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Enhancing sEMG finger gesture recognition using optimized 1D-convolutional neural network

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ABSTRACT

Robust and precise finger gesture recognition using surface electromyography (sEMG) is essential for developing intuitive prosthetic control systems. However, sEMG signals are inherently stochastic and non-stationary, posing significant challenges for high-accuracy classification in fine-grained movements. This study proposes an optimized 1D convolutional neural network (1D-CNN) framework for classifying 20 distinct fine-grained finger gestures using raw sEMG data from an 8-channel wearable Myo Armband sensor. Unlike traditional methods that rely on manual feature engineering, the proposed 1D-CNN performs end-to-end learning to automatically extract temporal features. The research specifically investigates the impact of temporal windowing strategies, ranging from 400 to 750 ms, on model performance. Experimental results demonstrate that the optimized 1D-CNN achieves a peak test accuracy of 94.4% with a 550 ms window size, demonstrating the model's robustness across complex gesture classes and significantly outperforming the baseline principal component analysis-support vector machine (PCA-SVM) method which only attained 73.0% accuracy. While the model achieved perfect classification (100%) for index, middle, and little finger movements, a performance drop was observed in thumb recognition (50%) due to muscular crosstalk from deeper anatomical layers. These findings indicate that the integration of optimized windowing and 1D-CNN architectures provides a highly reliable solution for complex large-scale gesture recognition, offering a robust foundation for the next generation of multi-functional prosthetic hands.

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1. INTRODUCTION

Human-computer interaction (HCI) has evolved from interface-based text and graphics to interaction-based, more natural, and immersive [1]. Hand gesture recognition (HGR) represents a pivotal component in contemporary interaction technology. This is because the hand has many degrees of freedom (DoF), allowing people to communicate in complex ways without words and to move things with great accuracy. HGR implementation includes a wide range of applications, from control-hand prosthetics [2], [3], and new navigation environments to virtual reality (VR) and augmented reality (AR) systems [4], [5], and touchless system control for medical equipment [6], [7]. All these meet strict sterility standards.

The quality of the data collected during HGR development depends on the sensors chosen. A data-based (vision-based) method that uses a camera depth sensor or an infrared sensor is often limited by line-of-sight issues, changing lighting conditions, and the need for substantial processing power to handle high-resolution images [8]. Wearable sensors like inertial measurement units (IMUs) [9] and Electromyography (EMG), on the other hand, are better at handling environmental changes and allow people to move more easily [10].

Electromyography or surface electromyography (sEMG) is a technology that records the bioelectric activity of muscle fibers during contraction and relaxation [11], [12]. sEMG acquisition is non-invasive and a good fit for wearable technologies like myo-armbands [13], [14]. Because the signal originates in the motor cortex and travels through the spinal nerves to the motor units of muscles, sEMG is thought to be particularly important in HGR [15]. This lets the HGR system figure out what a person wants (anticipation) even when they are moving around [16], [17].

Fine motor movements are delicate in this context; the main problems lie in the complex anatomy of the lower arm [18], [19]. The muscles that move the fingers and hands, such as flexor digitorum superficialis (FDS), flexor digitorum profundus (FDP), and extensor digitorum, are close to each other and often overlap [20]. With eight sensor channels that wrap around the arm, the Myo Armband lets the user send spatial signals from their muscles simultaneously. However, because small muscles are so close together, they can "crosstalk," meaning that sensors in one muscle can detect activity in a nearby muscle. This is because EMG signals from moving different fingers, such as the little finger and the thumb, look very similar [18], [21]. This spatial interference, known as muscular cross-talk, is exacerbated in fine-grained tasks involving 20 different classes. Conventional filters and heuristic-based thresholding are often insufficient to decouple these overlapping neural drives. Consequently, there is an urgent need for a computational framework that can autonomously learn deep latent representations from raw data, effectively "learning" to ignore the noise and focus on the unique temporal signatures of each finger's motor unit recruitment.

This study examines using sEMG because it can provide information about "intention." At 20 Hz on the Myo Armband, each channel gives the user a lot of information. To account for the variability in the sEMG signal, which is non-stationary and stochastic, the user needs a precise processing window and precise timing for catch characteristics that differ across the 20 fine-grained finger gestures of finger movement (5 fingers) with open and close actions [22]. To make prosthetics that are more responsive and accurate, the user needs to know a lot about how EMG signals show muscle contraction in the lower arm [23].

Historically, EMG-based hand movement pattern recognition has relied on traditional machine learning (ML) methods that necessitate extensive feature engineering [24]. Linear discriminant analysis (LDA) [25], support vector machine (SVM) [26], and k-nearest neighbors (k-NN) [27] are all examples of conventional machine learning (ML) algorithms that have become standard in the last ten years because they are easy to use. LDA method is often chosen because it is easy to use and works quickly. However, it does not work as well when there are many movement classes or when the data is highly variable [28]. SVMs work very well, especially on small or low-dimensional datasets. However, choosing the right kernel and tuning hyperparameters can be difficult and time-consuming [29]. k-NN and Naive Bayes algorithms are easy to use but are susceptible to noise and require careful feature preprocessing [30]. Although fundamental, shallow ANNs generally require manual extraction of time-domain (TD) or frequency-domain (FD) features to achieve optimal accuracy [31], [32]. A principal constraint of these conventional methodologies is their reliance on manual feature extraction or feature engineering [33]. Insufficient feature engineering hampers classification performance, especially for intricate finger movements characterized by substantial crosstalk among muscle signals. Despite their widespread use, traditional ML algorithms suffer from a significant 'information bottleneck' due to their reliance on stationarity assumptions. sEMG signals, particularly during multi-finger movements, exhibit non-linear and dynamic characteristics that static feature sets (like MAV or RMS) fail to capture entirely. Furthermore, the manual selection of features often introduces human bias, where certain frequency components or temporal shifts are overlooked, leading to degraded performance when the number of gesture classes increases.

A lot of preprocessing is needed for traditional ML methods. Feature engineering (manual feature extraction). The researcher must determine the most representative features from the time domain, including mean absolute value (MAV), root mean square (RMS), and zero crossing (ZC), or from the frequency domain utilizing the fast Fourier transform (FFT) [8]. This process is "handcrafted," meaning that the effectiveness of the features depends heavily on the skill of the person performing it and often misses complex temporal relationships in the raw EMG data. Also, dimension-reduction techniques such as principal component analysis (PCA) are often used to simplify complex data [34]. However, they risk losing important information about movements, such as those very similar to finger movements.

Deep learning (DL) has become a more effective method over the past ten years, enabling the automatic learning of features from raw data or with minimal preprocessing [24], [35]. DL specifically the convolutional neural network (CNN) architecture, represents a paradigm shift through automatic feature learning [36]–[38], and a 1D CNN is utilized in the study. CNNs are very good at processing both spatial (image) and temporal (time series) data [39]. This architecture learns hierarchical representations directly from the raw signal (end-to-end). Layer convolution functions serve as automatic filters that detect temporal patterns without manual intervention. The one-dimensional (1D) CNN architecture is particularly useful for EMG data, which consists of multichannel time-series signals. In contrast to SVM, which exhibits high bias when confronted with 20 classes with overlapping features, CNN can establish a more intricate decision boundary using millions of optimized parameters.

Also, traditional ML methods are often static and hard to adapt to the normal signal drift in biological EMG data. Deep learning, on the other hand, can generalize better thanks to techniques like dropout and batch normalization. In this research, the switch from SVM (which achieved only about 73% accuracy) [26] to a 1D CNN is used to leverage the model's ability to detect micro-temporal patterns that manual feature statistics cannot. This is very important for distinguishing the "opening" and "closing" actions of the fingers, which are controlled by overlapping muscles.

The 1D CNN architecture is based on efficient computation and its usefulness for time-series data. Unlike architecture, recurrent neural network (RNN) or LSTM, which often need longer training and are more likely to run into the vanishing gradient problem, 1D CNNs can process data more quickly and in parallel through temporal convolution. Automatic feature extraction: 1D CNNs use convolutional layers to automatically find the most discriminative temporal patterns (kernels) in EMG signals. This reduces the need for manual feature engineering, which can be error-prone [40]. Managing temporal dependencies: 1D kernels naturally capture time-based dependencies and short-term changes associated with muscle movement [41]. Better performance: Recent research shows that 1D CNNs are more accurate and stable than traditional ML methods, especially when the subject or environment changes [42]. This makes it a good choice for an application-introduction gesture that requires low latency. 1D CNN effectively extracts spatial intersensory (8 Myo channels) and temporal features, making it well-suited for processing complex motion datasets of fingers.

The study's novelty primarily resides in three essential aspects: firstly, the classification of 20 distinct fine-grained gestures; in contrast to most HGR studies that utilize only 5-7 gestures, this study employs hand roughness. Investigate the classification precision for each finger individually (open and close actions). Second, the study found that a 550 ms window is best for balancing resolution information and model stability. This window is better than the standard 600 ms window. Third, incorporation of a learning rate scheduler into EMG Data: Execution of a rate-adaptive learning schedule demonstrated substantial improvement in model convergence stability on variable bio-signal data, achieving a test accuracy of 94.4%.

The main goal of this project is to develop and deploy a 1D CNN architecture that reliably recognizes patterns of finger opening and closing motion by extracting features from raw sEMG data. The goal of this research is to build a model that automatically recognizes 20 different finger movements using an end-to-end learning approach. This would reduce the need for manual feature extraction, a common practice in traditional methods. This study also sought to identify the optimal input parameters by comparing the classification performance of window sizes of 600 ms and 550 ms. This was done to make sure the control worked perfectly.

This research aims to evaluate system stability by implementing a learning rate scheduler and analyzing its impact on the validation accuracy curve during model development. This is crucial for medical robots because they need to ensure that control remains consistent and works. This study aims to provide empirical evidence of the superiority of deep learning techniques over traditional machine learning algorithms, such as LDA and SVM. This research seeks to advance the development of more responsive and intuitive prosthetic hand technology by demonstrating significant accuracy improvements over traditional PCA-SVM methodologies.

This article will be structured as follows: section 1 is introduction. It describes the background of the study, the urgency of using sEMG signals for prosthetic control, the limitations of traditional methods, and the novelty and purpose of the 1D CNN architecture. This is followed by section 2: materials and methods, which explain in detail the data-acquisition procedure using the Myo Armband, the experimental protocol for 20 finger movements, signal preprocessing techniques, including windowing and segmentation, and the design of the proposed 1D CNN system architecture. The first part is followed by a comprehensive analysis of the experimental results in the results and discussion section and finally the conclusion and future works section, where this section summarizes the main findings of the study regarding the effectiveness of the proposed model and provides strategic directions for the development of more precise prosthetic control systems in the future.

2. METHOD

This chapter delineates systematic research, encompassing the data acquisition procedure, signal preprocessing, signal detection, the implementation of a 1D-CNN architecture, and the optimization strategy employed to enhance 20-class classification across 20 gesture classes. The data collection methods in studies are grounded in development protocols previously validated by Dela *et al.* [26].

The Myo Armband (Thalmic Labs Inc.) is used to acquire the sEMG signal. This device is chosen because it is wireless, non-invasive, and easy to use for wearable applications [43]. The Myo Armband has eight sEMG sensor channels with dry electrodes wrapped around the subject's lower arm. The signals we collected have 8-bit resolution and a sampling rate of 200 Hz, and they are sent through a Bluetooth low energy (BLE) module. Data acquisition for this pilot study was performed by a single healthy male subject (aged 25) to establish a baseline performance for the proposed 1D-CNN architecture across a high-dimensional gesture space. While focusing on a single participant, this study prioritizes the technical feasibility of classifying 20 distinct fine-grained finger movements, which is significantly higher than the 5-7 gestures typically found in existing literature [44]. This approach provides a rigorous initial validation of the model's feature extraction capabilities before future expansion to a broader demographic.

The subject is seated, with the right arm resting on the top of the table to minimize the burden on static muscles and artefact movement. Eight Myo Armband electrodes are positioned on the flexor digitorum superficialis muscle and the extensor muscles around the lower arm.

There are 20 different ways for the fingers to move, each with two main actions: opening and closing. The data collection protocol required the subject to perform each finger movement for a duration of 5 seconds. To keep muscles from getting tired, the relaxation phase (rest) lasts five seconds between movements. The movement is repeated up to 10 times per cycle to ensure sufficient data for training the network (deep neural network).

The Myo Armband's raw data needs to be cleaned and split up before it can be used in the 1D CNN model. To capture the temporal dynamics of EMG signals, a sliding window technique [45] was used. Based on empirical results, the window size is set to 550 ms. At 200 Hz, with a sample window of 110 points per channel, resulting in an input matrix of size 110×8. A sliding window technique with a 50% overlap was implemented to significantly expand the dataset size, addressing the data-intensive requirements of deep learning. Although the initial recording consisted of 10 controlled repetitions per cycle for each of the 20 classes, the windowing and overlap process augmented the dataset into thousands of individual segments. This strategy ensures that the 1D-CNN is exposed to sufficient temporal variations, thereby enhancing the model's generalization and preventing overfitting despite the focused number of participants.

Keep in mind that the sEMG signal is highly dependent on the subject's skin and contraction strength, and normalization is performed using Z-score Standardization. This method transforms the data so that it has a mean μ of 0 and a standard deviation σ of 1. This has been shown to speed up convergence in algorithms that use gradient descent [46], [47].

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where z is z score, μ is mean and σ is standard deviation.

This study suggests substituting traditional PCA and SVM with 1D CNNs, which excel at automatically extracting features from time-series data without requiring intricate handcrafted features [47]. The 1D CNN model architecture developed in this study comprises a series of integrated layers for automatic temporal feature extraction. The network structure begins with a 1D convolutional layer that uses a temporal convolution filter to extract local feature patterns from the raw sEMG signal, with the application of a rectified linear unit (ReLU) activation function to introduce non-linearity into the model [48]. To maintain the stability of the training process on fluctuating Bio signal data, a batch normalization layer is added immediately after the convolution process to normalize the activations [49]. Next, a pooling layer with the MaxPooling1D mechanism is used to reduce the spatial dimensionality while preserving the most dominant features, making the model more robust to small signal shifts [50].

To mitigate the risk of overfitting, a dropout layer is applied with a rate of 0.5, which works by randomly turning off neurons during the training phase [51]. The extracted high-level features are then integrated using a fully connected layer with 32 neurons. In the final stage, a SoftMax output layer is used to generate a probability distribution that classifies the data into 20 discrete finger movement classes [52]. This overall configuration enables the model to recognize complex motion patterns with greater precision than traditional methods.

The model training process was carried out using the Adam optimization algorithm [53]. An initial learning rate of 0.001 is set for this algorithm. To improve model performance and stability, two additional strategies were implemented: the learning rate scheduler and early stopping. The first strategy is dynamically adjusting the learning rate based on monitored validation metrics. This method allowing the model to reach the global minimum with a higher level of precision and accuracy. There is a second strategy, which is to have early stopping. This strategy automatically stops the training process if the validation loss does not decrease for 7 consecutive epochs or a patience period. The implementation of this mechanism is crucial to prevent overfitting and ensure that the saved model parameters represent the results with the best generalization ability on the test data. The proposed 1D-CNN architecture is designed to perform end-to-end feature extraction from raw sEMG signals. As detailed in Table 1.

Table 1. Architecture and layer parameters of 1D-CNN algorithm

Layer (Type)	Output Shape	Kernel Size	Parameters/ Note
Input Layer	(550, 8)	-	8-channel sEMG input
Conv1D	(548, 64)	3	Feature mapping
Batch normalization	(548, 64)	-	Regularization
ReLU (Activation)	(548, 64)	-	Non-linearity
MaxPooling1D	(274, 64)	2	Downsampling
Conv1D	(272, 128)	3	High-level features
ReLU (Activation)	(272, 128)	-	Non-linearity
GlobalAvgPooling 1D	-128	-	Parameter reduction
Dropout	-128	-	Rate: 0.5
Dense (Output)	-20	-	Softmax (20 classes)

The specific configuration of the 1D-CNN architecture was chosen to balance computational efficiency and classification accuracy. The Batch Normalization layers were integrated to stabilize the training process against the stochastic nature of sEMG signals, while the Dropout rate of 0.5 was strategically applied to mitigate overfitting during high-dimensional classification. Furthermore, the inclusion of a global average pooling (GAP) layer serves as a structural regularize, reducing the total parameter count and preventing the model from becoming overly complex, which is essential for potential real-time prosthetic applications.

The data is divided into three parts: 70% for training, 15% for validation, and 15% for testing. The evaluation used the metrics Accuracy, Precision, Recall, and F1-Score on the test data. The Usage Confusion Matrix was used to break down model performance on difficult classes, which were separated by muscular crosstalk phenomena [54]. Figure 1 shows the flowchart of the methods that are used in these experiments.

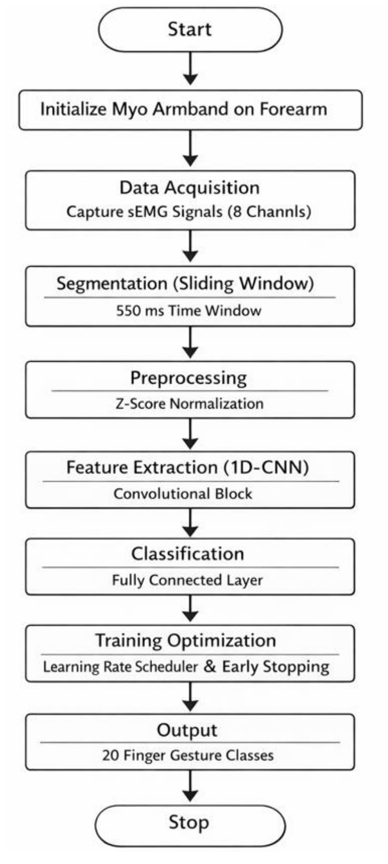


Figure 1. Flow chart of the methods

3. RESULTS AND DISCUSSION

This chapter shows the results of an experiment that used the current 1D CNN model to sort 20 finger movements. The analysis compared the results of the basic method (SVM) and evaluated the model's stability using a comprehensive performance metric.

Before the classification process using the 1D-CNN architecture, the raw sEMG signals were analyzed to ensure data quality. The sEMG signals obtained from the Myo Armband are inherently non-stationary and have highly variable amplitudes across electrodes. Signal visualization revealed high stochastic fluctuations in the raw data, which, if left unaddressed, could hinder the convergence of the deep learning model.

The application of normalization using Z-score standardization successfully transformed the data distribution to have a mean $\bar{\mu}$ of zero and a standard deviation $\bar{\sigma}$ of one. Visually, this process balanced the dynamic range (amplitude) across the eight sensor channels, allowing the 1D-CNN model to focus on extracting temporal features and muscle contraction patterns without being affected by differences in sensor pressure strength on the skin or variability in the subject's muscle strength. This provides a crucial foundation for the convolutional filter to automatically detect micro-temporal features in the next stage. Figure 2 illustrates the comparison between the raw sEMG signals and the output of the Z-score standardization process.

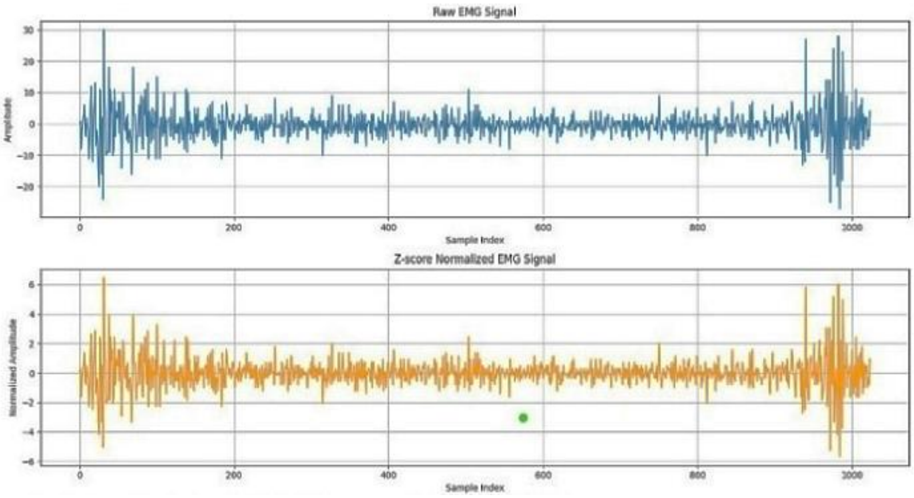


Figure 2. Raw sEMG signals and preprocessed signals

As demonstrated in Table 2 and visualized with a bar chart in Figure 3, the 1D-CNN model's performance is highly sensitive to the temporal window duration. The highest test accuracy of 0.944 (94.4%) was achieved with a window size of 550 ms. Interestingly, performance significantly degraded at 700 ms (0.185 accuracy), suggesting that excessively long windows introduce non-stationary noise that interferes with the convolutional filters' ability to extract stable motor unit activation patterns. As observed in Figure 3, the accuracy curve exhibits a non-linear relationship with the window duration. The sharp decline in accuracy at 450 ms and 700 ms indicates that the 1D-CNN is highly sensitive to temporal boundary conditions. A window that is too short (below 500 ms) fails to provide enough temporal information for the kernels to detect a complete firing pattern, while a window exceeding 650 ms introduces excessive non-stationary artifacts that blur the distinction between gesture classes. Therefore, 550 ms was selected as the optimal parameter for all subsequent experiments.

The shift from a 600 ms window (0.91% accuracy) to a 550 ms window (94.4% accuracy) indicates that temporal resolution is a critical factor in sEMG pattern recognition. A 550 ms duration provides an optimal balance; it is long enough to capture the essential motor unit firing patterns while remaining short enough to avoid the inclusion of excessive transition noise and stochastic fluctuations that often degrade deep learning performance.

The stability of the model during the training phase was ensured through the implementation of a learning rate scheduler and early stopping [55], [56]. Figure 4 illustrates the training and validation curves. While the training accuracy reached 96%, the validation accuracy stabilized at approximately 74% as shown in Figure 4(a). This gap suggests a degree of overfitting, which is a common challenge in sEMG-based deep learning due to the inherent stochasticity and signal-to-noise ratio variability in bio-signals. However, the implementation of a learning rate scheduler and dropout (0.5) successfully prevented the validation loss from diverging as shown in Figure 4(b), ensuring that the model maintains its ability to generalize across unseen testing data rather than merely memorizing the training set.

Table 2. The overall accuracy vs window size

Window Size (ms)	Test Accuracy
400	0.831
450	0.593
500	0.431
550	0.944
600	0.909
650	0.655
700	0.185
750	0.815

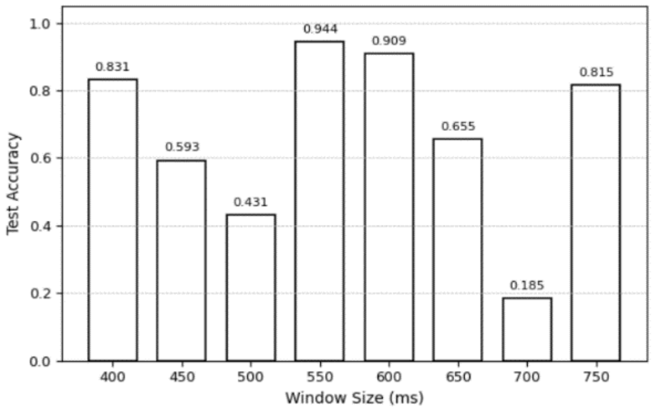
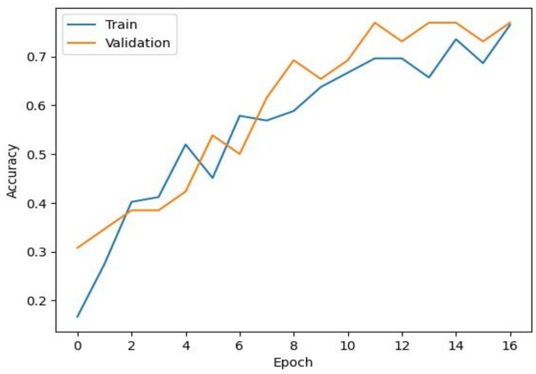
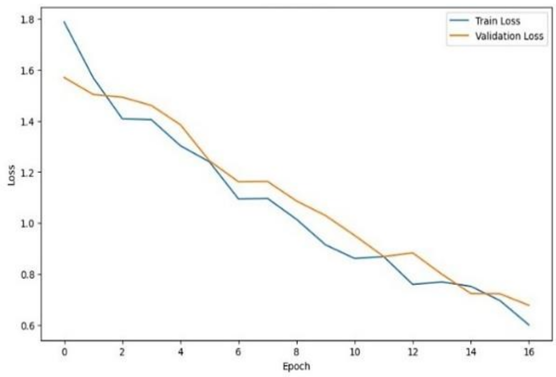


Figure 3. Impact of varying temporal window durations on the 1D-CNN classification accuracy



(a)



(b)

Figure 4. Training and validation performance curves illustrating (a) model convergence and (b) stability using a 550 ms window

The convergence observed at epoch 18, where the early stopping mechanism intervened, proves that the model successfully learned generalized features rather than merely memorizing the training data. The use of batch normalization further contributed to this stability by normalizing activations against the non-stationary nature of raw sEMG signals, allowing for faster and more reliable gradient descent.

The detailed performance of the 1D-CNN model in classifying finger gestures is evaluated using a Confusion Matrix, as shown in Figure 5. Table 3 also describes the results of the confusion matrix. This matrix provides a comprehensive overview of the distribution of the model's predictions against the true labels of the testing data.

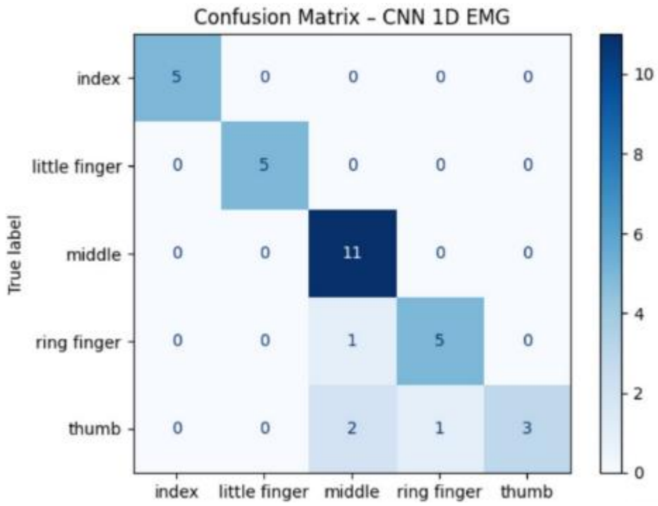


Figure 5. Confusion matrix for classification performance

Table 3. Summary accuracy for each finger group

Finger Group	Accuracy Class	Analysis Error
Index	100%	Perfect Classification
Little Finger	100%	Perfect Classification
Middle	100%	Perfect Classification
Ring	83.3%	1 sample misclassified as Middle Finger
Thumb	50.0%	Often confused with the middle finger and the ring finger

Based on testing results on 33 data samples, the model achieved an accuracy of 87.9%. Class-by-class analysis revealed the following significant findings: Perfect classification (100% accuracy): The model demonstrated excellent performance with perfect classification of the index finger (5/5), little finger (5/5), and middle finger (11/11). This demonstrates that the 1D-CNN architecture is highly effective in recognizing the unique contraction patterns of the flexor digitorum superficialis and extensor digitorum muscles that move these three fingers.

Minor misclassification (ring finger): The ring finger achieved 83.3% accuracy, with 5 out of 6 samples correctly classified. One sample was detected as the middle finger. Anatomically, this often occurs due to the tendon attachment between the ring and middle fingers, which causes the sEMG signals from the two fingers to have highly similar patterns [57].

The Thumb challenge (50% accuracy): The biggest challenge was found with the thumb, which only achieved 50% accuracy (3 out of 6 correct samples). The thumb was frequently misidentified as the middle finger (2 samples) or the ring finger (1 sample). This poor performance is scientifically attributed to the phenomenon of muscle crosstalk [58]–[60]. The 50% accuracy observed for thumb gestures is scientifically significant. Anatomically, the muscles responsible for thumb opposition, such as the opponents pollicis, are located in the deeper layers of the forearm. The Myo Armband's surface electrodes primarily capture superficial muscle activity, leading to a 'masking effect' where the stronger signals from the flexor digitorum (middle and ring fingers) dominate the recorded potential [61]. This muscular crosstalk creates high feature similarity in the latent space, making it difficult for the SoftMax layer to establish a clear decision boundary for thumb movements [61]. This phenomenon is clearly reflected in the confusion matrix as shown in Figure 5, where the misclassification clusters predominantly occur between the thumb and the fingers controlled by the superficial flexor muscles. As a result, the bioelectric signals captured by the Myo Armband's surface sensors are often attenuated or masked by stronger superficial muscle activity [62], [63].

Overall, despite the constraints on thumb detection, the model's ability to classify the majority of movements with very high accuracy (above 83% to 100%). This indicates that the use of Z-score normalization and 550 ms window size optimization has successfully minimized the variability of sEMG signals and provided stable temporal features for the 1D-CNN model.

The integration of a learning rate scheduler and early stopping successfully stabilized the validation curve, preventing the model from over-adjusting to noise in the EMG signal [64], [65]. Modern signal processing techniques and edge computing considerations further validate this approach for future wearable devices.

4. CONCLUSION

This study has successfully developed an optimized 1D convolutional neural network (1D-CNN) architecture for fine-grained finger gesture recognition using raw sEMG signals. The experimental results demonstrate that the proposed model achieves a peak classification accuracy of 94.4% for 20 distinct finger movements. This performance underscores the superiority of end-to-end deep learning in capturing complex temporal patterns directly from raw bioelectric signals without the need for manual feature extraction.

A key finding of this research is the significant impact of temporal windowing on model performance. Reducing the window size from 600 to 550 ms proved to be the optimal strategy, providing the necessary temporal resolution to capture muscle contraction dynamics while maintaining high stability. The implementation of a learning rate scheduler and early stopping further ensured the model's robustness, preventing overfitting despite the stochastic nature of sEMG data.

While the model achieved 100% accuracy for the index, middle, and little fingers, the lower performance observed for the thumb (50%) highlights the persistent challenge of muscle crosstalk from deeper anatomical layers, specifically the opponents pollicis, which are less accessible to surface electrodes. The model achieved a peak test accuracy of 94.4% under optimal conditions, with an overall average accuracy of 87.9% across all specific tests shown in the matrix. In conclusion, the optimized 1D-CNN framework offers a highly accurate and scalable solution for multiclass gesture recognition, paving the way for more intuitive and precise control systems in next-generation prosthetic hands.

For future development and research, several strategic needs should be addressed with the appropriate system. The primary focus should be on improving classification accuracy for finger and thumb, which can be achieved by adding an sEMG sensor over the thenar muscle or by combining frequency-domain features tailored to difficult classes. In addition, considering the study, this is still done offline. Implementation of the model for real-time in-system control is highly recommended to achieve test-level latency and responsiveness in hand prosthetics or robotics.

Further experimentation is necessary, involving additional subjects and testing in various positions and arm postures, to enhance the model's capacity to generalize to changes in sensor orientation and muscle fatigue. Additionally, exploring hybrid architectures, such as CNN-LSTM, is advisable. The ability to capture temporal dependencies can more effectively reduce errors in classifying fingers exhibiting pattern contractions akin to those of muscles. With the developments, it is anticipated that the system for introducing finger movement can evolve into a solution for more precise, reliable, and readily available hardware-integrated prosthetics.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author (DSP), upon reasonable request.

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