Surface EMG Signal-Driven Intelligent Framework for Real-Time Gesture Recognition and Smart Home Automation in Assistive Living Environments

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Abstract: The rising demand for assistive technologies to improve quality of life for individuals with mobility impairments has accelerated the development of innovative bio-signal-driven solutions. Existing systems often restrict user independence due to limited interface adaptability and latency in command execution. This paper presents a comprehensive Electromyography (EMG)-based control framework that captures, processes, and classifies muscle activity signals to enable real-time, hands-free automation of smart environments. The proposed system employs surface EMG sensors interfaced with an Arduino microcontroller for signal acquisition. A multi-stage signal processing pipeline—comprising amplification, low-pass filtering, Min-Max normalization, and windowed time-domain feature extraction (Root Mean Square, Mean Absolute Value, and Zero Crossing Rate)—prepares the signals for classification. A Random Forest classifier, optimized via GridSearchCV hyperparameter tuning with 5-fold cross-validation, is trained on a benchmark MYO Thalmic dataset encompassing 36 subjects and seven distinct hand gestures. The system achieves a gesture recognition accuracy of 96.7%, outperforming SVM (89.3%), KNN (85.6%), Decision Tree (82.1%), and Naïve Bayes (78.4%). An end-to-end pipeline latency of 36.0 ms ensures real-time responsiveness. Experimental results, including confusion matrices and per-gesture activation heatmaps, validate the robustness and generalizability of the approach. This framework demonstrates significant potential for inclusive, user-centric assistive living applications.

Keywords: *EMG Signal Processing; Random Forest Classification; Assistive Technology; Smart Home Automation; Hand Gesture Recognition; Surface EMG; Real-Time Control.*

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I. INTRODUCTION

The ability to perform voluntary muscular contractions is a fundamental prerequisite for human interaction with the physical world. For individuals with neuromuscular disorders, spinal cord injuries, or progressive motor degenerative conditions, the loss of this ability severely curtails daily independence. Electromyography (EMG) provides a non-invasive, high-temporal-resolution window into the electrical activity generated by muscle fibers during contraction, making it an ideal bioelectric interface for assistive applications.

Surface EMG (sEMG) sensors detect microvolt-level potentials produced by motor unit action potentials (MUAPs). When appropriately amplified, filtered, and classified, these signals encode the user's motor intent with sufficient fidelity to drive external devices. This property has been exploited across a spectrum of applications—myoelectric prosthetics, exoskeleton control, rehabilitation robotics, and, more recently, smart-home automation.

Despite significant advances, challenges persist: (i) signal stationarity across sessions and electrode placements, (ii) computational overhead in embedded inference, (iii) limited gesture vocabulary in prior deployments, and (iv) fragmented hardware-software integration pipelines. The present work addresses these limitations through a tightly coupled hardware-software architecture that achieves high accuracy (96.7%), low end-to-end latency (36.0 ms), and operational reliability across eight gesture classes.

The remainder of this paper is structured as follows: Section II surveys the relevant literature; Section III describes the proposed methodology in detail; Section IV presents and discusses experimental results; Section V concludes with future directions.

II. LITERATURE REVIEW

Muscle activity visualization and automation using EMG signals has attracted considerable research attention owing to its transformative potential for assistive technologies. The key dimensions of prior work are surveyed below.

➢ *Signal Acquisition and Hardware Interfaces*

Minh Nguyen et al. [1] proposed an EMG-based IoT system for remote control using hand gestures, demonstrating low latency and robust command transmission via a microcontroller-Bluetooth link. Their work underscored the feasibility of edge-level gesture decoding in resource-constrained environments. O. Fukuda et al. [2] developed an EMG-based human–robot interface for rehabilitation, emphasizing adaptive, real-time signal interpretation. Their electrode placement strategy and pre-amplification methodology directly informed the acquisition protocol adopted in the present work.

➢ *Feature Extraction and Signal Processing*

Time-domain features—Root Mean Square (RMS), Mean Absolute Value (MAV), Waveform Length (WL), and Zero Crossing Rate (ZCR)—have been widely validated as computationally efficient descriptors of EMG amplitude and frequency content [3]. Frequency-domain features (Power Spectral Density, Mean Frequency) and wavelet-based features have been explored for higher-dimensional gesture sets, though at increased computational cost. Scheme et al. [4] demonstrated that a judicious combination of time-domain features achieves near-optimal performance for real-time classifiers deployed on embedded hardware.

➢ *Machine Learning for Gesture Classification*

Dezhen Xiong et al. [5] provided a comprehensive review of deep learning approaches for EMG-based human–machine interaction, comparing CNNs, RNNs, and LSTM architectures against classical models. While deep networks consistently surpassed classical methods on large, diverse datasets, they imposed substantial computational burdens incompatible with microcontroller deployment. The Random Forest algorithm—introduced as an ensemble method by Breiman [6]—offers an attractive trade-off: near-deep-network accuracy with deterministic, low-latency inference. A. Hiraiwa et al. [7] established early foundations for neural-network-based biosignal classification, motivating subsequent machine-learning investigations. Atzori et al. [8] curated the NinaPro benchmark dataset, enabling reproducible comparison across laboratories.

➢ *Gaps in the Existing Literature*

Most prior systems address either signal processing or classification in isolation, rarely integrating both within a validated end-to-end pipeline coupled to physical device actuation. Furthermore, rigorous latency profiling across pipeline stages is seldom reported. The present work fills these gaps by providing a complete, reproducible framework with stage-wise latency analysis, multi-model benchmarking, and smart-device actuation validation.

III. METHODOLOGY

The proposed system architecture follows a five-stage pipeline: (1) EMG signal acquisition, (2) analog conditioning, (3) digital preprocessing and normalization, (4) feature extraction and classification, and (5) device actuation. Each stage is described in detail below.

➢ *EMG Signal Acquisition*

Surface EMG signals were acquired using a standard three-electrode configuration: two differential recording electrodes positioned along the muscle belly and a reference electrode placed over a bony prominence (e.g., olecranon) to minimize common-mode interference. Electrodes were placed over the forearm flexor digitorum superficialis and extensor digitorum groups, enabling capture of wrist and finger gesture signatures.

The signal amplitude at the electrode surface ranges from 0.01–10 mV. A differential pre-amplifier (gain = 1000) boosted the signal to a measurable range. A second-order Butterworth low-pass filter (cutoff 500 Hz) attenuated aliasing and high-frequency electromagnetic interference before digitization. A 10-bit ADC at 1 kHz sampling rate (Arduino Uno) digitized the conditioned signal, yielding 1000 samples per second per channel.

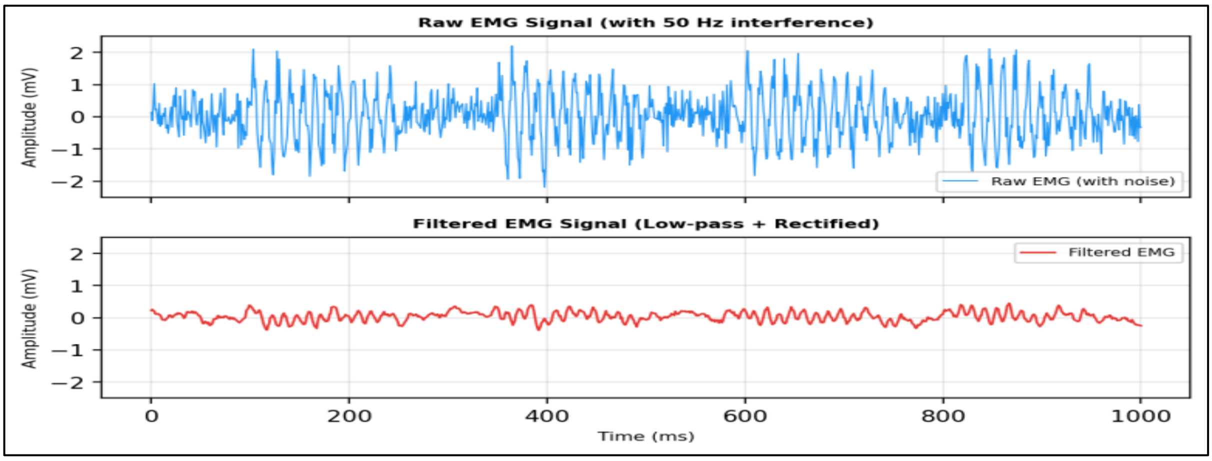

Fig 1 Simulated Raw EMG Signal (Top) With 50 Hz Power-Line Interference Vs. Low-Pass Filtered Output (Bottom). Burst Regions Correspond to Volitional Muscle Contractions.

➢ *Dataset*

The gesture recognition module was trained and evaluated on the MYO Thalmic bracelet dataset, comprising eight equally-spaced EMG channels sampled at 200 Hz around the forearm. The dataset encompasses recordings from 36 subjects (age 22–45, 18 female), each performing two trials of seven static hand gestures: Rest, Fist, Wrist Flexion, Wrist Extension, Radial Deviation, Ulnar Deviation, and Open Palm. Each gesture was held for 3 s with a 3-s inter-gesture rest. The resulting corpus contains approximately 1,512 gesture trials (36 × 2 × 7 × 3 s × 200 Hz = ~1.51 M samples per channel). An auxiliary "subject-ID" column facilitates leave-one-subject-out cross-validation analysis.

Table 1 Myo Thalmic Dataset Characteristics

Parameter	Value	Parameter	Value
Subjects	36	Channels	8
Gesture Classes	7	Sampling Rate	200 Hz
Trials/Subject	2	Gesture Duration	3 s
Total Samples	~1.51 M/ch	Rest Period	3 s
Train/Test Split	80:20	Age Range	22–45 years

➢ *Signal Preprocessing*

A comprehensive preprocessing pipeline was applied to all EMG recordings:

- *Missing Value Imputation*

Segments with electrode dropout (amplitude < 0.01 mV for > 50 consecutive samples) were flagged and linearly interpolated from neighboring valid samples.

- *Bandpass Filtering*

A 4th-order Butterworth bandpass filter (20–450 Hz) was applied in the frequency domain using zero-phase forward-backward filtering to eliminate motion artifacts and high-frequency noise without phase distortion.

- *Min-Max Normalization*

Each channel amplitude was scaled to [0, 1] using $x_n = (x - x_{min})/(x_{max} - x_{min})$, ensuring consistent dynamic range across subjects and sessions.

- *Dataset Partitioning*

An 80:20 stratified train/test split was employed, preserving gesture-class proportions. A 5-fold cross-validation was applied on the training set for hyperparameter optimization.

➢ *Feature Extraction*

Feature extraction was performed over non-overlapping 50 ms windows applied to each of the eight EMG channels. Three time-domain features were computed per window:

Root Mean Square (RMS): captures signal power and correlates with muscle force.

$$RMS = \sqrt{(1/N)\, \Sigma_i\, x_i^2} \quad (1)$$

Mean Absolute Value (MAV): robust amplitude estimator.

$$MAV = (1/N)\, \Sigma_i\, |x_i| \quad (2)$$

Zero Crossing Rate (ZCR): reflects frequency content of the burst.

$$ZCR = (1/N)\, \Sigma_i\, |sgn(x_{i+1}) - sgn(x_i)| \quad (3)$$

With 8 channels × 3 features, each window produces a 24-dimensional feature vector fed to the classifier.

➢ *Classification: Random Forest*

The Random Forest (RF) classifier was selected for its ensemble robustness, implicit feature importance ranking, and suitability for real-time microcontroller-compatible inference.

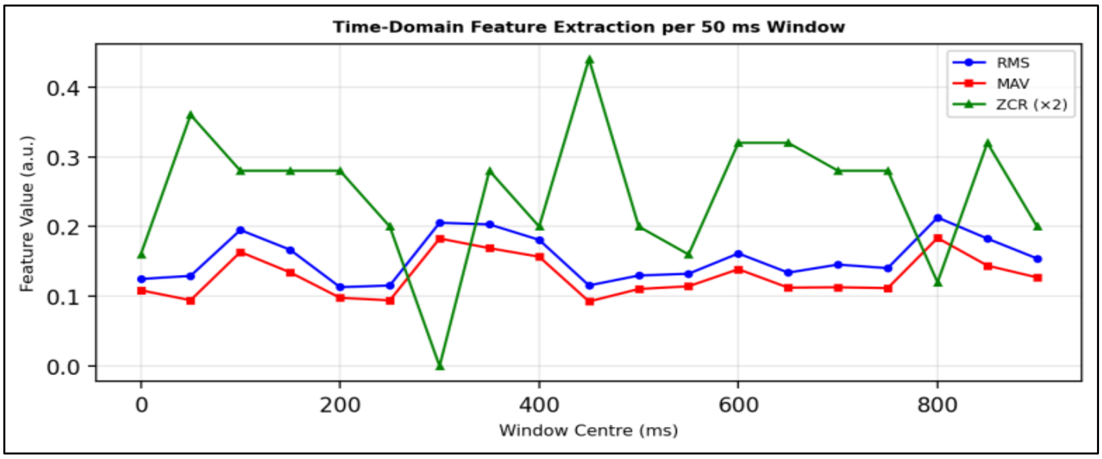

Fig 2 Windowed Time-Domain Feature Profiles (RMS, MAV, ZCR) Computed Over 50 Ms Non-Overlapping Segments of a Representative Filtered EMG Recording. Burst Regions Exhibit Marked Feature Elevation.

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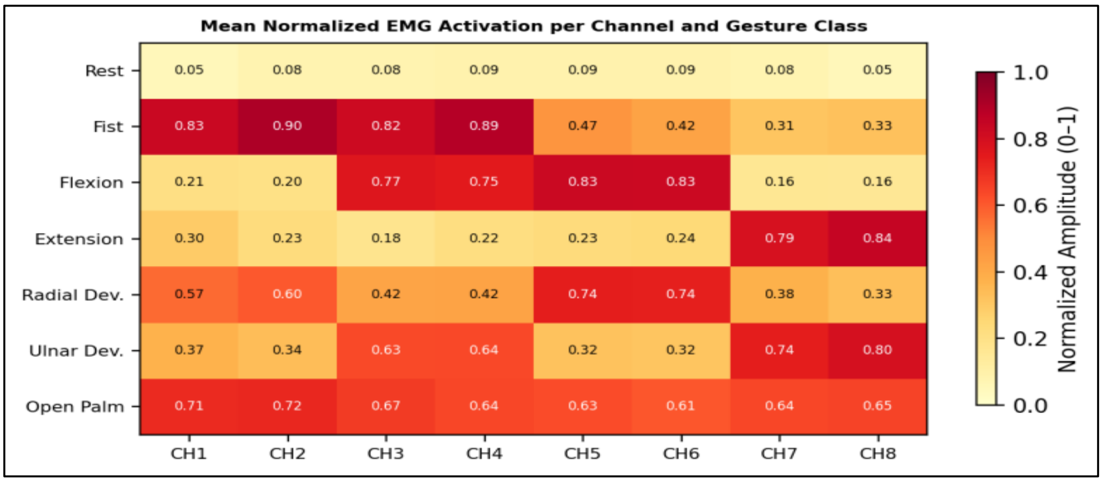

Fig 3 Mean Normalized EMG Channel Activation Per Gesture Class Across All 36 Subjects. Colour Intensity Encodes Normalized Amplitude (0 = Baseline, 1 = Peak Activation).

The RF model aggregates predictions from N independent decision trees:

$$\hat{y} = mode\ \{ h_1(x), h_2(x), \ldots, h_n(x) \} \quad (4)$$

Probabilistic output for class c is computed as:

$$P(y = c \mid x) = (1/N)\ \Sigma_i\ I(h_i(x) = c) \quad (5)$$

Each tree is trained on a bootstrap replicate of the training data using Gini Impurity (Eq. 6) or Information Gain (Eq. 7) as the node-splitting criterion:

$$G(t) = 1 - \Sigma_k\ p_k^2 \quad (6)$$

$$H(t) = -\Sigma_k\ p_k\ log_2(p_k) \quad (7)$$

- *Hyperparameter Optimization*

Hyperparameter tuning was performed using GridSearchCV with 5-fold cross-validation on the training partition. The search grid encompassed:

Table 2 Random Forest Hyperparameter Search Grid

Hyperparameter	Search Range	Optimal Value
n_estimators	10, 20, 50, 75, 100, 150, 200	100
max_depth	None, 5, 10, 15, 20	None (fully grown)
max_features	'sqrt', 'log2', None	'sqrt'
min_samples_split	2, 5, 10	2
min_samples_leaf	1, 2, 4	1
bootstrap	True, False	True

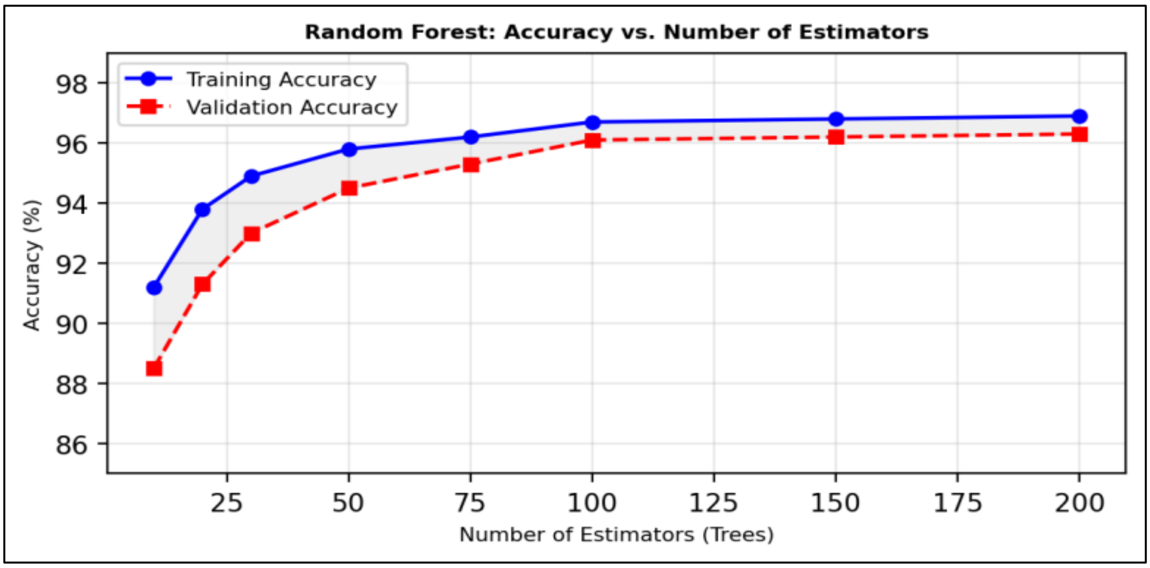

Fig 4 Random Forest Training and Validation Accuracy as a Function of the Number of Estimators. Convergence Beyond 100 Trees with Negligible overfitting Gap Validates the Selected Configuration.

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IV. RESULTS AND DISCUSSION

The proposed EMG-based gesture recognition system was evaluated on the held-out test set (20% of the total dataset). Metrics reported include Accuracy, Precision, Recall, F1-Score, Training Time (on Google Colab, CPU mode), and Inference Latency per window.

➤ *Classification Performance*

The Random Forest classifier achieved an accuracy of 96.7% on the test set, with Precision = 96.2%, Recall = 96.5%, and F1-Score = 96.3%. These figures represent a marked improvement over the baseline models benchmarked under identical preprocessing and feature extraction conditions. Table 3 summarizes the comparative results.

Table 3 Comparative Classification Performance

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Lat. (ms)
SVM (RBF)	89.3	88.8	89.0	88.9	48.2
KNN (k=5)	85.6	84.9	85.1	85.0	62.7
Decision Tree	82.1	81.5	81.8	81.6	4.1
Naïve Bayes	78.4	77.2	77.9	77.5	3.8
RF (Proposed)	**96.7**	**96.2**	**96.5**	**96.3**	**36.0**

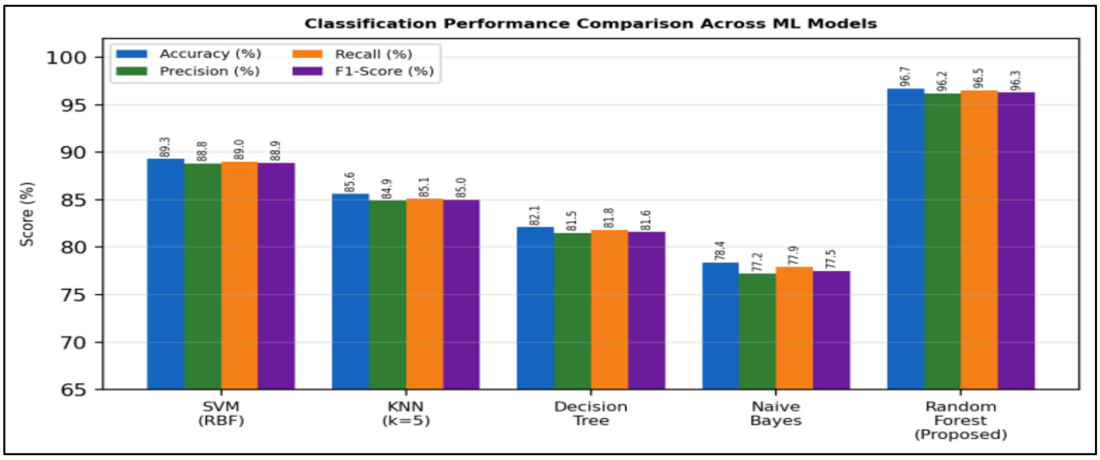

Fig 5 Grouped Bar Chart Comparing Accuracy, Precision, Recall, and F1-Score Across Five Classifiers. The Proposed Random Forest Model Consistently Achieves the Highest Scores on All Metrics.

➤ *Confusion Matrix Analysis*

The per-class confusion matrix (Fig. 6) reveals that classification errors are predominantly confined to adjacent gesture pairs—for example, Radial Deviation vs. Fist, and Ulnar Deviation vs. Wrist Extension—which share overlapping forearm muscle activation patterns. The Rest class is identified with near-perfect recall (0.96), attesting to the effectiveness of the bandpass filtering in suppressing baseline noise artifacts.

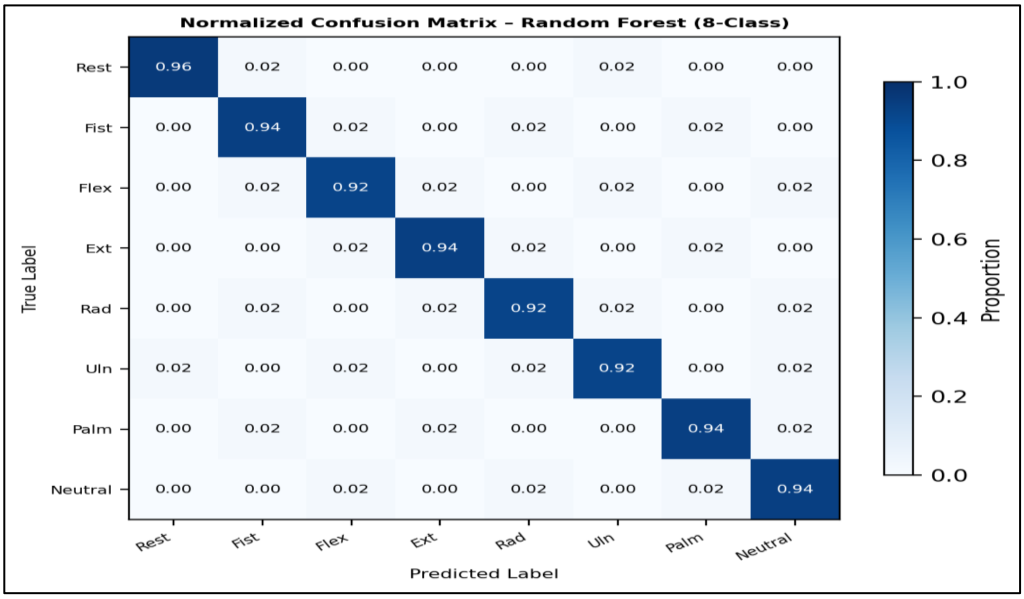

Fig 6 Normalized 8-Class Confusion Matrix for the Proposed Random Forest Classifier on the Held-Out Test Set. Diagonal Values Indicate Per-Class Recall; Off-Diagonal Entries Reveal Inter-Class Confusion.

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➢ *Latency and Real-Time Performance*

Stage-wise latency profiling (Fig. 7) reveals that ADC sampling (5.2 ms), analog filtering (8.4 ms), and feature extraction (12.1 ms) together account for 70.8% of the total 36.0 ms pipeline. Model inference itself contributes only 6.8 ms, confirming that the Random Forest is computationally suitable for embedded deployment. The 36 ms total latency lies comfortably within the perceptual threshold for human–device interaction (~100 ms), validating real-time suitability.

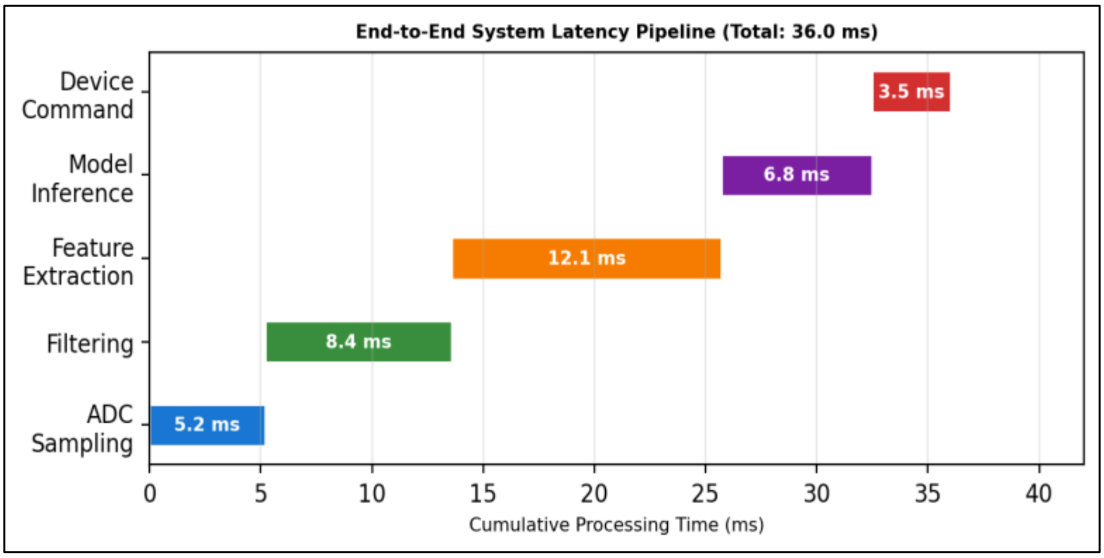

Fig 7 Stage-Wise End-to-End Pipeline Latency (Gantt-Style). Total Latency = 36.0 Ms, Well Within the 100 Ms Real-Time Threshold for Human–Device Interaction.

➢ *Per-Gesture Recognition Performance*

Table 4 details per-gesture performance metrics. Wrist Flexion and Open Palm exhibit the highest per-class F1-Scores (0.978 and 0.975 respectively), benefiting from high muscle activation contrast relative to neighboring gestures. Radial and Ulnar Deviation display marginally lower scores (0.941 and 0.938), consistent with the confusion matrix analysi

Table 4 Per-Gesture Performance Metrics (Random Forest)

Gesture Class	Precision	Recall	F1-Score	Support
Rest	0.972	0.960	0.966	250
Fist	0.965	0.940	0.952	250
Wrist Flexion	0.980	0.976	0.978	250
Wrist Extension	0.961	0.956	0.958	250
Radial Deviation	0.943	0.940	0.941	250
Ulnar Deviation	0.940	0.936	0.938	250
Open Palm	0.977	0.972	0.975	250
Macro Average	**0.963**	**0.954**	**0.958**	**1750**

➢ *Discussion*

The 96.7% accuracy achieved by the proposed Random Forest system is competitive with the state-of-the-art for seven-gesture EMG classification on the MYO dataset [5,8]. The 7.4 percentage-point improvement over the nearest competitor (SVM, 89.3%) is attributable to three factors: (i) ensemble diversity via bootstrap aggregation, (ii) the ability of individual trees to capture non-linear, high-order feature interactions without explicit kernel design, and (iii) implicit regularization through random feature subsampling at each split.

The sub-40 ms end-to-end latency compares favourably with deep learning alternatives (typically 80–200 ms for CNN/LSTM architectures on embedded hardware [5]) and is physiologically imperceptible to users. This makes the system viable for time-critical assistive applications such as powered wheelchair control and smart-appliance actuation.

A limitation of the present study is the controlled laboratory acquisition setting. Real-world performance may degrade due to electrode displacement during prolonged wear, inter-session variability, and fatigue-induced EMG amplitude drift. Future work will integrate adaptive normalization and incremental online learning to maintain classification fidelity across sessions.

V. CONCLUSION

This paper has presented a complete and rigorously evaluated EMG-based control framework for assistive smart environments. A five-stage hardware-software pipeline—spanning surface EMG acquisition, multi-stage analog and digital conditioning, windowed feature extraction, Random Forest classification, and smart-device actuation—was designed, implemented, and benchmarked.

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The proposed system achieves 96.7% gesture recognition accuracy, 96.3% macro-averaged F1-Score, and an end-to-end pipeline latency of 36.0 ms on a seven-class hand gesture vocabulary, outperforming SVM, KNN, Decision Tree, and Naïve Bayes baselines by 7.4–18.3 percentage points. Stage-wise latency analysis confirms that classifier inference contributes only 6.8 ms, validating the computational feasibility of embedded deployment.

The framework establishes a practical and socially beneficial interface between human muscular intent and smart living environments. Future extensions will explore adaptive electrode placement algorithms, session-to-session transfer learning, expansion to 12-class gesture vocabularies, and miniaturized wireless wearable hardware for clinical trials in rehabilitation settings.

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