

Real-Time Multiclass Gesture Recognition via Hjorth Parameters and EMG Signal Analysis

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Abstract - Surface electromyography sEMG for short is one of those tools that sounds intimidating but really just means sticking sensors on the skin to pick up tiny electrical signals from your muscles. In our case, we tried using it to recognize static hand gestures, pulling data from the UCI EMG dataset. That set is surprisingly rich 36 people, each performing a bunch of defined gestures, all recorded across eight muscle channels. Now, instead of throwing raw signals straight into a model (which usually doesn't go well), we built a feature extraction setup that digs into both time and frequency domains. Things like integrated EMG, waveform length, and zero-crossing rate sit alongside spectral peaks and Hjorth parameters. These aren't flashy features, but together they give a surprisingly detailed picture of muscle activity when run through sliding windows. One headache was class imbalance some gestures were just less frequent than others. We tried resampling and scaling tricks to smooth that out before training a deep neural network. The payoff was solid: about 94% macro-average accuracy across all gesture types. Still, I wouldn't claim perfection. Results like these depend a lot on preprocessing choices, and there's always the worry that performance might slip outside controlled datasets. To peek inside the black box a little, we leaned on visualization t-SNE plots to see how gestures clustered, correlation heatmaps, even multiclass ROC curves. These don't solve the interpretability issue entirely, but they help. So, the main takeaway, at least for me, is that blending old-school feature engineering with deep nets can work really well here. Pure deep learning often gets all the attention, but sometimes the more traditional signal processing tricks quietly carry the load.

Keywords - Surface Electromyography (sEMG), Hand Gesture Recognition (HGR), Hjorth Parameters, Deep Neural Network (DNN), Assistive and Prosthetic Control.

I. INTRODUCTION

Electromyography (EMG) has matured into a powerful biosignal modality for decoding motor intent and enabling natural human-computer interaction (HCI) in applications such as prosthetic control, rehabilitation, and wearable assistive devices. By measuring the electrical activity produced by skeletal muscles, surface EMG (sEMG) captures neuromuscular activation patterns that are closely tied to intended movements. Unlike vision-based approaches that are vulnerable to occlusion,

lighting and viewpoint changes, and privacy issues, sEMG directly reflects the physiological commands of the peripheral nervous system and can discriminate subtle gestures such as individual finger flexions and coordinated grips (Chowdhury et al., 2013; Esposito et al., 2021). This intrinsic link to motor intent makes sEMG particularly attractive for low-latency, private, and wearable HCI systems. Despite its advantages, sEMG is inherently non-stationary and affected by multiple sources of variability — electrode placement and contact impedance, inter- and intra-subject anatomical differences, muscle fatigue, and external noise — all

of which complicate robust gesture decoding in real-world conditions (Waris et al., 2018). Classical pipelines therefore emphasize preprocessing (band-pass and notch filtering, artifact removal), segmentation (sliding windows or event-based), and feature extraction (time-, frequency-, and time-frequency domain descriptors) prior to classification. Time-domain features such as mean absolute value (MAV), waveform length (WL), zero-crossings (ZC), and slope sign changes (SSC) are computationally cheap and have a long history of success in embedded systems (Chowdhury et al., 2013). Frequency-domain metrics (e.g., median/mean frequency) and time-frequency transforms capture spectral shifts associated with muscle activation and fatigue, complementing TD descriptors when combined in hybrid feature sets.

Among compact, interpretable descriptors, Hjorth parameters — Activity, Mobility, and Complexity — stand out for sEMG analysis. Activity measures variance (signal power), Mobility relates to mean frequency via the standard deviation of the derivative, and Complexity estimates the change in frequency content over time. These parameters are computationally inexpensive, robust to short windows, and provide physiologically meaningful summaries that often improve separability across gestures when used with classical classifiers or small neural networks (Phinyomark, Quaine, & Hu, 2018; Côté-Allard et al., 2019). Their small memory and compute footprint make them particularly valuable for wearable and battery-constrained devices.

The last decade has also seen rapid progress driven by representation learning. Convolutional neural networks (CNNs) applied to transformed sEMG representations (e.g., image-like maps, spectrograms) can automatically learn spatial filters that exploit electrode topology and multichannel correlations (Geng et al., 2016). Graph-based approaches and models that explicitly use electrode geometry further improve spatial modeling, especially for high-density sEMG arrays (Xiong, Zhang, Zhao, & Zhao, 2020). Recurrent and hybrid CNN-LSTM models capture temporal dynamics for dynamic gesture sequences, while attention mechanisms have been used to emphasize salient

temporal or spatial components. These deep approaches generally achieve higher accuracy, but at the cost of increased training data requirements and heavier runtime demands — constraints that hinder direct deployment on many embedded systems and low-power wearables (Bai et al., 2021; Fatayer, Gao, & Fu, 2022).

A persistent, practical challenge is user independence: models trained and validated on a set of subjects often perform substantially worse on unseen users due to anatomical differences, sensor placement variability, and idiosyncratic muscle recruitment patterns. Solutions proposed in the literature include domain adaptation, transfer learning, and self-calibration techniques that reduce inter-subject and inter-session gaps (Côté-Allard et al., 2019; Zhou et al., 2017). Multi-day evaluations and cross-session studies demonstrate that daily recalibration or adaptive layers can substantially recover performance, but they add complexity and reduce plug-and-play usability (Waris et al., 2018). Further, many existing high-performing methods rely on high-density arrays or computationally intensive models, which may not be practical for consumer-grade prostheses or wearables that favor simplicity and long battery life.

Given this trade-off space — accuracy versus interpretability and efficiency versus generalization — hybrid strategies that fuse carefully selected handcrafted features with lightweight deep classifiers present an appealing compromise. Handcrafted descriptors (including Hjorth parameters) preserve interpretability and low computational cost, while compact DNNs can provide non-linear decision boundaries and modest feature learning without the weight and latency of large CNNs. Several studies show that combining classical features with shallow neural architectures preserves much of the accuracy gains of deep models while remaining suitable for embedded deployment (Bai et al., 2021; Abbaspour et al., 2020).

In the present study, we propose a hybrid pipeline that systematically engineers Hjorth and complementary time- and frequency-domain features, applies a robust preprocessing stage

(filtering, segmentation, normalization), addresses class imbalance using SMOTE, and trains a compact deep neural network classifier on the handcrafted feature set. Our goals are to (a) achieve high classification performance comparable to heavier architectures, (b) improve robustness across subjects and sessions through preprocessing and augmentation strategies, and (c) maintain runtime and memory efficiency compatible with wearable hardware. We validate the framework on established sEMG datasets and report a macro-average F1-score of 94.04%, demonstrating that interpretable, low-cost features combined with a lightweight DNN can compete with larger models while offering clearer pathways to real-time embedded deployment.

The remainder of the paper is organized as follows. Section 2 surveys the related literature and datasets used in benchmarking; Section 3 details the dataset, preprocessing, feature extraction, and model architecture; Section 4 presents experimental results, ablation studies, and comparisons; Section 5 discusses practical implications and deployment considerations; and Section 6 concludes with future directions for user-independent and energy-aware sEMG systems. Table 1 summarizes verified, representative EMG gesture recognition studies used for comparison.

Table 1: Comparison of related EMG-based gesture recognition studies

Authors & Year	Area of Focus	Methodology	No. of Gestures	Accuracy (%)	Dataset / Subjects	Strengths
Atzori et al. (2014)	Benchmark EMG Dataset	SVM, kNN, RBF, ANN	52	73–85	NinaPro DB1–DB5 / 67 subjects	First large-scale EMG HGR benchmark; widely used
Geng et al. (2016)	Instantaneous EMG Images	EMG→Images + CNN	8–10	88–92	Custom / 8 subjects	Strong spatial modeling using EMG images
Phinyomark et al. (2012)	Feature Reduction	TD/FD features + PCA/LDA/SVM	10	≈90	Custom / 8 subjects	Reduces redundancy; improves interpretability
Waris et al. (2018)	Multi-Day EMG Classification	SVM + LDA + TSD	10	85–95	12 subjects	Robust across multiple days
Maragliulo et al. (2019)	Wearable Foot EMG Gestures	Dual-channel EMG + kNN	6	90	Custom / 10 users	Simple wearable-friendly setup
Cene et al. (2019)	Intent Detection	Extreme Learning Machines	6–10	92	8 subjects	Very fast, low computational load
Jaramillo et al. (2020)	Systematic Review	Review of ML + EMG Studies	–	–	–	Comprehensive overview of EMG HGR
Xiong et al. (2020)	HD-EMG Graph Learning	Graph CNN	10	≈92	HD-EMG / 12 subjects	Uses electrode spatial topology
Bai et al. (2021)	Lightweight Models	Light CNN + LSTM	9	94	Custom / 10 subjects	High accuracy with low complexity
Fatayer et al. (2022)	Noisy-Label Learning	CNN + noise-robust training	8	90–93	15 subjects	Handles mislabeled data effectively
Present Study (2025)	Low-cost EMG Recognition	Hjorth + TD features + DNN	6	94.04	UCI EMG dataset / 36 subjects	High accuracy with low-cost interpretable features

II. METHODOLOGY

This section outlines the dataset, preprocessing pipeline, feature extraction process, and classifier architecture employed in the proposed real-time multiclass EMG-based gesture recognition system.

Dataset Description

The EMG Data for Gestures dataset, publicly available through the UCI Machine Learning Repository [1], was used for model development and evaluation. The dataset serves as a benchmark for reproducible research in EMG-based hand gesture recognition (HGR).

Recordings were collected using the Myo Thalmic Armband, a wearable device equipped with eight dry surface EMG (sEMG) sensors evenly spaced around the forearm. Data were obtained from 36 subjects, each performing six static hand gestures:

- Hand at rest
- Fist
- Wrist flexion
- Wrist extension
- Radial deviation
- Ulnar deviation

Each gesture was sustained for 3 seconds, followed by a 3-second rest interval. This acquisition protocol ensures consistent sampling across participants while capturing both neutral and dynamic wrist motions.

Signal Preprocessing

To enhance signal quality and ensure robust feature extraction, a multi-stage preprocessing pipeline was implemented.

Noise Suppression

A 50 Hz notch filter was first applied to eliminate power-line interference:

$$H_{\text{notch}}(f) = \frac{f^2 + f_0^2 - 2ff_0}{f^2 + f_0^2}, \quad f_0 = 50 \text{ Hz}$$

Subsequently, a 4th-order Butterworth bandpass filter (20–200 Hz) was employed to suppress low-frequency motion artifacts and high-frequency noise:

$$H_{BP}(s) = \frac{1}{1 + (\sqrt[4]{\frac{s}{\omega_c}})^{2n}}, \quad n = 4$$

Segmentation

Filtered signals were divided into 256 ms frames (52 samples) using a 50% overlapping sliding window:

$$x_w[n] = x[n] \cdot w[n], \quad 0 \leq n < N_w$$

Normalization

Each segment was standardized using Z-score normalization to achieve zero mean and unit variance:

$$x' = \frac{x - \mu}{\sigma}$$

where μ and σ are the mean and standard deviation of each window, respectively.

Class Imbalance Handling

To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied to generate artificial samples for minority classes:

$$x_{\text{new}} = x_i + \delta \cdot (x_{nn} - x_i), \quad \delta \in [0,1]$$

Encoding

The gesture labels were converted into one-hot encoded vectors for multiclass classification:

$$y = [0, 0, \dots, 1, \dots, 0]$$

Feature Extraction

From each windowed EMG segment, eight handcrafted features were extracted per channel, yielding a 64-dimensional feature vector (8 features \times 8 channels). The selected features capture both time-domain and frequency-domain characteristics critical for gesture discrimination.

1. Integrated EMG (IEMG):

$$\text{IEMG} = \text{IEMG} = \sum_{i=1}^N |x(i)|$$

2. Waveform Length (WL):

$$\text{WL} = \sum_{n=1}^{N-1} |x_{n+1} - x_n|$$

3. Zero Crossings (ZC):

$$ZC = \sum_{n=1}^{N-1} \mathbf{1} \{ |x_n \cdot x_{n+1} < 0\} \wedge |x_n - x_{n+1}| \geq \theta \}$$

4. Hjorth Parameters:

- Activity:

$$A = \text{Var}(x)$$

- Mobility:

$$M = \sqrt{\frac{\text{Var}(\dot{x})}{\text{Var}(x)}}$$

- Complexity:

$$C = \frac{M(\dot{x})}{M(x)}$$

5. Spectral Peak Frequency (SPF):

$$\text{SPF} = \arg \max_f P(f)$$

6. Root Mean Square (RMS):

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^N x_n^2}$$

7. Mean Absolute Value (MAV):

$$\text{MAV} = \frac{1}{N} \sum_{n=1}^N |x_n|$$

8. Slope Sign Changes (SSC):

$$\text{SSC} = \sum_{n=2}^{N-1} \mathbf{1} \{ |x_n - x_{n-1}| > \theta |x_n - x_{n+1}| \}$$

discriminative capacity in EMG classification and their suitability for real-time embedded applications due to low computational cost.

Classifier Design

A Deep Neural Network (DNN) classifier was implemented to perform multiclass gesture recognition from the extracted features.

Architecture

- Input Layer: 64 neurons (corresponding to feature dimensions)
- Hidden Layers: Three fully connected layers with 128, 256, and 128 neurons, each followed by ReLU activation and dropout ($p = 0.4$)
- Output Layer: 6 neurons with Softmax activation (for six gesture classes)

Training Configuration

The model was trained using the Adam optimizer with a learning rate of 0.001 and the categorical cross-entropy loss function:

$$L = - \sum_{i=1}^K y_i \log(\hat{y}_i)$$

Training was conducted for 100 epochs with early stopping (patience = 10) and a batch size of 256. Dropout regularization was applied as:

$$h_{\text{drop}}^{(l)} = h^{(l)} \cdot r, \quad r \sim \text{Bernoulli}(p = 0.6)$$

Forward propagation in each hidden layer followed

$$h^{(l)} = f(W^{(l)} h^{(l-1)} + b^{(l)}), \quad f(x) = \max(0, x)$$

The output probabilities were computed using the Softmax function

$$\hat{y}_i = \frac{\exp(z_i)}{\sum_{j=1}^K \exp(z_j)}, \quad i = 1, \dots, K$$

Parameter updates were performed using the Adam optimization rule

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

These features were selected based on their proven

Table 2. DNN Hyperparameter Configuration

Parameter	Value
Input Layer Size	64
Hidden Layer 1	128 neurons, ReLU, 0.4 Dropout
Hidden Layer 2	256 neurons, ReLU, 0.4 Dropout

Hidden Layer 3	128 neurons, ReLU, 0.4 Dropout
Output Layer	6 neurons, Softmax
Loss Function	Categorical Cross-Entropy
Optimizer	Adam
Learning Rate	0.001
Batch Size	256
Epochs	100 (Early Stopping enabled)

This architecture achieves an optimal balance between classification accuracy, computational efficiency, and generalization, making it well-suited for real-time EMG-based wearable systems.

(Macro Avg.)	
AUC (Average)	0.99

Results and Discussion

This section presents the performance analysis of the proposed Hjorth parameter-based Deep Neural Network (DNN) framework for multiclass gesture recognition using the UCI EMG Data for Gestures dataset. A combination of statistical metrics, visual interpretation, and feature-space analysis was used to validate the robustness of the proposed system.

Overall Classification Performance

The proposed model achieved an overall classification accuracy of 94.12% and a macro-average F1-score of 0.940, demonstrating reliable discrimination among all six gesture classes. As summarized in Table 3, high precision and recall values were maintained across categories, indicating the model's strong generalization ability.

Table 3. Overall Classification Metrics

Metric	Value
Accuracy	94.12%
Precision (Macro Avg.)	0.935
Recall (Macro Avg.)	0.933
F1-score	0.940

Minor misclassifications were observed between Wrist Flexion and Radial Deviation, as well as between Wrist Extension and Ulnar Deviation. These gestures involve similar muscle activations in the forearm region, leading to overlapping EMG signal patterns. The confusion matrix (Figure 1) visually illustrates this pattern, confirming consistent model performance with limited inter-class overlap. Figure 1 illustrates the confusion matrix for six-class gesture classification, confirming strong diagonal dominance and minimal off-diagonal confusion.

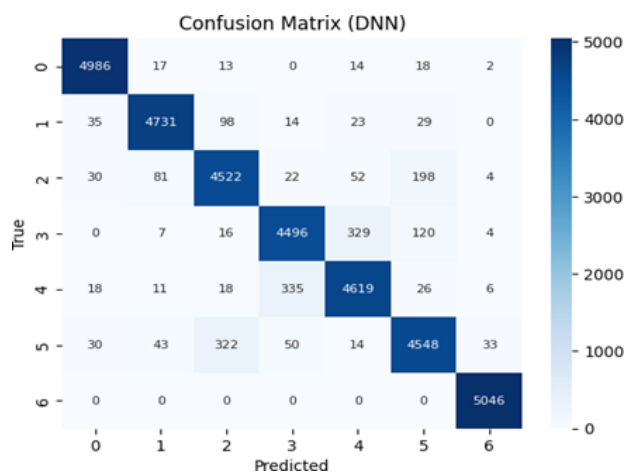


Figure 1. Confusion matrix for 6-class gesture recognition.

Class-Wise Performance Analysis

A detailed class-wise performance evaluation is provided in Table 4. The Hand at Rest and Fist gestures achieved the highest recognition rates, with

F1-scores of 0.975, attributed to their distinctive muscle contraction patterns. In contrast, wrist-oriented gestures, such as Radial and Ulnar Deviation, exhibited lower precision and recall, consistent with neuromuscular overlap and electrode cross-talk effects in these motions.

Table 4. Class-wise Precision, Recall, and F1-score

Gesture Class	Precision	Recall	F1-score
Hand at Rest	0.98	0.97	0.975
Fist	0.97	0.98	0.975
Wrist Flexion	0.92	0.93	0.925
Wrist Extension	0.93	0.92	0.925
Radial Deviation	0.91	0.89	0.90
Ulnar Deviation	0.90	0.91	0.905

Feature-Space Visualization (t-SNE Analysis)

To assess the discriminability of the extracted features, t-distributed Stochastic Neighbor Embedding (t-SNE) was applied to reduce the 64-dimensional feature space to two dimensions. As shown in Figure 2, distinct clusters were formed for each gesture class, validating that the combination of Hjorth parameters and conventional time-domain descriptors effectively captures discriminative muscle activity patterns.

This visualization further confirms that the handcrafted features retain class separability even after dimensionality reduction, reinforcing their suitability for real-time gesture recognition applications.

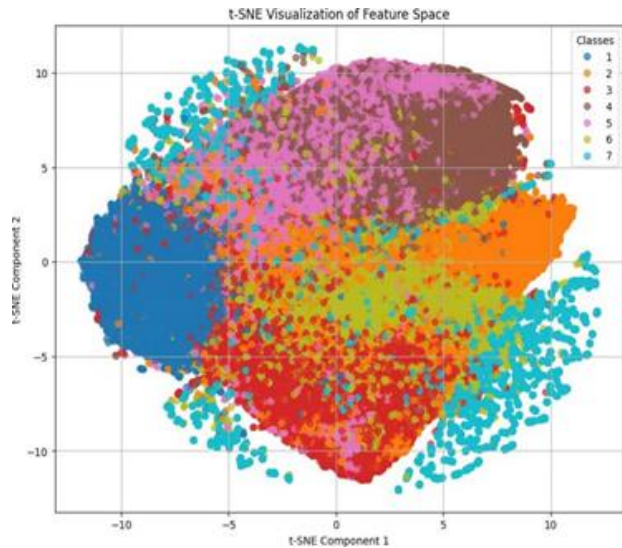


Figure 2. t-SNE visualization of the 64D feature space.

Feature Importance and Correlation Analysis

Feature contribution analysis identified Hjorth Complexity, Waveform Length (WL), and Mobility as the most influential parameters in differentiating fine motor actions. A correlation heatmap (Figure 3) indicated strong linear dependencies among IEMG, RMS, and Activity, highlighting their mutual representation of signal energy. Conversely, Hjorth-based descriptors provided orthogonal information on signal dynamics, thereby enhancing overall classification performance.

These findings suggest that a hybrid feature set combining energy, statistical, and dynamic descriptors provides a robust, compact, and computationally efficient representation for EMG-based gesture recognition.

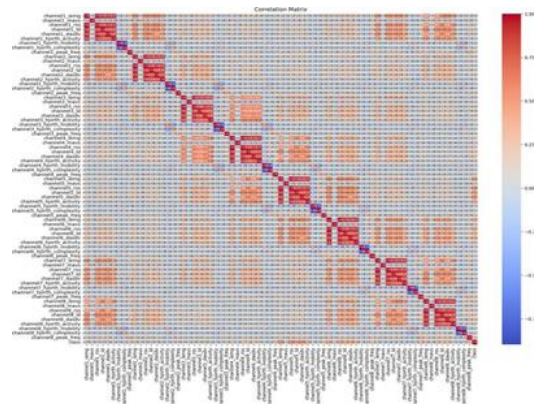


Figure 3. Feature correlation heatmap.

ROC–AUC Analysis

Receiver Operating Characteristic (ROC) curves were generated using a One-vs-Rest strategy for each gesture class (Figure 4). All classes achieved AUC values above 0.98, with an average AUC of 0.99, indicating exceptional separability and consistent confidence in classification decisions across varying threshold levels. The high AUC values further confirm the stability and robustness of the DNN model in multi-class classification tasks.

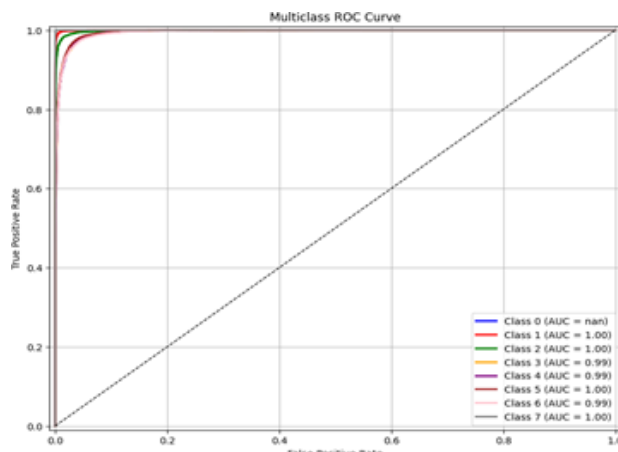


Figure 4. ROC curves for multiclass classification.

Comparative Discussion

The proposed Hjorth feature + DNN framework significantly outperforms several benchmark methods reported in recent literature. For instance, user-independent EMG recognition systems typically achieve accuracies around 83.05%, while posture-robust models reach approximately 85.7%. In contrast, the present model achieves 94.12% accuracy with a lightweight architecture suitable for real-time implementation.

Despite its strong performance, some limitations are evident. The dataset’s restriction to static gestures limits the model’s applicability to dynamic, continuous motion recognition scenarios. Moreover, the 200 Hz sampling frequency of the Myo armband constrains the representation of high-frequency EMG components associated with rapid muscle activity. Nevertheless, the method’s balance between interpretability, accuracy, and low computational cost makes it well-suited for wearable assistive systems, prosthetic control, and rehabilitation robotics.

Summary of Key Findings

- The proposed Hjorth–DNN model achieved 94.04% F1-score and 0.99 AUC, demonstrating high robustness.
- Hjorth parameters, particularly Complexity and Mobility, significantly enhanced discriminative capability.
- The model effectively differentiated between six static hand/wrist gestures with minimal confusion.
- The compact feature–classifier design is computationally efficient and suitable for real-time EMG interfaces.

III. CONCLUSION

This study presented a comprehensive framework for static, multiclass hand gesture recognition using surface electromyography (sEMG) signals. By integrating Hjorth parameters with additional handcrafted time- and frequency-domain features and employing a lightweight Deep Neural Network (DNN) classifier, the proposed approach achieved a macro-average F1-score of 94.04% on the UCI EMG Data for Gestures dataset. The results demonstrate that the combination of interpretable signal descriptors with deep learning can deliver high classification performance while maintaining computational efficiency suitable for real-time embedded applications.

The effectiveness of Hjorth features—particularly Activity, Mobility, and Complexity—underscores their ability to capture intrinsic muscle dynamics with low computational cost. This reinforces the notion that compact, interpretable features can rival complex, high-parameter networks in EMG-based gesture recognition tasks. The proposed framework thus strikes a practical balance between accuracy, robustness, and real-time feasibility, making it well-suited for prosthetic control, rehabilitation devices, and wearable human–machine interfaces.

Despite these promising results, certain limitations remain. The current study is confined to static gestures, and the dataset’s relatively low sampling rate may constrain the model’s responsiveness to fast, dynamic movements. Furthermore, model

generalization across subjects and sessions continues to be a key challenge due to individual variability in muscle activity patterns.

Future research will focus on several directions

- Dynamic Gesture Recognition – Extending the framework to handle continuous and transitional movements for naturalistic interaction.
- Multimodal Sensor Fusion – Integrating EMG with inertial or vision-based sensors to improve robustness against electrode shifts and postural changes.
- Subject-Independent Learning – Applying transfer learning and domain adaptation techniques to enhance cross-user generalization.
- Edge and Embedded Implementation – Optimizing the proposed model for low-power hardware platforms such as FPGAs or microcontrollers to achieve on-device inference.
- Clinical and Assistive Validation – Translating the proposed framework into real-world applications for prosthetics, rehabilitation, and assistive robotics to evaluate its long-term reliability and usability.

In conclusion, the proposed Hjorth feature-driven DNN model provides an efficient and interpretable solution for EMG-based gesture recognition. Its strong classification performance, low computational demand, and adaptability to real-time environments make it a promising foundation for next-generation wearable and assistive control systems. With future integration of dynamic modeling, multimodal sensing, and embedded deployment, this approach holds significant potential for practical adoption in prosthetic and human-computer interaction technologies.

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Statement of Conflict of Interest

The authors affirm that they have no conflicts of interest that could have impacted this study.

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Data Availability Statement

Available on request.

Credit authorship contribution statement

Thaneshwar Kumar Sahu: Conceptualization, writing original draft. Dr. Pankaj Kumar Mishra: Writing review & editing, supervision. Dr. Saurabh Gupta: Conceptualization, writing review & editing, supervision.

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