

Machine Learning-Based Hand Gesture Classification Using EMG Signals for Bionic Hand Applications

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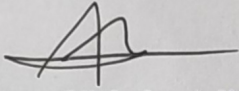
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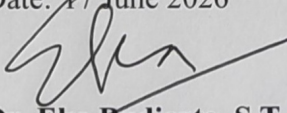
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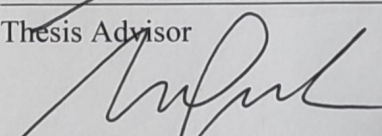

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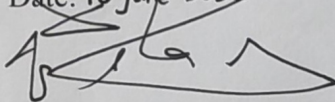
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ABSTRACT

The discontinued Myo Armband previously used in the Swiss German University bionic hand project created the need for a new EMG-based gesture classification pipeline using a newly adopted surface EMG sensor. This study collected and evaluated four-channel EMG data from MyoWare v1 surface EMG sensors connected to a DOIT ESP32 DevKit V1 for five gesture classes: fist, open hand, pointing, pen-grip, and rest. Data were transmitted to an Apple silicon Mac through USB serial communication, stored as CSV files, and organized into training, validation, and test folders. The methodology included data acquisition, preprocessing, time-domain feature extraction using MAV, RMS, ZCR, WL, and SSC, model training, and quantitative evaluation using accuracy, precision, recall, macro F1-score, and confusion matrix analysis. Random Forest, Support Vector Machine, Artificial Neural Network, and One-Dimensional Convolutional Neural Network models were compared using raw, normalized, and feature-based representations. The acquisition setup captured measurable gesture-related signal differences, with the average RMS of the main responsive channels increasing from 0.087255 during rest to 0.360770 during fist. The best balanced model was the SVM using 1-second windows, z-score raw normalization, moving average smoothing with a window size of 10, the RBF kernel, and $C = 10$, achieving 0.8065 accuracy, 0.8048 macro precision, 0.8063 macro recall, and 0.8038 macro F1-score. Random Forest and 1D CNN also achieved 0.8065 accuracy, but their macro F1-scores were slightly lower at 0.7990 and 0.7943, respectively, while the best ANN achieved 0.7527 accuracy and 0.7427 macro F1-score. Therefore, the newly adopted EMG sensor setup provided usable signal patterns for software-level hand gesture classification, and the SVM was identified as the most suitable balanced model, although open hand, pointing, and pen-grip remained the most difficult gestures to separate consistently.

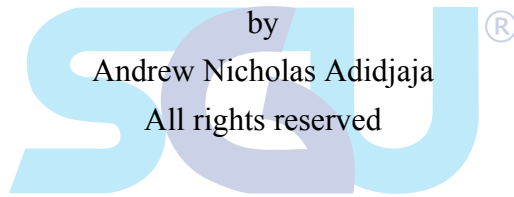
Keywords: electromyography, hand gesture classification, MyoWare sensor, ESP32, machine learning

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LIST OF ABBREVIATIONS

Abbreviation	Meaning	Abbreviation	Meaning
1D	One-dimensional	LLC	Local Linear Co-ordination
2D	Two-dimensional	LMD	Local Mean Decomposition
ADC	Analog-to-digital converter	LS-SVM	Least Squares Support Vector Machine
ADC1	Analog-to-digital converter unit 1 on the ESP32	LSTM	Long Short-Term Memory
AI	Artificial Intelligence	LTSA	Local Tangent Space Alignment
ANN	Artificial Neural Network	MAV	Mean Absolute Value
Bi-LSTM	Bidirectional Long Short-Term Memory	mDWT	Marginal Discrete Wavelet Transform
Ch	Channel	ML	Machine Learning
CNN	Convolutional Neural Network	NBC	Naive Bayes Classifier
CSV	Comma-Separated Values	PC	Personal Computer
CWT	Continuous Wavelet Transform	RBF	Radial Basis Function
CW-CNN	Channel-Wise Convolutional Neural Network	RF	Random Forest
DB	Database	RMS	Root Mean Square
DE-FCM-EWT	Differential Entropy–Fuzzy Cognitive Maps–Empirical Wavelet Transform	RQ	Research Question
EA-BBN-ELM	Evolutionary Algorithms–Bayesian Belief Network–Extreme Learning Machine	SGU	Swiss German University
EMAV	Enhanced Mean Absolute Value	SHAP	SHapley Additive exPlanations
EMG	Electromyography	SFS	Sequential Forward Selection
ESP32	Espressif 32-bit microcontroller platform	sEMG	Surface Electromyography
EWL	Enhanced Waveform Length	SSC	Slope Sign Changes
F1-score	Harmonic mean of precision and recall	SVM	Support Vector Machine
GB	Gigabyte	UNICEF	United Nations Children’s Fund
GPIO	General-Purpose Input/Output	USB	Universal Serial Bus
HDEMG	High-Density Electromyography	WHO	World Health Organization
HIST	Histogram feature	WIPO	World Intellectual Property Organization
ICA	Independent Component Analysis	WL	Waveform Length
IEMG	Integrated Electromyography	ZC	Zero Crossing
KNN	K-Nearest Neighbors	ZCR	Zero-Crossing Rate