EEG Based Prosthetic arm RoboGrip: A Grasp on Tomorrow

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***Abstract*—A prosthetic arm is a meticulously crafted replacement for a missing upper extremity, designed to functionally replicate an individual's post-amputation dexterity and enhance their overall well-being. This paper explores the potential of using EEG signals to control prosthetic hands. While recent advancements have focused on EMG-based prosthetics, EEG offers a promising alternative. This study investigates the development of a BCI (Brain-Computer Interface) prosthetic arm using pre-recorded EEG data for six recognized grip patterns. The goal is to create a cost-effective, lightweight prosthetic capable of performing these essential functions. The paper details the process of utilizing machine learning algorithms to train the prosthetic model based on EEG data.**

***Index Terms*—BCI (Brain Computer Interface), EEG(Electroencephalogram), Prosthetic Arm, Grip Patterns, Algorithms.**

I. INTRODUCTION

Prosthetic hands are artificial devices that mimic the functionality of normal hands for individuals who have or had upper extremity amputations. Due to a lack of medical understanding and the frequency of diseases that have been treated in the developed world, the number of cases of amputation loss in developing countries is much higher than in western countries. Losing an upper limb has numerous effects on an amputee, not just physically but also socially, economically, and psychologically. Artificial hands and wrists are used for everyday tasks including dressing, writing, and picking up objects in order to reduce these effects and help the amputee adjust to a regular life.

In India, approximately 5 million individuals experience disabilities related to movement or motor functions. Those affected by neuromuscular conditions like Multiple Sclerosis (MS) or Amyotrophic Lateral Sclerosis (ALS), as well as brain or spinal cord injuries, brainstem stroke, cerebral palsy, and similar disorders, often rely on augmentative and alternative communication methods to convey their thoughts and needs [1]. In recent years, the integration of Brain-Computer Interface (BCI) technology into medical applications has garnered considerable interest due to its potential to revolutionize patient care and rehabilitation processes. Electroencephalography (EEG), a non-invasive technique for recording electrical activity in the brain, holds promise in this regard. The efficacy of this EEG signal dependent functional prosthesis is particularly beneficial for individuals with upper limb amputations, especially those who struggle to obtain a consistent EMG signal due to the severity of their injury. Consequently, the device offers enhanced comfort, ease of operation, simplicity, and eliminates the need for multiple cables and sensors attached to the body [2]. One compelling avenue of research is the use of EEG signals for hand gesture recognition, as it presents an intuitive and natural interface for interacting with devices and computers, especially for individuals with motor impairments.

In this paper, we leverage real-time EEG data collected from a clinical laboratory setting, ensuring the authenticity and relevance of the dataset to medical applications. We focus on a set of six clinically relevant hand gestures, chosen for their importance in patient diagnostics, rehabilitation, and communication. Through meticulous data pre-processing, feature extraction, and machine learning techniques, we aim to develop a robust gesture recognition model capable of accurately classifying EEG signals associated with each hand movement in real time.

II. METHODOLOGY

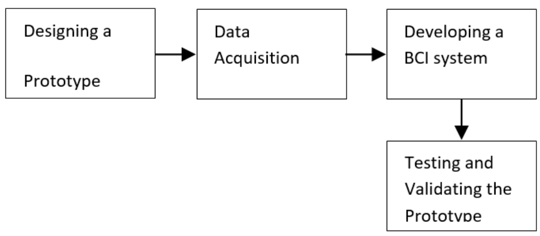


Fig 1: Flow Chart

A. Designing the 3D model

To create a functional myoelectrical prosthesis, it is essential to develop a meticulously engineered mechanical system capable of mimicking the functionalities of a human arm to the highest degree possible. This mechanical design encompasses various aspects, including the articulation of joints and the system's capacity to withstand applied forces. The bionic arm design outlined in this section is entirely manufacturable using a 3D printer and basic tools. The balance between torque and speed is regulated by the motor's gear ratio. At the outset of the research, the amputee emphasized the significance of grip strength over hand closing speed. Consequently, the choice was made to prioritize grip strength over speed [3].

In this system, each finger is connected to an individual servo motor. The servo horns are attached to the output shaft of the servo motors. They serve as connection points for the artificial tendons that control the movement of the fingers. These servo horns are custom designed and 3D printed to fit the specific requirements of the servo motor. Tendons are flexible cords of tissue that connect muscles to bones and transmit forces to produce movement. In this system, artificial tendons are used to mimic the function of natural tendons in the hand. The tendons wrap around the custom 3D printed servo horns in a closed loop configuration. The closed loop configuration ensures that as the servo motor rotates in one direction, it pulls on the tendon connected to the finger, causing it to close. Conversely, rotating the servo motor in the opposite direction releases tension on the tendon, allowing the finger to open. This mechanism replicates the natural movement of fingers in a human hand.

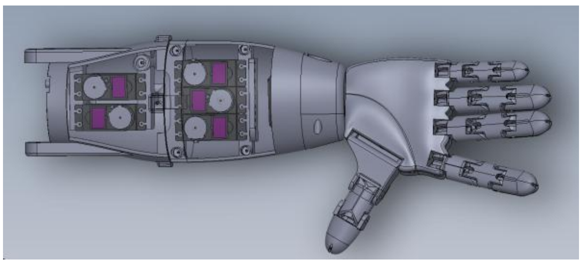


Fig 2: Final 3D Design

B. EEG Dataset Acquisition

The experiment starts with the participant comfortably seated in a chair. A technician will then carefully attach electrodes from the EEG machine to specific locations on the participant's scalp. To ensure clear brainwave readings, the participant will be instructed to take a deep breath and relax. Once attached, the EEG machine will record a brief sample of the participant's brain activity. This sample will be examined by the technician to eliminate any potential noise or interference in the signal. Next, the participant will be asked to perform a simple calibration task. This might involve opening and closing their eyes a few times. The technician will monitor the EEG readings during this calibration to ensure the system can accurately identify these basic brain activity changes. Following the calibration, the participant will be instructed to close their eyes and remain still for the remainder of the experiment. They will then receive voice prompts through instructing them on specific handgrip patterns to perform. It's important to note that before the experiment itself, the participant will undergo separate training to ensure they understand and can execute the required handgrip patterns effectively.

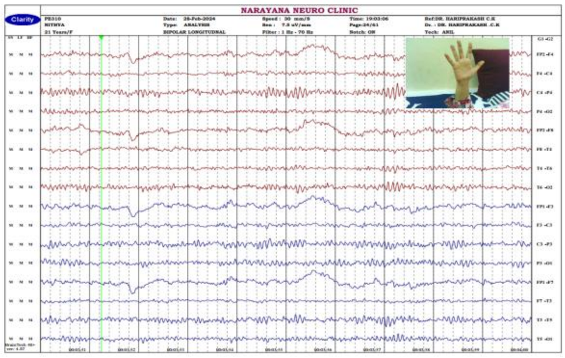


Fig 3: EEG recordings captured during the execution of an open-palm grip.

C. Developing the BCI System

In the proposed system we integrate both software and hardware components to create a comprehensive and interactive platform for hand gesture recognition and control. The software component involves processing EEG signals to extract relevant features associated with different hand gestures using signal processing techniques. Machine learning algorithms are then applied to classify these features into distinct gesture categories. The classified gestures trigger corresponding actions in real-time, controlling the movement of the robotic arm. Each recognized gesture maps to specific motor commands, facilitating precise and intuitive control of the robotic arm's movements.

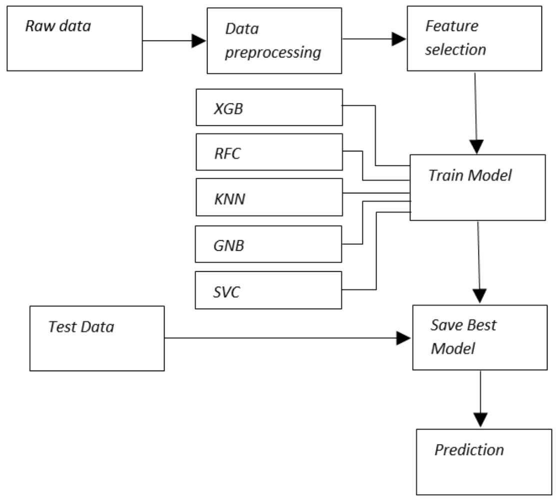


Fig 4: Steps for Developing BCI System

The conceptualized Brain-Computer Interface (BCI) system operates through a well-defined process. Initially, the system receives input in the form of a CSV file containing data to be analyzed and identified. Subsequently, leveraging appropriate machine learning algorithms, it endeavors to recognize the corresponding grip patterns inherent in the provided dataset. Before proceeding with pattern identification, it is imperative to preprocess the collected data meticulously. This involves the application of specific filters tailored to cleanse the data, ensuring its quality and reliability. Once the data is suitably refined, the next step involves training the BCI system. Through the utilization of various machine learning techniques, the system is exposed to the dataset, enabling it to discern patterns and associations inherent in the data.

During the training phase, multiple machine learning algorithms are employed, each vying for efficacy and accuracy. Through rigorous evaluation, the algorithm exhibiting the highest level of accuracy and reliability is meticulously selected to further train the system. This meticulous selection process ensures that the BCI system is equipped with the most proficient algorithm to drive its functionality.

By analyzing the final score on the testing set, we can assess the performance of the chosen algorithm for this specific task. Notably, both K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC) exhibit superior accuracy, surpassing 82%. If the score is unsatisfactory, we might consider trying a different algorithm or adjusting the hyperparameters of the current one. Ultimately, the goal is to select the algorithm that achieves the best performance on unseen data, which signifies its ability to generalize effectively.

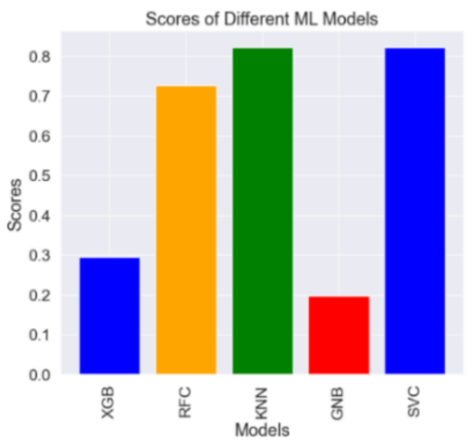


Fig 5: Accuracy graph of algorithms referred

The accuracy graph compares the performance of various machine learning models used in the EEG Hand Gesture Project. Among them, K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC) demonstrate superior performance, achieving higher accuracy than the other models. This highlights their effectiveness in accurately classifying hand gestures from EEG signals, making them strong and reliable choices for predictive modeling in this application.

D. Testing and Validating the Prototype

With the completion of the training process, the system stands prepared to execute its core function: the identification of grip patterns. Upon encountering input data, it swiftly applies the trained algorithm to discern the corresponding grip pattern, meticulously analyzing the dataset to provide accurate results. The output generated by the system manifests in a numerical format, offering clear and precise insights into the identified grip patterns, thereby facilitating seamless interaction and utilization of the BCI system.

III. RESULTS AND DISCUSSIONS

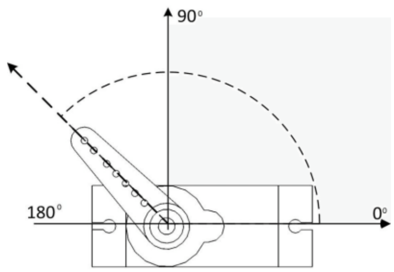
The results of our prosthetic arm using EEG signals to perform six grip patterns, including bowl or mouse grip, close grip, open grip, hook grip, pinch grip, and index finger grip, have been highly promising. Each grip pattern serves a specific purpose, mimicking the functionality of a natural hand. The bowl grip is useful for holding rounded objects and enables users to manipulate objects with precision. The close grip and open grip provide options for grasping objects of varying sizes, and the hook grip is ideal for carrying bags or hanging items. The pinch grip and index finger grip offer additional dexterity for tasks that require more delicate manipulation.

Table 1: Grip patterns performed by prototype

Human Hand Movement	*Prosthetic Hand Movement*	*Description*
		The open palm grip lightly holds objects, like trays or plates, without a firm grasp, using fingers and palm without fully wrapping the fingers around.
		The close palm grip firmly holds objects by wrapping fingers around and pressing the thumb against them, ideal for carrying heavy or bulky items securely.
		The active index grip uses the index finger to point or press against objects, ideal for tasks requiring precision or fine motor control, like typing, writing, or using touchscreens.
		The hook grip is used for objects with handles, where the fingers hook around the handle and the thumb secures the grip, commonly used for carrying bags, buckets, or items with handles.
		The bowl grip pattern is used for rounded objects like bowls, cups, or balls, wrapping the fingers and thumb around to secure the object in the hand.
		The pinch grip holds small objects between the thumb and fingers by pressing them together to create a pinch force, ideal for picking up small items or gripping tools.

A. Servo motor angular resolution

(a)



(b)

Fig 6: (a) shows the arrangement of servo with assigned numbers and (b) shows the angle specification of servo motor

The below table provides detailed information on the servomotor angular resolution required for a prosthetic arm, highlighting the specific angles needed to achieve six distinct grip patterns. Each grip pattern corresponds to a unique task, necessitating precise angular adjustments in the servomotor to ensure optimal performance. By specifying the exact angles, the table aids in fine-tuning the prosthetic arm's movements, allowing for accurate and efficient task execution. This level of detail is crucial for the development and optimization of prosthetic technology, ensuring that the device can perform a wide range of activities with high precision. The information helps in programming the servomotor to respond accurately to EEG signals, translating brain activity into specific movements. This enhances the user's ability to control the prosthetic arm intuitively and naturally.

Table 2: Servo motor angular resolution

Grip Patterns	*Servo 1*	*Servo 2*	*Servo 3*	*Servo 4*	*Servo 5*
Open palm grip	180	180	180	180	180
Close palm grip	60	60	60	60	60
Finger point grip	60	60	60	180	60
Pinch grip	180	180	180	60	30
Hook grip	60	60	60	60	180
Bowl/Mouse grip	160	160	160	160	160

B. BCI Output

The accuracy graph illustrates the performance of various machine learning models in the EEG Hand Gesture Project. Notably, both K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC) exhibit superior accuracy, surpassing 82%. This highlights their effectiveness in accurately classifying hand gestures from EEG signals, making them preferred choices for predictive modeling in this context. The k-nearest neighbor (KNN) algorithm is a straightforward and traditional classification method in machine learning. It categorizes samples by computing the distance, typically using Euclidean distance, between the "sorted data" and samples with known classes [4].

The final system provides relatively good performance and characteristics for a prototype 3D printed model. The device is fast and responsive to user input but offers limited strength. Over the course of testing the system has proven to be reliable and has required minimal maintenance since being assembled.

IV. CONCLUSION

In conclusion, the development of a fully functional prosthetic arm with six distinct grip patterns represents a significant advancement in assistive technology with an accuracy of 82%. By harnessing EEG signals and processing them through the K-Nearest Neighbors (KNN) algorithm, this paper has successfully translated neural activity into precise mechanical actions. This innovative approach not only enhances the quality of life for amputees but also showcases the potential of machine learning algorithms in creating intuitive and responsive prosthetic devices. The use of the K-Nearest Neighbors (KNN) algorithm for signal processing is particularly noteworthy. This choice reflects a deep understanding of the need for a robust yet straightforward method that can accurately interpret the complex patterns of EEG signals. The KNN algorithm's ability to classify data without requiring assumptions about the distribution of underlying data makes it an excellent fit for this application.

Moreover, the paper highlights the importance of user-centered design in biomedical engineering. By focusing on the practical application of grip patterns, the paper has ensured that the prosthetic arm can perform a variety of tasks, from the delicate action of holding a glass to the firm grip required to hold tools. The reduction in both the cost and weight of the project has been thoroughly achieved, presenting a significant advantage that directly aligns with our overarching objectives. Moreover, the advancements made by our paper extend beyond mere convenience, providing essential day-to-day tasks and operations. This versatility significantly enhances the user experience, making the prosthetic arm a valuable tool for everyday life.

V. FUTURE SCOPE

Efforts are being made to make high-quality prosthetics more accessible and affordable globally, ensuring that people from various socioeconomic backgrounds have access to advanced technology. As technology progresses, the aim is to make prosthetic arms not just tools for functionality but seamless extensions of the human body, restoring both physical ability and sensory experience for users.

For future developments, we can add another servo motor to the wrist for a more natural flexing movement of the wrist. Haptic sensors can be added at the finger tips for sensory feedback. Furthermore, a detailed device has to be built to detect the EEG signals with easier method. Developed device should be able to detect and send the data with less response time to the BCI System using wireless method.

In the realm of future enhancements, we can integrate pressure sensors individually on each finger to enhance user interaction. These sensors will furnish the microcontroller with real-time data concerning the applied force at each fingertip. Leveraging this data, we can regulate vibration motors nestled within a pliable band designed for upper arm wear. This implementation will offer rudimentary sensory feedback to users, facilitating awareness of their grip strength and the level of force exerted while handling objects.

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