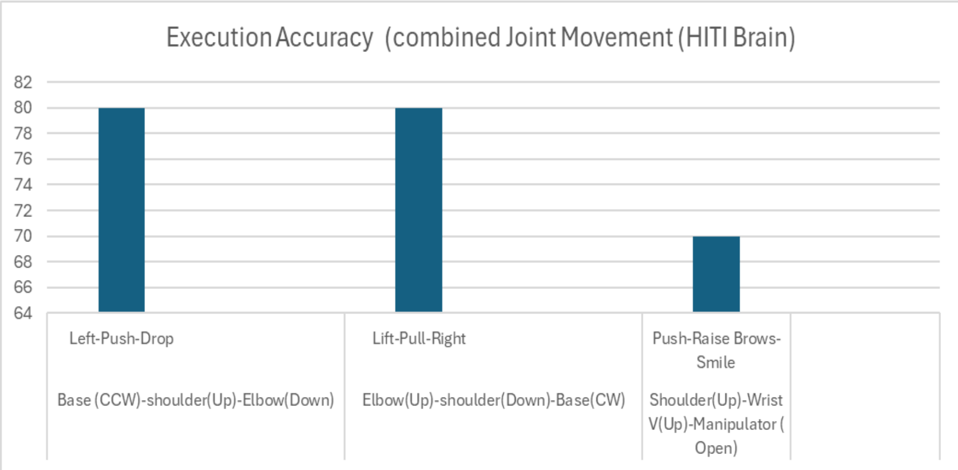

Figure (46) Execution Accuracy for Combined Joints Movement

Figure 47 (a-f) shows how full movement of an object is performed from one point to another

a

b

c

d


e


f

Figure (47) Pick and Place (Cont'd).

4- Safety and Security.

The system has two safety conditions in order to avoid colliding with other objects on the way and to avoid if the signal is too powerful that makes the joint move more than the desired motion. The first solution is to set the minimum and maximum interval range for the servo. This can be done in the code. The second solution is in the HITI brain software (Figure 48). When linking the joint movement to brain signals, there is an option called a threshold. This can determine the power the signal should reach before moving the motor. The safety of this system is very crucial to ensure smooth and safe working of the arm, as the system is also applicable for a prosthetic arm with 6 joints. And since the prosthetic attached to the body is different than the robotic arm, putting the safety conditions is required always.

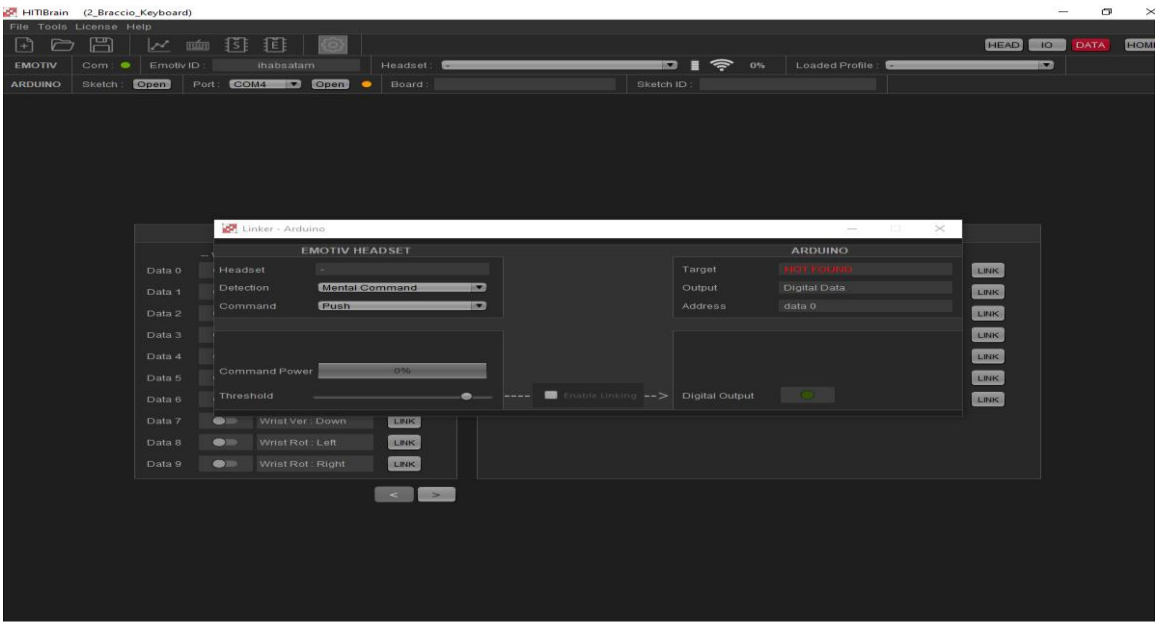

Figure (48) HITI Software Safety Option

4.3. Controlling a higher degree of freedom robotic arm with few mental commands.

One of the limitations in the previous sections is that the more degree of freedom for the robot the more mental commands are required to control it. For example, as in the previous section, 6 DOF robotic arm requires 12 mental command or 12 different type of brain signals. Due to that reason, the patient will require more training. To solve this problem, we can use four mental commands, two mental commands to control the movement of each joint, and two mental commands to control the transition between the joints. For this solution, Node-RED software was used as well as the Arduino software and Emotive software.

4.3.1. Node-RED

Node-RED is one of the flow-based programming tools. The flow programming described the application`s behavior as a black box network. Node-RED describes it as nodes [94]. Processing is defined in each node; data is given to it, processing is performed using that data, and that data is passed to the next node. The network plays the role of allowing data to flow between the nodes (Figure 49). Node-RED has the ability to combine the two-software necessary for this work (the Emotive and the Arduino). Node-RED basically is a programming tool for programming node.js applications with Graphical User Interface GUI tools [95].

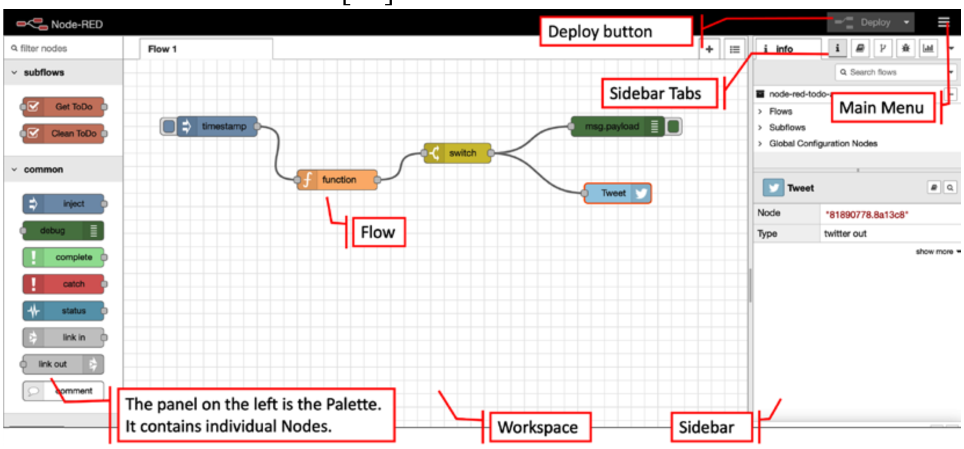

Figure (49) Node-RED

The human arm has a wide range of motion, starting at the shoulder and extending to the elbow, wrist, and hand [96]. Joint and muscle group contributes to arm movement, beginning with the shoulder:

1. Shoulder Joint.

The shoulder is a ball-and-socket joint composed of the humerus (upper arm bone) and the scapula (shoulder blade), especially the glenoid cavity [97].

This joint provides a wide range of motion [98], including:

- Flexion involves raising the arm forward.
- Extension: Moving the arm rearward.
- Abduction means lifting the arm horizontally away from the body.
- Adduction is bringing the arm back toward the body.
- rotation: internal (inward) and exterior (outward). Rotation
- Circumduction is the combination of the above actions that move the arm in a circular pattern.

Muscles Involved

- Deltoid: This muscle caps the shoulder and is responsible for abduction.
- The rotator cuff muscles (supraspinatus, infraspinatus, teres minor, and subscapularis) support the shoulder joint and help with numerous motions, notably rotation and abduction.
- The Pectoralis Major and Latissimus Dorsi muscles help with arm flexion, adduction, and rotation.
- Trapezius and Serratus Anterior: Stabilize the scapula and facilitate shoulder mobility.

2. Elbow joint.

The elbow is a hinge joint that links the humerus, ulna, and radius in the forearm [99].

It mainly allows:

- Flexion involves bending the arm.
- Extension: straightening the arm.

Muscles Involved

- Biceps Brachii: The muscle responsible for elbow flexion.
- Triceps Brachii: The muscle responsible for elbow extension.

3. Forearm Rotation.

This includes the proximal and distal radioulnar joints [99], which allow for:

- Pronation: Turning the palm downwards.
- Supination involves turning the palm upward.

Pronation is controlled by the Pronator Teres and Pronator Quadratus muscles. Supination requires the Biceps Brachii and Supinator muscles.

4. Wrist and Hand Joints.

The wrist and hand have multiple joints, enabling fine motor control and complex movements such as flexion, extension, abduction, adduction, and circumduction of the wrist, as well as grasping and manipulating objects with the fingers[100].

Muscles Involved:

- Flexor and Extensor Groups: These are found in the forearm and control movement at the wrist and fingers.

- Intrinsic Hand Muscles: Small muscles within the hand provide precise finger motions.

The coordination of these joints and muscles allows the human arm to perform a wide range of complex movements, from reaching and lifting to fine motor skills like writing. The central nervous system (CNS) plays a crucial role in controlling these movements by sending signals to the muscles, allowing for smooth, coordinated actions. From all above, the idea of controlling the robotic arm with less mental command. Each joint requires two movements, the clockwise and the counterclockwise movement. These two can be controlled with two mental commands. The transition between the joints can be controlled in two mental commands. One command is to transfer to the next joint and one is to back to the previous joint. So, to perform the full pick and place, the movement starts to move the shoulder joint to the required position, followed by the elbow, wrists and manipulator. The Node-Red flow blocks are shown in the figure 50. There are five mental commands (Push, Pull) for the CW and CCW movement, (Lift, Drop) for the transition between the joints. Neutral for stop command.

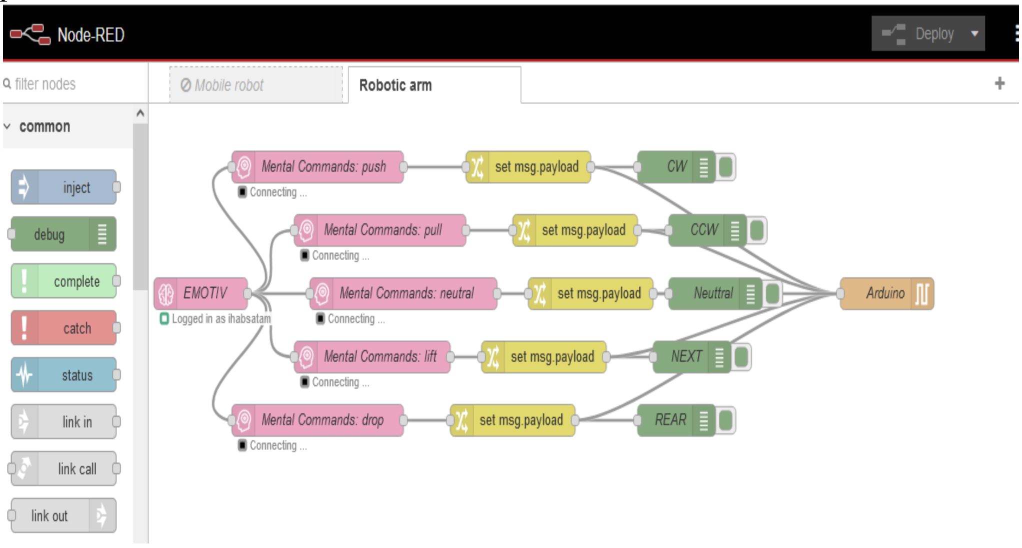

Figure (50) Robot Arm Control

Table 10 presents the execution accuracy of switch control between different joints. To evaluate the system's robustness, tests were performed in both quiet and noisy environments, simulating varying real-world conditions. The quiet environment aimed to minimize external distractions and enhance focus, while the noisy environment introduced auditory and visual disturbances to test the system's reliability under challenging conditions. These experiments aimed to assess the feasibility and accuracy of controlling a robotic arm with limited mental commands in diverse scenarios.

Table (10) Execution Accuracy of Joint Switch Control

Quiet Environment		Forward movement			Noisy Environment			Forward movement	
Joints movement	Command	No. of Trials	No. of True Excution	Accuracy	Joints movement	Command	No. of Trials	No. of True Excution	Accuracy
Base-Shoulder	Lift	10	10	100	Base-Shoulder	Lift	15	11	73.33333333
Base to Elbow	Lift	10	8	80	Base to Elbow	Lift	15	10	66.66666667
Base-Wrist Vertical	Lift	10	8	80	Base-Wrist Vertical	Lift	15	10	66.66666667
Base-Wrist Rotational	Lift	10	7	70	Base-Wrist Rotational	Lift	15	10	66.66666667
Base-Manipulator	Lift	10	8	80	Base-Manipulator	Lift	15	8	53.33333333
Quiet Environment		Backward Movement			Noisy Environment			Backward Movement	
Joints movement	Command	No. of Trials	No. of True Excution	Accuracy	Joints movement	Command	No. of Trials	No. of True Excution	Accuracy
Shoulder-base	Drop	10	10	100	Shoulder-base	Drop	15	10	66.66666667
Wrist Rotational-shoulder	Drop	10	7	70	Wrist Rotational-shoulder	Drop	15	8	53.33333333
Manipulator-base	Drop	10	5	50	Manipulator-base	Drop	15	8	53.33333333
Manipulator-Wrist Vertical	Drop	10	7	70	Manipulator-Wrist Vertical	Drop	15	9	60
Elbow-shoulder	Drop	10	10	100	Elbow-shoulder	Drop	15	11	73.33333333

In figures 51, 52 we can observe that there is a noticeable difference of execution accuracy between the Quiet environment and the Noisy environment.

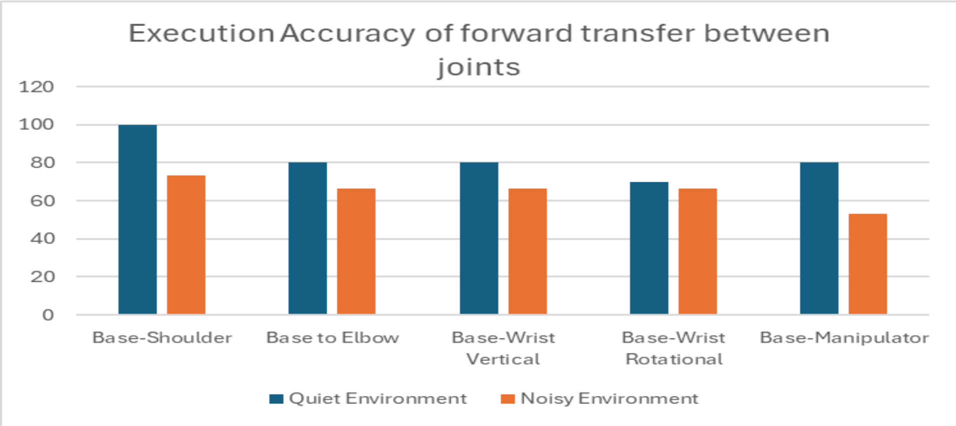

Figure (51) Execution Accuracy of Forward Transition Between Joints

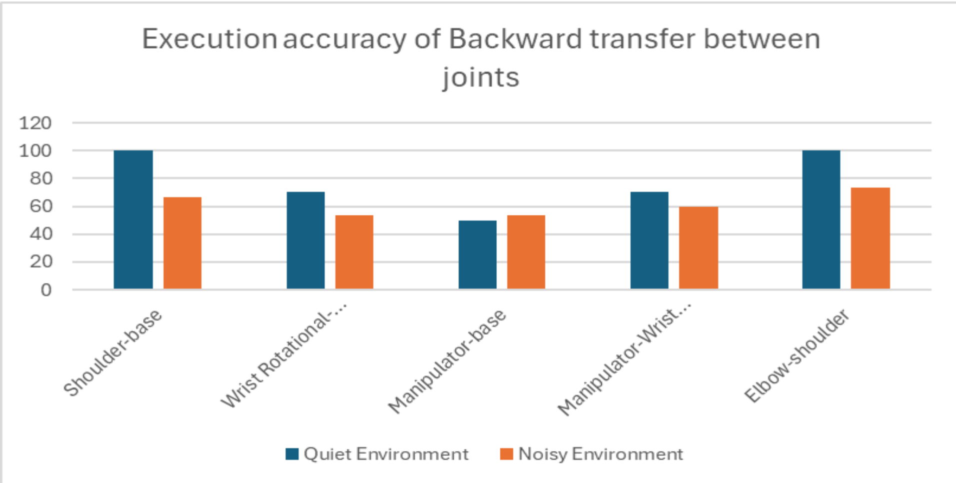

Figure (52) Execution Accuracy of Backward Transition between Joints

Table 11 and figure 53 show the combined switch control between joints at the same time. In this test, we only performed it in a Quiet environment condition.

Table (11) Execution Accuracy of Combined Movement

Joints movement	No. of Trials	No. of True Excution	Accuracy
Base-Shoulder-Base	20	19	95

Shoulder-Elbow-Base	20	17	85
Wrist Vertical-Wrist-Rotational-Manipulator-Base	20	14	70

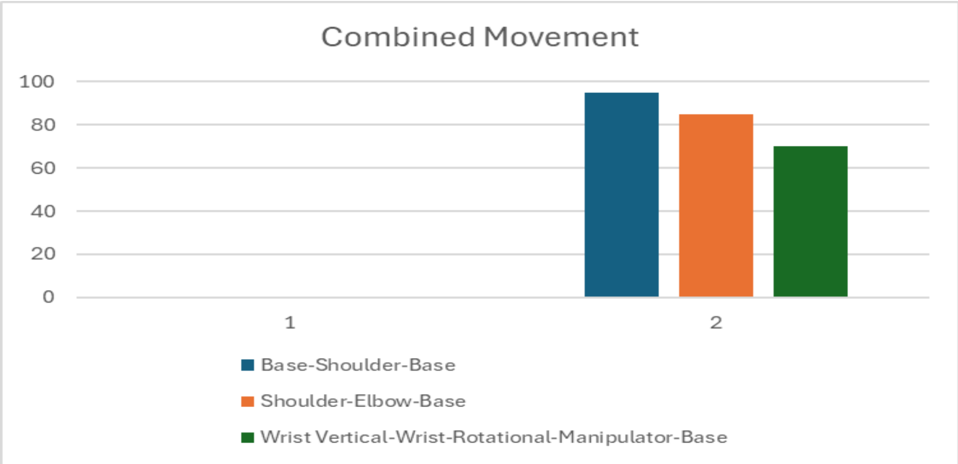

Figure (53) Execution Accuracy of Combined Movement

The more complicated the operation is the more focused and training the patient needs. It is important to mention that the execution of the robot arm in Pick and Place movement was applied in a quiet environment condition.

4.4. Conclusion

Disability problem is widespread in the last decade. Paralyzed or people with lost limbs (especially the upper limb) face a real challenge performing daily life activities. The aim of this research is to help them to perform simple daily life activities using their brain signal. The work shows great results regarding the motion control of the robotics arm, and at the same time the system is safe and smooth. The patient before using the system needs to be trained for a period of time, and this time is different from person to person depends on power of focus in the patient. The overall system can be applicable for prosthetics. This finding supports **Hypothesis 3:** Employing a Brain-Computer Interface (BCI) for controlling a 6 Degrees of Freedom (DOF) robotic arm that closely replicates human arm movements facilitates more intuitive and precise robotic control. And **Hypothesis 4:** An innovative technique to control higher degrees of freedom of a robotic arm with reduced cognitive commands from the brain can improve usability and efficiency.

5. BCI control for wheeled robot

Brain-controlled robots capture and use brain wave data to control movement. This, when combined with a mobile robot or wheelchair for handicapped people who cannot talk or move their hands, will allow them to move around independently [101]. To control the wheelchair, EEG signals are required. In this technique, the intention is to employ five electrodes to record EEG signals from various positions on the head. A Brain-Computer Interface (BCI) typically operates mobility robots or electric wheelchairs via Bluetooth. A BCI includes three components: input (e.g., user electrophysiological activity), output (i.e., device commands), and operation. Electrodes on the scalp or in the skull collect brain signals and extract certain properties, such as evoked potential amplitudes, sensory-motor cortex rhythms, and cortical neuron firing rates, to determine the user's intent. These characteristics are turned into commands that control a device (such as a mobile robot, wheelchair, or neuro-prosthesis [102]. The success of BCI operation is dependent on the interplay of two adaptive controllers: the user and the system. The user must create and maintain a strong link between his or her purpose and the signal characteristics used by the BCI, and the BCI must choose, and extract features that the user can influence before appropriately and effectively translating those features into device commands.

5.1. Material

This section presents the resources utilized in the creation of BCI system. The components include the Emotive insight headset, the development software, the communication system, and the mobile robot. The Emotive Insight is a multi-sensory headset including 5 electrodes and two reference sensors. It acquires the EEG signals from the user's brain. Initially, Emotive Insight was introduced as an innovative control mechanism for video game interactivity. The mobile robot used in this work is Alphabot 2.0 (figure 54). It is an advanced robotic development platform designed by Waveshare. The robot is compatible with different types of controllers such as Arduino and Raspberry Pi.

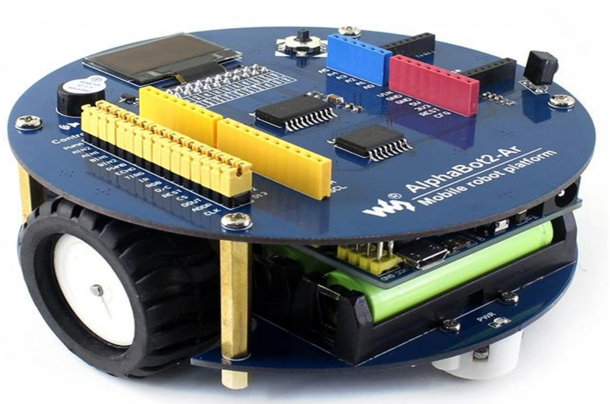

Figure (54) Alphabot

5.1.1. Mobile Robot.

A mobile robot is a software-controlled machine that uses sensors and various technologies to perceive its environment and navigate within it. Mobile robots operate by a synthesis of artificial intelligence (AI) and mechanical components, including wheels, tracks, and legs. Mobile robots are gaining prominence in several commercial areas [103]. They are employed to facilitate work processes and execute jobs that are infeasible or hazardous for human laborers. It is possible to categorize mobile robots according to two criteria: the working environment and the means of propulsion. A few examples of mobile robots that can adapt to their surroundings are:

- Arctic robots that can navigate rough, icy terrain.
- Flying robots, often called drones or unmanned aerial vehicles (UAVs).
- Robots that move about on dry land or inside homes are known as unmanned ground vehicles (UGVs).
- Robots that can navigate themselves through water, also known as autonomous underwater vehicles (AUVs).
- Transportation and delivery robots are movable machines that can convey goods and supplies from one location to another.

A mobile robot may be classified using many devices, such as:

- legs, which can be either animal-like or human-like
- wheels.
- Tracks

In addition, autonomous mobile robots and non-autonomous mobile robots are the two most common varieties. When it comes to moving around, non-autonomous mobile robots need some type of instruction or guidance system, whereas non-autonomous mobile robots (AMRs) can navigate and discover their environment on their own [104]. A driving system called differential drive is used by several mobile robots. Each of its two wheels may be turned in the direction by itself; these wheels are positioned on a shared axis. Although the robot can roll by changing the velocities of its individual wheels, it can only do so by rotating around a point that lies along the axes of its two front wheels (Figure 55). The Instantaneous Center of Curvature (ICC) is the point around which the robot revolves [105]. By varying the velocity of each wheel, the trajectories taken by the robot can be changed accordingly.

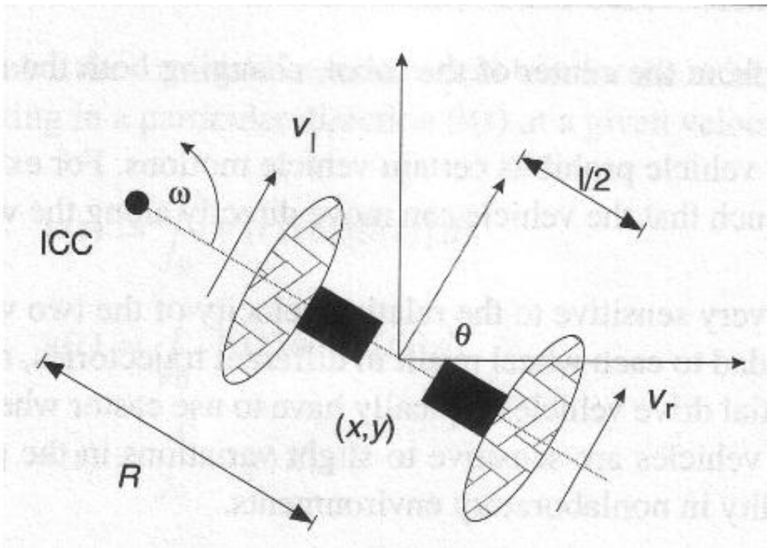

Figure (55) ICC of Mobile Robot.

5.1.2. Method of controlling the mobile robot.

A mobile robot known as a differential wheeled robot can move about thanks to its two wheels, one on each side of the body, which are controlled independently. It doesn't need any extra steering motion because it can change its direction just by adjusting the respective speeds of its wheels [106]. To avoid tipping over, robots using this type of propulsion usually incorporate one or more caster wheels. The robot will go in a straight path if the two wheels are turned at the same speed and in the same direction. The robot will spin around its axis if its two wheels are moved in opposing directions at the same speed. The point where the tires make contact is not always the center of rotation; rather, it can fall anywhere along that line, depending on the direction and speed of rotation. Even though the robot is moving in a straight path, the distance to the center of rotation is unlimited [107]. Accurate sensing and control of the speed and direction of rotation of the two driven wheels is crucial for the robot's direction. In this work, the Arduino controller is used to control Alphabot 2.0. With the combination of Node-Red, Arduino IDE and Emotive software, the control of Alphabot was achieved. Based on mental commands (Push, Pull, Right, Left, Neutral) the robot was moved (Forward, Backward, turn right, Turn Left, Stop) respectively. The Emotive Software sends the mental commands to Node-Red which acts as a medium that transfer the signals to the Arduino controller, and according to the code in the controller the movement of the mobile robot is executed. Figure (56) shows the flow diagram in Node-RED.

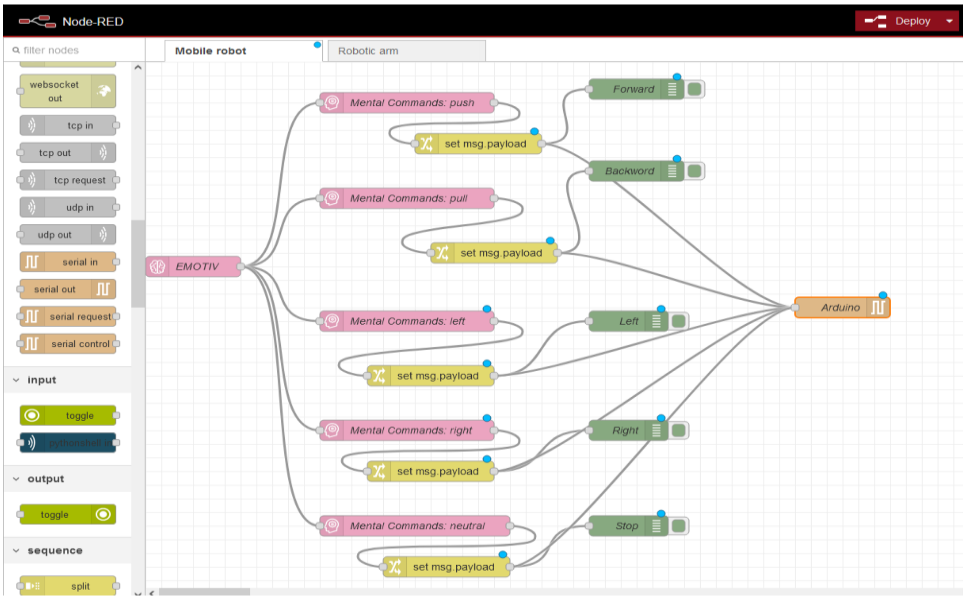

Figure (56) Node-RED Flow for Mobile Robot Control

5.2. Results

The simplest way to make the mobile robot reach the goal point is to guide it. There are various methods to achieve that. In this work, the guidance using mental commands was used (Figure 57). The robot has to move between two points. The start point (A) and the end point (B). As in the previous chapter, the mobile robot was given instructions with brain signals to move in different directions. Figure 58 a, b, c, d shows how the mobile robot moves between points A and B. The subject sits in a relaxed state focusing on the robot movement. Five commands were used (Push= Forward, Pull = Backward, Left = Turn Left, Right = Turn Right, Neutral = Stop). It’s important to mention that the subject had a training for 5 sessions and 40 trials, before testing.

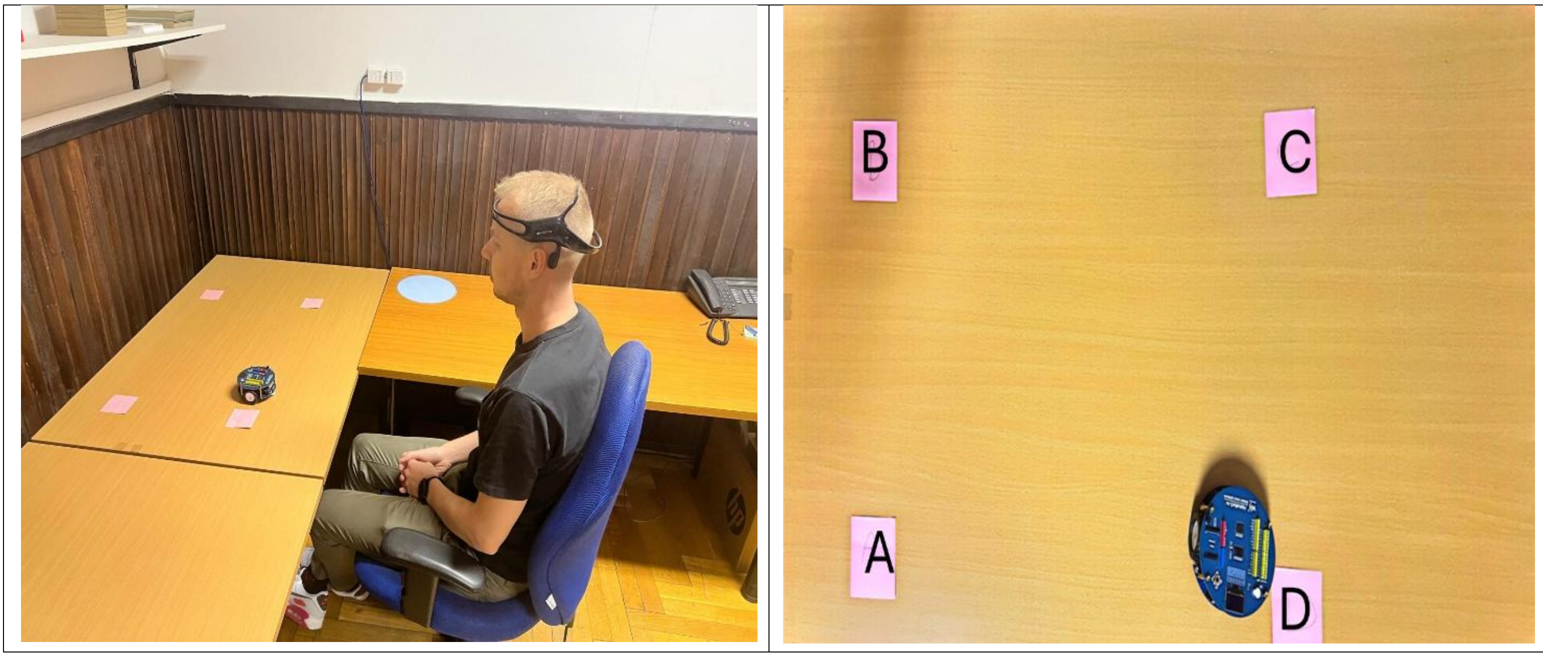

Figure (57) Controlling Mobile Robot using BCI

A B C D

Figure (58) Mental Commands Robot Controlling

The Execution accuracy was calculated as the same as the robotic arm. The ratio of the number of correctly executed actions to the total number of actions attempted. Table 12 and figure 59 present the results of the accuracy of the systems in the two conditions, the Quiet and noisy environment.

Table (12) Execution Accuracy of Mobile Robot

Quiet Environment				Noisy Environment			
Command	No. of trials	No. of corrected executed	Accuracy	Command	No. of trials	No. of corrected executed	Accuracy
Forward - Right	10	10	100	Forward - Right	10	8	80
Forward - Left	10	10	100	Forward - Left	10	8	80
Backward- Right	10	9	90	Backward- Right	10	7	70
Backward-Left	10	10	100	Backward-Left	10	8	80
Full Move	10	8	80	Full Move	10	7	70

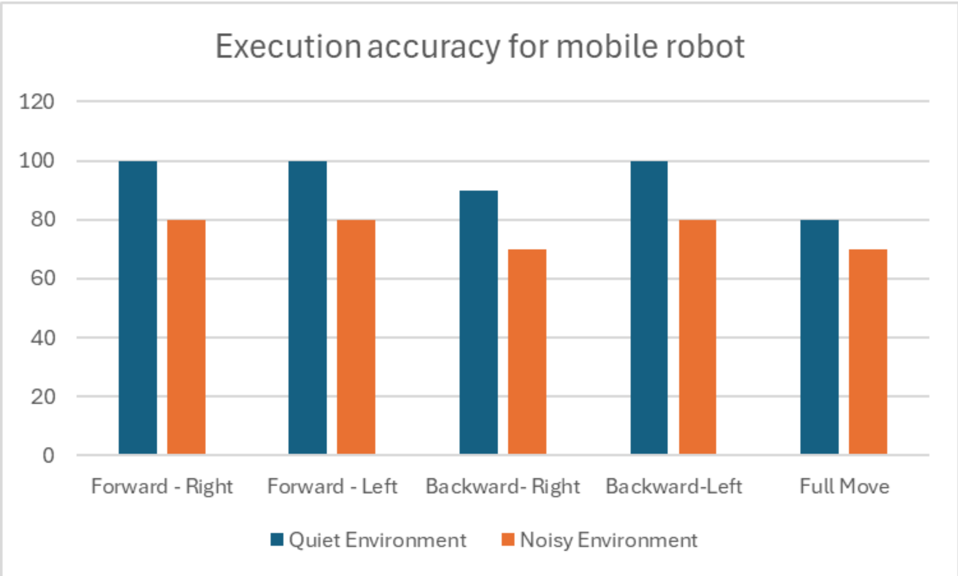

Figure (59) Execution Accuracy of Mobile Robot

The results for the mobile robot were higher than in robotic arm as the robot doesn`t have complex movements as the arm.

5.3. Conclusion

The Emotive Insight BCI, Arduino, and Node-RED were successfully integrated to drive a mobile robot, demonstrating the possibility and usefulness of employing EEG-based brain signals for real-time robotic control. This technique demonstrates BCI technology's ability to provide intuitive and direct control of robotic devices in the absence of conventional interfaces. By mapping mental instructions to robot motions using Node-RED, I was able to obtain responsive and accurate control, demonstrating the utility of non-invasive EEG for mobile robotic applications. This experiment also lays the path for future advancements in BCI-controlled robots, with potential applications in assistive technology and beyond. This work supports **Hypothesis 5**: Using Brain-Computer Interface (BCI) technology with a fewer number of recording channels for the controlling of mobile robots will facilitate efficient and effective robotic control. Optimizing signal collection and processing with fewer channels enables accurate command execution while decreasing the complexity of the BCI system.

6. CONCLUSION

The use of EEG signals from the brain to operate robotic systems, including robotic arms and mobile robots, represents a significant progression in assistive technology and brain-computer interface (BCI) applications. The statistics of Hungary, indicating that around 10% of the population is listed as handicapped, emphasize the social significance of this study. Assistive technology, such as robotic arms and mobile robots, operated using non-invasive EEG impulses, may provide significant answers to the issues encountered by this demographic. Prosthetic robotic arms operated by brainwaves might restore functionality and enhance autonomy for persons with motor disabilities, while brain-controlled mobile robots could facilitate movement and everyday activities, providing more freedom and dignity. The incorporation of EEG-controlled robotic systems signifies a crucial advancement in assistive technology for those with impairments. The results not only fulfill a significant social need, as shown by Hungary's disability statistics, but also facilitate worldwide progress in human-robot interaction. Through ongoing innovation in this domain, researchers and engineers may foster a more inclusive society, wherein technology enables people to surmount physical constraints and attain more autonomy in their lives.

7. New Scientific Results

The following theses encapsulate the essence and significance of my scientific research conducted during my Ph.D. studies:

Thesis No. 1

I have demonstrated the practicality, safety, and applicability of non-invasive BCIs in real-world robotic applications, with a particular emphasis on assistive technologies for the disabled users. (Chapter 9/9.1 [3],[5], [**??**])

Discussion

The following important elements are emphasized in my statement:

1. Real-World Applications: Non-invasive BCIs are more practicable and easier to use, making them more suitable for deployment in practical, everyday contexts. This is consistent with the requirements of incapacitated users, who need systems that are both user-friendly and dependable.
2. Safety Benefits: Non-invasive BCIs mitigate the health risks and complications that are linked to invasive and semi-invasive technologies, such as long-term maintenance, infection risks, and surgical procedures. This renders them a more acceptable and secure option for a broad user base, particularly for assistive purposes.
3. Emphasize Disabled Users: The objective is to establish systems that prioritize safety, comfort, and simplicity of adoption for individuals with disabilities. These criteria are more effectively met by non-invasive BCIs than by their invasive counterparts.
4. Adoption and Accessibility: Non-invasive BCIs are more likely to be widely adopted due to the fact that they do not necessitate specialized expertise for setup and maintenance or complex medical procedures. This renders them more suitable for mass-market assistive devices.

I reaffirm the thesis that non-invasive BCIs are not only technologically viable but also ethically and socially preferable options for assistive robotic systems

Thesis No. 2

I have proven the effectiveness of combining advanced feature extraction techniques with robust classification methods in EEG data analysis, specifically for applications in BCI-controlled robotic systems (Chapter 9/ 9.1 [1], [3]).

Discussion:

The following is illustrated by my statement:

1. Wavelet Transforms for Feature Extraction: I have demonstrated that wavelet transforms are highly effective in the extraction of meaningful and relevant features from EEG signals. This is of particular significance due to the fact that EEG data are frequently complex and chaotic, necessitating sophisticated preprocessing methods to enhance the signal-to-noise ratio and emphasize patterns during classification.
2. ANFIS for Classification: I demonstrated that the accuracy of EEG data analysis is considerably improved by employing the Adaptive Neuro-Fuzzy Inference System (ANFIS) as a classification method. This implies that ANFIS is an exceptional candidate for the classification of mental commands from EEG signals, as it is well-suited for the interpretation of nonlinear and equivocal data.
3. Supervised Machine Learning Applicability: The fact that supervised machine learning algorithms can similarly improve classification accuracy demonstrates that a variety of advanced methods, in addition to ANFIS, can be effectively employed for the classification of EEG signals. This broadens the scope of my findings, demonstrating that the results are not constrained to a single approach but rather to a general framework that integrates sophisticated classifiers and feature extraction.
4. Improved Accuracy: Your research demonstrates that the integration of sophisticated preprocessing (wavelet transformations) with potent classifiers (e.g., ANFIS or supervised machine learning algorithms like SVM and neural networks) leads to a substantial increase in classification accuracy. This enhancement is essential for real-world applications that require precision and reliability in the interpretation of EEG signals.

Thesis No. 3:
I have demonstrated the practicality and efficacy of employing Brain-Computer Interfaces (BCIs) to attain intuitive and precise control of intricate robotic systems, specifically a six-degrees-of-freedom (DOF) robotic arm (Chapter 9/9.1 [2], [**6**].

Discussion:
The following important elements are emphasized in the statement:

1. Human Arm Movement Replication: Your demonstration of the ability of BCIs to reconcile the divide between human intention and robotic execution was achieved through the use of a 6-DOF robotic arm that closely resembles human arm movements. This results in a more intuitive and natural control of the robotic limb for the user.

2. Intuitive Control: The capacity to operate a robotic arm through mental commands enables users to operate it without the need for extensive physical interfaces or manual inputs. The interaction is simplified, and cognitive and physical distress are reduced, which is particularly beneficial for users with disabilities.

3. Robotic Control Precision: The robotic arm's high degree of accuracy demonstrates that BCIs are capable of translating mental commands into precise, fine-grained movements. This is essential for applications that necessitate delicate or coordinated duties, such as industrial automation, prosthetics, or assistive devices.

4. Developing BCI Applications: Your research underscores the potential of BCIs to evolve from basic robotic duties to more complex systems with greater degrees of freedom. You contribute to the body of evidence that supports the scalability and versatility of BCIs in robotics by demonstrating successful control of a 6 DOF robotic arm.

5. Practical Significance: The emphasis on intuitive and precision control demonstrates the practical applicability of this technology in real-world scenarios, particularly in assistive technologies for individuals with motor impairments or in environments that necessitate seamless human-robot interaction.

Thesis No. 4:
By using a simple approach, I demonstrated a new method to control a higher degree of freedom robotic arm with only four commands. Instead of assigning two mental commands to every joint in the robotic arm which leads (which leads to the fact that the higher DOF the more double Number mental commands required) only four mental commands used. With this method (Chapter 9/ 9.1 [**8**]).

Discussions:
I demonstrated that:

1- Complex tasks can be managed by fewer mental commands.
2- This method could be applicable for different fields, like assistive devices.
3- The reduction in cognitive loads highlights the potential for reducing mental fatigue.

Thesis No. 5:
I endorsed a statement emphasizing the prospective advantages of using Brain-Computer Interface (BCI) technology for the control of mobile robots. The assertion indicates that BCI may improve the efficiency and efficacy of robotic control by enabling direct brain inputs that control robot motions and commands. This integration may enhance accessibility and engagement with robots, particularly for those with physical disabilities (Chapter 9/9.1 [**8**]).

8. Future Work and Outlook

Following the successful deployment of Brain-Computer Interfaces (BCIs) for the control of a 6 Degrees of Freedom (DOF) robotic arm, several avenues for future study may be delineated to improve the application, usefulness, and efficiency of this technology.

Below is the list of possible developments to work on in the future:

1. **Increasing Degrees of Freedom and Complexity**

   Future research may concentrate on enhancing control capabilities for robotic systems with more degrees of freedom or supplementary functionality, such as robotic hands exhibiting finger-level dexterity. This would enhance the system's capability to emulate the whole spectrum of human arm and hand motions, hence making it more appropriate for intricate motor tasks and sophisticated assistive applications.

2. **Multimodal Interfaces:**

   Integrating BCIs with other control modalities, such as vocal commands, ocular tracking, or tactile sensors, may provide hybrid control systems. These systems would provide redundant control alternatives, enhancing their robustness and user-friendliness in complicated or high-stress situations.

3. **Minimizing Reliance on Training.**

   Although existing BCI systems often need extensive user training, future endeavors may aim to diminish this need by creating more sophisticated classifiers or integrating transfer learning methodologies. This would improve the technology's accessibility for a wider array of users.

4. **A generalization Among Users:**

   Creating systems that function efficiently for a varied array of users, irrespective of individual disparities in brain signal patterns, is a significant focus for future study. This may include developing adaptive brain-computer interfaces that can learn and adapt to individual users in real-time.

9. Author's Publications

9.1. Publications related to the research

[1] I. A. Satam, "EEG signal ANFIS classification for motor imagery for different joints of the same limb," *Military Technical Courier*, vol. 72, no. 1, pp. 330–350, 2024, doi: 10.5937/vojtehg72-46601.

[2] I. A. Satam and I. A. Satam, "Review Studying of the Latest Development of Prosthetic Limbs Technologies," *Int J Sci Eng Res*, vol. 12, 2021, [Online]. Available: http://www.ijser.org

[3] I. A. Satam and R. Szabolcsi, "Supervised machine learning algorithms for brain signal classification," *Military Technical Courier/Vojnotehnicki glasnik*, vol. 72, no. 2, pp. 727–749, Apr. 2024, doi: 10.5937/vojtehg72-48620.

[4] I. A. Satam "Safety and Security Aspects of Implanted Brain-Computer Interface (BCI) for Human-Robot Interaction," *International Journal of Multidisciplinary Research and Publications (IJMRAP)*, vol. 6, no. 6, pp. 268–276, 2023, [Online]. Available: https://www.researchgate.net/publication/376488488

[5] I. Satam, "A comprehensive study of EEG-based control of artificial arms," *Vojnotehnicki glasnik*, vol. 71, no. 1, pp. 9–41, 2023, doi: 10.5937/vojtehg71-41366.

[6] I. A. Satam and R. Szabolcsi, Implantable BCI: Ethical Concerns (Under Review).

[7] I. A. Satam and R. Szabolcsi Neurofeedback-Driven 6-DOF Robotic Arm: Integration of Brain-Computer Interface with Arduino for Advanced Control (Under Review).

[8] I. A. Satam and R. Szabolcsi Advanced Brain-Controlled Actuation: Harnessing EEG Signals for Multi-Actuator Coordination in Robotics (Under Review)

9.2. Further publications

[1] R. W. Daoud, O. M. Ali, O. K. Ahmed, and I. A. Satam, "Arduino-based design and implementation of experimental rooms with a trombe wall for solar cells applications," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 1248–1255, Jun. 2023, doi: 10.11591/eei.v12i3.4522.

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[2] D. Delisle-Rodriguez *et al.*, "Multi-channel EEG-based BCI using regression and classification methods for attention training by serious game," *Biomed Signal Process Control*, vol. 85, Aug. 2023, doi: 10.1016/j.bspc.2023.104937.

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