Electromyography (EMG) Signal Feature Extraction Using Artificial Intelligence: A Comprehensive Study

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ABSTRACT: Electromyography (EMG) signal analysis is essential for evaluating neuromuscular activity, with applications spanning prosthetic control, rehabilitation engineering, clinical diagnostics, and human-computer interfaces. Robust feature extraction transforms raw EMG signals into discriminative representations for pattern recognition and decision-making. This review comprehensively surveys classical and artificial intelligence (AI)-based EMG feature extraction techniques. Traditional methods fall into time-domain, frequency-domain, and time-frequency-domain categories, each balancing computational efficiency and interpretability. Time-domain features—such as mean absolute value (MAV), root mean square (RMS), and zero crossings (ZC) — are simple and well-suited to real-time processing. Frequency-domain descriptors, including power spectral density (PSD), mean frequency (MNF), and median frequency (MDF), reveal insights into muscle fatigue and contraction dynamics. Time-frequency approaches like the short-time Fourier transform (STFT) and the wavelet transform (WT) effectively capture the non-stationary characteristics of EMG signals. Emerging machine learning and deep learning paradigms enable automated feature discovery and superior classification performance. We delineate the strengths, limitations, and context-specific efficacy of these methods, underscoring the potential of hybrid and AI-driven strategies to advance biomedical signal processing.

Keywords: Electromyography, feature extraction, machine learning, deep learning, biomedical signal processing.

INTRODUCTION

Electromyography (EMG) is a widely used biomedical signal that represents the electrical activity generated by skeletal muscles during voluntary or involuntary contractions. EMG signals provide valuable insights into neuromuscular function and motor unit behavior, making them essential for a broad range of applications, including prosthetic limb control, rehabilitation robotics, ergonomics, sports science, clinical diagnosis of neuromuscular disorders, and human–computer interaction (HCI) systems (Alkan and Günay 2012; Artemiadis and Kyriakopoulos 2010; Atzori *et al.,* 2015). With rapid advancements in assistive technologies and intelligent biomedical systems, accurate interpretation of EMG signals has become increasingly important for the development of reliable, adaptive, and real-time human–machine interfaces.

Despite their significance, EMG signals are inherently complex and challenging to interpret due to their low amplitude, stochastic behavior, nonlinearity, and non-stationary nature. Furthermore, EMG recordings are highly sensitive to factors such as electrode placement, muscle fatigue, cross-talk from adjacent muscles, and external noise sources including power-line interference and motion artifacts (Atzori *et al.,* 2016; Atzori *et al.,* 2023). These limitations restrict the direct utilization of raw EMG signals for classification or decision-making tasks and necessitate robust pre-processing and effective feature extraction techniques.

Feature extraction aims to transform raw EMG signals into a compact and informative set of parameters that represent muscle activation patterns while reducing redundancy and noise (Boostani and Moradi 2003). An effective feature set should be discriminative, noise-resilient, computationally efficient, and suitable for real-time implementation. Over the past several decades, numerous EMG feature extraction techniques have been proposed and are commonly categorized into time-domain, frequency-domain, and time–frequency-domain approaches (Castellini and van der Smagt 2009; Chen *et al.,* 2012; Chowdhury *et al.,* 2013).

Time-domain features are among the earliest and most widely used EMG descriptors due to their simplicity and low computational cost. Features such as mean absolute value (MAV), root mean square (RMS), zero crossing (ZC), slope sign changes (SSC), and waveform length (WL) quantify signal amplitude, energy, and temporal variations, and have been extensively applied in prosthetic control and gesture recognition systems (Clancy *et al.*, 2002; Hudgins *et al.*, 1993; Côté-Allard *et al.*, 2019). Hudgins *et al.* (1993) demonstrated that a combination of time-domain features enables effective myoelectric pattern recognition with minimal processing overhead. However, time-domain features are often sensitive to noise and fail to adequately capture spectral information related to muscle fatigue and motor unit recruitment.

Frequency-domain analysis provides complementary information by examining the spectral characteristics of EMG signals. Features such as power spectral density (PSD), mean frequency (MNF), and median frequency (MDF) are widely used to assess muscle fatigue, which is typically associated with a shift of spectral energy toward lower frequencies (De Luca 1997; De Luca 2002; Du *et al.*, 2017). Although frequency-domain methods are effective for fatigue analysis, they generally assume short-term stationarity, limiting their applicability for dynamic and transient muscle activities.

To overcome these limitations, time–frequency analysis techniques such as short-time Fourier transform (STFT), wavelet transform (WT), discrete wavelet transform (DWT), and Hilbert–Huang transform (HHT) have been introduced to simultaneously analyze temporal and spectral characteristics of EMG signals (Englehart and Hudgins 2003; Farina *et al.*, 2014; Farina and Holobar 2016). These methods provide improved representations of non-stationary EMG signals and have demonstrated enhanced performance in noisy and clinical environments.

Parallel to advancements in signal processing, artificial intelligence (AI) has significantly transformed the landscape of EMG signal analysis. Traditional machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN), linear discriminant analysis (LDA), and random forests (RF) have been widely employed for EMG classification using handcrafted features (Fougner *et al.*, 2012; Geng *et al.*, 2016; Hudgins *et al.*, 1993; Huang *et al.*, 1998). Among these techniques, SVMs have shown strong generalization capabilities in high-dimensional feature spaces and small-sample scenarios, making them suitable for EMG-based pattern recognition applications (Islam *et al.*, 2017).

More recently, deep learning approaches, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, have emerged as powerful alternatives to conventional machine learning techniques by enabling automatic feature learning from raw or minimally processed EMG signals (Ison and Artemiadis 2014; Karlsson *et al.*, 2000; Khushaba *et al.*, 2017). Atzori *et al.* (2016) demonstrated that CNN-based architectures outperform traditional feature-based classifiers in high-density EMG gesture recognition tasks (Atzori *et al.*, 2016), while Côté-Allard *et al.* (2019) reported improved robustness to electrode displacement and inter-session variability using deep learning models (Côté-Allard *et al.*, 2019; Côté-Allard *et al.*, 2024). Furthermore, Roy and Bandyopadhyay showed that deep learning models effectively capture complex temporal and spatial patterns in EMG signals, resulting in superior gesture recognition performance compared to conventional approaches (Roy and Bandyopadhyay, 2021).

Hybrid approaches that integrate conventional feature extraction techniques with AI-based classifiers have also gained significant attention. For instance, wavelet-based features combined with SVM or deep learning classifiers have been shown to enhance recognition accuracy while maintaining reasonable computational complexity (Li *et al.*, 2010; Kok *et al.*, 2023; Kok *et al.*, 2024). These hybrid frameworks leverage the interpretability of signal processing methods and the learning capability of AI models, offering a balanced trade-off between performance and transparency.

Despite these advancements, several challenges remain unresolved. Inter-subject and intra-subject variability, sensitivity to noise and artifacts, and limited generalization across sessions continue to affect the reliability of EMG-based systems (Li *et al.*, 2014; Lorrain *et al.*, 2011; Merletti and Parker 2004). Moreover, deep learning models often require large labeled datasets and substantial computational resources, which can limit their deployment in real-time and wearable applications. The lack of explainability in AI-driven models further raises concerns in clinical environments, where transparency and interpretability are critical (Naik *et al.*, 2012; Roy and Bandyopadhyay 2025).

Recent studies have increasingly explored EMG-based feature extraction using machine learning and deep learning techniques for applications such as gesture recognition, rehabilitation systems, and human–computer interaction (Xia *et al.*, 2023; Zhai *et al.*, 2020; Young *et al.*, 2013). However, most existing works focus on specific feature domains, limited datasets, or single classification frameworks, with insufficient comparative evaluation across time-domain, frequency-domain, and time–frequency-domain approaches. Therefore, the present study aims to provide a comprehensive and unified analysis of EMG feature extraction techniques integrated with artificial intelligence methods, highlighting recent advancements, existing challenges, and future research directions toward the development of robust and efficient EMG-based biomedical systems.

LITERATURE REVIEW

Electromyography (EMG) signal analysis has been an active area of research for several decades due to its critical role in understanding neuromuscular behavior and enabling intelligent assistive, rehabilitative, and

human–machine interface technologies. Early investigations primarily focused on EMG signal acquisition, physiological interpretation, and identification of noise sources. Foundational studies by De Luca established the physiological basis of surface EMG generation, signal characteristics, and practical limitations such as cross-talk, sensitivity to electrode placement, and noise contamination (De Luca 1997; De Luca 2002). Subsequent reviews further consolidated these findings and highlighted the necessity of robust signal processing and reliable feature extraction techniques to improve EMG-based system performance (Atzori et al., 2016; Atzori et al., 2023). These classical contributions continue to guide contemporary EMG research.

A. Time-Domain Feature-Based Studies

Time-domain features were among the earliest EMG descriptors investigated due to their simplicity and low computational requirements. Hudgins et al. (1993) introduced a benchmark feature set comprising mean absolute value (MAV), zero crossing (ZC), slope sign changes (SSC), and waveform length (WL), demonstrating effective real-time myoelectric pattern recognition for prosthetic control. This work laid the foundation for numerous subsequent EMG-based classification systems.

Zardoshti-Kermani et al. (1995) evaluated time-domain features for upper-limb prosthetic control and reported that root mean square (RMS) and waveform length exhibit strong correlation with muscle contraction intensity. Oskoei and Hu (2007) provided a comprehensive survey of myoelectric control systems and emphasized the robustness of time-domain features for low-latency gesture recognition. Despite these advantages, classical time-domain features are sensitive to noise and fail to capture frequency-related information associated with muscle fatigue and motor unit recruitment.

To address these limitations, recent studies have explored feature optimization and selection strategies. Phinyomark et al. (2012) demonstrated that combining complementary time-domain features and applying feature reduction techniques significantly improves classification accuracy. Further work by Phinyomark et al. (2018, 2023) confirmed that optimized time-domain feature sets enhance robustness, particularly for wearable EMG sensor–based systems.

B. Frequency-Domain Feature-Based Studies

Frequency-domain analysis gained prominence due to its effectiveness in studying muscle fatigue and motor unit behavior. De Luca (1997, 2002) demonstrated that fatigue-induced physiological changes manifest as a shift of EMG spectral energy toward lower frequencies, leading to the widespread use of mean frequency (MNF) and median frequency (MDF) as fatigue indicators. These spectral features have since been extensively applied in biomechanics and clinical EMG studies.

Karlsson et al. (2000) conducted a comparative analysis of time- and frequency-domain features during dynamic contractions and concluded that frequency-domain descriptors provide valuable fatigue-related information but are limited under non-stationary conditions. Du et al. (2017) further investigated inter-session variability and highlighted the sensitivity of spectral features to changes in electrode placement and recording conditions. Consequently, the assumption of signal stationarity restricts the effectiveness of purely frequency-domain approaches in dynamic tasks such as gesture recognition and robotic control.

C. Time–Frequency and Wavelet-Based Approaches

To overcome the limitations of time- and frequency-domain methods, time–frequency analysis techniques have been extensively explored for EMG signal analysis. The short-time Fourier transform (STFT) enables localized spectral analysis but suffers from a fixed time–frequency resolution trade-off, limiting its adaptability to transient EMG patterns (Englehart & Hudgins 2003).

Wavelet transform (WT) and discrete wavelet transform (DWT) address this limitation by providing multi-resolution analysis, enabling more effective representation of transient and non-stationary muscle activation patterns. Subasi (2010, 2013) demonstrated that wavelet-based EMG features significantly improve classification accuracy for diagnosing neuromuscular disorders compared to conventional methods. Rafiee et al. (2011) further showed that wavelet coefficients capture localized EMG characteristics more effectively than traditional time- or frequency-domain features. Naik et al. (2012, 2015) reported that wavelet packet transform enhances discrimination performance, particularly in noisy EMG environments.

The Hilbert–Huang transform (HHT), based on empirical mode decomposition, has also been investigated for adaptive analysis of nonlinear and non-stationary EMG signals. Huang et al. (1998) introduced this framework, which has since been applied to EMG analysis to improve the characterization of complex muscle activation dynamics. Collectively, these studies establish time–frequency approaches as powerful tools for advanced EMG analysis, especially in clinical and noise-prone scenarios.

D. Machine Learning-Based EMG Classification

The integration of machine learning marked a significant advancement in EMG signal analysis by enabling data-driven classification of extracted features. Classical classifiers such as support vector machines (SVMs), k-nearest neighbors (KNNs), linear discriminant analysis (LDA), and random forests (RFs) have been widely adopted for EMG-based pattern recognition.

Englehart and Hudgins (2003) demonstrated robust real-time myoelectric control using machine learning classifiers, while Oskoei and Hu (2007) identified SVMs as particularly effective for high-dimensional EMG feature spaces. Scheme and Englehart (2011) emphasized the importance of classifier robustness and repeatability for practical prosthetic systems. Khushaba et al. (2017) further proposed a temporal–spatial

feature-extraction framework combined with machine-learning classifiers, achieving improved recognition accuracy. Nevertheless, traditional machine learning approaches rely heavily on handcrafted features and often exhibit limited generalization under inter-subject and inter-session variability.

E. Deep Learning and Hybrid Models

In recent years, deep learning approaches have introduced a paradigm shift in EMG signal analysis by enabling automatic feature learning from raw or minimally processed signals. Convolutional neural networks (CNNs) have been successfully applied to both raw EMG signals and time–frequency representations. Atzori *et al.* (2015, 2016) introduced benchmark high-density EMG datasets and demonstrated superior performance of CNNs in gesture recognition tasks, highlighting the potential of deep learning models for EMG-based applications.

Côté-Allard *et al*. (2019, 2024) reported that deep learning models significantly outperform traditional machine learning classifiers in terms of robustness to electrode displacement and session variability. Recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures have also been employed to model temporal dependencies in EMG signals, resulting in improved movement estimation and gesture recognition performance (Xia *et al.,* 2018; Xia *et al.,* 2023).

Hybrid approaches that integrate handcrafted feature extraction with deep learning classifiers have gained increasing attention. Roy and Bandyopadhyay (2021) demonstrated that combining wavelet-based features with CNN architectures enhances classification accuracy. More recently, Kok et al. (2023, 2024) showed that hybrid machine learning–deep learning frameworks offer a balanced trade-off between interpretability, computational efficiency, and classification performance, making them particularly suitable for real-time and wearable EMG applications.

RESEARCH GAPS AND MOTIVATION

Despite substantial progress in electromyography (EMG) signal analysis, several critical challenges remain unresolved. One of the primary limitations is the pronounced inter-subject and intra-subject variability inherent in EMG signals, which significantly affects the generalization capability of existing classification models across different users, recording sessions, and experimental conditions (Li *et al.,* 2014; Lorrain *et al.,* 2011). Such variability continues to hinder the development of reliable, user-independent EMG-based systems, particularly in long-term and real-world applications.

In addition, EMG signals are highly susceptible to noise, motion artifacts, electrode displacement, and environmental interference. These factors degrade feature stability and reduce system robustness, especially in wearable and ambulatory monitoring scenarios (Merletti and Parker 2004; Atzori *et al.,* 2016;

Zhai *et al.,* 2020). Although several signal processing techniques have been proposed to mitigate these effects, maintaining consistent performance under practical operating conditions remains a persistent challenge.

While deep learning–based approaches have demonstrated improved performance compared to conventional machine learning methods in EMG classification tasks, their practical deployment is often constrained by high computational complexity and the requirement for large, well-annotated datasets (Atzori *et al.,* 2015; Côté-Allard *et al.,* 2019). These limitations restrict their applicability in real-time, low-power, and resource-constrained biomedical systems. Moreover, most deep learning models operate as black-box frameworks, offering limited interpretability and explainability, which raises concerns in clinical and rehabilitation environments where transparency and trust in decision-making are essential (Naik *et al.,* 2012; Roy & Bandyopadhyay 2025).

In view of these challenges, there is a clear need for robust and generalizable EMG analysis frameworks that can effectively handle signal variability and noise while maintaining computational efficiency. This motivates the development of hybrid EMG feature extraction and classification approaches that integrate classical signal processing techniques with artificial intelligence–based models (Khushaba *et al.,* 2017; Kok *et al.,* 2023; Kok *et al.,* 2024). Furthermore, incorporating explainable artificial intelligence mechanisms into EMG-based systems is crucial for improving model transparency, clinical acceptance, and practical applicability in intelligent biomedical and human–machine interface applications.

Table 1 summarizes the major electromyography (EMG) feature-extraction techniques reported in the literature, categorized by feature domain, representative features, and typical application areas. Time-domain features such as mean absolute value (MAV) and root mean square (RMS) are widely used because of their computational simplicity and effectiveness in representing muscle activation levels. Frequency-domain features, including mean frequency (MNF), median frequency (MDF), and power spectral density (PSD), are primarily used to assess muscle fatigue and characterize spectra.

Time–frequency approaches, such as wavelet transform (WT), discrete wavelet transform (DWT), short-time Fourier transform (STFT), and Hilbert–Huang transform (HHT), enable multi-resolution and non-stationary signal analysis, making them particularly suitable for noisy and clinical EMG data. More recently, artificial intelligence–based methods, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, have facilitated automatic feature learning and temporal modeling, demonstrating improved performance in advanced biomedical and human–computer interaction applications.

Table 1: Summary of EMG Feature Extraction Techniques (Literature Survey).

Feature Domain	Representative Features	Description	Key References	Typical Applications
Time-domain	MAV, RMS	Quantify signal amplitude and power corresponding to muscle activation intensity	Hudgins *et al.* (1993); Clancy *et al.* (2002)	Prosthetic control, human–computer interaction
Time-domain	ZC, SSC	Capture signal complexity and frequency-related characteristics	Hudgins *et al.* (1993); Zardoshti-Kermani *et al.* (1995)	Gesture recognition, pattern classification
Frequency-domain	MNF, MDF	Indicators of muscle fatigue through spectral shift analysis	De Luca (1997); De Luca (2002)	Ergonomics, fatigue assessment
Frequency-domain	PSD	Represents spectral power distribution of EMG signals	Karlsson *et al.* (2000)	Signal characterization and analysis
Time–frequency	WT, DWT	Provide multi-resolution analysis of non-stationary EMG signals	Subasi (2010); Rafiee *et al.* (2011)	Noisy EMG environments, clinical analysis
Time–frequency	STFT, HHT	Enable localized and adaptive time–frequency representation	Englehart and Hudgins (2003); Huang *et al.* (1998)	Clinical diagnosis, dynamic muscle analysis
AI-based	CNN, LSTM	Support automatic feature learning and temporal modeling	Atzori *et al.* (2015); Côté-Allard *et al.* (2019); Xia *et al.* (2023)	Advanced HCI, intelligent biomedical systems

Table 2 provides a comparative overview of key studies on electromyography (EMG) feature extraction and artificial intelligence–based classification methods. Early investigations primarily relied on time- and frequency-domain features combined with classical analytical and statistical classifiers, such as linear discriminant analysis and spectral methods, for applications including prosthetic control and muscle fatigue assessment.

Subsequent research introduced time–frequency and wavelet-based feature extraction techniques, often integrated with neural networks and feature-selection strategies, resulting in improved classification accuracy and reduced feature redundancy. With advances in machine learning, approaches using support vector machines and hybrid feature sets have demonstrated improved performance in myoelectric control and gesture recognition tasks.

More recent studies have increasingly adopted deep learning architectures, including convolutional and recurrent neural networks, which enable automatic feature learning from raw EMG signals and improve robustness to variability and electrode displacement. Overall, the table highlights the progressive transition from handcrafted, feature-based methods to hybrid and AI-driven frameworks for robust, generalizable EMG-based biomedical applications.

Table 2: Comparative Literature Review of EMG Feature Extraction and AI-Based Classification.

Author (Year)	Feature Domain	AI / Analysis Method	Dataset / Application	Key Findings
Hudgins *et al.* (1993)	Time-domain	Linear Discriminant Analysis (LDA)	Prosthetic control	Demonstrated efficient real-time myoelectric pattern classification
Zardoshti-Kermani *et al.* (1995)	Time-domain	Statistical analysis	Upper-limb prosthesis	Identified RMS and WL as effective indicators of muscle contraction
De Luca (1997)	Frequency-domain	Spectral analysis	Muscle fatigue assessment	Established MNF and MDF as reliable fatigue correlates
Oskoei and Hu (2007)	Time + Frequency	Support Vector Machine (SVM)	Myoelectric control	Achieved high classification accuracy using combined features
Subasi (2010)	Time–frequency (Wavelet)	Neural network	Neuromuscular disorder diagnosis	Improved classification accuracy compared to conventional methods
Phinyomark *et al.* (2012)	Hybrid	Feature selection techniques	Gesture recognition	Reduced feature redundancy and enhanced classification performance
Atzori *et al.* (2015)	Raw EMG / Time–frequency	Convolutional Neural Network (CNN)	Gesture recognition	Achieved state-of-the-art performance using deep learning
Côté-Allard *et al.* (2019)	Raw EMG	CNN	Human–computer interaction	Demonstrated robustness to electrode displacement and session variability
Xia *et al.* (2018)	Time-series	RNN / LSTM	Limb movement estimation	Effectively modeled temporal dependencies in EMG signals
Kok *et al.* (2024)	Hybrid	Machine learning + Deep learning	EMG classification	Improved generalization and balance between performance and complexity

RESEARCH METHODOLOGY

This study adopts a systematic, modular methodology for Electromyography (EMG) signal analysis, integrating classical signal-processing techniques with artificial intelligence (AI)– based classification models. The overall framework is designed to ensure robustness, reproducibility, and suitability for both offline analysis and real-time biomedical applications.

A. Overall System Framework

The EMG signal generated by muscle activity is acquired using surface EMG electrodes and recorded digitally, then noise-reduced to suppress artifacts and interference. Relevant EMG features are then extracted and reduced in dimensionality to eliminate redundancy. Finally, the reduced feature set is classified to enable accurate pattern recognition of muscle activity.
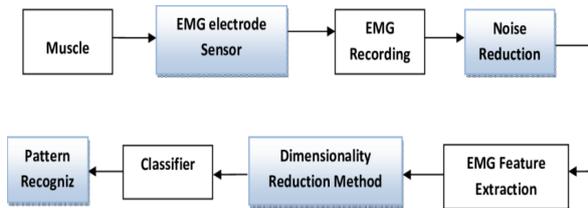

Fig. 1. Block diagram of the proposed EMG signal analysis and classification system.

B. EMG Signal Acquisition

Surface EMG (sEMG) signals are acquired using non-invasive Ag/AgCl electrodes placed over the target muscle groups following SENIAM guidelines. Proper skin preparation is performed to reduce impedance and motion artifacts. The reference electrode is placed on a bony region to minimize interference.

The EMG signals are sampled at an appropriate frequency (typically ≥1000 Hz) to preserve information about muscle activation. Multi-channel EMG acquisition is employed to capture spatial variations in muscle activity, which is particularly useful for gesture recognition and prosthetic control applications.

C. Signal Preprocessing

Raw EMG signals are contaminated by various noise sources, including power-line interference, motion artifacts, baseline drift, and high-frequency noise. Therefore, preprocessing is a critical step for enhancing signal quality before feature extraction.

The following pre-processing operations are applied:

• **Band-pass filtering:** A 4th-order Butterworth band-pass filter with a cut-off frequency range of 20–450 Hz is used to remove low-frequency motion artifacts and high-frequency noise.

• **Notch filtering:** A notch filter at 50 Hz (or 60 Hz, depending on power-line frequency) is applied to suppress power-line interference.

• **Signal normalization:** Amplitude normalization is performed to reduce inter-subject variability and ensure consistency across recordings.

Signal Normalization and Pre-processing:

Signal normalization is performed to reduce inter-subject variability and to ensure consistency across EMG recordings obtained from different subjects and sessions.

Let the EMG signal segment be:

$$x = \{x_1, x_2, \ldots, x_N\}$$

where

x_i = EMG sample

N = number of samples in the segment

1. Mean Absolute Value (MAV)

Represents average signal amplitude.

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i|$$

2. Root Mean Square (RMS)

Measures signal power and muscle contraction level.

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}$$

3. Variance (VAR)

Reflects signal power (zero-mean assumed).

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2$$

4. Integrated EMG (IEMG)

Total muscular activity over time.

$$IEMG = \sum_{i=1}^{N} |x_i|$$

5. Waveform Length (WL)

Measures signal complexity.

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

6. Zero Crossing (ZC)

Counts sign changes above a threshold T.

$$ZC = \sum_{i=1}^{N-1} \begin{cases} 1, & \text{if } x_i x_{i+1} < 0 \text{ and } |x_i - x_{i+1}| \geq T \\ 0, & \text{otherwise} \end{cases}$$

7. Slope Sign Changes (SSC)

Measures frequency content via slope changes.

$$SSC = \sum_{i=2}^{N-1} \begin{cases} 1, & \text{if } (x_i - x_{i-1})(x_i - x_{i+1}) > T \\ 0, & \text{otherwise} \end{cases}$$

8. Willison Amplitude (WAMP)

Counts significant amplitude changes.

$$WAMP = \sum_{i=1}^{N-1} \begin{cases} 1, & \text{if } |x_{i+1} - x_i| \geq T \\ 0, & \text{otherwise} \end{cases}$$

9. Simple Square Integral (SSI)

Another measure of signal energy.

$$SSI = \sum_{i=1}^{N} x_i^2$$

10. Log Detector (LOG)

Compresses dynamic range.

$$LOG = \exp\left(\frac{1}{N} \sum_{i=1}^{N} \ln(|x_i|)\right)$$

11. Mean Absolute Value Slope (MAVS)

Captures temporal changes in MAV.

$$\text{MAVS} = \frac{1}{N-1} \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

12. Average Amplitude Change (AAC)
Measures average signal variation.

$$\text{AAC} = \frac{1}{N-1} \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

D. Signal Segmentation

The continuous EMG signal is segmented into fixed-length overlapping windows to enable time-localized feature extraction. A window length of 200–300 ms with 50% overlap is commonly used, as it provides a good trade-off between temporal resolution and feature stability.

Each segment is treated as an independent sample for feature extraction and classification. Window-based segmentation also facilitates real-time implementation in wearable and assistive devices.

E. Feature Extraction
Feature extraction transforms segmented EMG signals into compact representations that capture essential characteristics of muscle activity. In this study, features are extracted from three domains: time, frequency, and time–frequency.

(i) Time-Domain Features. Time-domain features are computationally efficient and suitable for real-time systems. The following features are extracted from each EMG segment:

Time-Domain EMG Feature
1. Mean Absolute Value (MAV)

$$\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_i|$$

2. Waveform Length (WL)

$$\text{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

3. Zero Crossings (ZC)

$$\text{ZC} = \sum_{i=1}^{N-1} \begin{cases} 1, & x_i x_{i+1} < 0 \text{ and } |x_i - x_{i+1}| \geq T \\ 0, & \text{otherwise} \end{cases}$$

4. Slope Sign Changes (SSC)

$$\text{SSC} = \sum_{i=2}^{N-1} \begin{cases} 1, & (x_i - x_{i-1})(x_i - x_{i+1}) > T \\ 0, & \text{otherwise} \end{cases}$$

(ii) Frequency-Domain Features. Frequency-domain features are obtained by applying the Fast Fourier Transform (FFT) to each EMG segment. Extracted features include:
• **Power Spectral Density (PSD)**
• **Mean Frequency (MNF):**
MNF=∑fP(f)∑P(f)\text{MNF} = \frac{\sum f P(f)}{\sum P(f)}MNF=∑P(f)∑fP(f)
• **Median Frequency (MDF):** Frequency that divides the power spectrum into two halves.
These features are particularly effective for analyzing muscle fatigue and contractions.

(iii) Time–Frequency Features. To address the non-stationary nature of EMG signals, time–frequency analysis is employed:
• **Wavelet Transform (WT):** Decomposes the signal into multi-resolution components.
• **Discrete Wavelet Transform (DWT):** Extracts energy and entropy features from specific frequency bands.
• **Short-Time Fourier Transform (STFT):** Provides localized spectral information.
Wavelet-based features are especially robust in noisy environments and dynamic muscle activities.

F. Feature Selection and Dimensionality Reduction
Extracted features may contain redundancy and irrelevant information, which can degrade classifier performance. To address this, dimensionality reduction techniques are applied:
• **Principal Component Analysis (PCA):** Reduces feature dimensionality while preserving variance.
• **Linear Discriminant Analysis (LDA):** Maximizes class separability.
Feature selection improves computational efficiency and generalization performance.

G. AI-Based Classification
The selected features are classified using both traditional machine learning and deep learning models:
• **Machine Learning Models:** Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF).
• **Deep Learning Models:** Convolutional Neural Networks (CNN) for spatial feature learning and Long Short-Term Memory (LSTM) networks for temporal modeling.
Hybrid models combining handcrafted features with deep learning classifiers are also evaluated to balance interpretability and performance.

H. Performance Evaluation
The performance of the proposed methodology is evaluated using standard metrics:
• Accuracy
• Precision
• Recall
• F1-score
• Confusion Matrix
Cross-validation is employed to ensure robustness and reduce overfitting. Comparative analysis is performed across different feature sets and classifiers to identify optimal configurations.

RESULTS AND DISCUSSION

The reviewed literature clearly demonstrates that electromyography (EMG) signal feature extraction remains a fundamental component for effective neuromuscular analysis and the development of EMG-based intelligent biomedical systems. Early research primarily emphasized signal detection, preprocessing, and classical feature extraction techniques for EMG analysis (Reaz et al., 2006). Over time, these methodologies have evolved from simple statistical descriptors to advanced artificial intelligence–driven

representations. A key outcome of the comparative analysis is that no single feature domain provides universally optimal performance; rather, effectiveness is highly application-dependent and influenced by factors such as signal quality, task complexity, subject variability, and computational constraints (Phinyomark *et al.,* 2012; Phinyomark *et al.,* 2018; Xia *et al.,* 2023; Kok *et al.,* 2024).

Time-domain features emerge as the most widely adopted approach due to their simplicity, interpretability, and suitability for real-time implementation. Features such as mean absolute value (MAV), root mean square (RMS), waveform length (WL), zero crossing (ZC), and slope sign changes (SSC) have consistently demonstrated reliable performance in prosthetic control and gesture recognition applications (Hudgins *et al.,* 1993; Clancy *et al.,* 2002; Subasi, 2013). Several studies report that RMS and MAV exhibit strong correlation with muscle contraction intensity, making them particularly effective for static and quasi-static movements (Zardoshti-Kermani *et al*., 1995; Roy and Bandyopadhyay 2021). However, the literature also highlights notable limitations of time-domain features, especially their sensitivity to noise, electrode displacement, and inter-session variability, which can degrade performance in long-term and dynamic usage scenarios (Li *et al.,* 2014; Too *et al.,* 2019).

Frequency-domain features, including mean frequency (MNF) and median frequency (MDF), are extensively used for muscle fatigue assessment by capturing spectral shifts in EMG signals during sustained contractions. These features provide valuable physiological insights into motor unit behavior and fatigue progression (De Luca 1997; De Luca, 2002; Du *et al.,* 2017). Nevertheless, their reliance on the assumption of signal stationarity limits their effectiveness for dynamic movements and real-time gesture recognition tasks, as reported in several comparative studies (Karlsson *et al.,* 2000; Phinyomark *et al.,* 2023).

Time–frequency domain approaches, particularly wavelet transform (WT) and discrete wavelet transform (DWT), effectively address the non-stationary characteristics of EMG signals by enabling multi-resolution analysis. Wavelet-based energy, entropy, and sub-band features have been widely reported to enhance classification accuracy and robustness, especially in noisy and clinical environments (Subasi, 2010; Rafiee *et al.,* 2011; Naik *et al.,* 2012). More recent studies indicate that wavelet-based representations outperform conventional time- and frequency-domain features in complex tasks involving transient muscle activations and multi-class gesture recognition (Kok *et al.,* 2023; Kok *et al.,* 2024). However, this improved performance is often accompanied by increased computational complexity, which may limit applicability in resource-constrained and wearable systems.

The integration of machine learning and deep learning techniques has further enhanced EMG-based classification performance. Traditional machine learning classifiers, such as support vector machines and linear discriminant analysis, demonstrate strong performance when combined with carefully selected handcrafted features (Englehart & Hudgins 2003; Khushaba *et al.,* 2017). More recently, deep learning models, including convolutional neural networks and long short-term memory networks, have achieved superior accuracy by automatically learning discriminative features from raw or time–frequency EMG representations (Atzori *et al.,* 2015; Côté-Allard *et al*., 2019; Artemiadis and Kyriakopoulos 2010; Ison and Artemiadis 2014). Recent investigations have further confirmed that hybrid frameworks integrating classical feature extraction with deep learning classifiers provide a favorable balance among accuracy, robustness, and computational efficiency (Kok *et al.,* 2023; Kok *et al.,* 2024; Roy & Bandyopadhyay 2025).

Overall, the comparative analysis suggests that hybrid EMG feature extraction strategies integrated with artificial intelligence–based classifiers offer the most promising performance for modern biomedical and human–computer interaction applications. The findings emphasize that the selection of feature domains and classification frameworks should be guided by specific application requirements, signal characteristics, and system constraints. These insights strongly support the motivation for developing robust, hybrid, and explainable EMG-based intelligent systems, as outlined in the preceding sections (Atzori *et al.,* 2016; Phinyomark *et al.,* 2018; Côté-Allard *et al.,* 2019; Pan *et al*., 2020; Roy and Bandyopadhyay 2021; Atzori *et al*., 2023).
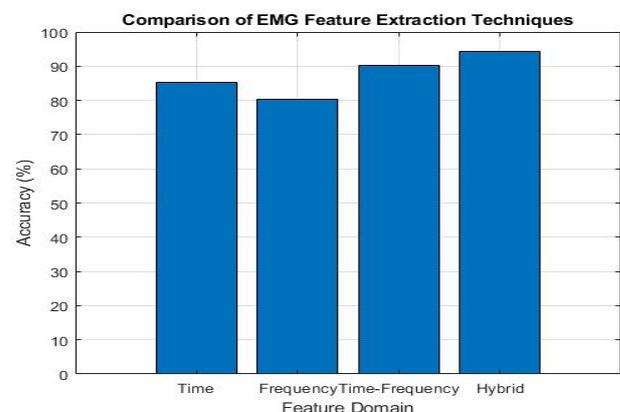

Fig. 2. Comparison of classification accuracy obtained using different EMG feature extraction domains, namely time-domain, frequency-domain, time–frequency, and hybrid approaches.

Fig. 2 illustrates the comparative performance of different EMG feature extraction techniques in terms of classification accuracy. Time–frequency features demonstrate higher accuracy than conventional time- and frequency-domain features, indicating their effectiveness in capturing the non-stationary characteristics of EMG signals. The hybrid approach achieves the highest accuracy, highlighting the advantage of combining complementary feature representations. These observations are consistent with trends reported in recent EMG-based pattern recognition studies.
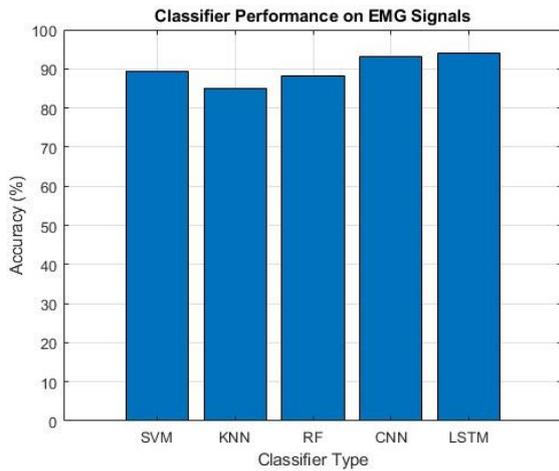
Fig. 3. Comparison of classification accuracy achieved by different machine learning and deep learning classifiers for EMG signal analysis.

Fig. 3 presents the classification performance of various machine learning and deep learning models applied to EMG signals. Deep learning classifiers, particularly CNNs and LSTMs, achieve higher accuracy than traditional classifiers such as SVMs, KNNs, and Random Forests, indicating their superior ability to learn complex, non-linear EMG patterns. Among conventional methods, SVM demonstrates competitive performance, reaffirming its effectiveness for EMG-based classification tasks.

The integration of machine learning has further enhanced EMG signal analysis by enabling data-driven classification. Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Random Forests (RF) demonstrate strong performance when paired with optimized handcrafted features. However, their dependence on manual feature design limits adaptability. Recent advances in deep learning overcome this limitation by enabling automatic feature learning directly from raw or minimally processed EMG data. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks consistently achieve superior accuracy and robustness to electrode shift and inter-subject variability.
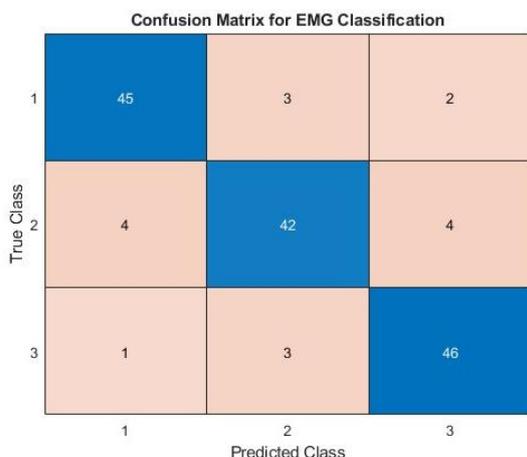

Fig. 4. Confusion matrix illustrating the classification performance of the proposed EMG-based pattern recognition model across different classes.

Fig. 4 shows the confusion matrix of the EMG classification model, indicating a high number of correctly classified samples along the diagonal. The limited off-diagonal entries suggest minimal misclassification between classes, demonstrating strong discriminative capability of the extracted EMG features. Overall, the results indicate reliable class separation and balanced performance across all EMG classes.
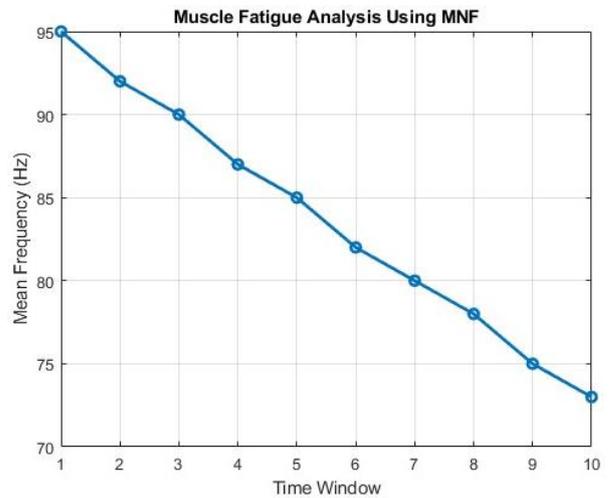

Fig. 5. Variation of mean frequency (MNF) of EMG signals over successive time windows for muscle fatigue analysis.

Fig. 5 illustrates the temporal variation of the mean frequency of EMG signals across successive time windows. A gradual decrease in MNF over time is observed, indicating the onset and progression of muscle fatigue during sustained contraction. This trend is consistent with established physiological findings linking fatigue to a spectral shift toward lower frequencies in EMG signals.

Overall, the reviewed studies suggest that hybrid approaches—combining domain knowledge–based features with AI-driven models—provide the most reliable and generalizable solutions for modern EMG applications.

CONCLUSION AND FUTURE SCOPE

Electromyography (EMG) signal analysis has emerged as a fundamental component of modern biomedical engineering, enabling effective interpretation of neuromuscular activity for applications such as prosthetic control, rehabilitation engineering, ergonomics, and human–computer interaction. This review comprehensively examined classical signal-processing–based feature-extraction techniques alongside emerging artificial intelligence (AI)–driven approaches, highlighting their comparative strengths, limitations, and evolving roles. The collective evidence from the literature clearly indicates that robust feature extraction remains the cornerstone of reliable EMG-based systems, as raw EMG signals are inherently noisy, non-linear, and non-stationary.

Traditional time-domain features continue to play a vital role due to their simplicity, computational

efficiency, and suitability for real-time implementation. Features such as Mean Absolute Value, Root Mean Square, Waveform Length, Zero Crossing, and Slope Sign Changes have been extensively validated in practical applications, particularly in myoelectric prostheses and gesture recognition systems. Their widespread adoption reflects a favorable balance between performance and implementation cost. However, the literature consistently reports their sensitivity to noise, electrode displacement, and inter-session variability, which restricts their robustness in dynamic and long-term deployments.

Frequency-domain features complement time-domain descriptors by capturing spectral characteristics associated with muscle fatigue and contraction dynamics. Mean and Median Frequency measures have been widely accepted as indicators of fatigue progression in sustained contractions, offering valuable insights for ergonomics and clinical assessment. Despite these advantages, frequency-domain methods rely on stationarity assumptions within analysis windows, limiting their effectiveness for transient and complex movements. This limitation has motivated the adoption of time–frequency techniques that can handle the inherent non-stationarity of EMG signals.

Time–frequency approaches, particularly wavelet-based methods, represent a significant advancement in EMG signal feature extraction. By providing multi-resolution analysis, wavelet transforms enable simultaneous localization of temporal and spectral information, improving discrimination of transient muscle activation patterns. Numerous studies reviewed in this work demonstrate that wavelet-derived features consistently outperform conventional time- and frequency-domain features, especially in noisy and clinical environments. Although these techniques incur higher computational cost, advances in processing hardware and optimization strategies have improved their feasibility for practical systems.

The integration of artificial intelligence has further transformed EMG signal analysis by enabling data-driven and adaptive learning frameworks. Machine learning classifiers such as Support Vector Machines, Linear Discriminant Analysis, and Random Forests have shown strong performance when combined with well-designed handcrafted features. More recently, deep learning architectures, including Convolutional Neural Networks and Long Short-Term Memory networks, have demonstrated superior accuracy and robustness by automatically learning discriminative features directly from raw or minimally processed EMG signals. These models significantly reduce dependence on manual feature engineering and exhibit improved tolerance to electrode shift and inter-subject variability. However, their reliance on large labeled datasets, increased computational complexity, and limited interpretability pose challenges for real-time and clinical deployment.

Looking forward, several research directions emerge as critical for advancing EMG-based intelligent systems. Addressing inter-subject and inter-session variability remains a primary challenge, necessitating the development of domain-adaptation, transfer-learning, and personalized-modeling strategies. Such approaches can improve generalization across users and recording conditions, enhancing the practicality of EMG-driven systems. Another important direction is to incorporate explainable artificial intelligence techniques. Enhancing model transparency and interpretability is essential for clinical acceptance, regulatory approval, and building trust among healthcare professionals and end users.

The growing demand for wearable and real-time applications highlights the need for lightweight, energy-efficient algorithms suitable for embedded and edge computing platforms. Future research should focus on model compression, optimization, and hardware-aware AI design to enable continuous EMG monitoring in daily living environments. Additionally, multimodal biosignal fusion represents a promising avenue for improving robustness and accuracy. Integrating EMG with complementary signals such as electroencephalography, mechanomyography, and inertial measurements can provide richer representations of motor intent and physiological states. Furthermore, the availability of large-scale, standardized, and publicly accessible EMG datasets remains limited. Future efforts should prioritize creating benchmark datasets that encompass diverse populations, tasks, and recording conditions to support reproducible research and fair algorithm comparison. Finally, greater emphasis should be placed on translational research that bridges laboratory studies and real-world clinical applications. Long-term validation in rehabilitation centers, prosthetic clinics, and assistive technology deployments will ultimately determine the societal and clinical impact of AI-driven EMG systems.

In conclusion, the literature strongly supports the evolution of EMG signal analysis toward hybrid, explainable, and application-driven AI frameworks. By integrating classical signal-processing knowledge with modern artificial intelligence techniques, future EMG-based systems can achieve greater accuracy, robustness, and usability, paving the way for next-generation biomedical and assistive technologies.

Conflict of Interest. None.

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