AI-Powered EMG-Based Deep Learning Model for Multi-Gesture Classification in a Prosthetic Hand System

Aqsa Nadir, Muhammad Noman Umer*, Syed Atif Ali, Jibran George
Faculty of Engineering Sciences and Technology, Hamdard University, Karachi, Sindh, Pakistan.
*E-mail: mnomanumer1@outlook.com

ABSTRACT

INTRODUCTION

The impact of losing a limb is both physical and psychological, deeply affecting the daily lives of amputees. While prosthetic technology has advanced, many sophisticated solutions remain inaccessible and affordable due to heavier hardware production cost. Current high-end systems are based on utilization of brain-signal sensors (EEG), while highly capable, they require expensive sensors. Our research addresses this by utilizing muscle-signal sensors (s-EMG) on the residual limb, offering a more affordable and practical alternative. To translate these signals, we employ Artificial Intelligence, specifically Deep Learning model because modern deep learning frameworks allow for the automated learning of discriminative patterns directly from raw muscle data, bypassing the need for manual feature engineering [1]. In addition these models when integrated with surface electromyography provide a reliable method for enhancing hand gesture recognition in prosthetic control [2]. By developing a streamlined architecture, we have focused and enhanced the recognition of five essential gestures: hand open, hand close, lateral, sign, and rock. Though the recognition of complex gestures such as 'rock' and 'sign' has been improved in accuracy by the utilization of fine-grained feature extraction [3].This ensures that advanced, intuitive prosthetics are not only technologically precise across a variety of movements but also economically reachable for those who need them most.

OBJECTIVES

The central objective of this research was to develop a reliable and intelligent EMG-based gesture classification model capable of supporting real-time prosthetic hand control.The integration of machine

learning and deep learning with surface electromyography provides a non-invasive and highly reliable control interface for amputees which guides us to use deep learning as the go-to approach [4].The study was designed around four major goals:

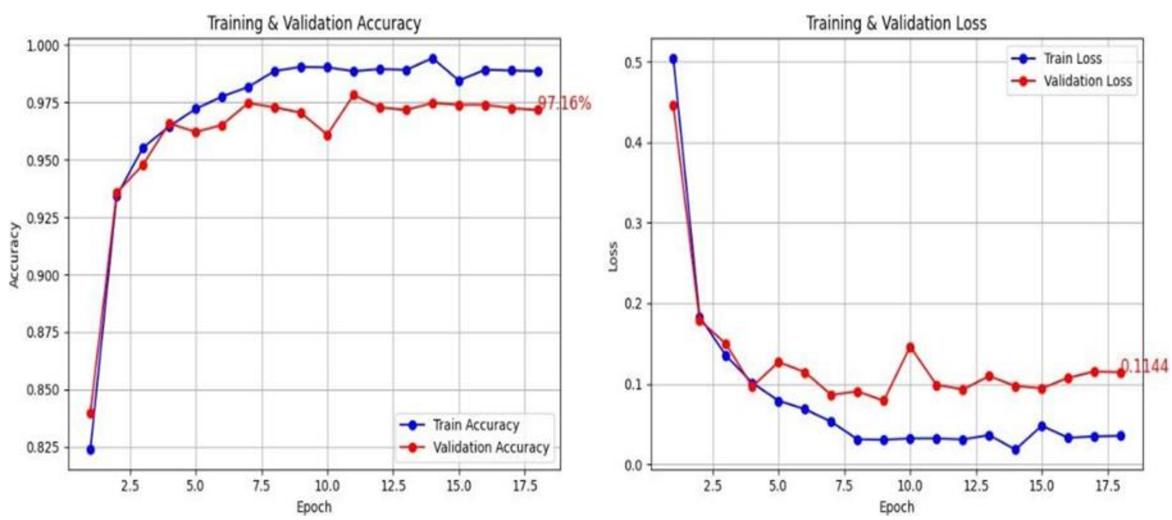
1. To design a deep learning model that can accurately classify multiple hand gestures using raw s-EMG signals, eliminating the need for complex feature engineering.
2. To train a lightweight and computationally efficient CNN architecture suitable for real-time deployment on low-cost hardware typically used in prosthetic systems.
3. To achieve high-precision recognition of gestures essential for prosthetic functionality, particularly open-hand and closed-hand movements, which directly correspond to release and grip actions, including lateral pinch, rock, and sign gestures.
4. To validate the model’s performance across multiple subjects and gesture types, demonstrating its generalizability and practical potential for integration into intuitive, user-friendly prosthetic hand solutions.

METHODOLOGY

The requisite data for this study was obtained from the publicly available EMG Hand Gestures Dataset, which is housed in the Zenodo research archive. This dataset includes raw electromyography (EMG) signals recorded across multiple channels from eight separate participants who performed five distinct hand gestures. The signals were captured using s-EMG sensor with four specific EMG channels, placed precisely on the relevant muscles of the forearm. These s-EMG sensors being non-invasive, reduce complications such as stiffness of muscles and provide high performance [4]. To reduce the natural signal differences that occur between subjects, the data was normalized for each channel, ensuring all signals were standardized. A deep one-dimensional CNN architecture was developed as streamlined deep learning approach is essential for balancing the high computational demands of AI with the need for high-speed gesture classification [1]. It consista of three convolutional blocks with batch normalization and max pooling to extract temporal spatial patterns from the EMG data as the implementation of residual modules within deep networks helps maintain signal integrity and prevents data loss during deep feature extraction [2]. A dense layer with dropout provided regularization before the final softmax classifier. Evaluation metrics included overall accuracy, learning curves, and confusion matrices.

KEY FINDINGS

The model demonstrated strong learning behavior and rapid convergence. It achieved a validation accuracy of 97.16% and a training accuracy of 98.97%. When tested on unseen data, the model reached an impressive 97.43% accuracy, indicating excellent robustness and generalization. It worked extremely well on every gesture as the development of high-precision models requires that essential gestures, such as "lateral" and "sign," are recognized with the same accuracy as simpler "open" and "close" movements [5].



Training Accuracy & Loss Curves with Annotations.

Confusion Matrix Heatmap.

Visualization of the EMG windows showed clear differences in waveform patterns between gestures, supporting the CNN's ability to extract distinctive signal features. The confusion matrix revealed that the classifier handled all five gestures with minimal overlap, with especially accurate detection of open-hand and closed-hand gestures critical for control of grip and release mechanisms in prosthetics. The model,

containing approximately 400,000 trainable parameters, is compact enough for real-time inference on modest hardware such as standard consumer laptops or embedded processors, making it a viable candidate for low-cost prosthetic systems as processing s-EMG signals on edge devices reduces the reliance on external hardware, making prosthetics more independent and mobile for the user [6].

CONCLUSION

This paper delivers a complete, easy-to-use deep learning system for recognizing gestures based on muscle signals, specifically built for smart prosthetic hand control. Our proposed CNN strikes an excellent balance: it's accurate, computationally efficient, and very reliable. This makes it ideal for running in real-time on budget-friendly prosthetic devices. The fact that our system performs so well on essential movements, like gripping and releasing, shows just how practical it is. Looking ahead, we plan to work on models that adjust to individual users and modify the deep learning model into hybrid models because hybrid neural networks utilizing smart skip connections are now capable of achieving high-precision recognition while significantly reducing system latency [5]. Update the model to handle more gestures, and can be completely integrated onto microcontrollers for totally portable, real-time prosthetic use.

Keywords: EMG Classification, Deep Learning, Prosthetic Hand, Convolutional Neural Networks, Bio-Signal Processing.

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