

# Prosthetic Arm Controller Based on the sEMG Signal and Deep Learning Network

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**Abstract**—Prosthetic hands help patients gain greater confidence in daily life, and enabling automatic control of prosthetic hands using real biosignals is an essential task. This paper proposes a prosthetic hand control system based on surface electromyography (sEMG) signals. In particular, the sEMG signals are collected in real time corresponding to each hand gesture and pre-processed to eliminate noise components. A deep learning network is then employed to recognize hand gestures from the pre-processed sEMG signals. Recognized gestures are subsequently used to control the prosthetic hand to perform the corresponding movements. The proposed deep learning network achieves a recognition accuracy of 98.15 % for hand gestures from sEMG signals. Furthermore, the experimental results demonstrate that the proposed system can control the prosthetic hand with an accuracy of up to 96.97 % and a variance of 3.2194 across multiple subjects. These results suggest that the proposed system holds great potential for real-time prosthetic hand control based on sEMG signals, thereby supporting patients in gaining confidence in social interactions.

**Index Terms**—Prosthetic hand; sEMG signals; Hand gestures; Deep learning network.

## I. INTRODUCTION

According to the World Health Organization (WHO), approximately 1.3 billion people - accounting for approximately 16 % of the global population - currently live with significant disabilities, and this number is projected to continue to increase in the coming years [1]. Among them, individuals with upper limb amputations constitute a considerable proportion, which substantially affects their daily lives [2]. Therefore, advancing research and developing reliable methods for controlling prosthetic hands for amputees is a critical task. Automatic control of prosthetic hands using patent biosignals can support individuals with disabilities in performing daily activities and thereby enhance their overall quality of life.

Surface electromyography (sEMG) signals are electrical signals recorded from the human skin surface using electrodes [3]–[5]. When muscles contract, the muscle fibers generate small electrical potentials that can be detected by electrodes, thereby enabling the assessment of muscle activity, as well as supporting various applications. With

significant advancements in the medical field, individuals with motor impairments have experienced an improved quality of life through medical devices such as prosthetic limbs, assistive robots, and other supportive technologies. Moreover, sEMG signals have been widely applied in the monitoring of the health conditions of athletes [6]–[8], the control of prosthetic hands [9]–[11], and many other domains [12]–[14].

Deep learning networks have been developed and applied in a wide range of fields, including industry, healthcare, aerospace, automotive, and agriculture [15]–[19]. Specifically, in the healthcare domain, deep learning has been utilized for disease classification and hand gesture recognition for control of electronic devices [20], [21]. Moreover, the application of deep learning to sEMG signal recognition for prosthetic hand control has attracted significant research interest in recent years. In practice, Budiharto [22] introduced a low-cost prosthetic hand system controlled by electromyography (EMG) signals combined with single-channel electroencephalography (EEG) signals. In this system, EMG signals were employed to control wrist movements, while EEG signals - based on attention levels - were used to perform grasp and release actions. Experiments conducted on the MechaX prosthetic hand with ten degrees of freedom demonstrated that the system achieved an accuracy of 80 % for grasping and releasing actions, and 90 % for moving wrist, with average response times of one second for EMG and 3.5 seconds for EEG. These findings highlight the feasibility of integrating EMG and EEG for prosthetic hand control and open promising directions for developing more powerful and effective assistive devices. Moreover, the results of the recognized hand gestures have not yet been utilized to directly control the prosthetic hand.

Gehlot, Kumar, Hans, and Nkomozepi [23] proposed the 1D-CNAS model, which integrates a one-dimensional convolutional neural network (1D-CNN) with neural architecture search (NAS) optimized using the LSHADE algorithm, for hand gesture recognition based on sEMG signals. Data collected from 10 participants who performed six hand gestures were processed using filtering, normalization, and sliding window techniques prior to training. The results showed that 1D-CNAS achieved an average accuracy of 80.29 %, with a precision of 81.13 %, recall of 80.29 %, and F1-score of 79.77 %, representing an

Manuscript received 4 October, 2025; accepted 23 December, 2025.

This research was supported by the Ho Chi Minh City University of Technology and Engineering (HCM-UTE) under Grant No. T2025-203.

improvement of approximately 9.57 % compared to the baseline 1D-CNN. The study demonstrates the potential of this approach for applications in prosthetic control and rehabilitation; however, it remains limited in terms of the number of gestures and experimental conditions. Moreover, recognized hand gestures have not yet been utilized to directly control a prosthetic hand.

This study proposes a prosthetic hand gesture control system based on sEMG signals and deep learning. Specifically, sEMG signals are collected and pre-processed to remove noise and enhance signal quality. The pre-processed sEMG signals are then fed into a deep learning network for training and recognition of corresponding hand gestures. The recognized gestures are subsequently used to control the prosthetic hand to perform the associated movements. The main contributions of this paper include the following:

- Collecting an sEMG dataset corresponding to various gestures from volunteers;
- Proposing a deep learning-based system for recognizing hand gestures from sEMG signals;
- Controlling a prosthetic hand to perform the gestures identified by the deep learning network.

The experimental results demonstrate the effectiveness of the proposed method. The methodology, results, discussions, and conclusions are presented in detail in the subsequent sections.

## II. MATERIALS AND METHODS

Controlling prosthetic hands through the integration of deep learning and sEMG signals is a novel approach that can assist amputee patients improve their quality of life. This section presents the proposed system for prosthetic hand control based on sEMG signals and a deep learning network.

### A. Proposed System for Prosthetic Hand Control

The overall methodology for prosthetic hand control based on sEMG signals and a deep learning network is illustrated in Fig. 1. The system comprises the following four main stages.

**Surface electrode placement:** Electrodes are positioned on the forearm to record sEMG signals generated by muscle contractions. These signals reflect the intended gestures of the user and serve as the primary input to the system.

**Pre-processing system:** The raw signals undergo pre-processing stage, including analog-to-digital conversion, filtering, and amplification, to improve signal quality and minimize noise prior to further analysis.

**Central processing:** Pre-processed signals are fed into the central processing unit, where a deep learning network is employed for model training and testing to recognize the hand gestures from the sEMG signal. The results of hand gesture recognition are then obtained, and they are transferred to the prosthetic hand control stage. In this paper, the central processing unit is a Raspberry Pi 4.

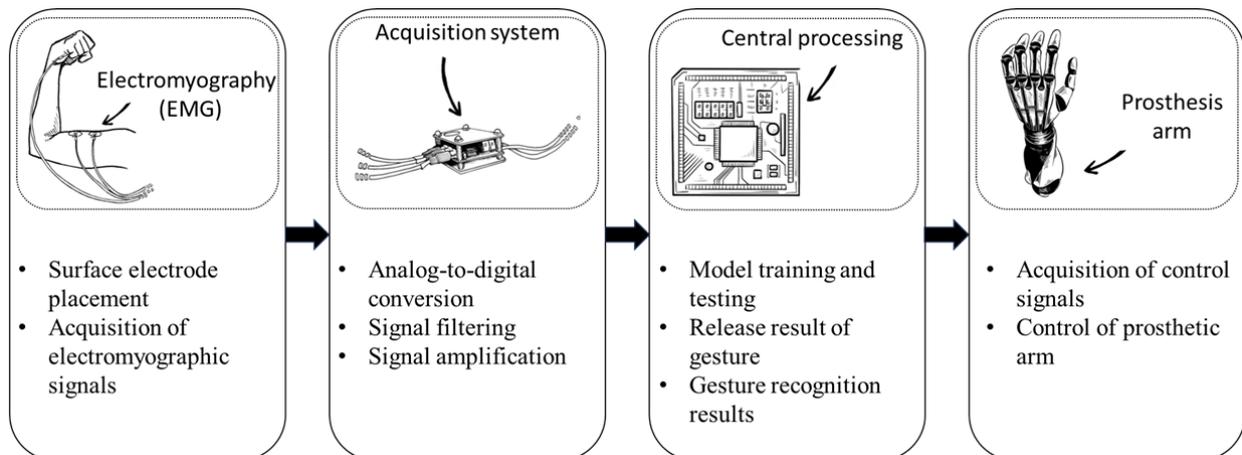


Fig. 1. Proposed system for prosthetic hand control based on sEMG signals and deep neural network.

**Prosthetic hand control:** The recognized hand gestures are translated into control signals that drive the prosthetic hand actuators, thereby enabling the prosthetic hand to perform the corresponding hand gestures in real time.

### B. The sEMG Signal Dataset

sEMG signals are collected from the acquisition circuit corresponding to specific hand gestures to support training and recognition in the deep learning network. This section presents the process of sEMG signal acquisition.

#### – EMG Signal Acquisition

The sEMG is a biomedical technique that is used to record the electrical activity of muscles. Signal acquisition can be performed using two primary methods: surface EMG and needle EMG. In this study, three surface electrode channels were placed at specific locations on the forearms of the participants, as illustrated in Fig. 2.

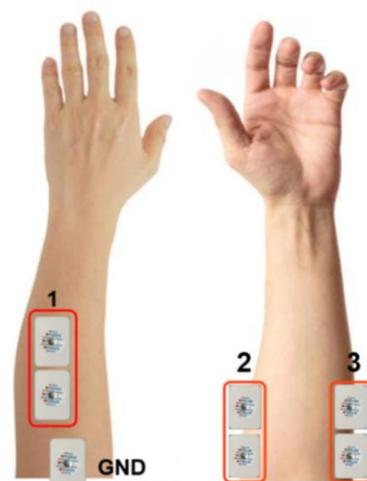


Fig. 2. Electrode placement.

Each channel consisted of a bipolar pair (positive and negative electrodes) along with a common reference electrode. To ensure reliable signal acquisition, disposable Ag/AgCl electrodes were used. After electrode placement, the participants performed the acquisition protocol summarized in Fig. 3. The protocol comprised repeated in five-second cycles: the first second for rest, the following three seconds for performing and maintaining the target hand gesture, and the final second for relaxation before the next trial.

Resting state	Finger flexion	Resting state
1s	3s	1s

Fig. 3. Protocol for sEMG signal acquisition.

#### – sEMG Pre-Processing and Segmentation

The peak-to-peak amplitude of sEMG signals typically ranges from several tens of  $\mu\text{V}$  to approximately 1 mV–2 mV during voluntary contractions, and can reach 5 mV–6 mV under electrically elicited contractions, such as compound muscle action potentials or M-waves [24], [25]. Due to their relatively low amplitude, raw sEMG signals require amplification prior to further processing. In the proposed system, the amplified signal is transmitted to an Arduino Nano 33 BLE board for subsequent noise filtering. Since the analog input pins of this board are limited to a maximum voltage of 3.3 V, the gain must be designed to provide sufficient signal strength without exceeding this threshold. An overall gain of 660 was selected to amplify the sEMG signal.

However, applying such a large gain in a single stage risks amplifying noise together with the desired signal, thereby compromising measurement accuracy. To mitigate this issue, a multi-stage amplification strategy was adopted [26], [27]. In the first stage, an instrumentation amplifier was employed to enhance the differential signal while attenuating common-mode noise, followed by filtering stages to suppress unwanted components. The main sources of noise in sEMG acquisition include motion artifacts and power-line interference. To address these issues, high-pass and low-pass filters were implemented. Consistent with previous studies reporting that the primary frequency content of sEMG signals lies between 20 Hz and 500 Hz [14], [28], [29], the high-pass filter was configured with a cut-off frequency of 20 Hz, while the low-pass filter was set to 500 Hz. After initial pre-processing and amplification, the analog sEMG signal was transmitted to the Arduino Nano 33 BLE as an analog voltage. At this stage, the signal was digitized using the 12-bit analog-to-digital converter on the board, with a sampling frequency of 100 Hz. To further suppress residual noise, a Kalman filter was applied as the final denoising step.

After preprocessing, the sEMG signals were segmented into independent samples to construct the dataset for CNN training. The acquisition system operated at a sampling rate of 100 Hz with a trial duration of five seconds, yielding a window size of 500 samples. To partition the signals, a queue-based segmentation method with a fixed window size of 500 was employed. To ensure the diversity and generalizability of the model, the dataset used for training was collected from multiple individuals. Each participant was instructed to

perform six distinct hand gestures. This variability in participants helps the model better adapt to inter-subject differences in EMG signal patterns. For ease of model training and evaluation, the dataset was organized into two main folders: train and valid, corresponding to the training and validation sets, respectively. Each folder contains six files, with each file representing data from one of the six predefined gestures. This structure enables straightforward data loading and class-wise segmentation during the model development process.

#### – Deep Learning Network Model

Based on the characteristics of sEMG signals and hand gestures, a classification model was developed to achieve high-accuracy recognition of hand gestures. The model was designed with specific constraints to align with the requirements of real-time prosthetic control applications. These design objectives led to the selection of a lightweight convolutional neural network architecture capable of efficiently learning discriminative features from multi-channel sEMG inputs without excessive computational overhead. Based on the objectives described above, a CNN was selected as the classification method because it can automatically extract spatial and temporal features from sEMG signals - a type of signal that is nonlinear, noisy, and highly variable across measurements. In addition, CNNs are well suited for biomedical signal recognition tasks and can be easily deployed in practical applications. The architecture of the proposed CNN model used in the sEMG-based hand gesture recognition system is shown in Fig. 4.

**Input layer:** The input layer is a 2D tensor with dimensions  $500 \times 3$ , where 500 represents the number of time-domain samples per acquisition cycle, and 3 denotes the number of sEMG channels.

**Convolutional layer:** This is the core component of the network, where convolution operations are performed using learnable filters (kernels). Each filter slides across the input data, performing element-wise multiplications and summations to extract local features. In the proposed architecture, the convolutional filters have a kernel size of (1, 5), a stride of 1, and the *same* padding, ensuring that the output maintains the same temporal dimensions as the input, except for the number of channels (which increases with filter depth). These filters enable the network to detect spatiotemporal features such as signal transitions and frequency patterns over time.

**Activation layer:** Following each convolutional operation, a non-linear activation function is applied. In this model, the rectified linear unit (ReLU) function is used to introduce non-linearity, enabling the network to learn complex mappings between input signals and gesture labels.

**Pooling layer:** To reduce the dimensionality of the feature maps and minimize computational complexity, max pooling layers are employed. These layers down-sample the output by selecting the maximum value within fixed-size windows, thereby preserving dominant features while discarding redundant information.

**Fully connected layers:** After passing through the convolutional and pooling layers, the resulting feature maps are flattened and forwarded to three fully connected (dense) layers. In these layers, each neuron is connected to every neuron in the previous layer, allowing high-level reasoning

and classification based on abstracted features. The final dense layer employs a Softmax activation function to produce

class probabilities corresponding to six gesture categories.

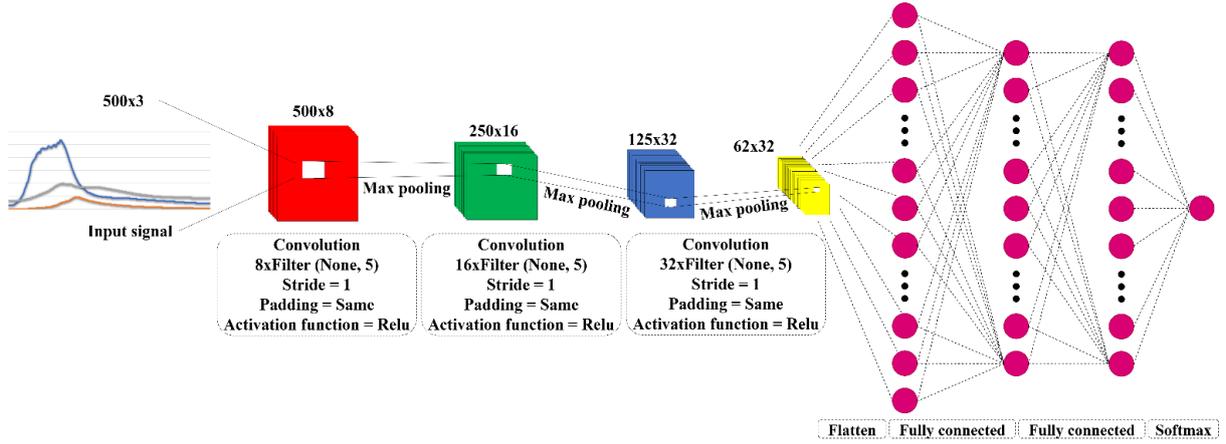


Fig. 4. The proposed deep neural network for hand gesture classification based on the sEMG signal to control the prosthetic hand.

The proposed network model for hand gesture recognition based on sEMG signals consists of three convolutional layers. Each convolutional layer uses the ReLU activation function, a filter size of  $1 \times 5$ , and the “same” padding to preserve the length of the input signal. The number of filters increases across the convolutional layers (8, 16, 32) to extract features at different levels of abstraction. After each convolutional layer, a Batch Normalization layer is added to stabilize the training process and accelerate convergence, followed by a MaxPooling layer with a window size of 2 to reduce noise and dimensionality. The classification part includes two fully connected layers, each containing 100 neurons and using the ReLU activation function, combined with a Dropout layer (rate of 0.5) to mitigate overfitting. The output layer uses the Softmax function to generate a probability distribution over the hand gesture classes. This architecture was designed and tuned through experimental trials to optimize accuracy and generalization performance on the sEMG dataset.

*Loss function.* During the training process, the loss function employed was sparse categorical cross-entropy (SCCE), which measures the divergence between the predicted probability distribution and the true class labels. This approach is particularly suitable when the labels are represented as integer values rather than one-hot encoded vectors. The loss is formally defined as

$$\mathcal{L}(z, y) = -\log\left(\frac{e^{z_y}}{\sum_{k=0}^5 e^{z_k}}\right), \quad (1)$$

where  $z = (z_0, \dots, z_5) \in \mathbb{R}^6$  is the logit vector produced by the network for a given sample,  $z_k$  is the logit corresponding to class  $k$ ,  $k = (0, \dots, 5)$ , and  $y$  is the index of the correct class. The overall training loss is computed by averaging this value across all samples in a batch, ensuring both efficiency and stability in multi-class classification tasks. The use of sparse categorical cross-entropy eliminates the need for one-hot label encoding, thereby reducing memory consumption and computational complexity while maintaining numerical stability. By optimizing this loss function, the model is guided to assign higher probabilities to the correct class while proportionally penalizing incorrect predictions according to their confidence levels.

### – Prosthetic Hand Control

The prosthetic hand was designed and fabricated using 3D printing, and the fingers are actuated by MG90S servo motors. The central control circuit is based on an Arduino Nano. The recognition results from the deep learning-based signal classification module correspond to six different hand gestures, represented by integer values from 0 to 5, with each value associated with a specific gesture. The output signal from the recognition module is transmitted to the prosthetic hand module via UART, and the arm control circuit drives the actuators through four digital output pins (D5, D6, D9, and D10). With this modular architecture, the system offers flexible scalability, allowing additional gestures or movements to be incorporated in the future to enhance the expressive capabilities of the prosthetic hand.

## III. RESULTS AND DISCUSSION

The results obtained from the proposed deep learning system, which recognizes hand gestures from sEMG signals for prosthetic hand control, are presented in detail in the following section.

### A. The sEMG Signal Dataset

In this study, the sEMG datasets corresponding to hand gestures for training the deep learning network were obtained during the acquisition stage. Volunteers were university students aged 21 to 25, including six males and four females. The male participants weighed between 58 kg and 72 kg, with heights ranging from 159 cm to 173 cm. All participants had no history of neurological or musculoskeletal disorders to ensure the consistency of the acquired electromyography signals. Each participant performed the same number of repetitions for each gesture to maintain a balanced dataset between individuals and reduce statistical bias. Furthermore, all volunteers fully understood and agreed to participate in this study. A standardized protocol was established to ensure consistent data collection. The acquired sEMG signals were pre-processed using a Kalman filter to remove noise. The Kalman filter is particularly well-suited for this task due to its ability to effectively suppress both electrical noise and motion artifacts by estimating the next state of the system based on prior observations. This adaptive estimation

capability makes it especially robust in real-time signal processing of low-amplitude physiological signals, such as sEMG. For implementation, the SimpleKalman library available in the Arduino IDE was employed, which significantly simplified integration into the signal processing pipeline. The filter requires initialization with three parameters: processNoise, measurementNoise, and estimatedError. These parameters were empirically tuned by visually comparing signals before and after filtering to optimize the balance between responsiveness and noise suppression. Finally, the sEMG dataset was summarized in terms of the number of samples corresponding to each gesture, as shown in Table I.

TABLE I. TABLE OF THE NUMBER OF SAMPLES FOR EACH HAND GESTURE.

No.	Types of gesture	Number of samples	Describe
0	Thumb flexion	1538	The subject flexes the thumb inward towards the palm, while the other fingers remain in their natural position.
1	Index finger flexion	1450	The subject flexes only the index finger toward the palm, while maintaining the other fingers in an extended position.
2	Flexion of the middle, ring, and little fingers	1542	The subject flexes the middle, ring, and little fingers simultaneously, while keeping the thumb and index finger extended.
3	Pinch using the thumb, index, and middle fingers	1382	The subject performs a pinch gesture by bringing the thumb into contact with the tips of both the index and the middle fingers simultaneously.
4	Full hand grip	1488	The subject flexes all fingers simultaneously, resulting in a complete hand grasp.
5	Relaxed (no contraction)	1810	The subject maintains the hand in a relaxed, natural posture without any finger flexion.

Each sEMG sample in Table I consists of three channels, with 500 data points per channel, as shown in Fig. 5. The reconstructed waveform representations are presented in Table II, where the differences among the various gesture classes can be clearly observed. In particular, for each hand gesture, one sample with three channels is plotted in detail to illustrate the corresponding sEMG signals. These datasets are subsequently used as input to the deep learning network for classification into six hand gesture categories, which are then employed to control the prosthetic hand.

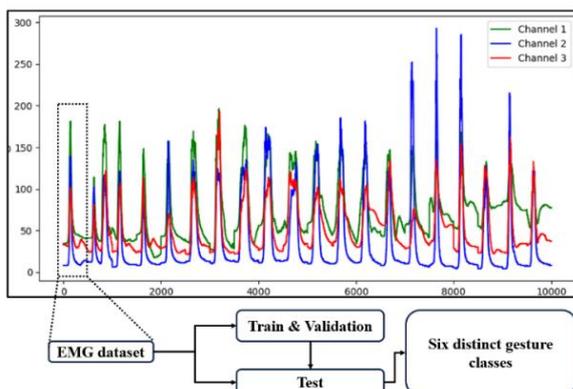
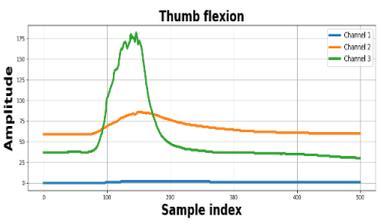
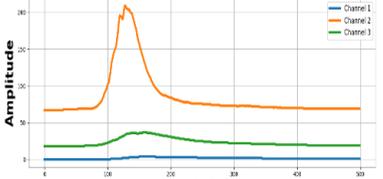
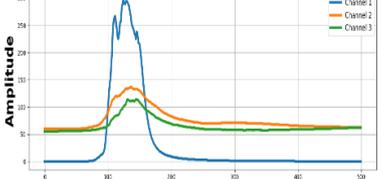
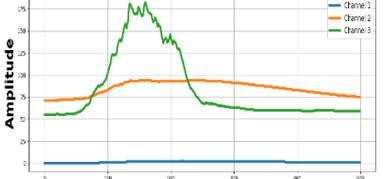
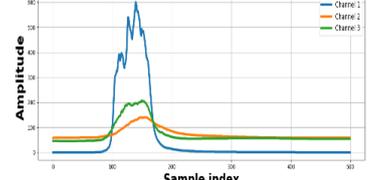
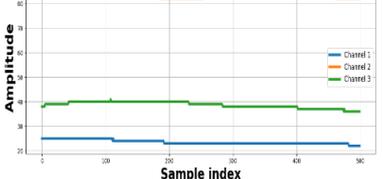


Fig. 5. Representation of the sEMG dataset for training and testing the deep learning network.

TABLE II. HAND GESTURES UTILIZED IN THE SYSTEM AND THEIR CORRESPONDING RECORDED SIGNALS.

No.	Hand gesture	Representation of the three-channel sEMG signal
0		
1		
2		
3		
4		
5		

### B. The Proposed Deep Learning Model

Figure 6 illustrates the confusion matrix for the classification results of six hand gestures using the proposed deep learning network. The model achieves very high accuracy across most classes, particularly for Gestures 1 and 5, where all 277 and 386 samples, respectively, are correctly classified without any misclassification. Gesture 4 also performs well, with 289 correct predictions and only minor (one sample misclassified as Gesture 2 and two as Gesture 3). Gestures 0 and 2 also exhibit high accuracy, with 309 and 298 correct classifications, although a few samples are confused with neighboring gestures. However, Gesture 3 shows a

higher number of misclassification errors, with 14 samples predicted as Gesture 0 and one as Gesture 4, which can be attributed to similarities in EMG signal characteristics between these gestures.

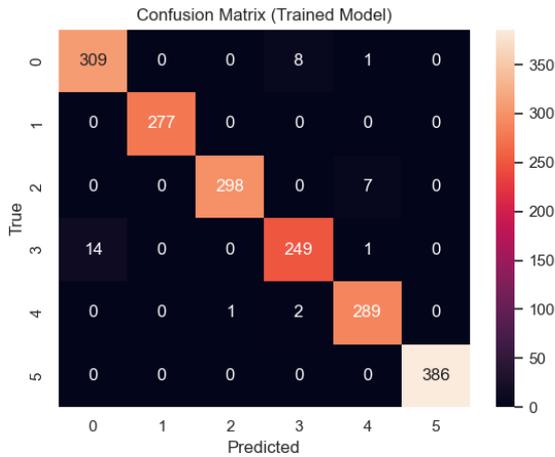


Fig. 6. Confusion matrix of classification results for hand gestures using the proposed deep learning network.

Figure 7 presents the loss and accuracy results during the training and validation processes of the proposed deep learning network over 100 epochs.

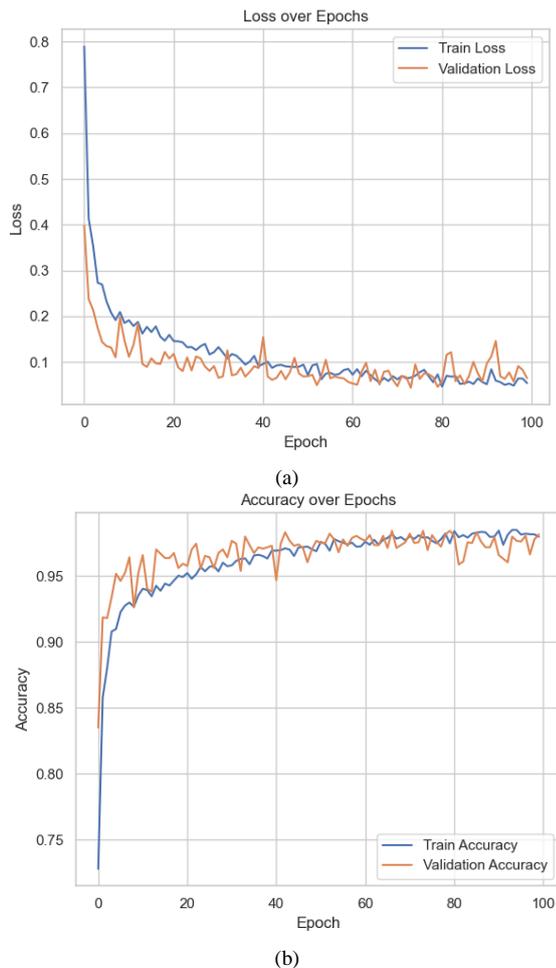


Fig. 7. (a) Loss and (b) accuracy curves of the proposed deep learning network during training and validation phases.

The loss function decreases rapidly and remains stable, while the accuracy of training and validation surpasses 95.50 % after approximately 50 epochs, fluctuating within

the range of 96 %–98 %. The close alignment between the training and validation curves demonstrates that the model converges quickly, generalizes well, and avoids overfitting during training. Based on the loss and accuracy outcomes, the model is well-suited for recognizing six hand gestures from the sEMG signals to control the prosthetic hand.

Table III presents the results of the deep learning network evaluation to recognize individual hand gestures from sEMG signals, using the evaluation metrics adopted in this study [30]. The results indicate that the proposed network achieves excellent performance in hand gesture recognition. Specifically, Gestures 1 and 5 are classified with perfect accuracy, achieving 100 % across all metrics. In contrast, Gesture 3 shows the lowest performance, with both accuracy and F1-score at 95.22 %. Overall, these results confirm the reliability and generalization capability of the model, demonstrating its effectiveness for real-time prosthetic control applications.

TABLE III. THE PERFORMANT OF THE DEEP LEARNING NETWORK FOR HAND GESTURES CLASSIFICATION (UNIT IN PERCENT).

Types of gesture	Precision	Recall	F1-score	Accuracy
0	95.66	97.17	96.41	96.84
1	100	100	100	100
2	99.66	97.70	98.67	98.69
3	96.13	94.32	95.22	95.22
4	96.98	98.97	97.97	97.95
5	100	100	100	100

To accurately evaluate the effectiveness of the proposed model, several deep learning architectures reported in prior studies [31]–[35] were also re-implemented and trained on the same dataset used in this research. In addition, the reported results of these studies were considered for comparison to further assess the performance of the proposed system. Table IV summarizes the comparative results between the proposed system and previous work based on two evaluation metrics: accuracy and the number of trainable parameters in two scenarios: using the same self-collected dataset [31]–[35] and using different datasets [23], [31]–[35]. When trained on the sEMG dataset collected in this study, the comparison models achieved accuracies ranging from 85.72 % to 93.86 %, with the number of trainable parameters varying between approximately 1.34 million and more than 4.04 million. In contrast, the proposed system achieved the highest accuracy of 98.15 % while maintaining one of the lowest parameters counts. The only exception is the model reported in [34], which required 41,032 parameters compared to 212,808 parameters in the proposed system. However, the proposed system outperformed [34] in terms of accuracy, achieving 98.15 % compared to 96.25 %.

Statistical results show that the variances of the evaluation metrics - Precision, Recall, F1-score, and Accuracy - are 3.46, 3.88, 3.12, and 2.91, respectively, as reported in Table III. This demonstrates that the proposed model exhibits highly stable performance in recognizing hand gestures based on sEMG signals, achieving consistently high accuracy across most gesture classes. These findings confirm the high reliability of the system in gesture recognition and control. However, gesture class 3 still shows more confusion

compared to the other gestures.

In the scenarios of using different datasets, i.e., datasets collected within the respective comparative studies, the recognition accuracy of hand gestures based on sEMG signals using the proposed deep learning network outperforms that of the work in [23], [32]–[34]. In particular, the authors in [35] reported a recognition accuracy of 99 % for classifying heart diseases from the MITDB electrocardiogram (ECG) signals. However, when applying the same model to recognize hand gestures from sEMG signals, the accuracy decreased to

91.15 %. This reduction in accuracy may stem from the intrinsic differences between the ECG and sEMG signals. Furthermore, the number of parameters in the models used for comparisons with different datasets was not reported. Based on the aforementioned results, the proposed system demonstrates excellent performance in recognizing hand gestures from sEMG signals for prosthetic hand control. Consequently, the system holds potential for practical applications in prosthetic hand control for patients with limb loss.

TABLE IV. COMPARISON OF THE PERFORMANCE OF THE PROPOSED SYSTEM WITH OTHER STUDIES IN TWO SCENARIOS: USING THE SAME SELF-COLLECTED DATASET AND USING DIFFERENT DATASETS.

Authors, year	Dataset	Method	No. of output	Accuracy (%)	Param.
Bauer, Tavakolian, Xiao, Blaber, and Khosrow-Khavar, [31], 2021	My sEMG dataset	three convolution layers and three dense layers	6	93.86	2,946,792
	Coronary Artery Disease		2	85.00	549,091
Côté-Allard <i>et al.</i> , [32], 2019	My sEMG dataset	three convolution layers and one dense layer	6	85.72	1,342,388
	Hand gesture dataset (sEMG)		7	97.88	NA
Bakırcıoğlu and Özkurt, [33], 2020	My sEMG dataset	two convolution layers and two dense layers	6	87.45	4,044,920
	sEMG from UCI Machine Learning Repository		6	95.90	NA
Hassan <i>et al.</i> , [34], 2022	My sEMG dataset	three convolution layers and two dense layers	6	96.25	41,032
	N2001 EMGLAB		2	97.74	NA
Ahmed, Ali, Abdullah, and Malebary, [35], 2023	My sEMG dataset	five convolution layers and two dense layers	6	91.15	3,843,592
	ECG signal from MITDB		4	99.00	NA
Gehlot, Kumar, Hans, and Nkomozepe, [23], 2025	sEMG signal	two convolution layers and two dense layers	6	80.29	NA
Proposed, 2025	My sEMG dataset	three convolution layers and three dense layers	6	98.15	212,808

### C. Prosthetic Hand Control Results

With the results of hand gesture recognition obtained from the proposed deep learning model, the outputs were employed to control the prosthetic hand, enabling it to perform the corresponding gestures. Figures 8(a)–8(f) illustrate the prosthetic hand control outcomes based on the gesture recognition results of the deep learning network. The findings demonstrate that the arm accurately executes the gestures corresponding to the recognized outputs. Furthermore, the proposed system for hand gesture recognition and prosthetic hand control was evaluated with ten volunteers to assess its recognition and control performance.

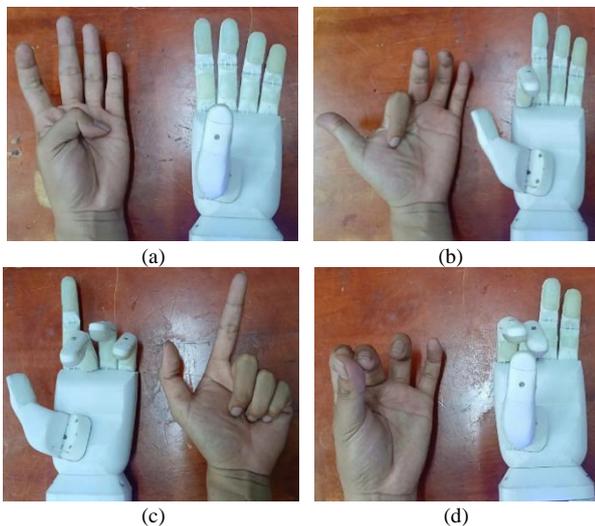


Fig. 8. Results of the prosthetic hand control based on the hand gesture classification.

Each participant was instructed on electrode placement and predefined hand gestures. In this experiment, each subject performed 50 trials for each hand gesture type.

The summarized recognition results for the prosthetic hand control are presented in Table VI. To quantify variations in recognition performance, the sample variance and standard deviation were calculated to evaluate the system. The formulas for variance and standard deviation in this context are presented as follows:

$$s^2 = \frac{\sum (x_i - \bar{x})^2}{N}, \quad (2)$$

$$s = \sqrt{s^2} = \sqrt{\frac{\sum (x_i - \bar{x})^2}{N}}, \quad (3)$$

where  $s$  denotes the standard deviation,  $\bar{x}$  represents the mean value of the trials,  $x_i$  is the value of the  $i^{\text{th}}$  trial, and  $N$  is the total number of trials. The mean value  $\bar{x}$  is calculated as

follows

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i. \quad (4)$$

Table V presents the results of the evaluation of the proposed system for controlling the prosthetic hand, with each subject performing 50 trials for each hand gesture. The experimental results of ten participants indicate that the average accuracy of the prosthetic hand control reached 96.97 %, with a variance of 3.2194. Moreover, the

recognition and control of all hand gestures achieved very high performance, except Gesture 3, which showed relatively lower accuracy. This observation is consistent with the recognition results of the deep learning model presented in the previous section. Misclassification of Gesture 3 may be attributed to the similarity of its sEMG signals with those of other hand gestures, leading to potential confusion during recognition. Moreover, incorrect control may arise from factors such as the influence of arm movements when the subject is in motion during execution, variations in electrode contact, and other external causes. These limitations will be considered and addressed in future studies.

TABLE V. PRESENTATION OF PROSTHETIC HAND CONTROL RESULTS WITH TEN DIFFERENT PARTICIPANTS.

Subjects	Number of trials	Gesture Types control						Accuracy (%)	Variance	Standard Deviation
		(a)	(b)	(c)	(d)	(e)	(f)			
1	50	48	50	49	46	50	50	97.67	2.1389	1.4625
2	50	49	49	48	46	50	50	97.33	1.8889	1.3744
3	50	49	48	47	45	50	50	96.33	3.1389	1.7717
4	50	47	49	48	44	50	50	96.00	4.3333	2.0817
5	50	48	50	47	43	50	50	96.00	6.3333	2.5166
6	50	49	50	49	44	50	50	97.33	4.5556	2.0304
7	50	49	48	48	45	50	50	96.67	2.8889	1.6782
8	50	50	49	49	47	50	50	98.33	1.1389	1.0302
9	50	48	50	48	46	50	50	97.33	2.2222	1.4569
10	50	47	50	48	45	50	50	96.67	3.5556	1.8406
Average								96.97	3.2194	1.7050

#### IV. CONCLUSIONS

A system was proposed for classifying hand gestures based on sEMG signals and a deep learning network, aiming at controlling a prosthetic arm to perform the corresponding hand gestures. In particular, the sEMG signals were collected and pre-processed to remove noise and unwanted components. The processed sEMG signals were then inputted into a deep learning network for training and recognition of the corresponding hand gestures. The proposed network successfully recognized six distinct hand gestures with an average accuracy of 98.15 %. Moreover, ten participants were attended to evaluate the accuracy of prosthetic arm control. The experimental results indicated an average control accuracy of 96.97 % with a mean variance of 3.2194. However, Gesture 3 exhibited slightly lower recognition accuracy, which limited the maximum achievable control accuracy. In future work, more advanced deep learning architectures, such as vision transformers, will be explored to further improve control accuracy. The promising results of the proposed deep learning system for recognizing hand gestures from sEMG signals suggest strong potential for practical implementation in prosthetic arm control.

#### CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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