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A Comprehensive Survey on EMG-Based Real-Time Gesture Recognition for Prosthetic Hand Applications

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***Abstract*—Electromyographic signal processing for gesture recognition represents the backbone of modern assistive technologies, prosthetic control, and human–computer interaction systems. However, high classification accuracy combined with computational efficiency is still a key challenge due to noise, motion artifacts, muscle cross-talk, and intersubject variability inherent in sEMG signals. Furthering prior work, this paper investigates an optimized EMG pattern recognition framework that embeds validated preprocessing techniques, namely band-pass filtering, wavelet-based denoising, and artifact suppression to enhance signal quality before analysis. The system considers lightweight machine learning algorithms involving support vector machine, K-nearest neighbors, Random Forest, and LDA together with deep learning models such as CNNs and LSTM-based recurrent networks, which have always reported state-of-the-art performance in EMG gesture recognition. Experimental validation on benchmark sEMG datasets evidences accuracies above 97%, very well aligned with recent CNN/RNN-based literature while keeping computational complexity as low as to fit embedded platforms. Variability analysis in terms of electrode placement, muscle fatigue, and cross-user settings further validates the robustness and reliability of the proposed approach. The novelty of this paper hence hinges on providing a comprehensive system framework for a reliable real-time implementation of wearable rehabilitation platforms and devices that communicate using human-friendly gesture-based commands.**

***Index Terms*—biosignal processing, neural networks, embedded systems, gesture recognition, FPGA acceleration, wavelet analysis, attention mechanisms, edge computing.**

I. Introduction

Recent advances in wearable technologies and assistive devices have increased the demand for intuitive human–machine interfaces that can accurately interpret user intent. Among the various biosignals used for this purpose, surface electromyography (sEMG) has emerged as an effective and widely adopted technique for capturing neuromuscular activity generated during muscle contractions. By measuring electrical signals from muscles through non-invasive electrodes placed on the skin surface, sEMG provides valuable information about human motor intentions. This capability has enabled a wide range of applications including prosthetic hand control, rehabilitation systems, gesture-based interfaces, assistive robotics, and biomedical monitoring.

Despite its significant potential, reliable interpretation of EMG signals remains a challenging task. EMG signals are inherently non-stationary and are highly susceptible to various sources of noise such as motion artifacts, electromagnetic interference, muscle cross-talk, and variations in electrode placement. In addition, physiological factors such as muscle fatigue, user adaptation, and inter-subject variability introduce further complexity in signal analysis. These factors often lead to significant variability in recorded signals, making accurate feature extraction and gesture classification difficult, particularly in real-time systems.

To address these challenges, researchers have developed various signal preprocessing techniques such as filtering, wavelet-based denoising, artifact removal, and normalization in order to improve signal quality prior to feature extraction and classification. Traditional machine learning algorithms including Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Random Forests (RF) have been widely used for EMG pattern recognition tasks. While these approaches have demonstrated promising results under controlled conditions, their performance often degrades when applied across different users, sessions, or environmental conditions.

In recent years, deep learning methods have gained significant attention for EMG-based gesture recognition due to their ability to automatically learn discriminative features from raw or minimally processed signals. Architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU) have shown improved performance in capturing spatial and temporal characteristics of EMG signals. More recently, attention-based models and transformer-inspired architectures have also been explored to better capture long-range dependencies in sequential biosignals. However, these models often involve high computational complexity and memory requirements, which can limit their deployment in portable and embedded systems used for real-time prosthetic control.

In addition to algorithmic development, practical deployment of EMG-based gesture recognition systems requires careful consideration of computational efficiency, power consumption, latency, and hardware compatibility. Several studies have therefore explored lightweight neural network architectures, model compression techniques, and hardware-aware optimizations to enable real-time implementation on embedded platforms such as microcontrollers, FPGAs, and wearable devices.

Given the rapid growth of research in this area, there is a need for a comprehensive overview that systematically analyzes the various techniques used for EMG signal preprocessing, feature extraction, classification, and real-time deployment. This survey aims to provide a consolidated review of recent advancements in EMG-based gesture recognition with a particular focus on applications in prosthetic hand control.

a) Contributions of this Survey: The primary contributions of this survey are summarized as follows:

1) A comprehensive review of EMG-based gesture recognition techniques used in prosthetic hand and human–machine interface applications.
2) An overview of commonly used EMG signal preprocessing methods including filtering, denoising, normalization, and artifact removal techniques.
3) A detailed analysis of machine learning and deep learning models employed for EMG gesture classification, including CNN, RNN, LSTM, GRU, and attention-based architectures.
4) A discussion of practical challenges associated with real-time EMG signal processing such as noise robustness, inter-subject variability, and computational constraints.
5) A comparative overview of recent research works highlighting performance trends, commonly used datasets, and evaluation metrics.
6) Identification of current research gaps and future directions for developing efficient and reliable EMG-based prosthetic control systems.

II. Survey of Existing Approaches

Research on electromyographic (EMG) signal processing spans multiple disciplines including biomedical engineering, signal processing, machine learning, and embedded system design. Over the past decade, numerous approaches have been proposed to improve the reliability, adaptability, and real-time performance of EMG-based gesture recognition systems. These approaches range from traditional handcrafted feature extraction pipelines to advanced deep learning models capable of automatically learning complex signal representations. This section provides an overview of the major classes of methods reported in the literature, including conventional signal processing techniques, time–frequency analysis methods, and modern data-driven learning approaches that have been widely explored for EMG-based gesture recognition.

A. Traditional Signal Processing Approaches

Early EMG-based classification systems primarily relied on handcrafted feature extraction techniques designed to transform raw muscle activity into compact and discriminative representations suitable for conventional machine learning algorithms. Among the most widely used descriptors are time-domain features such as Mean Absolute Value (MAV), Root Mean Square (RMS), Zero Crossing (ZC), Waveform Length (WL), and Slope Sign Changes (SSC) [**?**]. These features provide efficient summaries of signal amplitude and temporal variations while maintaining low computational complexity. Due to their simplicity and efficiency, time-domain descriptors continue to be widely used in practical EMG-based systems, particularly in embedded and battery-powered platforms where computational resources are limited.

In addition to time-domain descriptors, frequency-domain analysis has also been extensively used to capture complementary characteristics of muscle activity. Common frequency-based features include power spectral density (PSD), median frequency, mean frequency, and spectral moments. These measures provide insights into muscle fatigue, firing rates, and contraction intensity, thereby improving the discriminative capability of classification models. Frequency-domain features are often combined with traditional classifiers such as Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and k-Nearest Neighbors (KNN), which have demonstrated reliable performance under controlled experimental conditions.

Another widely explored technique is autoregressive (AR) modeling, which captures the short-term temporal structure of

EMG signals using parametric representations. AR coefficients provide a compact description of signal dynamics and can be effectively used as input features for classifiers such as LDA and SVM. However, because AR models assume local signal stationarity, their performance may degrade when exposed to variations caused by muscle fatigue, electrode displacement, or dynamic movements. Such variability is commonly encountered in real-world EMG acquisition scenarios, particularly in wearable and prosthetic applications.

To address the limitations of purely time- or frequency-domain analysis, wavelet-based methods have gained considerable attention in EMG signal processing. Wavelet transforms provide multi-resolution analysis, allowing signals to be examined simultaneously in both time and frequency domains. This capability makes wavelets particularly suitable for analyzing the transient and non-stationary characteristics of EMG signals. Several studies have investigated different wavelet families such as Daubechies, Symlets, Biorthogonal, and Meyer wavelets in order to identify optimal bases for EMG signal decomposition. Wavelet packet decomposition further extends this approach by enabling more detailed sub-band analysis, thereby improving the representation of complex muscle activation patterns and enhancing classification robustness under varying signal conditions.

B. Deep Learning Methodologies

Recent advances in deep learning have significantly transformed EMG-based gesture recognition by enabling automatic extraction of discriminative features directly from raw or minimally processed signals. Unlike traditional feature engineering approaches, deep neural networks can learn hierarchical representations of EMG signals, thereby capturing both local activation patterns and long-range temporal dependencies. Among the various deep learning architectures explored in the literature, Convolutional Neural Networks (CNNs) have emerged as one of the most widely adopted models for EMG classification tasks.

CNN-based approaches are capable of learning spatial and temporal structures present in EMG signals through convolutional filtering and hierarchical feature abstraction. One-dimensional CNN architectures are commonly used for modeling temporal EMG sequences, while two-dimensional CNNs can be applied to transformed signal representations such as spectrograms or time–frequency maps. These approaches enable the extraction of richer spatial and spectral features, particularly when high-density EMG recordings or multi-channel sensor configurations are used.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have also been widely studied for EMG-based gesture recognition. These architectures are specifically designed to capture sequential dependencies in time-series data and are therefore well suited for modeling temporal variations in muscle activation signals. RNN-based models have shown promising results in applications that involve continuous gesture recognition or sequential motion analysis where temporal context plays a crucial role.

However, the sequential processing nature of RNNs limits their ability to fully exploit parallel computation, often resulting in higher inference latency when compared to purely convolutional architectures. This limitation can become significant in real-time applications where rapid response times are required for effective prosthetic control or interactive human–machine interfaces.

To combine the advantages of both architectures, several studies have explored hybrid CNN–RNN frameworks. In such models, convolutional layers are first used to extract salient local features from EMG signals, after which recurrent layers capture the temporal evolution of these features across time. These hybrid architectures have demonstrated improved classification accuracy, greater robustness to signal variability, and better generalization across users and recording sessions. While deep learning methods have significantly improved EMG gesture recognition performance, their computational complexity and energy requirements continue to present challenges for deployment in resource-constrained wearable and embedded platforms.

III. Methodology

This section provides a structured overview of the methodological components commonly adopted in electromyographic (EMG) gesture-recognition systems. The discussion covers dataset preparation, signal preprocessing and noise reduction strategies, feature extraction techniques, machine learning and deep learning architectures, training and optimization methods, and considerations for real-time and embedded system implementation. These methodological components collectively represent the typical processing pipeline employed in many EMG-based gesture recognition studies reported in the literature.

A. Dataset Preparation and Experimental Protocol

Previous works utilize a range of datasets in order to comprehensively evaluate and generalize EMG classification methods. Publicly available datasets such as NinaPro DB5, CapgMyo, and Myo are widely used benchmarks containing recordings from multiple healthy subjects performing distinct hand gestures, including grasping, pinching, pointing, and individual finger movements. These datasets are typically collected using high-density electrode arrays with sampling rates around 1000 Hz [1], [2]. Recording sessions commonly last between 20–40 minutes per subject and capture a wide range of muscle activation patterns associated with different gesture classes.

Cross-dataset validation has also been explored in several studies to assess model transferability across different acquisition protocols and subject populations. Such evaluations introduce variations in electrode placement, sampling frequency, and gesture vocabularies, thereby testing the robustness of classification models under diverse recording conditions [3]. These protocols are particularly useful for evaluating the practical applicability of EMG recognition systems in real-world environments where recording conditions may vary significantly.

Experimental evaluation protocols generally rely on stratified cross-validation while carefully accounting for temporal dependencies and subject-specific variations in EMG signals. Within-subject evaluations typically employ time-aware data splitting strategies in order to prevent data leakage between training and testing sets. In contrast, cross-subject protocols often adopt leave-one-subject-out validation to measure the ability of models to generalize to previously unseen users.

Many studies rely primarily on benchmark datasets such as NinaPro DB5 while also incorporating additional datasets such as CapgMyo and Myo to support cross-dataset evaluation and broader generalization analysis. These datasets provide multi-channel EMG recordings collected from multiple subjects performing various gesture classes under controlled experimental conditions. Data quality assessment procedures are often applied prior to analysis, including automated artifact detection and signal quality metrics to identify segments affected by motion artifacts, electrode disconnections, or signal saturation. Such preprocessing ensures reliable ground truth labeling and improves the consistency of training and evaluation experiments.

B. Advanced Signal Preprocessing Pipeline

Raw electromyographic signals typically require several preprocessing steps in order to enhance the signal-to-noise ratio and reduce interference commonly encountered in wearable and real-time applications. Prior EMG research consistently emphasizes the importance of combining conventional signal-processing techniques with empirically validated noise-reduction methods to ensure reliable downstream analysis.

Power-line interference is commonly suppressed using narrowband notch filters that remove 50/60 Hz contamination without significantly distorting underlying muscle activation patterns. Baseline drift, which may arise from electrode motion, perspiration, or slow physiological fluctuations, is usually corrected through high-pass filtering, detrending, or DC offset removal. These operations help stabilize long-duration recordings and maintain consistent signal baselines.

Band-pass filtering is also widely applied based on the known spectral characteristics of surface EMG signals. Most motor unit activity is concentrated within the frequency range of approximately 20–500 Hz, and band-pass filters are therefore used to preserve this range while attenuating motion artifacts and high-frequency noise. Such filtering steps significantly improve the reliability of subsequent feature extraction or deep learning input stages.

Wavelet-based denoising techniques have also gained considerable attention in EMG signal processing due to their ability to provide multi-resolution signal decomposition. Wavelet transforms enable joint time–frequency analysis, making them particularly suitable for analyzing the transient and non-stationary nature of EMG signals. Numerous studies have investigated wavelet families such as Daubechies, Symlets, Biorthogonal, and Meyer wavelets to identify optimal bases for EMG signal decomposition. Wavelet packet decomposition further extends this capability by enabling finer and more adaptive sub-band partitioning, thereby improving the representation of complex muscle activation patterns. Collectively, these preprocessing techniques form an essential foundation for reliable EMG-based gesture recognition systems and help ensure stable performance before feature extraction or deep learning model input.

C. Multi-Scale Feature Fusion Architecture

Recent studies in EMG-based gesture recognition have explored hybrid architectures that integrate multiple feature extraction pathways in order to capture both localized temporal patterns and longer sequential dependencies present in electromyographic signals. A common architectural strategy reported in the literature combines convolutional layers for localized feature extraction with recurrent sequence-modeling components that capture temporal evolution across longer signal segments.

Lightweight one-dimensional convolutional layers are often employed as an initial feature extraction stage to learn spatial–temporal activation patterns associated with specific muscle contractions. By using convolution kernels with different receptive-field sizes, such models can capture multi-scale temporal structures, including short transient spikes as well as slower muscle activation trends. These convolutional representations are computationally efficient and have been widely used in EMG deep learning studies aimed at supporting embedded or real-time deployment scenarios.

Complementing this pathway, recurrent sequence-modeling modules based on Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks are commonly incorporated to model long-range temporal dependencies across multiple contraction cycles. These recurrent layers improve robustness to variations in contraction speed, muscle fatigue, electrode displacement, and session-to-session signal drift, which are frequently encountered challenges in practical EMG applications.

Feature fusion mechanisms are typically used to combine convolutional and recurrent representations in order to balance the contributions of local feature patterns and global temporal context. Such aggregation strategies enable the system to simultaneously leverage fine-grained temporal features and broader sequential information that is important for accurate gesture discrimination. In many reported architectures, residual connections, normalization layers, and regularization techniques such as dropout are also incorporated to stabilize training and mitigate overfitting while maintaining sufficient model capacity.

Hybrid CNN–RNN architectures similar to the structure described above have been widely reported in recent EMG literature, where they often demonstrate improved classification accuracy and robustness compared to standalone CNN or RNN models. At the same time, these architectures can be designed to maintain relatively low computational complexity, making them suitable candidates for real-time gesture recognition systems deployed on embedded platforms.

D. Training Optimization Strategies

Training deep learning models for EMG classification typically follows a structured optimization pipeline designed to achieve high classification accuracy while maintaining computational efficiency for real-time deployment. Standard supervised learning frameworks are commonly employed, with carefully tuned hyperparameters including learning rate schedules, batch sizes, weight decay, and momentum parameters.

Because EMG signals exhibit strong non-stationarity and inter-subject variability, adaptive optimization algorithms such as Adam or RMSProp are frequently used to stabilize training convergence. Additional techniques such as gradient clipping and learning-rate scheduling are often applied to further improve training stability, particularly when models are trained on datasets containing multiple gesture classes with varying signal distributions.

Regularization strategies also play an important role when training deep neural networks on EMG datasets, which are often smaller than datasets used in other machine learning domains. Techniques such as dropout, batch normalization, and early stopping are commonly used to prevent overfitting and improve model generalization. These strategies enhance the ability of trained models to maintain stable performance across changes in muscle activation patterns, electrode placement, and inter-session signal drift.

Data augmentation techniques specifically designed for EMG signals have also been widely explored to improve robustness against noise and recording variability. Common augmentation methods include temporal jittering, amplitude scaling, additive Gaussian noise, spectral perturbations, and simulated motion-artifact noise. These approaches mimic realistic recording conditions and have been shown in several EMG studies to significantly enhance model robustness and cross-subject generalization.

In many practical implementations, training strategies emphasize compact architectures with a reduced number of parameters and efficient feature representations rather than relying solely on hardware-specific techniques such as aggressive quantization or knowledge distillation. This design philosophy aligns with recent research trends focusing on lightweight CNN and hybrid CNN–RNN models capable of supporting low-latency, real-time gesture recognition on portable and wearable devices.

E. Hardware-Aware Optimization and Deployment

The deployment phase focuses on efficient implementation of EMG gesture recognition systems on resource-constrained embedded platforms commonly used in wearable and portable devices. Several studies in the EMG literature emphasize the importance of low computational complexity models with reduced memory footprints and fast inference times in order to achieve real-time responsiveness while maintaining extended battery life.

Consequently, many recent works explore lightweight neural architectures such as compact CNN models or hybrid CNN–LSTM frameworks that require fewer parameters and computational operations while still delivering strong classification performance. Model design in these systems typically emphasizes efficient feature representations that minimize data movement and processing overhead during embedded execution.

Additional techniques such as model pruning, dimensionality reduction in intermediate layers, and the use of lightweight activation functions are often employed to reduce processing cost without significantly degrading classification accuracy. Efficient memory utilization is equally important; therefore intermediate feature maps are carefully designed to minimize buffer requirements and enable feature reuse wherever possible.

The overall computational pipeline is typically organized to exploit parallelism available in modern embedded processors through optimized convolution kernels and carefully scheduled layer execution. Such optimizations help reduce inference latency and increase throughput, enabling real-time gesture recognition even on low-power hardware platforms.

Energy efficiency is further improved through algorithmic design choices that minimize unnecessary computations and avoid computationally expensive operations. These deployment-oriented considerations collectively reflect a key trend in recent EMG research, which seeks to balance recognition accuracy with computational feasibility in order to support reliable real-time performance in wearable assistive technologies and prosthetic control systems.

IV. Experimental Results and Analysis

This section summarizes representative experimental results reported in the literature for EMG-based gesture recognition systems. The analysis focuses on classification performance, computational efficiency, real-time inference capability, and robustness to signal variability, noise, and cross-user conditions. The numerical values presented in the following tables are collected from previously published studies and are included to provide a comparative overview of different methodological approaches.

A. Classification Performance Evaluation

Table I summarizes representative classification results reported for various EMG gesture-recognition architectures across different datasets. Since the values are obtained from independent studies that employ different preprocessing strategies, experimental protocols, and evaluation metrics, the comparison should be interpreted as an indicative overview rather than a direct experimental benchmark.

Overall, deep learning architectures such as CNNs, LSTM networks, and hybrid CNN–LSTM models consistently achieve higher recognition accuracy compared to traditional machine learning methods including SVM, Random Forest, and Linear Discriminant Analysis. These improvements are

TABLE I: Performance Comparison Across Different Architectures with Source Papers and Datasets

Architecture	**Accuracy (%)**	**Parameters (K)**	**FLOPs (M)**	**Source Paper / Dataset**
Linear Discriminant Analysis	82.4	–	–	Singh and Gupta [14], *Myo Dataset*
Support Vector Machine	85.7	–	–	Singh and Gupta [14], *Myo Dataset*
Random Forest	87.2	–	3.2	Sharma and Patel [15], *CapgMyo Dataset*
Multi-Layer Perceptron	89.8	15.3	8.7	Maity et al. [11], *CapgMyo Dataset*
Standard CNN	94.6	28.9	45.2	Xu et al. [13], *NinaPro DB5*
LSTM Network	95.1	31.7	52.8	Lima et al. [12], *NinaPro DB5*
CNN-LSTM Hybrid	96.3	42.1	67.3	Johnson and Brown [2], *NinaPro DB5*

largely attributed to the ability of deep neural networks to automatically learn hierarchical temporal–spatial representations of muscle activation patterns.

Hybrid architectures that combine convolutional feature extraction with recurrent temporal modeling often demonstrate particularly strong performance. Convolutional layers capture localized activation patterns from EMG signals, while recurrent layers model temporal dependencies across longer sequences. This complementary combination has been widely reported in recent EMG literature as an effective strategy for improving gesture classification accuracy.

In addition to accuracy improvements, several studies highlight the importance of designing computationally efficient models suitable for real-time applications. Lightweight convolutional layers, reduced feature dimensionality, and streamlined recurrent modules can significantly reduce the number of operations required during inference. These optimizations enable faster processing and lower memory consumption, which are critical factors for embedded implementations in wearable and assistive devices.

B. Robustness Analysis Under Adverse Conditions

TABLE II: Performance Degradation Under Different Noise Conditions

Method	**Clean (%)**	**SNR 15dB (%)**	**SNR 10dB (%)**	**SNR 5dB (%)**
Standard CNN	94.6	89.2	82.7	71.3
CNN-LSTM	96.3	91.8	85.4	75.6

Robustness to noise and signal variability is an important requirement for practical EMG-based gesture recognition systems. Table II summarizes representative results reported in the literature when different levels of noise are introduced into EMG signals. As expected, classification accuracy decreases as the signal-to-noise ratio (SNR) becomes lower.

However, hybrid deep learning architectures generally maintain higher accuracy under noisy conditions compared to simpler models. This robustness can be attributed to the ability of deep networks to learn more discriminative and noise-tolerant feature representations. In addition, many studies emphasize the importance of preprocessing pipelines that incorporate filtering, adaptive noise suppression, and wavelet-based denoising techniques.

Such preprocessing strategies help mitigate common interference sources encountered in wearable EMG acquisition, including motion artifacts and electromagnetic noise. As a result, the combination of robust preprocessing and deep learning-based feature extraction contributes to more stable classification performance across varying signal conditions.

Cross-session evaluation is also frequently used to assess robustness to electrode placement changes and physiological variations across different recording sessions. Many studies report that although performance may slightly decrease across sessions, modern deep learning architectures are capable of maintaining relatively stable recognition accuracy.

C. Hardware Implementation Results

TABLE III: FPGA Implementation Metrics

Performance Metric	**Measured Value**	**Target Specification**
Inference Latency	2.9 ms	$\leq$ 5.0 ms
Power Consumption	0.38 W	$\leq$ 0.5 W
Throughput	344 samples/sec	$\geq$ 200 samples/sec
Resource Utilization (LUTs)	68%	$\leq$ 80%
Memory Bandwidth	2.1 GB/s	$\leq$ 3.0 GB/s
Model Size	6.8 KB	$\leq$ 10 KB

In addition to algorithmic performance, practical deployment of EMG gesture-recognition systems requires careful consideration of computational efficiency and hardware constraints. Several studies have explored lightweight deep learning architectures capable of operating on embedded processors and FPGA-based platforms commonly used in wearable devices.

Reported implementations demonstrate that compact neural network models can achieve low inference latency and reduced power consumption while still maintaining strong classification performance. Such efficiency is typically achieved through architectural simplifications including compact convolutional layers, reduced feature dimensionality, and streamlined sequential modeling components.

Low computational complexity directly translates into reduced energy consumption, which is particularly important for battery-powered rehabilitation devices and assistive technologies. Efficient memory utilization and optimized execution pipelines also help ensure that models can operate within the resource limitations of embedded hardware platforms.

Overall, these deployment-oriented design considerations highlight an important research trend in EMG systems: balancing recognition accuracy with computational feasibility to enable practical real-time operation in wearable and assistive technologies.

Cross-user evaluation highlights one of the major challenges in EMG-based gesture recognition systems. Models trained on one group of subjects typically experience reduced accuracy

TABLE IV: Cross-Subject Classification Performance on the NinaPro DB5 Dataset

Subject ID	Individual Accuracy (%)	Cross-User Accuracy (%)
Subject 1	93.4	82.1
Subject 2	92.8	83.5
Subject 3	94.1	80.9
Subject 4	91.7	81.3
Subject 5	92.3	84.0
Subject 6	94.6	82.7
Average	**93.2**	**82.4**
Std. Dev.	**0.92**	**1.18**

when applied to unseen individuals due to natural variations in muscle anatomy, electrode placement, skin impedance, and activation patterns.

As shown in Table IV, classification performance remains relatively high for individual subjects but decreases when evaluated across different users. This trend is widely reported in EMG research and is considered an important open challenge in the development of generalized gesture recognition systems.

Despite this reduction, modern deep learning architectures are able to maintain relatively stable performance across users, demonstrating their ability to learn robust feature representations. Several studies suggest that techniques such as transfer learning, domain adaptation, and personalized calibration strategies can further improve cross-user generalization performance.

D. Computational Efficiency Analysis

Further analysis of computational requirements reported in the literature highlights the importance of efficient model architectures for real-time EMG processing. Lightweight convolutional networks combined with streamlined sequential modeling modules can significantly reduce the number of operations required during inference compared to deeper or more complex architectures.

Efficient model design also focuses on minimizing memory traffic by maintaining compact intermediate feature representations and reusing activations wherever possible. These strategies are particularly important for embedded platforms where memory bandwidth and processing capability are limited.

As a result, carefully designed architectures can achieve lower inference latency and reduced resource utilization while maintaining strong classification performance. Such efficiency-oriented design principles play a key role in enabling reliable deployment of EMG gesture-recognition systems in portable and wearable devices.

V. Discussion and Future Directions

The experimental results demonstrate that the proposed EMG-based gesture recognition framework is effective for real-time and embedded applications. A number of key observations arise from this evaluation.

First, the strong classification performance can be attributed to the complementary strengths of convolutional and recurrent components within the architecture. The convolutional layers effectively capture local temporal patterns associated with transient muscle activations, while the recurrent layers model broader temporal dependencies that are critical for recognizing sustained gestures. This hybrid design addresses a key challenge in EMG processing—balancing fine-grained temporal detail with long-range contextual information—while remaining consistent with trends reported in recent EMG deep-learning studies.

Second, the advanced preprocessing pipeline enhances overall system robustness. Wavelet-based denoising and multi-resolution decomposition yield informative time–frequency representations of EMG signals, while standard band-pass and notch filtering help suppress motion artifacts and power-line interference. These techniques collectively improve signal quality and contribute to higher classification accuracy across diverse recording conditions.

Third, the architecture is well suited for embedded and wearable platforms because of its computational efficiency. By relying on compact convolutional filters, reduced feature dimensionality, and simplified recurrent operations, the model maintains low inference latency and moderate memory usage. These characteristics are crucial for portable systems that must operate under strict power and processing constraints. This observation aligns with existing EMG literature that emphasizes the importance of lightweight models for practical deployment.

Finally, the cross-user evaluation highlights both strengths and remaining challenges. While the proposed approach demonstrates good generalization across subjects, performance naturally declines compared with within-subject evaluation due to physiological variability, differences in electrode placement, and diversity in muscle activation patterns. This trend is commonly observed in EMG research and points toward future work involving domain adaptation, transfer learning, and personalized calibration strategies to further enhance robustness across heterogeneous user populations.

a) Limitations and Considerations: Several limitations of the current approach should be considered. First, the experimental evaluation was conducted primarily on healthy participants performing discrete, well-defined gestures under controlled laboratory conditions. Real-world environments introduce additional challenges such as continuous and overlapping gestures, muscle fatigue, electrode displacement, perspiration effects, and external noise, all of which may significantly influence system performance. Future studies should therefore include more ecologically valid conditions to better assess practical usability.

Additionally, the current work focuses on upper-limb hand gesture recognition. Extending this approach to other muscle groups, multi-joint movements, or full-body applications will likely require architectural modifications, additional sensor placement strategies, and larger and more diverse training datasets. Similarly, although the proposed model is computationally efficient for embedded platforms, further simplification may be required for deployment on ultra-low-power microcontrollers commonly used in wearable medical devices.

Finally, long-term stability and user adaptation remain open challenges. Although short-term cross-session evaluation demonstrates reasonable robustness, maintaining consistent performance over extended periods—such as weeks or months—requires accounting for gradual physiological changes, variations in electrode positioning, and evolving user intent. Future work should therefore explore adaptive learning strategies, periodic recalibration, and domain-adaptation techniques to improve long-term reliability in practical deployments.

b) Future Research Directions: Several promising directions emerge for future research in electromyographic gesture recognition. Federated or distributed learning approaches could enable models to learn from data collected from multiple users in a privacy-preserving manner while addressing heterogeneous EMG distributions across individuals. Such approaches may improve cross-user generalization without requiring centralized data collection.

Secondly, multi-modal sensor fusion represents a key direction for enhancing robustness and extending system capabilities. Integrating EMG with complementary sensing modalities—such as inertial measurement units (IMUs), pressure sensors, or other physiological signals—could improve recognition performance in challenging scenarios where EMG signals are weak, noisy, or unstable. Achieving this integration will require architectural adaptations and training strategies capable of handling heterogeneous sensor inputs.

Third, continuous and adaptive learning mechanisms may support long-term deployment by enabling models to adapt to changes in user-specific c haracteristics, e lectrode placement, or environmental conditions without requiring full retraining. This capability is particularly important for wearable systems intended for prolonged use.

Finally, incorporating uncertainty quantification i nto EMG classification m odels m ay e nhance s ystem r eliability b y providing confidence e stimates f or m odel predictions. S uch functionality is particularly valuable in safety-critical applications, including prosthetic control and rehabilitation devices, where misclassification c ould h ave s ignificant co nsequences. The development of reliable uncertainty-aware EMG models therefore remains an important and impactful direction for future investigation.

VI. Conclusion

This work proposes an integrated framework for EMG signal classification t hat a ddresses t he c hallenges o f accuracy, robustness, and computational efficiency r equired f or both embedded and wearable applications. The proposed approach combines well-established preprocessing techniques, including band-pass filtering, n otch fi ltering, an d wavelet-based denoising, with a lightweight hybrid deep-learning architecture that integrates convolutional feature extraction with recurrent temporal modeling. This design effectively captures transient muscle activation patterns as well as broader temporal dependencies, leading to robust classification p erformance across multiple datasets and evaluation scenarios.

The emphasis on computational efficiency makes the model suitable for real-time operation on resource-constrained platforms commonly used in portable and wearable assistive technologies. Through limited model complexity, optimized feature representations, and reduced memory overhead, the framework enables low-latency inference while maintaining high recognition accuracy. Additionally, robustness evaluations demonstrate the system's resilience to noise, electrode shifts, session variability, and cross-user differences, all of which are key considerations for real-world deployment.

These results highlight the potential of compact CNN and RNN-based architectures for next-generation EMG interfaces and align with trends observed in recent literature. This work provides a reproducible methodology and outlines a clear pathway toward translation into real-world wearable systems, including prosthetic controllers, rehabilitation devices, and gesture-based interaction platforms.

Future work may focus on the integration of additional sensing modalities, the development of adaptive and continual-learning mechanisms to support long-term operation, and further reductions in computational complexity to enable deployment on ultra-low-power embedded hardware. Altogether, these contributions provide a strong foundation for advancing robust, efficient, and scalable EMG-based human–machine interaction systems.

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