SEMG-Based Prosthetic Hand with an Integrated Mobile Application

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Abstract. The main focus of this study was to design and develop an assistive device in the form of a low-cost prototype prosthetic hand that utilizes cords as tendons, inexpensive servos, and a simplified actuation method. Additionally, the objective was to create a neural network using only two surface electromyography (sEMG) sensors. Various methods were experimented with to achieve the desired outcome, including transfer learning with RESNET50 and the implementation of a Convolutional Neural Network. The UCI-sEMG dataset was used to train the proposed model for hand movements. Furthermore, a mobile application was developed to control the prosthetic hand, aiming to enhance interactivity and expand the range of control. The entire system communicates through gRPC. The results demonstrate the feasibility of creating a prosthetic hand that internally stores all the cords and servos, while still providing a satisfactory range of motion for each finger. The evaluation process also indicates the algorithm's ability to predict hand gestures, although its performance may not be on par with state-of-the-art models. Nevertheless, considering the limited number of sensors used, the achieved accuracy of 58% shows promise. Additionally, the mobile application features a simple yet functional design that meets the requirements for support, ease of use, and flexibility.

Keywords: Prosthetic hand · sEMG · Convolutional Neural Network

1 Introduction

Hand amputations or loss affect nearly four million individuals globally, with causes ranging from infections, congenital absence, diabetes, cancer, and other conditions [1]. Partial amputations make up the majority, accounting for over 75% of these cases. The loss of a hand significantly impacts the functional abilities of individuals. Fortunately, prosthetic hands offer the opportunity to restore some functionality.

A typical prosthetic hand consists of three main interconnected parts: an input signal acquisition unit, a processing and control unit, and an end effector. The cost of a prosthetic device is quite expensive, ranging from 30,000 to 40,000 USD. However, a low-cost prosthetic hand prototype was designed in [14],

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with a cost of only 1,000 USD, and a commercial version priced at 7,000 USD. Nowadays, high-performing artificial hands (or prostheses) commonly use surface electromyography signals (sEMG or myosignals) for control. sEMG records the electrical muscle movements from the surface of muscle cells when they are electrically or neurologically activated. The amplitude of sEMG signals ranges from 0 to 10 mV (peak to peak). Collecting sEMG signals requires the proper placement of EMG electrodes after applying a layer of gel on the skin surface.

Traditional prosthetic hands based on sEMG typically require more than 6 channels of data for accurate classification of control signals. However, using multiple sensors to capture EMG signals can lead to muscle fatigue during hand operation. In the study [11], the authors successfully classified 4 control signals using only 3 channels of data.

In this study, we conducted research and designed a prototype of a prosthetic hand called HMI Prosthetic Hand, based on 2 channels of EMG signals, aiming to provide an affordable solution suitable for the Vietnamese market. Our contributions include: (1) designing a flexible and expandable prosthetic hand with 4 fingers, (2) conducting tests and mapping the control device to finger rotations corresponding to 6 basic hand movements, and (3) applying a CNN network to classify the 2-channel sEMG signals into 6 classes corresponding to the 6 basic hand movements.

2 Backgrounds and Related Works

2.1 Backgrounds

The human hand is composed of 27 bones that can be divided into 3 main groups [3]:

- Wrist: Consists of 8 carpal bones.
- Palm: Comprises 5 metacarpal bones.
- Fingers: Contains 14 phalanges.

To delve deeper, each finger consists of 3 bones: the Distal Interphalangeal Joint (DIP), the Proximal Interphalangeal Joint (PIP), and the Metacarpophalangeal Joint (MCP). The DIP joint is situated at the fingertip, just before the fingernail. The PIP joint is the first joint of the finger and is located between the first two bones, allowing the bending and extending of the finger. The MCP joint is where the hand bone, known as the metacarpal, connects with the finger bones, known as the phalanges. Aside from the bones and muscles, the human body also comprises fibrous connective tissues like tendons and ligaments. Tendons play the role of connecting bone to bone and can be replicated using mechanical joints. Ligaments, on the other hand, serve as attachments between muscles and bones, enabling finger movements such as bending and straightening. So, the human finger consists of 3 joints: MCP, PIP, DIP. In terms of the human anatomy aspect that the prosthetic hand needs to replicate, it is the finger movement, which can be compared and evaluated by the trajectory of the fingertip.

Below is the formula to determine the trajectory of fingertip movement.

$$\begin{aligned} x &= lph_1 \times cos(\theta_1) + lph_2 \times cos(\theta_1 + \theta_2) + lph_3 \times cos(\theta_1 + \theta_2 + \theta_3) \\ y &= lph_1 \times sin(\theta_1) + lph_2 \times sin(\theta_1 + \theta_2) + lph_3 \times sin(\theta_1 + \theta_2 + \theta_3) \end{aligned} \quad (1)$$

where, lph_1, lph_2, and lph_3 are the length of Proximal phalanx, Middle Phalanx, and Distal Phalanx respectively. θ_1, θ_2, θ_3 is the rotation angle (from 0^0 - 90^0) of MCP, PIP, DIP in that order.

There are six basic types of hand movements (Fig. 1): *spherical*, *pinch*, *palmar*, *lateral*, *cylindrical*, and *hook*.

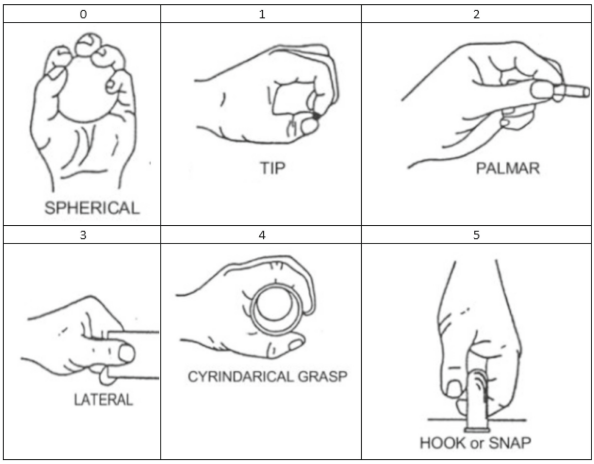

Fig. 1. Six basic hand movements

Over the years, there has been significant advancement in prosthetic hands, offering a wide range of applications and types. These hands can be categorized as passive or active artificial hands, providing replacements for different levels of amputation. Moreover, they can replicate human movements. Passive prosthetic hands encompass both prosthetic hands and tools. They can either be completely static or adjustable. Generally, they are designed with a specific purpose in mind and cannot dynamically adapt to the user's needs. In contrast, active prosthetic hands are bio-compatible mechatronic or mechanical devices that provide a broad range of functionalities. These prostheses can be mechanically powered by the user's body or rely on an external power source and control module for operation. Each type has its advantages and disadvantages. Body-powered prostheses, though not requiring an external power source like a battery, rely on the user's physical strength, which can lead to fatigue over time. On the other hand, externally powered prostheses can assist users in conserving energy and offer a strong grip for prosthetic hands or the ability to handle heavy loads for prosthetic arms.

2.2 Related Works

The LUKE arm/Deka arm system[1] is considered one of the most advanced mechatronic devices ever created. While it has received approval from the United States Food and Drug Administration, it is currently not available for commercial use. To obtain one, buyers must comply with Federal law, which requires the involvement of a licensed healthcare professional in the ordering process. Additionally, this equipment comes with a price tag of around $\$100,000$ or more.

Open Bionics[2] is a UK-based company known for offering a diverse range of products including Hero arm. The Hero arm, which shares a similar design principle to the Brunel hand, is priced between $\$3,000$ and $\$20,000$. Although their products are open-source, acquiring the specific materials required for their Brunel hand, such as sheets of elastic material, can be challenging.

Currently, the field of sEMG signal classification lacks state-of-the-art models compared to image classification, despite its active nature. Among the existing models, the generative flow model (GFM) [2] stands out as one of the most effective models for hand gesture recognition. It achieves an accuracy of $63.86 \pm 5.12\%$ when classifying 53 different hand gestures in the popular NinaPro 5 database, which employs multiple sensors including 2 Thalmic Myo armbands.

Moreover, the MYO armband with 8 channels has been extensively used in numerous datasets and research studies. However, the limited accessibility of this equipment poses additional challenges in the field. The nature of sEMG signals makes generalization challenging, even with a large amount of data. These signals are susceptible to various factors, such as electrode relocation, user fatigue, and inter-subject variability. Technological advancements have greatly improved the field of prosthetic hands and machine learning algorithms for hand gesture classification. However, accessibility remains a challenge in certain regions due to the high cost and limited availability of prosthetic manufacturers and vendors. Various designs of robotic/prosthetic hands have been developed, especially those inspired by human anatomy, where the fingers are controlled by synthetic tendons instead of gears. Nevertheless, most of these designs still place the cords and actuators in the forearm, mimicking the positioning of tendons and muscles in the human body. While this approach is effective, it limits the storage capacity and functionality of the hand module. Additionally, implementing cutting-edge machine learning models with bionic limbs often requires expensive and difficult-to-obtain high-channel datasets and specific use cases. The studies [5–11] utilized sEMG signals to control prosthetic hands; however, these studies used a minimum of 6 sEMG channels. In [12], only 3 sEMG channels were used, but they classified only 4 control signals corresponding to 4 hand movements. The authors in [13] also highlighted that muscle fatigue can occur at the sensor placement locations for signal acquisition. Therefore, using fewer channels of sEMG data, if possible, would be a good choice.

The authors in [4] also aim to design an affordable prosthetic arm for the Indian market, using EMG signals and 5 servo motors. However, the implemen-

[1] https://mobiusbionics.com/.
[2] https://openbionics.com/en/.

tation of EMG signal analysis has not been specified, and the design prototype has been noted to require several improvements to be better suited for real-life usage.

3 Our Method

We have developed a prosthetic hand and its operation based on the process depicted in Fig. 2, which consists of four modules: (1) Prosthetic hand shape design, (2) Basic hand movement learning (optional), (3) Servo parameter estimation, and (4) Control module. In the Prosthetic hand shape design module, we simulated a flexible 4-finger hand design, taking inspiration from the biological structure of the human hand. This design is capable of performing the six basic hand movements mentioned in Sect. 2.1. Subsequently, we fabricated and assembled the hand according to this design.

In the Basic hand movement learning module, we employed a CNN network to classify the six basic hand movements based on SEMG signals. If the user prefers to provide the basic hand movements themselves, we offer the option to perform them through a mobile application. Building upon the prosthetic hand shape and the basic hand movements, we conducted experiments to establish a mapping between hand movements and servo control parameters for each finger in the prosthetic hand. This mapping was accomplished in the servo parameter estimation module. Finally, we programmed the Arduino+ circuit to control the servo operation and activate the finger movements corresponding to each basic hand movement in the control module. Detailed explanations of each module will be provided in the subsequent sections.

4 Prosthetic Hand Design

4.1 Prosthetic Hand Shape Design

We have designed a HMI 4-finger mechanical hand (refer to Fig. 3) that utilizes a combination of servo actuators for joint movement and synthetic tendons to connect the joints. The four fingers included are the Thumb, Index, Middle, and Pinkie. Each finger consists of three joints: MCP, PIP, and DIP. The components that form the shape of the prosthetic hand are described in detail in Fig. 4. These components include (0) connector, which connects each phalanx; (1) string port, where the string or cable passes through; (2) cap, which prevents the finger from falling out; (3) pin, which connects the finger to the hand; (4) fingertip, which represents the distal phalanx; (5) intermediate phalanx (longer); (6) intermediate phalanx (shorter); (7) finger base, which represents the proximal phalanx; (8) hand; and (9) thumb base.

The necessary electronic components for the project include: Arduino Nano; Potentiometers; 3-pin switches; Pins push button; LED (optional); Servos; and Resistors

In particular, four servos are utilized to control the movements of the four fingers (refer to Fig. 5).

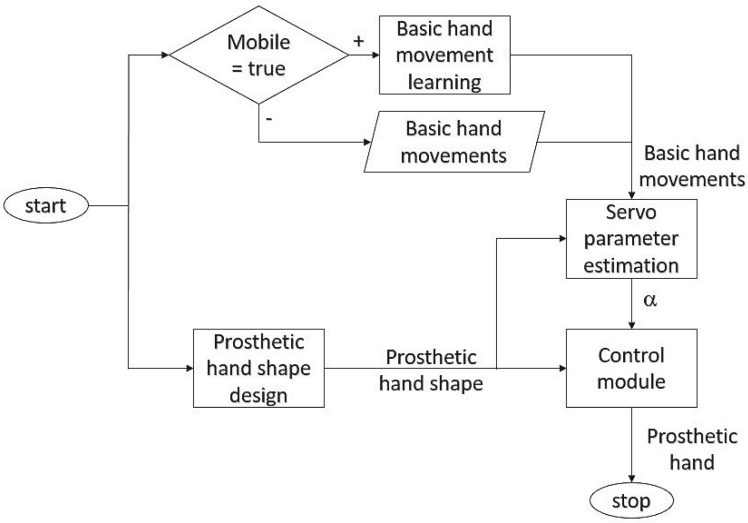

Fig. 2. Our proposal

4.2 Servo Parameter Estimation and Control Module

Experimental validation has confirmed that the maximum identification delay does not exceed $180ms$. Each finger position, ranging from Thumb to Pinkie, corresponds to a specific servo rotation angle. The corresponding angles for the proposed prototype are provided in Table 1 and Fig. 6. In addition to the six basic hand movements mentioned earlier (which are detailed in the first six rows of the table), we have defined additional common hand movements. These movements include Flip off (fully extending the middle finger), Peace (fully extending the index and middle fingers), Point (fully extending the index finger), Open (fully extending all four fingers), and Close (fully flexing all four fingers). The mapping of servo angles concerning finger positions is referred to as the Lookup Table ($LookupTab$). Let α be the rotation angle that activates the servo. We have the following formula to calculate α:

$$\alpha = (Degree - om) \times (iM - im)/(oM - om) + im \tag{2}$$

where, $im = 0$, $iM = 1023$ are the minimum and maximum of the servo rotation angle. $om = 0$, $oM = 180$ are the minimum and maximum of the finger rotation angle.

After the sEMG signals are classified (Sect. 5) into one of the six classes (β ranging from 0 to 5) corresponding to the six basic hand movements (Fig. 1), the parameter α, representing the servo rotation angle for each finger, is estimated and activated.

Input: β $//0-5$ basic hand movements

Output: Activated hand

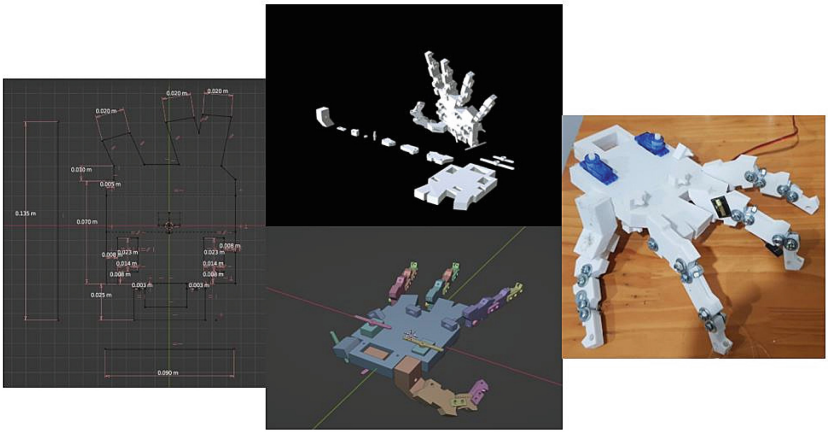

Fig. 3. Detail of the HMI prosthetic hand shape design

Table 1. Mapping servo angle with respect to finger position.

Movements	Thumb	Index	Middle	Pinkie	Movements	Thumb	Index	Middle	Pinkie
Spherical	70	90	40	40	Flip off	0	180	0	0
Tip	100	60	50	50	Peace	0	180	180	0
Palma	40	90	0	0	Point	0	180	0	0
Lateral	40	40	0	0	Open	180	180	180	180
Cylinder	65	45	45	45	Close	0	0	0	0
Hook	180	100	90	90					

Begin
For each finger
α=ServoParEstimation(β,$LookupTab$);
ServoActivation(α);
End

5 SEMG Based Basic Hand Movement Classification

5.1 Dataset

UCI sEMG[3], which stands for surface electromyography, is a dataset named "sEMG for Basic Hand Movements." This dataset comprises surface electromyographic signals (sEMG) recorded during the execution of six fundamental hand movements using the Delsys EMG System. The data was collected from healthy participants while they performed every day grasping actions.

[3] https://archive.ics.uci.edu/dataset/313/semg+for+basic+hand+movements.

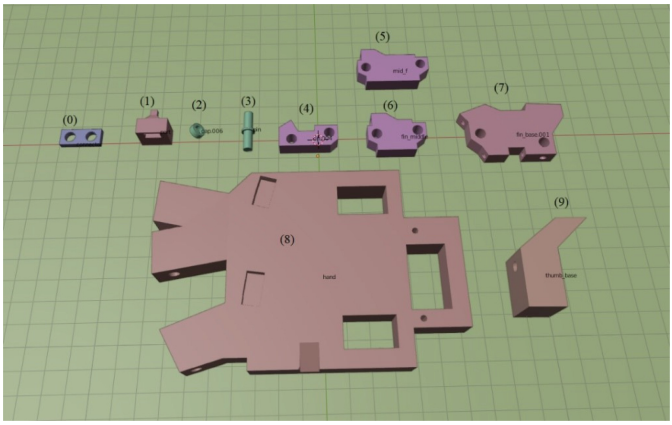

Fig. 4. Detail of the HMI prosthetic hand shape components

The data, stored in MATLAB (.mat) files, with separate tables for each grasping technique and each channel, and each row of these tables represents a trial and contains voltage values of the signals, possesses the following characteristics:

- Data type: Time-series
- Topic domain: Health and Medicine
- Related tasks: Classification
- Feature type: Real numbers
- Number of examples: 3000
- Number of features: 2500

The dataset is divided into two parts:

- Part 1 includes data from five healthy participants (two males and three females) within a similar age range (20 to 22 years old). Each participant performed six hand movements 30 times, with each trial lasting 6 s.
- Part 2 contains data from a single healthy participant (a 22-year-old male) performing six hand movements, repeated 100 times per movement over three consecutive days. The duration of each trial in this part is 5 s.

The data was gathered at a sampling rate of 500 Hz using National Instrument's (NI) Labview as the programming framework. The signals underwent filtering through a Butterworth Band Pass filter and a notch filter to eliminate power line interference. The hardware employed was an NI analog-to-digital conversion card connected to a personal computer, and the signals were captured from two differential voltage EMG electrodes and transmitted to the dual-channel EMG system using Delsys Bagnoli™ Handheld EMG Systems.

The experiments involved both voluntary and repetitive grasping of various objects, enabling participants to independently determine the speed and force of their movements. Surface EMG electrodes placed on the forearm were used to

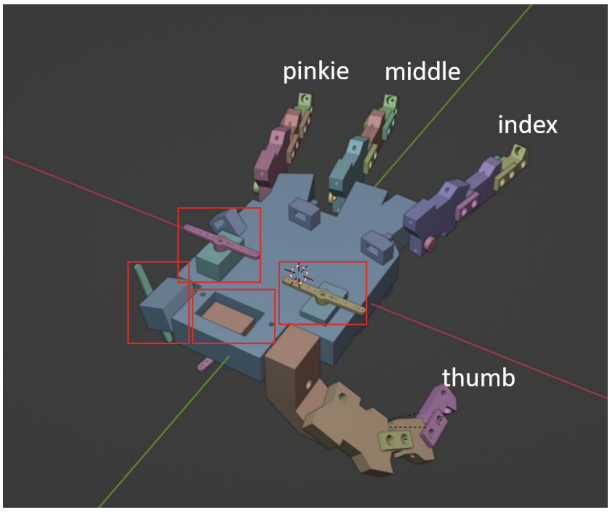

Fig. 5. Servo positions for the fingers.

collect muscle activity information. The dataset encompasses six types of hand movements: *spherical*, *pinch*, *palmar*, *lateral*, *cylindrical*, and *hook* Fig. 1, each corresponding to distinct grasping techniques.

5.2 Data Normalization

To facilitate the use of the Convolutional Layer and ResNet50 in transfer learning, the data is reshaped into an n × n array while preserving its sequential nature. This is achieved by extracting an equal number of samples from both channels and reshaping them according to their sequence position.

With a sampling rate of $500Hz$ and a duration of 6 s, there are 3000 data samples per action. Although we have only two channels, creating a neural network with only two inputs $[chn_1, chn_2]$ is not advisable. This approach is prone to overfitting due to the limited information provided to the network and does not accurately represent the nature of the signal. Muscle signals exhibit time-related properties, so grouping samples together enhances training success and enables effective utilization of CNNs and pre-trained models like ResNet50, which are typically designed for image data.

To ensure compatibility with training and resemble real sensor data, the acquired dataset is reformatted into pairs of channels accompanied by their corresponding labels. Following that, the signals need to be normalized. The signal $x_{1.T}$ can be represented as $(x_{11}, x_{12}, ..., x_{1n})$, and similarly, $x_{2.T}$ can be expressed as $(x_{21}, x_{22}, ..., x_{2n})$,. Both signals are then normalized.

Figure 7 illustrates the process of signal normalization. Subsequently, the normalized data is obtained by extracting n samples from *channel*1 and n samples from *channel*2. This acquired data can be represented as an image (Fig. 7) with

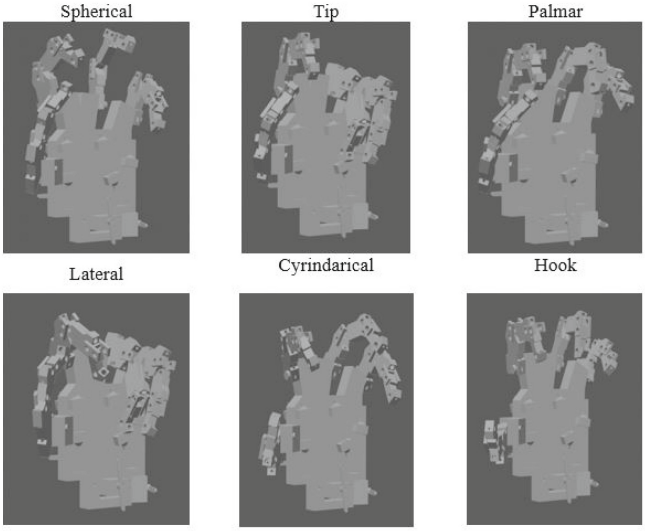

Fig. 6. Six defined basic prosthetic hand movements.

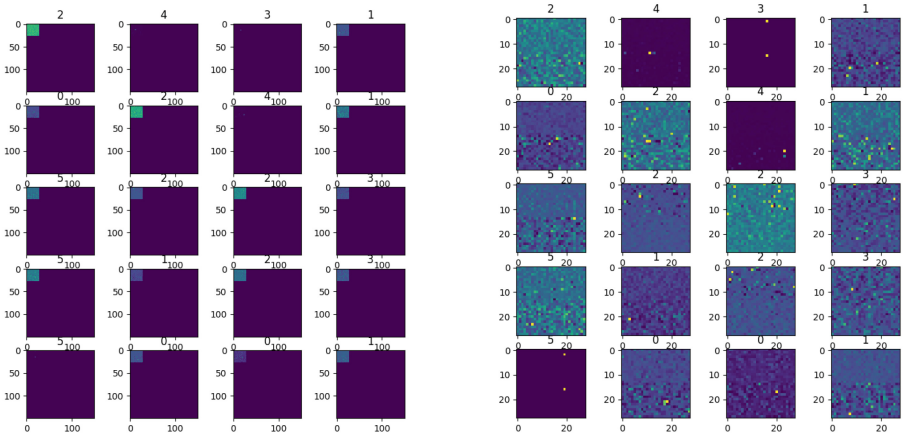

Fig. 7. Signals in discrete space

a 40×40 shape (image on the right). To align with the requirements of transfer learning using ResNet50, it can be padded with zeros (image on the left) to achieve a suitable dimension, typically 224×224.

5.3 CNN Model

We trained a CNN model structure (as shown in Fig. 9) that achieved the best performance. The best-performing model achieved a loss of 0.7 and an accuracy of 0.7 (on a scale of 0 to 1) during evaluation. The training process history is depicted in Fig. 8, where a learning rate (LR) of 0.03 was used.

Using the same model but training it with a different number of epochs and a lower learning rate (LR = 0.01), we obtained a second model with a loss of 0.4 and an accuracy of 0.2.

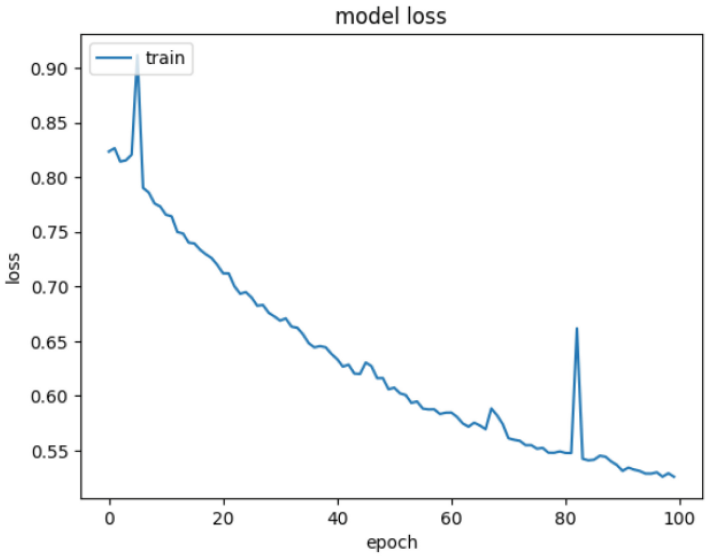

Fig. 8. A training session history.

Using the Keras Tuner, a Keras model with optimal layers and a hyperparameter-like learning rate is set.

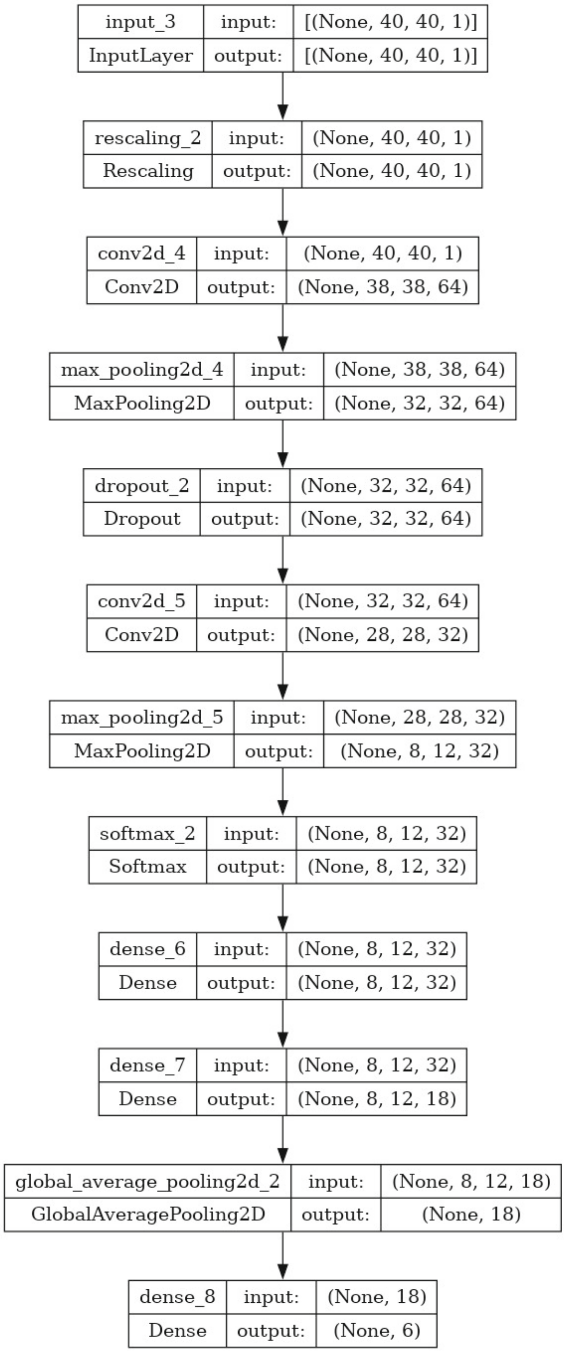

Fig. 9. CNN model architecture.

6 Experiments and Evaluations

We have successfully designed HMI prosthetic hand - a cost-effective 4-finger prosthetic hand with 4 DOF (Degrees Of Freedom). Some technical comparisons regarding the hand's design are illustrated in Table 2 and Fig. 10. The HMI prosthetic hand also demonstrates the potential for expanding hand designs with more fingers and greater degrees of freedom at an affordable price.

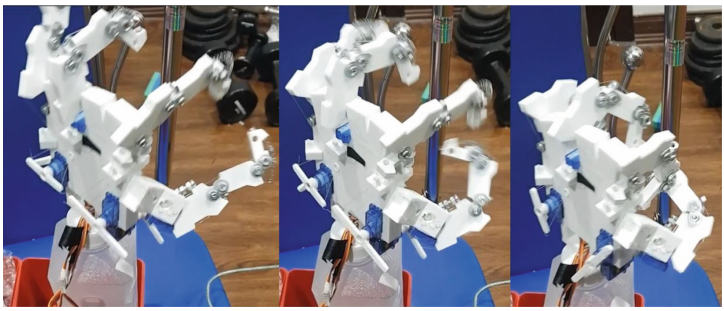

Fig. 10. Movement of prosthetic hand.

Table 2. Technical comparison.

Names	Branches	No of joints	Methods	DOF
Bebionic stepper	RSL	11	DC motor lead screw	6
HeroArm	Open bionhics	10	Linear actuator screw	6
Brunel	Open bionics	9	Linear actuator screw	5
Luke arm	Mobius Bionics	14	Not given	7
HMIhand	Ours	12	180°C Servo screw	4

We have developed a control mechanism for the HMI hand using sEMG signals from the forearm muscles for individuals with hand disabilities. The signals are captured through sensors and fed into a CNN network that we have built to recognize the intended hand movements for controlling the HMI hand. With Dataset UCI sEMG (ratio 80:20 for training and testing, respectively), we have successfully trained the initial model with 2 input channels and 6 basic hand movements. The accuracy is illustrated in Fig. 11 more than 58%, where movement Hook exhibits the highest accuracy around 66%. Additionally, we have expanded the mechanism to provide hand movement input through a mobile application, enhancing the flexibility of using the HMI hand. As mentioned before, we have also experimented and developed additional hand movements beyond the 6 basic gestures, including Flip of, Peace, Point, Open, and Close. This highlights the significant potential for expansion and adaptability of the hand, opening up possibilities for affordable robotic arms in various fields.

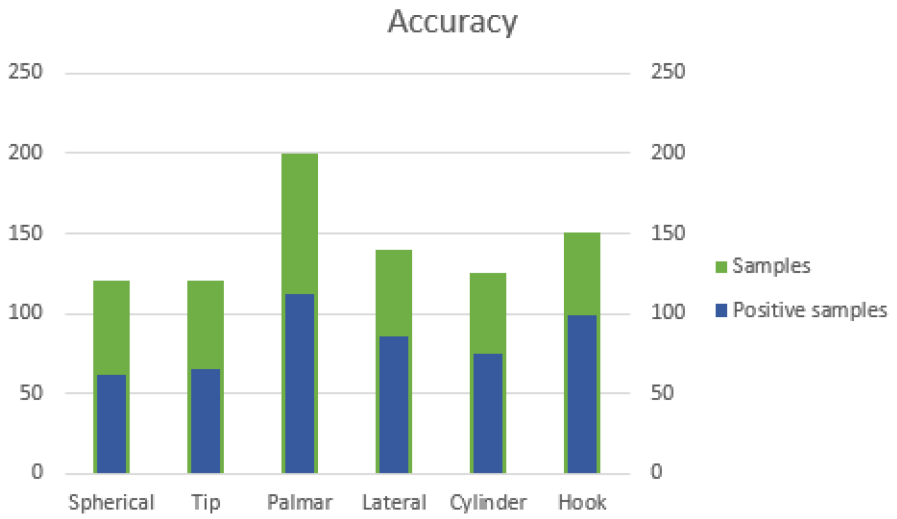

Fig. 11. Prediction result of fine tune model.

7 Conclusion

We have successfully designed and developed an advanced prosthetic hand with four fingers, incorporating state-of-the-art technology that enables it to perform six fundamental movements based on SEMG signals. In addition to the prosthetic hand, we have also developed a user-friendly mobile application that allows for a broader range of gestures, significantly enhancing the flexibility and assistance provided by the robotic arm.

Our groundbreaking research findings present a practical and affordable solution for individuals who have lost their hands and lack access to specialized devices for their daily activities. By utilizing cutting-edge technology, we have overcome numerous challenges to create a device that not only meets the functional needs of users but also addresses the financial constraints that often accompany such devices.

Although our work faced certain limitations, including challenges in data collection and limited testing opportunities, our prosthetic hand stands as a valuable support system for individuals with disabilities and offers a means of controlling robots. By continually refining our design and addressing these limitations, we aim to improve the functionality and accessibility of prosthetics, ultimately enhancing the quality of life for individuals with limb loss.

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