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Mind Control Robotic Arm: Augmentative and Alternative Communication in the Classroom Environment

Dr. G. N. Keshava Murthy[1], Dr. Rekha H.[2], Riddhi Rajendra Mirajkar[3], Dr. Sammy F.[4], Dr. Yogesh Suresh Deshmukh[5], Prasad Raghunath Mutkule[6]

[1] Assistant Professor, Department of Electronics and Instrumentation Engineering,
Siddaganga Institute of Technology,
Tumakuru, Karnataka, India-572 101
gnk@sit.ac.in

[2] Professor, Department of Information Science and Engineering,
Shridevi Institute of Engineering and Technology,
Tumakuru, Karnataka, India-572 106
rekhah.girish@gmail.com

[3] Assistant Professor, Department of Information Technology,
Vishwakarma Institute of Information Technology,
Pune, Maharashtra, India- 411 048
mirajkarriddhi@gmail.com

[4] Assistant Professor, Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Andhrapradesh, India- 522 502
sammy@kluniversity.in

[5] Assistant Professor, Department of Information Technology,
Sanjivani College of Engineering,
Kopargaon, Maharashtra, India- 423 603
yogesh.d151@gmail.com

[6] Assistant Professor, Department of Information Technology,
Sanjivani College of Engineering,
Kopargaon, Maharashtra, India- 423 603
mutkuleprasad000@gmail.com

Abstract— In recent years, technological advancements have greatly benefited the field of prosthetics. A large number of disabled people depend on prosthetics because they are an important technology. In order to provide augmentative and alternative methods of communication to these disabled people with various neuromuscular disorders, we must make sure they are provided with appropriate equipment to express themselves. Different types of arms are evaluated under robotic technology in terms of resistance, usability, flexibility, cost, and potential (such as robotic, surgical, bionic, prosthetic, and static arms). The main problems with these techniques are their high cost, the difficulty of installing and maintaining them, and the possibility of requiring surgery may arise. As a result, this paper is going to provide a description of the idea for combining an EEG controlled smart prosthetic arm with a smart robotic hand. An electrode headset is used to capture the signals from the robotic hand in order to control the device. Creating a robot arm that can help disabled people lead a more independent life is the main objective of this paper.

Keywords- EEG, Robotic Technology, Prosthetic arm, Robotic hand, Robot Arm

I. INTRODUCTION

Among all the parts of the body, the hands are among the most important. Humans are able to perform multiple complex actions with their hands due to the excellent flexibility and mobility of their hands. The use of hands can also be seen in the use of body language and sign language, which enables us to express ourselves and contact others more effectively. Humans are able to interact with our environment and build the world through the use of their hands, and therefore, the use of hands is incredibly important [1]. There has been a growing concern among the international community regarding limb dysfunctions that has been identified in recent studies by the world health organization (WHO). Prosthetic limbs have existed for decades,

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but their ability to function and interface with the environment are quite different from those of human limbs. Also, patients in need of prosthetic limbs are required to go through very dangerous surgical procedures. Artificial hands have been used by humans for over a thousand years, which makes artificial limbs not a new technology. It was possible to accomplish certain daily tasks with artificial hands, although only to a limited extent, for people with no natural hands [2]. Traditionally, artificial hands have only been used cosmetically for the purpose of enhancing appearances. 4000 years ago, the first artificial prostheses were created. A book written between 3500 and 1800 B.C., the Vedas, mentions the first use of artificial prosthetics. A wooden and iron leg was substituted for Queen Vishpla's lost leg in the book. The wood and leather thumb of an Egyptian mummy was discovered in 2000 AD. Prostheses like these date back to the earliest days of human history.

Wherever Times is specified, Times Roman or Times New Roman may be used. If neither is available on your word processor, please use the font closest in appearance to Times. Avoid using bit-mapped fonts if possible. True-Type 1 or Open Type fonts are preferred. Please embed symbol fonts, as well, for math, etc.

Figure 1. An Artificial Toe found by Egypt

If one were to lose his or her hands, the thought of controlling a robotic replacement hand with his or her mind may sound like a fantastic idea at first. But what most people don't consider is the act of having to undergo serious surgery that involves the opening of the patient's skull and having to perform a potential deadly brain transplant, which are all required steps in order to obtain a robotic replacement hand [3]. Fortunately, researchers at the University of Minnesota have devised an alternative: a system that allows humans to move a robotic appendage through the sole use of their thoughts, and which does not require surgery or brain implants. It's a significant step forward in the development of non-invasive brain-computer interfaces (BCIs), which establish direct contact between the brain and an external device [4,5]. The purpose of the paper is to create a robot arm that could assist people with disabilities in their daily lives and make their work independent of others. It is for that purpose that the mind-controlled robotic arm was created. Some other objectives of this technology include identifying proper signals for detecting hand movements, using proper methodology for signal classification & analysis, development of artificial robot arms and controllers for them, and using brain signals to control the robot arm [6]. Robotic arms can be monitored using a variety of techniques. Below are the two most commonly used methods. When a person thinks about a specific action or expresses a facial expression, a device called an electroencephalogram (EEG) records their brain waves. Commands are generated based on these readings. Electroencephalograms can be used to record electrochemical impulses generated by the brain to control the mind's activities. Beta waves, for instance, have frequencies ranging from 13 to 60 Hertz when an individual feels anxious or scared [6,7]. People produce alpha waves, which range in frequency between 7 and 13 Hertz, when they are mentally and physically comfortable. An unconscious person produces delta waves, on the other hand. The use of brain computer interfaces, a combination of hardware and software, allows for direct real-time processing of these EEG frequencies and data. Signal processing is being transformed by new technologies such as Brain-Computer Interfaces (BCI). As human and machine become increasingly intertwined, BCI assists in facilitating their evolution. The second process involves surgical implantation. A surgical attachment is made be- tween the arm and the individual's body. A nerve is often connected to read electrical signals for filtration and translation into commands using electrical signals [8]. An arm with sensors attached is used to take precise measurements as part of the control method. Sensors such as EMG, gyroscopes, and accelerometers are commonly used for these applications. Users will be able to locate their arms and their hands, as well as know where their arms should be. EEG signals were the main focus of this research. Brain activity can be tracked non- invasively with EEG [9]. Brain-computer interface (BCI) concepts are used to analyze EEG signals. For acquisition and processing of EEG signals, sophisticated environments are required since EEG signals have low amplitudes and low frequencies and are very sensitive to disturbances such as noise. This project requires the acquisition, amplification, and digitization of EEG signals, which will be analyzed and interpreted by a machine that can process the signals. The EEG approach is not only cost-effective but also reliable and gives the patient full control of his or her robotic arm. It also allows users the option of taking it off if they experience discomfort.

II. LITERATURE REVIEW

A. Brain Computer Interface

The potential of Brain Computer Interfaces (BCIs) explores in transforming the realm of signal processing. BCIs are

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sophisticated non-muscular communication pathways that allow humans to control automated systems such as robotic arms. These systems amalgamate technologies from diverse fields like electrical engineering, computer science, biomedical en- gineering, and neurosurgery. BCIs have the capability to monitor brain activity, interpret the acquired data, and convert this into output that can improve human activities [16]. The potential applications span from restoring lost functions like speech and voluntary move- ment, to enhancing neurological pathways for skills like grasping, to aiding as additional limbs [5]. The paper discusses different methods of assessing brain activity with BCIs, en- compassing invasive techniques like cortical electrode insertion to noninvasive techniques like scalp electroencephalography (EEG) electrodes. The ultimate objective of BCIs is to enhance human functions by monitoring and interpreting brain activity [17].

B. Brain Waves

It presents a comprehensive study on the evolution and prominence of the analysis industry in the past century. Emphasizing the measurement of brain's electrical signals, the re- search provides in-depth understanding of the application of ThinkGear technology-enabled headsets; specifically, their capability to quantify and render these analog signals into digital form [18-20]. Exploring further it provides key insights into the five major recognized brain waves, accompanied by a descriptive table outlining the respective frequencies and characteristic features of these waves.

TABLE I. FREQUENCIES GENERATED BY DIFFERENT TYPES OF ACTIVITIES IN THE BRAIN

Brainwave Type	Frequency Range	Mental States and Condition
Delta	0.1Hz to 3Hz	Deep, Dreamless, Unconscious, Sleep
Theta	4Hz to 7Hz	Deeply relaxed, Inward focused
Alpha	8Hz to 12Hz	Relaxed, but not drowsy, Tranquil, Conscious,
Low Beta	13Hz to 15Hz	Relaxed yet focused, Integrated
Midrange Beta	16Hz to 20Hz	Thinking, Aware of self & surroundings
High Beta	21Hz to 30Hz	Alertness, Agitation

C. ThinkGear Technology

Think Gear is the single dry sensor technology that have in each Neuro Sky product and those products can interface with the wearers' brainwaves. Think Gear Technology allows the measurements, amplification, filtering and analysis of EEG signals and brainwaves. TGAM was the chip that use Think Gear Technology [6,7]. Wired transmission was locked by the TGAM and can only use Bluetooth for data transmission. TGAM is the main part of our brainwave sensing technology. It is TGAM that allows Neuro Sky partners to bring EEG- based consumer technologies to the market, quickly and efficiently. Lastly note that the TGAM is the most popular EEG solution in the world [14].

D. Decision Tree Algorithm

The decision tree is a supervised classification technique that divides a complex problem into multiple sub problems and then recursively generates a tree from these sub problems. Each leaf node in a decision tree is assigned a class label, whereas non-terminal nodes, such as the root node and other internal nodes, include attribute testing requirements to distinguish records with distinct features [7]. A typical decision tree structure is shown in Figure 4. The decision nodes are the X variables. Each node has an attribute linked with it, and variables a and b denote the attributes' bounds, which divide the choice into three tree pathways that might be nominal or numerical. The Class variables represent the tree's leaves, which allow the object under investigation to be classified. [10] The decision tree method benefits those who have a simple knowledge and classification of the observed data set. Depending on the specified properties or features of the data set, the J48 or C4.5 method uses a basic if-else' based classification. An inverted tree representation is the result of a decision tree method, starting with the root or the attribute that contributes the most to categorization of the provided classes. The root is followed by branches that provide further information about the classification, and leaves are the classification's conclusion nodes. In a decision tree method, appropriate pruning factors and confidence factors are managed to achieve the best categorization output. In this case, the decision tree was generated with data set of alpha, beta, gamma, delta and theta signals that come from head. A model was created using a data set with all values. The reason for focusing on the decision tree is that its accuracy is high and it is very simple and easy to make prediction as it is divided into different sub groups.

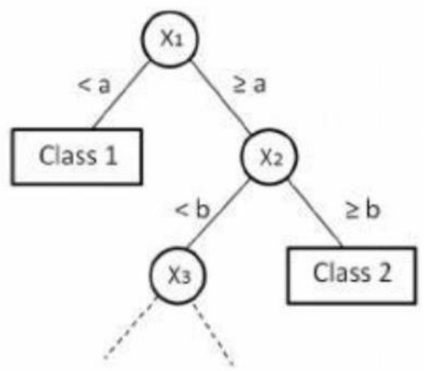

Figure. 2 Decision Tree Algorithm

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E. KNN Classifier

An in-depth analysis of the k-Nearest Neighbor (k-NN) classification method as a means to approximate the function locally and defer computation until function evaluation. The study illuminates the importance of normalizing the training data for improved performance when the features have varying scales. It further explores the effectiveness of assigning weights to the contributions of neighbors in both classification and regression strategies. These weights are typically computed as 1/d, reflecting the distance between neighbors. The neighbors, in turn, are chosen from a pool of objects with known class or property values - the training set of the algorithm. The system underscores the uniqueness of the k-NN method in exhibiting sensitivity to the local structure of the data it works with.

F. Linear Discriminant

Thoroughly investigated Linear Discriminant Analysis (LDA), a linear model primarily utilized for its classification and dimensionality reduction characteristics, and its specific use in feature extraction within the field of pattern classification. Proposed by Fisher in 1936, and subsequently expanded by C.R Rao for multiple class categorizations in 1948, the system analyses how LDA expertly reduces within-class variability and bolsters between- class variability via data projection from a D-dimensional space to a lesser D’ space. It specifically highlights LDA’s comparative benefits over logistic regression in instances of multiple classification problems with well-separated classes. Additionally, the paper delves into the use of LDA for data pre-processing in reducing feature numbers, mirroring the cost- cutting abilities of PCA, and its integral application within face detection methodology, especially in Fisher faces. Lastly, it examines the potent results of LDA when partnered with eigenfaces.

G. Gussian Filter

An in-depth study of Gaussian Processes (GPs), their generalization from the Gaussian probability distribution, and their crucial role in non-parametric machine learning algo-rithms for classification and regression tasks. Highlight the similarities between GPs and kernel models, with an emphasis on GPs’ distinctive ability to predict highly calibrated class membership probabilities. A significant aspect of this study is addressing the challenging task of selecting and configuring the kernel for GPs, which are critical for dictating how samples in the data associate with each other and control the data’s latent or "nuisance" function. As a comprehensive exploration, this system underscores the potential of GPs as a formidable machine learning algorithm for classification predictive modeling, given the appropriate specification of a kernel.

H. Logistic Regression

Logical regression is one of the types of parametric classification models that can be classified despite having the word regression in its name. Essentially, logistic regression models generate categorical predictions based on the amount of input features and depend on the amount of input features. Similar to Linear Regression, Logistic Regression works on the same principle.

III. SYSTEM SPECIFICATION

A. EEG Mindwave Headset

As mentioned above, it was decided to create a robot arm that controls the mind. While studying the system, its observed that our system needed an EEG module to retrieve data from the brain. Then, the sensor module types were studied, and first, a module with a single electrode was selected. That module is made in India. But according to our studies, we were able to find that it works with the eyes. Also, we found that its accuracy was very low compared to other modules. For these reasons, it became clear to us that the module did not fit into system. Then with the help of our supervisors, a module was selected with average accuracy and low cost. It is a neuro sky mind wave headset. It is because system budget exceeded its limit that we chose a module with average accuracy [8] [13].

B. Neurosky Mindwave Headset

In figure, the Mind Wave Headset was provided by Neuro Sky Technologies, and those signals were transferred using Bluetooth which was supported by the Mind wave headset. This system explores the utilization of a noninvasive, painless Mind wave headset fueled by a AAA battery. This technology, produced by NeuroSky, harnesses Brain-Computer Interface (BCI) for widespread application in industries as diverse as entertainment, education, auto- motive, and health. Reliable LED indicators track device activity, including power status, Bluetooth connectivity, and battery life. The Mind wave headset, underscoring innovation in neurotechnology, collects bio-signals via electroencephalography (EEG) and electromyog-raphy (EMG) technologies, employing a primary electrode connected to the forehead.

Figure. 3 Neurosky mindwave mobile 2

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Thus, this ground-breaking device models versatile, user-friendly BCI applications with immense potential for industry and neuroscience advancement. The electrode that connects with the forehead is showed in the figure below [6]. Cost effective and easy to use were the main advantages of this NeuroSky mindwave headset. The way the NeuroSky mindwave headset works is that the brainwaves from the brain are detected by the mind wave headset and sent to the device. It is illustrated as a diagram below [2].

1) 3D Printed Robot ARM:

The robot arm was designed in a three-dimensional shape. It was also used as a plastic material to make the hand. In spite of this, I had to face some problems while assembling the hand. One of them is that the operations of bending and stretching the fingers were not done properly. This is because the wires used for the fingers were not flexible. Therefore, it was decided to use thin wire for the system. The robot arm consists mainly of four servo motors used to move the fingers of the hand.

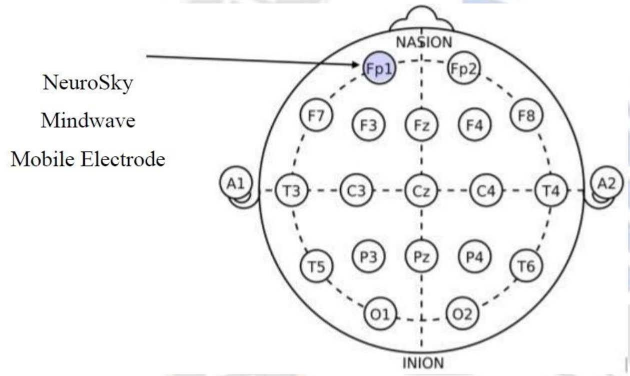

Figure. 4 NeuroSky Mindwave Mobile electrode position

All four of those servo motors are connected to the fingers. MG90S micro servo motors were used for this system, although we used SG90 servo motors in the beginning. Due to the low power of the SG90 servo motors, we had to use MG90 type servo motors [12]. The MG90S is an upgrade version of the SG90 with even more torque and speed than the previous version. Also, the MG90S has a metal cover which means when the motor is in a jam, the gears are not likely to strip. The MG90S micro servo is rotated up to 180 degrees and these micro servos are much smaller and can fit into tighter spaces. Even though it has metal gears, the MG90 servo weights only 13.4g, which is one of the reasons for choosing these servo motors for the system. Each servo motor comes with 3 arms and 3 screws along with female wires.

- Color code of the three female wires
- PWM (Signal) is Orange
- VCC (Power) is Red
- GND (Ground) is Brown
- Specifications:

i) Weight: 13.4g
ii) Dimension: 22.8*12.2*28.5mm
iii) Stall torque: 1.8kg/cm(4.8V)2.2kg/cm(6V)
iv) Operating speed: 0.1sec/60degree (4.8v), 0.08sec/ 60degree (6v)
v) Operating voltage: 4.8-6.0V
vi) Dead band width: 5us

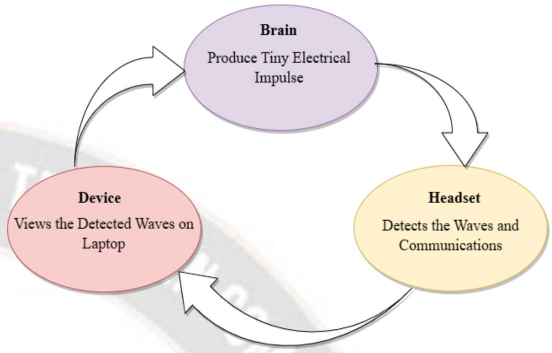

Figure. 5 Working of Neurosky mindwave headset

The ATmega 2560 microcontroller was used to help control the servo motors. The At- mega 2560 microprocessor is used in the Arduino Mega board, which is an opensource microcontroller board. The processing or wiring language is executed by this board's grow- ing environment. With their simple to use platform, these boards have re-energized the automation sector, allowing anyone with only a limited or even no technical background to begin learning the essential skills to program and run the Arduino board. The Arduino mega board only functions as a controller in this system. That is, it only executes servos according to the commands received by the Arduino IDE.

2) Laptop: The laptop was used for receiving the signal, analyzing the signal, and sending the signal commands to the Arduino board. The Python platform was used for all these processes. The laptop is used by NeuroSky Mind wave Headset as a platform to run Python code in order to collect the raw brainwave signals. Python code was used to collect the real time raw brainwave data which aids in controlling the robotic arm. After the acquiring of the raw brainwaves process was done, all the data was sent to the microcontroller by laptop.

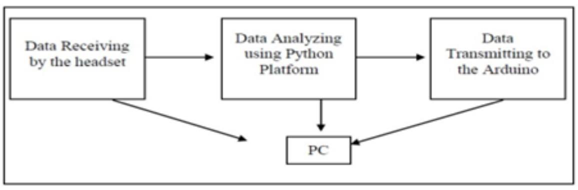

Figure. 6 Signal Processing Unit

3) Arduino IDE: Servo code was used by me to track if the servo motors work properly. In the first case, only two servo motors were used. One servo motor was used for the thumb

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finger and a single servo motor for the other four fingers. All in all, four servo motors were used for final system. First a piece of code was created using the Arduino IDE to check the servo motors. The library <servo.h> was used for this purpose. The servo motors were connected to the digital pins 8, 9, 10 and 11 on the Arduino board. A 5V voltage was also connected to the red wires of the four servo motors. In addition, the ground pin of the Arduino was connected to the brown wire of the servo motors and the orange wires of the servo motors were connected to the D8, D9, D10 and D11 pins of the Arduino. The servo motors were then checked to create servo code and finger movements were monitored.

C. Neurosky Mindwave Headset

The main part of this system is the signal analyzing process. It was tested in several ways and the signal analyzing process was done with the most accurate method. A detailed description of all these methods are given below:

1) Method 1: According to a literature survey, many scientists have found that signal acquisition is done through MATLAB, and MATLAB graphs have been obtained using that concept. First an Amplitude Vs Time chart was obtained. It was obtained by raising the right hand and left hand. This can be described as the first step in this system. The chart is shown below [2]

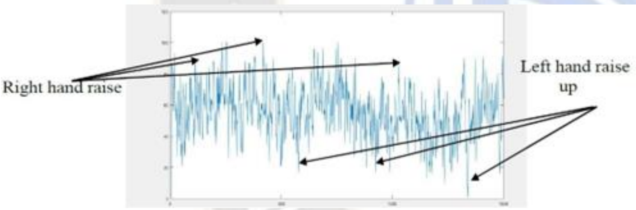

Figure. 7 Amplitude vs Time

But no threshold value can be taken from this graph. Therefore, brain signal graphs were taken as frequency vs amplitude. The discrete Fourier series method was used to convert time to frequency. The discrete Fourier transform (DFT) is a complex valued function of frequency that turns a finite sequence of equally-spaced samples of a function into a same- length sequence of equally-spaced samples of the discrete time Fourier transform (DTFT). The sampling interval for the DTFT is the reciprocal of the input sequence's duration. The DTFT samples are used as coefficients of complex sinusoids at the relevant DTFT frequencies in an inverse DFT, which is a Fourier series. The graph is also shown below [9]

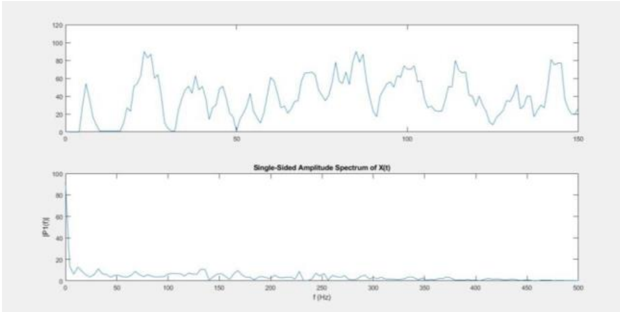

Figure. 8 Amplitude vs frequency Spectrum

Here too, a specific threshold value could not be obtained. The main reason for the failure of this method was the inability to find a threshold value. For this reason, another method had to be found to analyze the signal. Accordingly, the focus was on the 2nd method.

2) Method 2: After many studies, the Python Platform was selected for the system. The main reason for choosing it is that Python is more familiar than MATLAB and many researchers have done their researches through Python. The first step in Python was to use two frequency values from a literature survey. That is, one value for extending the fingers and another for bending the fingers. This step focused mainly on the two stages as the attention and meditation. The two ranges were obtained as below 70 for finger opening and above 69 for finger closing. Similarly, attention level was obtained for finger closing and meditation level was also used for finger opening. Those ranges are given below,

TABLE II. ATTENTION AND MEDITATION LEVEL

Actions	Range Assigned
Flexion (Closing Fingers)	69 above
Extension (Opening Fingers)	70 below

The output of this method is not clear. That is, the stretching and bending of the hand is not controlled by the mind. For this reason, the values of separate attention and meditation were observed. The received values are as follows.


[{'Time': 1618837638.9846826, 'Attention': '11', 'Meditation': '23'
[{'Time': 1618837639.0076234, 'Attention': '11', 'Meditation': '23'
[{'Time': 1618837639.0206127, 'Attention': '37', 'Meditation': '38'
[{'Time': 1618837640.006948, 'Attention': '48', 'Meditation': '43',
[{'Time': 1618837641.050188, 'Attention': '44', 'Meditation': '27',
[{'Time': 1618837642.0527995, 'Attention': '30', 'Meditation': '27'
[{'Time': 1618837643.0559404, 'Attention': '10', 'Meditation': '30'
[{'Time': 1618837644.0123599, 'Attention': '7', 'Meditation': '23',
[{'Time': 1618837644.203838, 'Attention': '7', 'Meditation': '23',
[{'Time': 1618837645.2230656, 'Attention': '7', 'Meditation': '23',
[{'Time': 1618837646.236438, 'Attention': '35', 'Meditation': '27',
[{'Time': 1618837646.2793221, 'Attention': '41', 'Meditation': '14'
[{'Time': 1618837648.0013962, 'Attention': '64', 'Meditation': '20'
[{'Time': 1618837648.921932, 'Attention': '64', 'Meditation': '20',

[{'Time': 1618837649.941377, 'Attention': '64', 'Meditation': '20',
[{'Time': 1618837649.9513485, 'Attention': '64', 'Meditation': '20'
[{'Time': 1618837649.9613223, 'Attention': '57', 'Meditation': '26'
[{'Time': 1618837650.0421066, 'Attention': '53', 'Meditation': '41'
[{'Time': 1618837651.9931505, 'Attention': '35', 'Meditation': '48'

Figure. 9 Attention Meditation level of Headset output

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It is clear from the figure above that the two values of the above type are not obtained. That is, the range of attention and meditation varies in each case. One exact value is not available. Therefore our output was not successful.

3) Method 3:

Due to the shortcomings of the above step, another method had to be found. The previous method focused mainly on attention and meditation levels. In the study of attention and meditation levels, it was observed that these levels can be divided into several sub- sections. Accordingly, in the study of those subdivisions, it was identified that brain signals can be divided into four main signals. Namely alpha, beta, gamma and delta. After focusing on all these signal levels, we focused on making a manual prediction. That is, the value ranges were manually obtained for the above alpha, beta, gamma and delta. This system is primarily concerned with attention. According to brain signals, beta signals provide attention-related values. Also, the values related to the relaxation period should be obtained here. The range of values for both cases is given below. After obtaining a data set, the beta signals were manually analyzed and a range of values was taken. The range of those values is as follows. But even these steps did not successfully bend or extend the arm. Therefore, the focus was on all brain signals, namely alpha, beta, gamma and delta. That is, values were obtained:

TABLE III. ALPHA AND BETA FREQUENCIES

Type	Frequency Range	Mental States and Conditions
Alpha	8Hz to 12Hz	Relaxed, but not drowsy, Tranquil, Conscious, passive attention
Low Beta	13Hz to 15Hz	Relaxed yet focused, Integrated
Midrange Beta	16Hz to 20Hz	Thinking, Aware of self & surroundings
High Beta	21Hz to 30Hz	Alertness, Agitation

```
if((betaInt>25)and(betaInt<30)):
    print("Open")
    ser.write(str.encode('a'));
    time.sleep(1)

if((betaInt>10)and(betaInt<15)):
    print("Close")
    ser.write(str.encode('c'));
    time.sleep(1)
```

Figure. 10 Manually selected Beta Range

for all ranges. In this step all ranges were obtained comparatively manually. The values thus obtained are given below:

```
config = {
      'lowGamma': [17],
      'highGamma': [82],
      'highAlpha': [17-55],
      'delta': [4-10],
      'highBeta': [12],
      'lowAlpha': [18-84],
      'lowBeta': [15],
      'theta': [77]
}

# 0 - close ? 1 - Open

predict_mpg(config, model)
array([0])
```

Figure. 11 Manually selected Data Range

This figure shows the ranges related to finger closing. The array 0 is called as a finger closing situation. But in both cases the fingers did not work properly. That is, the robotic arm was activated without our control. In all three steps 1, 2 and 3 above, maximum effort was made to activate the robot arm with threshold values. But as mentioned above, all three steps failed. For this reason, another step had to be taken.

4) Method 4:

Signal values for finger movements from the brain were stored with the help of a CSV file. The unwanted signal between those values was then deleted and a data pre process was performed. A model was created using the file with the new values created by deleting that unwanted signal. The decision tree algorithm was used for that model. Created a data set with values related to alpha, beta, gamma, delta and theta EEG signals. The model was created using the values obtained for the alpha, beta, gamma, delta and theta as inputs. Divide those values into different roots and finally give two binary values, one or zero, as the output. That is, the command zero is given for bending the fingers and the command one is given for extending the fingers. Since we could not determine the values related to the roots of the decision tree, we created a decision tray algorithm through the python platform. But the values in those graphs were so complex that it was difficult for us to understand [3,4]. The reason for using this algorithm is that the accuracy of this algorithm is higher than other algorithms. 70% of the data set was used as training data and 30% as testing data. Algorithms were trained using that training data set. After training the algorithm by the training data set, the accuracy of the model is determined using the testing data set. Thus, after calculating the accuracy of each algorithm, the most accurate algorithm was selected for model creation.

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IV. DECISION TREE CLASSIFIER

In the first case, the model was created using the decision tree classification algorithm, and in the end, the accuracy check was 84.28%. It is as follows,

```
In [15]:  from sklearn.tree import DecisionTreeClassifier
          model = DecisionTreeClassifier()

          # model training
          model.fit(x_train, y_train)
Out[15]: DecisionTreeClassifier()

In [16]:  # print metric to get performance
          print("Accuracy: ",model.score(x_test, y_test) * 100)
Accuracy:   84.28571428571429
```

Figure. 12 Decision Tree algorithm Accuracy

A. Neighbours Classifier:

Unsatisfied with the decision tree classifier, the model was also trained using the K Neighbors classifier. It is as follows,

```
In [15]:  #from sklearn.tree import DecisionTreeClassifier
          from sklearn.neighbors import KNeighborsClassifier
          #model = DecisionTreeClassifier()
          model = KNeighborsClassifier()
          # model training
          model.fit(x_train, y_train)
Out[15]: KNeighborsClassifier()

In [16]:  # print metric to get performance
          print("Accuracy: ",model.score(x_test, y_test) * 100)
Accuracy:   71.42857142857143
```

Figure. 13 K-Neighbors Classifier Accuracy

1) Linear Discriminant:

Model accuracy was also monitored using a linear discriminant algorithm also. The accuracy check was 75.71% and it was shown as follow,

```
In [36]:  #from sklearn.tree import DecisionTreeClassifier
          from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
          #model = DecisionTreeClassifier()
          model = LinearDiscriminantAnalysis()
          # model training
          model.fit(x_train, y_train)
Out[36]: LinearDiscriminantAnalysis()

In [37]:  # print metric to get performance
          print("Accuracy: ",model.score(x_test, y_test) * 100)
Accuracy:   75.71428571428571
```

Figure. 14 Linear Regression Accuracy

2) Logistic Regrssion:

Unsatisfied with the decision tree classifier, the model was also trained using the Logistic Regression classifier. It is as follows, After focusing on all these algorithms, the model was created using the higher accuracy algorithm which is decision tree algorithm. After creating the model, it remains as a memory in the computer. Then when new data is received by the computer through the headset, the model makes a prediction. In that comparison, if the new data matches the values of the model, either finger closing or finger opening occurs.

```
In [78]:  #from sklearn.tree import DecisionTreeClassifier
          from sklearn.linear_model import LogisticRegression
          #model = DecisionTreeClassifier()
          model = LogisticRegression()
          # model training
          model.fit(x_train, y_train)
Out[78]: LogisticRegression()

In [79]:  # print metric to get performance
          print("Accuracy: ",model.score(x_test, y_test) * 100)
Accuracy:   67.14285714285714
```

Figure. 15 Logistic Regression Accuracy

V. FINAL SPECIFICATION

A Neuro Sky mind wave headset was used to receive signals from the brain. The model was created using a data set through the Python platform and the data was analyzed using that model. The data received after the comparison is sequentially transferred to the Arduino IDE. The servo motor is then activated using the Arduino IDE. The block diagram of the system is shown below [7]. As mentioned above, the system consists of three main parts. As part of hardware implementation, software implementation and signal analysing. In terms of hardware implementation, the focus was on the Arduino board, mind wave headset, and servo motors. Choosing the right and low cost headset for the system was a big challenge. The Neuro Sky mind wave headset, five SG 90 servo motors and an Arduino mega board are the main hardware components used in the system. The other part is the software part. The python platform is used as the main software. In addition, servo motors were checked using the Arduino IDE. The telnet library was used to connect the headset to the Python platform. All raw data is displayed in JSON format. All data is recorded in an excel file for easy for the data analysis. The software part can be mentioned as another important part of the system. Python and Arduino IDE are the main software used for the system. In addition, the MATLAB platform was used in the first step for signal analyzing. In this case, python was used to receive, analyze and classify the signal, while Arduino IDE was used to control the servo motors.

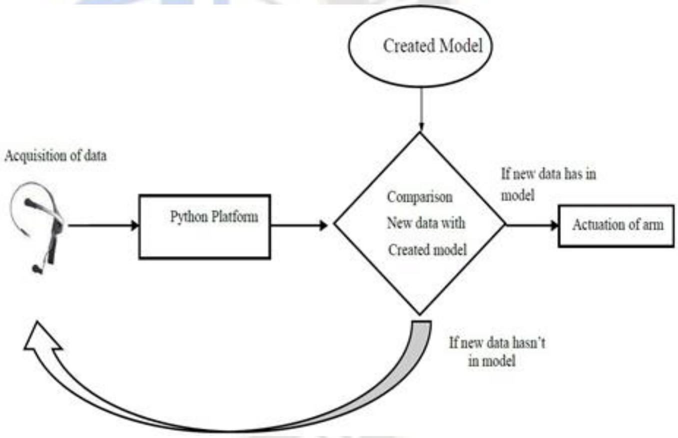

Figure. 16 Block Diagram of the System

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VI. RESULTS AND DISCUSSION

The development of this robotic arm have achieved great attention because they enhanced disable people for their facility of life. The main section of system was the signal analyzing part. We performed the signal analyzing part in mainly four ways. After studying all those methods, the most accurate method was chosen.

A. Method 1:

As mentioned above, the first step was to analyze the selected MATLAB graphs without success. That is, no successful threshold value could be found. Therefore the focus shifted to another method.

B. Method 2:

Due to the inability to find a threshold value in method 01, attention was drawn to the second step. That is, the focus was on finding a threshold value. Two threshold values were found according to the research papers. The focus was on activating the robot arm using those values. But the robot arm did not work properly.

C. Method 3:

Method 02 failed and was concerned about the 3rd method. That is, a data set was obtained and a manual prediction was made. The range of values for brain signals was obtained manually. Even if the hand was activated from those values, a successful output could not be obtained. The values as follows, According to our analysis, there were three main frequency ranges. These are high alpha, low alpha and beta.

```
config = {
    'lowGamma': [17],
    'highGamma': [82],
    'highAlpha': [17-55],
    'delta': [4-10],
    'highBeta': [12],
    'lowAlpha': [18-84],
    'lowBeta': [15],
    'theta': [77]
}

# 0 - close ? 1 - Open

predict_mpg(config, model)
```

```
array([0])
```

Figure. 17 Frequency Ranges

D. Method 4:

The work was unsuccessful as the accuracy of the third method was also very low. So a new method were implemented. That was, a data set is trained that from the CSV file and a model is created. For this method, About 233 data had been included in to the CSV file. The model that was created has an accuracy of 92% and this method was found by us to be more successful than both of the above methods. So in the end this method is used to built model. For that decision tree classification algorithm used to train model.

```
In [15]:
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()

# model training
model.fit(x_train, y_train)

Out[15]: DecisionTreeClassifier()

In [16]:
# print metric to get performance
print("Accuracy: ",model.score(x_test, y_test) * 100)

Accuracy:  84.28571428571429
```

Figure. 18 Train Model Accuracy

VII. CONCLUSION AND FUTURE SCOPE

There are a lot of people in the world who had lost limbs and there are a lot of experts and inventors who are trying to create artificial limbs as an alternative. The first is an arm that was processed using an electrolytic signal, and the second is a prosthetic arm that is made using a surgical implant. But today, many inventors around the world are turning to EEG technology because it was cost effective and easy-to-use method. The main objective of this proposed system was to create an artificial hand that can be controlled by the mind, for which we EEG technology was decided to use for our system. The robot arm were inspired to create using 3D printing technology, and we were mainly focused on hand movements only. An Arduino Mega board was used just to activate the servo motor in this artificial arm. In the future, this robot arm will be able to upgrade by us and can be show the movements of other parts of the hand as well. If high capacity servo motors can be used then a robot arm can be updated by us to lift more weight by performing more finger movements. Although the prosthetic arm was designed as described above, the basic element it requires was how to create an artificial arm to control with the EEG data that obtained by the brain. For that, NeuroSky Mindwave Headset was decided to use as a sensor module in the brain. The EEG data related to the electrical activities that take place in our mind was transmitted to our laptop using a Bluetooth medium. In order to complete a task, The complexity of the task was need to reduce or increased the effective productivity of our classification system. For that we can be further improve the system by adding more data and using different optimization methods to increase the data rating of the range. This means that the most accurate data can be obtained if a module with large electrodes is used. A single electrode module was used by us for the system. Because it was a cost effective module. Our mind was need to train much to increase the accuracy of the line data that comes with this. This gives the user the ability to more accurately control the hand that was created. If the module with large number of electrodes was used a very accurate data classification can be get and give the user the ability to successfully control the artificial hand successfully in a real world situation.

REFERENCES

[1] S, Jung CW. Wearable fabric antenna on upper arm for MedRadio band applications with Beam capability. Electronics Letters 2015;51:1314–6. :10.1049/.2015.2105.

[2] TL, G, M, D. Design of a wearable interface for lightweight robotic arm for people with mobility impairments. 2017 International Conference on Rehabilitation Robotics (ICORR) 2017. :10.1109/.2017.8009471.

[3] Elastically Actuated Small Robotic Arm for CubeSat Platforms 2021. :10.2514/6.2021- 4168.

[4] K, Suzuki K. Gesture based robotic arm control for Meal Time Care using a wear- able sensory jacket. 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS) 2016. :10.1109/iris.2016.8066077.

[5] Anand, L., Rane, K.P., Bewoor, L.A., Bangare, J.L., Surve, J., Raghunath, M.P., Sankaran, K.S., Osei, B.: Development of machine learning and medical enabled multimodal for segmentation and classification of brain tumor using MRI images. Computational Intelligence and Neuroscience. 2022, 1–8 (2022).

[6] P, P, K, J, Hughes M, Yang G-Z. Three-dimensional robotic-assisted with a force adap- tive robotic arm. 2017 IEEE International Conference on Robotics and Automation (ICRA) 2017. :10.1109/.2017.7989276.

[7] PD, C. Robotic Force amplification with free space motion capability. 2014 IEEE International Conference on Robotics and Automation (ICRA) 2014.10.1109/.2014.6906600.

[8] A, Sanchez B. Long Reach Robotic Arm 2020. :10.2172/1668389.

[9] Kolli, C.S., Raghunath, M.P., Meenakshi, S., Maheswari, K., Britto, C.F., Kushwaha, S.: Efficient development of supervised learning algorithm for Kidney Stone Prediction. 2022 International Conference on Inventive Computation Technologies (ICICT). (2022).

[10] Nguyen P, P. Towards the design of a soft robotic third arm for Assisted Living Tasks. 2017 International Symposium on Wearable Robotics and Rehabilitation (WeRob) 2017. :10.1109/.2017.8383814.

[11] M, M, A, J. I need a third arm! body-based interactions with a wearable robotic arm. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems 2023. :10.1145/3544548.3581184.

[12] Bhosale, J.D., Thorat, S.S., Pancholi, P.V., Mutkule, P.R.: Machine learning-based algorithms for the detection of leaf disease in agriculture crops. International Journal on Recent and Innovation Trends in Computing and Communication. 11, 45–50 (2023).

[13] Clark JP, G, F, MG, M, O' MK. On the role of wearable for force feedback in control for dual-arm robotic . 2019 International Conference on Robotics and Automation (ICRA) 2019. :10.1109/.2019.8793652.

[14] Low latency prefix accumulation driven compound MAC unit for efficient FIR filter implementation. Journal of Scientific ; Industrial Research 2020;79. :10.56042/.v79i2.68450.

[15] Abidin, S., Prasad Raghunath, M., Rajasekar, P., Kumar, A., Ghosal, D., Ishrat, M.: Identification of disease based on symptoms by employing ML. 2022 International Conference on Inventive Computation Technologies (ICICT). (2022).

[16] Singh TC, M. Design and Implementation of Two-Dimensional & Parallel FIR Filter Architectures 2022. :10.21203/rs.3.rs-1678777/v1.

[17] Thommandru, A., Mutkule, P., Bandi, A., Tongkachok, K.: Towards applicability of artificial intelligence in healthcare, banking and education sector. ECS Transactions. 107, 16665–16671 (2022).

[18] Singh, S. ., Wable, S. ., & Kharose, P. . (2021). A Review Of E-Voting System Based on Blockchain Technology. International Journal of New Practices in Management and Engineering, 10(04), 09–13. https://doi.org/10.17762/ijnpme.v10i04.125

[19] Ali Raad Mohammed, Sepanta Naimi. (2023). The Effectiveness of Thermal Insulation of the Exterior Composite Walls of Buildings in Iraq Based on Different Materials and Climate Regions using Engineering Applications. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 594–601. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2731

[20] Q, J, Wu J, Y, Wang H. Design and implementation of GNSS disciplined clock based on unbiased FIR filter. 3rd International Conference on Control Technology and Trans- portation 2018. :10.5220/0006969903180322.

[21] Andrew Hernandez, Stephen Wright, Yosef Ben-David, Rodrigo Costa, David Botha. Optimizing Resource Allocation using Machine Learning in Decision Science. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/195

[22] G. Design and Implementation of Programmable FIR Filter in FPGA 2021. :10.32920/.14661276.

[23] W, Sun F, L, Wang Y, Song L, Shi J. Path loss model for wearable robotic arm system at MHz Band. 2022 IEEE 22nd International Conference on Communication Technology (ICCT) 2022. :10.1109/icct56141.2022.10073232.

[24] Paul Garcia, Anthony Walker, Luis Gonzalez, Carlos Pérez, Luis Pérez. Improving Question Generation and Answering Systems with Machine Learning. Kuwait Journal of Machine Learning, 2(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/187

[25] H, V, S. Applying force perturbations using a wearable robotic neck brace. 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2020. 10.1109/iros45743.2020.9340638.

[26] V, Hoffman G. Wearing your arm on your sleeve: Studying usage contexts for a wear- able robotic forearm. 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN) 2017. :10.1109/roman.2017.8172421.

[27] A, A. A 2D-CNN-SCALOGRAM based approach to classify the mental tasks using EEG signals. 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS) 2022. :10.1109/iciccs53718.2022.9787994.

[28] Raghunath, M.P., Ankayarkanni, B.: An empirical review on brain tumor classification approaches. Information Systems and Management Science. 15–27 (2022).

[29] Zhan Hong L, A, Victor J, Thing GT. EEG-based Brain Wave Controlled Intelligent Prosthetic Arm. 2020 IEEE 8th Conference

on Systems, Process and Control (ICSPC) 2020. :10.1109/icspc50992.2020.9305784.
[30] A, M, E, M. An EEG and FTCD based BCI for control. 2016 50th Asilomar Conference on Signals, Systems and Computers 2016. :10.1109/.2016.7869581.
[31] S, Y. A novel classification strategy of motor imagery EEG signals utilizing WT-PSR-SVD-based MTSVM. Expert Systems with Applications 2022;199:116901. :10.1016/j..2022.116901.
[32] AK, G,Ann based feature extraction from EEG test signals in generating control com- mands for prosthetic application. 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon) 2022. :10.1109/mysurucon55714.2022.9972535.