Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

Intelligent Bio Robotic Arm For Mapping Signal Control And Synchronisation For Motor Control System Using Human Computer Interface.

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Cite this paper as: Anuj Singh, Sachin Sharma, Kamlesh Chandra Purohit (2024) Intelligent Bio Robotic Arm For Mapping Signal Control And Synchronisation For Motor Control System Using Human Computer Interface. *Frontiers in Health Informatics, 13* (3), 1923-1936

Abstract:

Humans rely so heavily on their hands to do everyday activities, communicate, and show emotion that losing a hand might make you feel as though you have lost your entire sense of independence. There are several excellent prosthetic hands available today that offer extraordinary movement flexibility. Because they are difficult to operate, they aren't used to their full potential. They can almost match the whole range of motion of the natural hand. In the proposed model, we are aiming to achieve natural intuitive control of prosthetic hands by using electrical activity in the surviving muscles to send control signals to the motors of the prosthetic hands. However, the number of signals you can record is constrained, limiting the movements you can make. In addition, the lack of feeling or feedback provided to the user results in unnatural control, as users lack the sense of touch and force on the hands. This suggests that controlling the gadgets requires a great deal of concentration and is not especially natural. Therefore, to enhance prosthetic hand control, we use machine learning modelling with smart cameras. From the recorded muscle signals, artificial intelligence may infer how the missing hand would naturally move. These movement commands can then be processed using real-time object detection and sent to the prosthetic hand. This method has the benefit that by considering information about the biomechanics of the hand, we can predict what users are trying to accomplish more accurately. Additionally, the model created is straightforward, so there is no need for special mental training to carry out simple activities. The accuracy of object grasping varies from 65% (Minimum) to 85 % (maximum). The cost of this proposed model is less as compared to the models available in the market or the researchers proposed.

Keywords: *Python, Machine learning, open CV, camera, Motor controlled devices, 3D printed Prosthetic arm, Electromyography (EMG), Raspberry Pi, Arduino, AD8226-based EMG, Arduino IDE.*

1. Introduction:

According to the WHO, one billion people worldwide are disabled. With up to 190 million (3.8%) people aged 15 and up facing significant functional problems and regularly needing medical care, this translates to more than 15% of the world's population. Disability is on the rise as a result of aging populations and chronic health issues. Due to their impairment, people with disabilities often encounter several human rights violations, such as acts of violence, abuse, prejudice, and contempt, which are related to other types of discrimination based on factors like age and gender, among others. Disability is the outcome of the interaction between a person's personal and environmental conditions and their health condition (such as depression, Down syndrome, or cerebral palsy) [1].

In the United States, 1.6 million persons have lost a limb, with upper limb amputees making up 35% of them [2] and transformer amputees accounting for 30% of those [3]. Amputees can resume activities of daily living including community, leisure, and even employment with prosthesis-based rehabilitation [4]. Bionic prosthetic hands are a fast developing field. Only a limited percentage of professionals working in highly specialised areas are now needed to have in-depth knowledge of this area of medicine. But as technology develops, it's conceivable that demand for and use of bionic hands may rise, calling for a deeper comprehension [5-8].

Electromyography (EMG), a medical examination, evaluates the condition of muscles and nerve cells. These cells cause the muscles to contract or relax by sending electrical impulses to them. EMG analyses these impulses and displays the results as numbers or graphs. EMG is one of the diagnostic tools that doctors employ to check for potential muscular or nervous diseases. EMG sensors are also used in electronic devices that are controlled by muscles, such as servo motors and robotic arms, which are operated by muscle-like motions. The EMG graph from an AD8226-based EMG sensor is plotted using Arduino [9]. The instrumentation amplifier AD8226 is extensively used in sensor development. Gains range from one to one thousand. It is also widely used in industrial process control, bridge amplifiers, medical devices, and portable data-acquisition systems [11]. When we connect an AD8226-based EMG sensor to an Arduino Microcontroller and use the Arduino to map the electrical activity of a muscle area. Any muscle group, including the biceps, quadriceps, calves, and others, may be measured by the sensor. EMG signals have a voltage range of 50u to 30mV. Using the AD8266 sensor, which has a gain of up to 1000, EMG potentials may be amplified to the mV level. The instrumentation amplifier AD8226 amplifies, rectifies, and smoothest the EMG signals that are being "read." Muscles that are properly electrode and contract and relax create EMG potentials [13]. The sensor detects these potentials and amplifies them to measurable levels. The gain of the sensor board may be adjusted using an on-board potentiometer [14]. This work focus on the design and development of smart/intelligent arm.

2. Literature review:

The creation of prostheses laid the ground for a thriving engineering sector for many years. The first prostheses, which comprised of hooks for hand prostheses and peg legs for foot prostheses, were intended for simple practical use. Several different craftsmen, including blacksmiths, watchmakers, and locksmiths, produced more complex prosthesis over time to improve comfort and usefulness [22-24]. Aluminium and plastic provided the same functions but with lighter materials that were more comfortable for the amputee. These new materials took the place of steel and iron. Devices that include biological motions from the body may now perform a wide range of activities. Today, as robotic prosthetic options become increasingly popular, prostheses continue to evolve (Norton, 2009). The detailed critical review discussed below.

2.1 Critical literature review

The critical review is shown in Table 1

Table 1. Critical Review

Author /year	What was done	How it was done	What is the outcome/ limitations

Junyou Yang,et al. 2016[30]	The BCI system was created and implemented to enable prostheses control. It makes use of electrooculography (EOG) and electroencephalography (EEG), as well as an SVM and a number of command instructions.	The EEG frequency range was selected using the common spatial pattern (CSP) method, and after that, a support vector machine (SVM) was built to determine the characteristics of the data. In order to increase the hybrid BCI's effectiveness, the ERS/ERD EEG signals and the EOG signals arising from visual attention were both simultaneously given as the input. In a lab context, the proposed method was assessed utilising a versatile robotic prosthesis.	Despite the benefits of EOG and EEG, the system's overall recognition rate is just 91.1 percent.
Rinku Roy, et al. 2016[29]	For the path planning of an EEG-driven robotic arm, a genetic technique is presented in this paper.	Using an SVM with the variables Power feature co-efficient and Wavelet co-efficient, the left-right hand movement was identified. Five healthy individuals provided motor imagery EEG data. Utilizing Matlab, the GA method and EEG processing were created.	The goal of this research work is to design a path for an EEG-controlled the robotic arm. Only 75.77% of the left-to-right arm movement could be correctly classified.
Daniel Elstob, and Emanuele L. S. 2016[28]	They suggested two software frameworks for controlling a robotic and prosthetic hand with five degrees of freedom.	The taught actions of the Emotionally evocative Cognitive Suite, the original framework, may be utilised to control the hand when it is combined with an embedded software system (an open source Arduino board). in the second structure. The latter enabled EEG signals to be trained and classified for tasks involving motor imaging. When the system is analysed, an accuracy measurement, a confusion matrix, and a feedback bar that shows signal intensity are used to produce unambiguous visual representations of efficiency and accuracy in the findings.	The usefulness of the suggested framework was predicated on the viability of using brain signals to control the selected prosthesis.

Taha Beyrouthy, et al. 2016[27]	The earliest prototype of an intelligent, mind-controlled bionic arm created via 3D printing is the main subject of this study.	The patient receives informed feedback about their surroundings and the thing they are in contact with through the arm's network of sophisticated sensors and actuators. An electroencephalography (EEG) headset records brain impulses that are used to control the arm. This network facilitates smooth arm motions, quick reflexes, and regular hand movements. Temperature, pressure, proximity sensors using ultrasonic waves, accelerometers, potentiometers, strain gauges, and gyroscopes are just a few of the many different types of sensors that are employed.	Despite the product's low cost, the technology is not sophisticated. Since the sensor data is not being analysed using artificial intelligence (AI) or any other methods.
Anderson H M, et al.2017[25]	EEG signals have been used to drive a hybrid arm prosthesis..	The signals provided by a headset that reads brain activity were processed by a microprocessor inside the prosthesis.	In comparison to the expense of the existing prosthesis, they made inexpensive devices.
Orgil Chinbat, et al. 2018[21]	Develop an EEG based BCI prosthetic arm for disabled people in their regular activities.	Create a prosthetic arm with an EEG-based BCI to assist persons with disabilities in their daily tasks.	The planned work is not very effective at carrying out daily tasks..
O P Idowu, et al. 2018[20]	The signals produced by an EMG-based pattern recognition system weren't enough. Intelligent robotic (or prosthetic) control is required. Five distinct motor imagery Tasks were classified using a softmax layer after features were generated using a stacked autoencoder.	A strong learning algorithm that can manage the prosthetic arm while interacting with the environment must be used in order to develop an artificially intelligent (or prosthetics) device that would move objects smoothly with numerous degrees of freedom (DoF). However, it is impossible to develop a robot controller that can handle a range of tasks using the traditional machine learning technique of exploitation of handmade characteristics. As a result, they suggest a solid learning control that is based on the deep autoencoder's unsupervised learning technique.	This approach offered a practical means of operation and control for robotic (or prosthetic) devices.

Bhavesh P, et al. 2019[19]	The Brain-PC interface was created using a Brainwave external device to operate the arm prosthesis.	The brain wave signal's frequency was divided. The prosthesis was controlled by these signals, and static analysis was done to comprehend the behaviour of the arm joint.	They were unable to accurately manipulate the arm in order to finish all the movement jobs.
Isuru Ruhunage, et al. 2019[18]	Electromyography (EMG) and Electroencephalography (EEG) data were used to control transhumeral prosthesis hand motions.	A 6 DOF robotic prosthetic dubbed UOMPro and a 1 DOF elbow joint make up the prostheses utilised in this study. In this study, the hand ripping sequence is identified using a neural network (NN) classification of user-generated EEG motor imagery/motor movement-related data. When the EMG signals from the biceps and wrist muscles are categorised, the opening and shutting of the hand is then realised.	The movement control of the transhumeral prosthesis was demonstrated efficiently through a number of experiments.
Shihab Ahmed, et al. 2020[16]	In order to create a prosthesis that is affordable, this effort focuses on actuating prosthetic arms utilizing EEG (Electroencephalogram) signals using a modified classifier.	Utilizing the OpenBCI Ganglion board, EEG data is gathered. The OpenBCI ganglion is a top-notch, reasonably priced biosensor. At 200 Hz, the data is sampled. Data is sent through Bluetooth from a device to a PC. SVM and Ensemble, two independent classifiers, are used to categorise these signals. The 3D-printed prosthetic was used in combination with controls..	The system's architecture was more complex. Despite using ML, the prosthesis must be straightforward and user-friendly.
Arsyad Cahya Subrata, et al. 2020[15]	They proposed a method to analyse and develop a framework for a prosthesis that uses extensively the signals generated by the brain (EEG) with the integration of ADL, FFT-SVM.	Prosthetic arm motion can be accomplished utilising EEG, which records the electrical movement of the brain. A system that can provide these demands when necessary is needed since the motion of gripping an item to perform ADL was difficult. The Motor Imagery (MI) on a Bionic Arm Using the Fast Fourier Transform (FFT) and Support Vector BMI (SVM). This combination results in a more precise operation of the prosthesis.	This system was developed to manage intricate movements involving many different objects, and it was tested for usage during prolonged pauses using the FFT-SVM

			combo and ADL.
Pranali Kokate, et al. 2021[12]	A novel technique was put out using a multi-layer perceptron neural network to categorise left- and right-hand motions.	For categorising left and right motions from EEG data, a novel method was given. EEG signals might pick up undesired signals and contaminants. Using ICA and a fresh method, pollution is successfully removed. When the feature vectors from both domains were used, the algorithm performed better. Different participants were validated using the intra-subject validation technique. compared to the deep learning model in terms of how the suggested model was implemented.	This technique used to control upper arm effectively.
Achim Buerkle, et al. 2021[11]	Intimate collaboration is made difficult by the limitations and rules that protect human operators. This is thus that safety systems often respond rather than foresee behaviours or intents. Predicting human behaviour is still a difficult task, despite the existence of probabilistic models that try to overcome these constraints. The objective of this job is to safeguard the person from protective harm brought on by prosthesis.	Upper-limb motion objectives can be assessed using a portable electroencephalogram (EEG). Up to 0.5 seconds prior to the onset of motor movements, the human brain continuously evaluates and assesses them. So that an expected movement may be forewarned of, a safety system could be improved. A unique data processing approach was proposed to identify EEG signals as quickly as feasible while minimising fine-tuning efforts. These require classifying movement intentions using Time Series K Means, and then training a Long Short-Term Memory Recurrent Neural Network with those categories (LSTM-RNN).	This was only tested on a human-robot collaboration setting, but it would be better if it had been evaluated on human and prosthetic interfaces as well.

2.2 Research Gap

The literature review is carried out to understand the new technological developments in prosthetic arm design. In this study we considered the research work carried out by the researchers for previous years. The following are the key findings in this review are as follows.

- The prostheses developed by the many researchers are manually working and the response time is too large and as well as operation these will be complicated for the end-user. That means a more intelligent can be designed.
- The intelligent interface can be established to control prostheses with an increase in Degrees of Freedom (DoF) of the prosthesis.

3. Purposed model of Artificial intelligence and object recognition:

The proposed model is shown in Figure 1. The proposed model working is explained in the following steps.

Step 1: The EMG sensor which is attached to the skin such that it can sense EMG waves of the arm and is connected through serial port Arduino to convert analogue signals into digital signals. These signals used for tensor-flow also well as Python (Raspberry Pi).

Step 2: In this step a camera is attached and based on the movement the real time images were feed into the Raspberry Pi that has installed raspbian.

Step 3: The signal from the EMG sensor and the real time data from camera were used to train the robotic arm movement through different object grasping.

Step 4: Once the objective in which is to be grasped id decided then the signals were sent to Arduino to control the servo motor which intern controls the bionic/robotic arm.

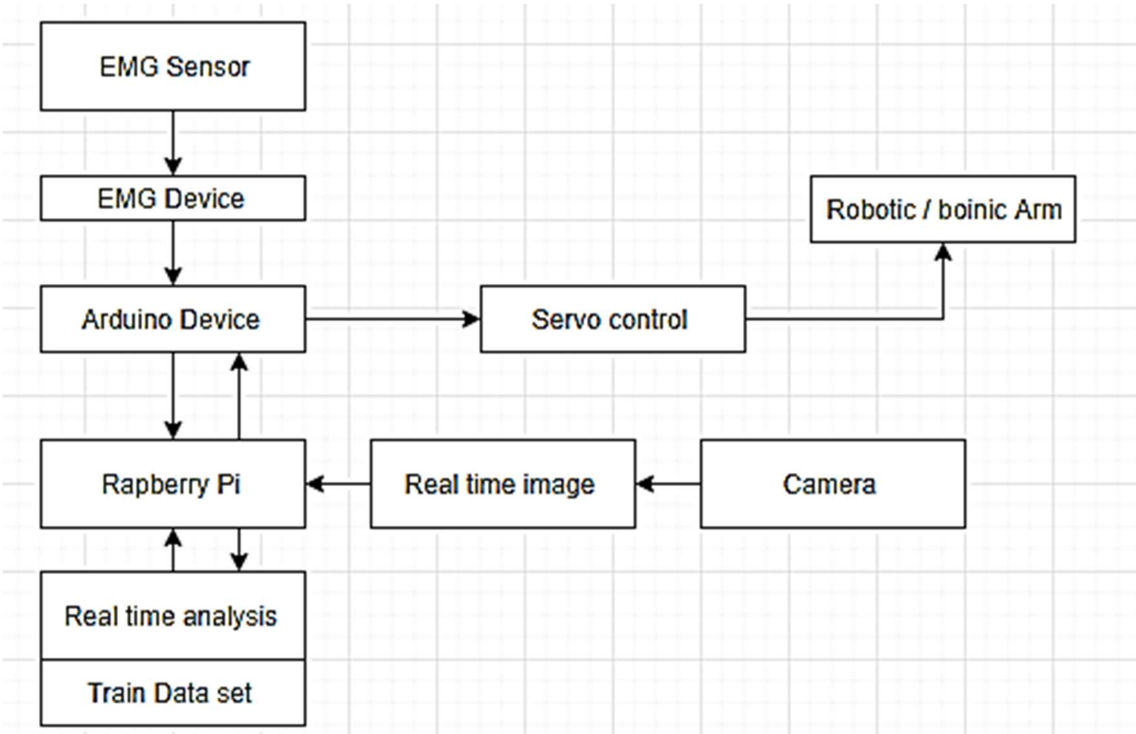


Figure 1. Proposed model

4. Experimental Result analysis and discussion:

The goal of the proposed research is to develop a low-cost, autonomous AI bionic hand utilising an EMG sensor and an Arduino board with a Raspberry Pi computer. Python programming and machine learning algorithms are utilised to communicate EMG data to the Raspberry Pi. Figure 2 shows the experimental setup.

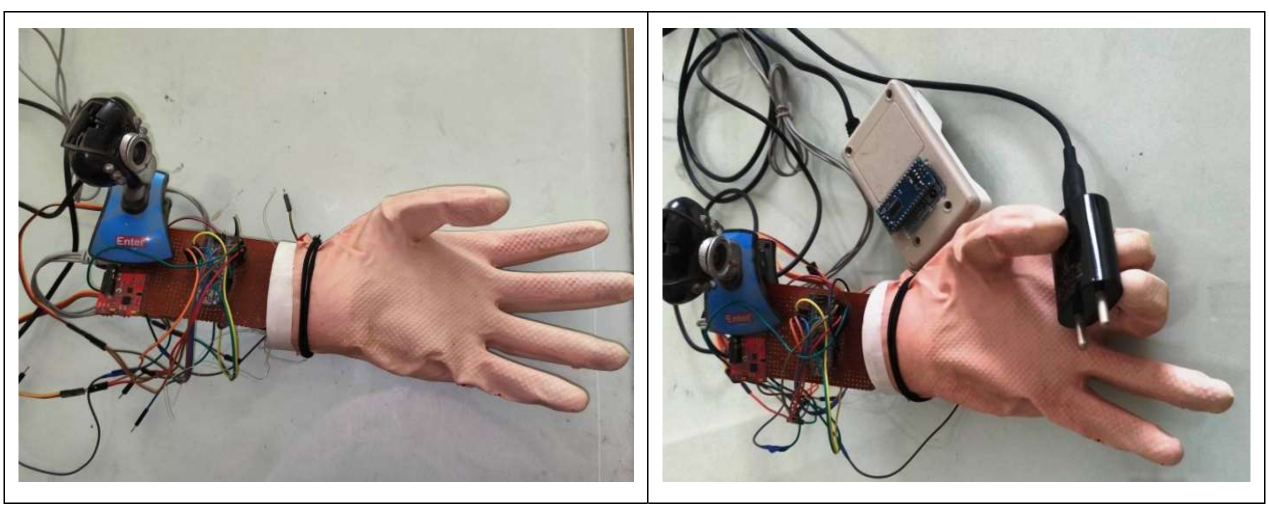


Figure 2 Experimental Setup

Frontiers in Health Informatics
ISSN-Online: 2676-7104
2024; Vol 13: Issue 3

The sensor is attached to a rubber band that expands and contracts to adjust its pressure on, and we connected using either a serial port or a bluetooth serial port.tensorflow and python to run on the skin in order to read better data from movement We'll utilise a Raspberry Pi that has installed raspbian. With already installed tensorflow and python platforms, with code accessibility through jupyter lab for convenience and for debugging purposes. Figure 3 shows the result of received dats and the procesed data.

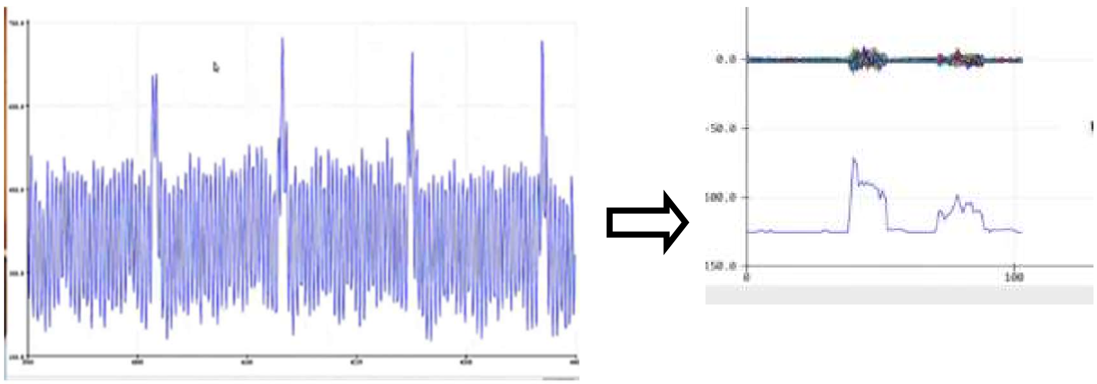
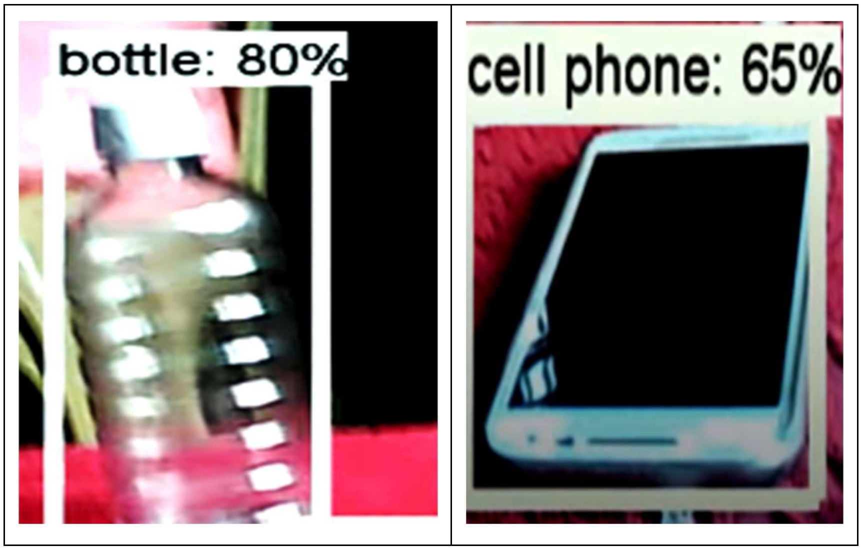


Figure 3 result of received dats and the procesed data

First, the sensor will be connected to an Arduino, which will then input data into a fast period transform, shrink the output to 128 to 8 numbers, and then write that over a serial port or a Bluetooth serial port to a Raspberry Pi. The training section and the testing section. The training section will use Python, which will input a text file containing sample data and its label and load the text file to create a multilayer perceptron (MLP)

The second part is the real-time analysis, which will also use Python, and here the script will receive the serial port the script will receive the serial data from arduino and it will read and then it will also load the saved model that was created previously by the training script and it will load the model and then this will apply the input data receive data to the model and make an assumption it will print out the name or label percentage using the model. Figure 3 (3a and 3b) shows the Accuracy of object grasping of Mobile phone and water bottle.



(4a) Water Bottle (4b) Water Bottle

Figure 4. Accuracy of object grasping (3a and 3b)

In this Experimental data we are using Microsoft Cocoa dataset, which contains approximately 300,000 images and 90 categories or classes, was used to train the tensor flow object detection API, which will be detecting a variety of objects that we use in our daily lives. Some of these classes, for example, include dog, mobile phone, clock, chair, teddy person, TV, laptop, etc. The CoCoa data set five different models the recognition detection model so one is a single-shot multitec to SST ,mobile net an SSD with inception, fully conversion based fully convolutional net ,RFC n with resonate and heart CN n with resident 1 0 1 and this v 1 faster RC n so this are the five data set and the speed and MEP MEP is a minimum average precision so higher lightweight one and has fast one it will be able to recognize any objects we have few exampal (Figure 1)objects like bottle, cellphone, cup and provides approx 65 to 80% accurate result to implement. The Table 2 shows the results with the finger movement and servomotor operation with accuracy of each object grasping. In the table 2 Where , S1 si servomotor 1 which is used to control F1 and F2, , S2 si servomotor 2 which is used to control F3 and F4 and where as S3 ia sermotor 3 is used to control T1. F1 is Index finger, F2 is middle finger, F3 is ring finger, F4 is little finger and T1 is Tumb

Table 2 Results

Real Time object recognition(label)	**Accuracy Percentage**	**Servo Motor (S1),(S2),(ST1)**	**Fingers Move (F1,F2)(T1)(F3,F4)**	**Servo Motors movement in Degrees**
Bottle	80%	S1,ST1	F1,F2,T1	0-90
Laptop	83%	S1,S2,ST1	F1,F2,F3,F4,T1	0-100

Cell Phone Charger	76%	S1,ST1	F1,F2,T1	0-95
Ball Pen	79%	S1,ST1	F1,F2,T1	0-140
Cell phone	65%	S1,S2,ST1	F1,F2,F3,F4,T1	0-120
Sport Ball	85%	S1,S2,ST1	F1,F2,F3,F4,T1	0-95
Mouse	73%	S1,S2,ST1	F1,F2,F3,F4,T1	0-90
TV	81%	S1,S2,ST1	F1,F2,F3,F4,T1	0-95
Chair	67%	S1,S2,ST1	F1,F2,F3,F4,T1	0-140
Book	69%	S1,S2,ST1	F1,F2,F3,F4,T1	0-120
Mouse	82%	S1,ST1	F1,F2,T1	0-90
Wristh watch	85%	S1,ST1	F1,F2,T1	0-140
Remort	76%	S1,ST1	F1,F2,T1	0-100

5. Challenges

The following are the challenges in the design and development of smart/intelligent bionic /robotic arm

- As we work on the heterogeneous type of environment. The devices are not the same, so there are challenges to make a standard for communication, security, and identification in the case of horizontal silos.
- The cost of the setup should be low so that everyone can achieve it. All the researchers are focusing to reduce the cost.
- One of the most significant concerns that the prior methods do not address is fault tolerance. The fault tolerance level must be extremely high to create a perfect system, ensuring that the system continues to function in the face of any hardware or software problem (such as a low battery, memory shortage, sensor interruptions, etc.). The battery running out of power or other factors, such the working environment, might cause the hardware components to malfunction.

6. Conclusion and future recommendation:

The following conclusions were drawn from this work

- The model developed is simple and there is no requirement of mental training to perform the simple tasks.
- The accuracy of object grasping varies from 65% (Minimum) to 85 % (maximum).

- The cost of this proposed model is less as compared to the models available in the market or the researchers proposed.
- Further there is a scope for developing the most cost effective and more intelligent model for the disabled and for the under developing countries.
- The security of such devices must be of great concern. There is a need of security system to protect these devices from cyber-attacks by including encrypted data security or blockchain technology.

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