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Advancements in Electromyography (EMG) Signal Processing and Classification Techniques for Prosthetic Hand Control Applications: A Comprehensive Review

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Abstract: Prosthetic hand control lies at the critical intersection of biomedical engineering and rehabilitation medicine, aiming to restore natural hand function in amputees through precise interpretation of neuromuscular signals. Electromyography (EMG) has become the predominant technique for achieving intuitive control, yet despite promising outcomes in research environments, significant challenges persist in translating these advances into reliable, real-world clinical applications. To assess the current state of the field, a systematic literature review was conducted in accordance with PRISMA guidelines, drawing from PubMed, IEEE Xplore, and Google Scholar. A total of 285 studies were initially identified, of which 52 met the inclusion criteria based on classification accuracy, real-time implementation feasibility, and clinical viability. The analysis revealed that deep learning techniques consistently outperformed traditional approaches, while the integration of multimodal data and the use of advanced preprocessing methods significantly improved system robustness. However, real-time implementation introduced critical performance trade-offs, particularly in terms of latency and power efficiency. Although EMG-based control systems have reached a stage of clinical viability, especially with the superior offline performance of deep learning models, successful deployment still requires hybrid strategies that can balance high accuracy (>90%), low power consumption (<2W), and rapid response times (<300ms). Persistent barriers, such as electrode stability degradation resulting in an 18–25% drop in accuracy, and inter-session variability, underscore the necessity for adaptive calibration mechanisms to ensure consistent, long-term performance and enable widespread.

Keywords: electromyography; prosthetic hand control; signal processing; machine learning; deep learning; gesture recognition; clinical implementation

1. Introduction

Upper limb amputation significantly impairs an individual's ability to carry out daily tasks, with approximately 185,000 people affected in the United States alone [1]. Restoring hand function through prosthetic devices remains one of the most complex challenges in rehabilitation engineering, requiring intelligent control systems capable of accurately interpreting user intent and converting it into natural, intuitive movement. Surface electromyography (sEMG) has emerged as the leading biosignal for myoelectric prosthesis control due to its non-invasive nature and its direct correlation with muscle activation patterns [2]. However, despite substantial progress in laboratory settings, translating these systems into clinically viable solutions still faces major technical and practical challenges.

The development of EMG-based prosthetic control has evolved from simple on–off mechanisms to advanced pattern recognition systems capable of controlling multiple degrees of freedom [1]. Early amplitude-based approaches, which mapped EMG signal magnitude to the speed or force of prosthetic movement [3], offered basic functionality but were limited to single-DoF control and imposed high cognitive loads on users [4]. The emergence of pattern recognition techniques marked a significant shift, enabling the classification of various hand gestures using multichannel EMG signals [5].

Contemporary research in EMG-based prosthetic control has been substantially influenced by advances in machine learning and signal processing methodologies. Traditional machine learning approaches, including Support Vector Machines, Linear Discriminant Analysis, and Random Forest classifiers, have demonstrated promising results in laboratory settings, with classification accuracies often exceeding 90% for basic gesture recognition tasks [1]. However, these methods typically require extensive feature engineering and are sensitive to variations in electrode placement, muscle fatigue, and inter-session variability [6]. The emergence of deep learning architectures, particularly Convolutional Neural Networks, has offered new possibilities for automated feature extraction and improved generalization across users and sessions [5].

Despite significant technological advances, several fundamental challenges continue to limit the widespread clinical adoption of advanced EMG-based prosthetic systems. Signal variability due to electrode shift, muscle fatigue, and changes in skin impedance can significantly degrade system performance over time [6]. Additionally, the computational requirements of sophisticated classification algorithms often conflict with the power consumption constraints of wearable prosthetic devices [7]. User training requirements and the learning curve associated with myoelectric control present additional barriers to successful clinical implementation [8].

The integration of multiple signal processing domains, including time-domain, frequency-domain, and time-frequency analysis, has shown promise for improving classification robustness and accuracy [9]. Recent investigations have explored the combination of traditional handcrafted features with automatically learned representations from deep neural networks, suggesting that hybrid approaches may offer optimal performance for real-world applications [5]. Furthermore, the development of adaptive algorithms that can accommodate changes in signal characteristics over time represents a critical area of ongoing research [8].

Nevertheless, a clear research gap persists in unifying and benchmarking the multitude of EMG processing and classification strategies under clinically realistic conditions. Previous studies have often relied on controlled laboratory settings, healthy participants, and offline datasets, without adequately addressing real-world deployment issues such as session-to-session variability, long-term signal stability, user-specific adaptation, and low-power implementation constraints. Additionally, few reviews have provided a comparative, performance-driven synthesis across traditional and deep learning methods with clinical viability in mind. This review aims to bridge that gap by offering a comprehensive, performance-focused evaluation of EMG-based control systems and highlighting pathways toward robust, real-time prosthetic solutions.

This review critically examines current EMG signal processing and classification techniques for prosthetic hand control, comparing traditional machine learning approaches with modern deep learning architectures, and highlighting their respective strengths, limitations, and clinical viability. It further identifies the most promising solutions for real-world implementation while outlining the persistent challenges that must be addressed to achieve practical, scalable clinical adoption.

2. Methodology

2.1 Research Objectives and Questions

This systematic review was conducted to evaluate recent advancements in the use of electromyography (EMG) signals for controlling upper-limb prosthetic hands. The main aim was to explore how EMG signal processing and classification techniques have evolved, with particular attention to the integration of machine learning and deep learning methods. Additionally, the review sought to identify persistent challenges in implementing accurate and real-time myoelectric control systems.

To guide the review process, three primary research questions were formulated:

What are the most recent techniques used for EMG signal acquisition, preprocessing, and classification in upper-limb prosthetic control?

How have machine learning and deep learning methods improved the performance and accuracy of EMG-based control systems?

What limitations and challenges remain in achieving reliable and real-time classification of EMG signals for prosthetic applications?

2.2 Search Strategy and Databases

A comprehensive literature search was conducted across three electronic databases: PubMed, IEEE Xplore, and Google Scholar. These databases were chosen to cover a wide range of disciplines, including biomedical engineering, neuroscience, rehabilitation, and computer science. The search was limited to studies published between January 2015 and May 2025 to reflect the most current developments in the field.

2.3 Detailed Inclusion and Exclusion Criteria

To ensure methodological rigor and thematic relevance, specific inclusion and exclusion criteria were established:

2.3.1 Inclusion Criteria:

Studies published in the English language
Original experimental research presenting quantitative data
Studies involving the use of EMG signals for upper-limb or prosthetic hand control
Research presenting quantitative results related to classification accuracy or control performance
Studies with sufficient methodological detail to support cross-study comparison

2.3.2 Exclusion Criteria:

Studies focusing on lower-limb prosthetics or non-EMG-based control systems
Review articles, editorials, or opinion pieces
Studies published in languages other than English
Research lacking classification or performance evaluation data

2.4 Study Selection Process

Following PRISMA 2020 guidelines, Figure 1 [10] The search identified a total of 285 studies: 125 from Google Scholar, 98 from PubMed, and 62 from IEEE Xplore. After removing 87 duplicates, 198 unique records remained for title and abstract screening.

During the abstract screening stage, 89 studies were excluded after careful evaluation of their titles and abstracts, as their content did not align with the primary focus of this review. Subsequently, 109 full-text articles were retrieved and assessed for eligibility, and during this phase, 57 studies were excluded—35 for not focusing on upper-limb prosthetic control, and 22 were review articles or editorials.

The application of all inclusion criteria resulted in the selection of 52 studies for the final systematic review.

2.5 Data Extraction and Analysis

The review followed the PRISMA 2020 guidelines, shown in Figure 1, to ensure a transparent and systematic selection process [11]. For each included study, data were extracted regarding participant demographics, EMG acquisition setup, electrode configurations, preprocessing methods, feature extraction techniques, classification algorithms, and performance metrics. This data formed the basis for a thematic synthesis, allowing for comparative analysis across studies and the identification of key trends and research gaps.

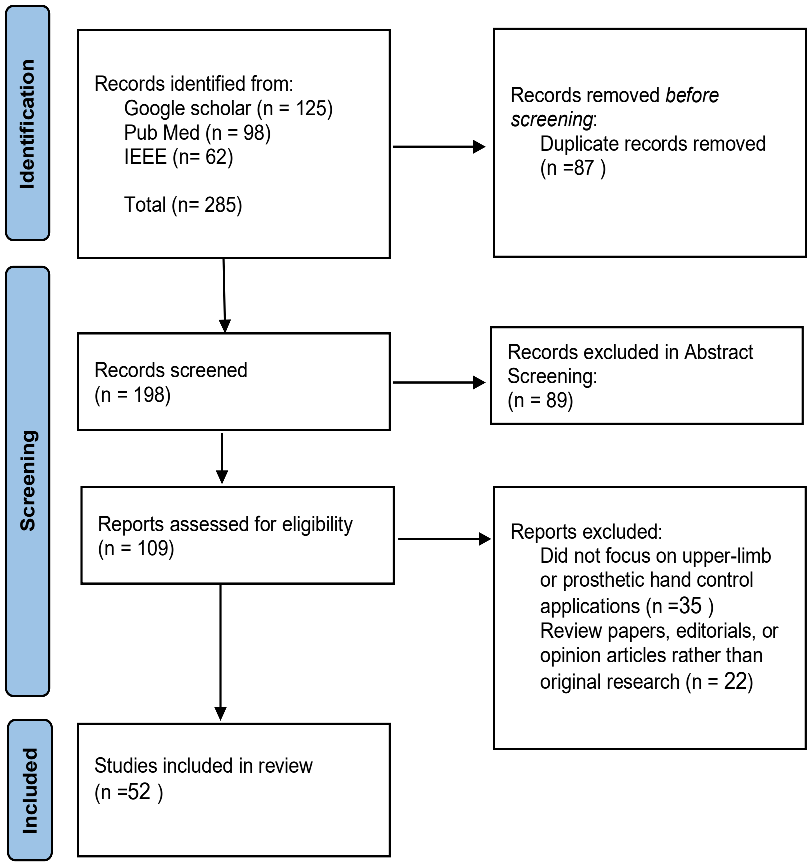

Figure 1: PRISMA 2020 flowchart of study selection (2015–2025): 285 records identified, 87 duplicates removed, 198 screened, 109 full-text articles assessed, 57 excluded, and 52 included in the final review.

3. Results

The sEMG signal processing framework illustrated in Figure 2 represents the fundamental approach employed across most studies reviewed in this systematic analysis. This comprehensive workflow demonstrates the sequential stages required to transform raw electromyographic signals captured from residual muscles into reliable control commands for prosthetic hand devices. The process begins with signal acquisition from surface electrodes placed on the residual limb, followed by analog-to-digital conversion to enable digital signal processing. The subsequent preprocessing stages include filtering to remove noise and artifacts, rectification to obtain signal magnitude information, and smoothing to reduce signal variability and enhance stability.

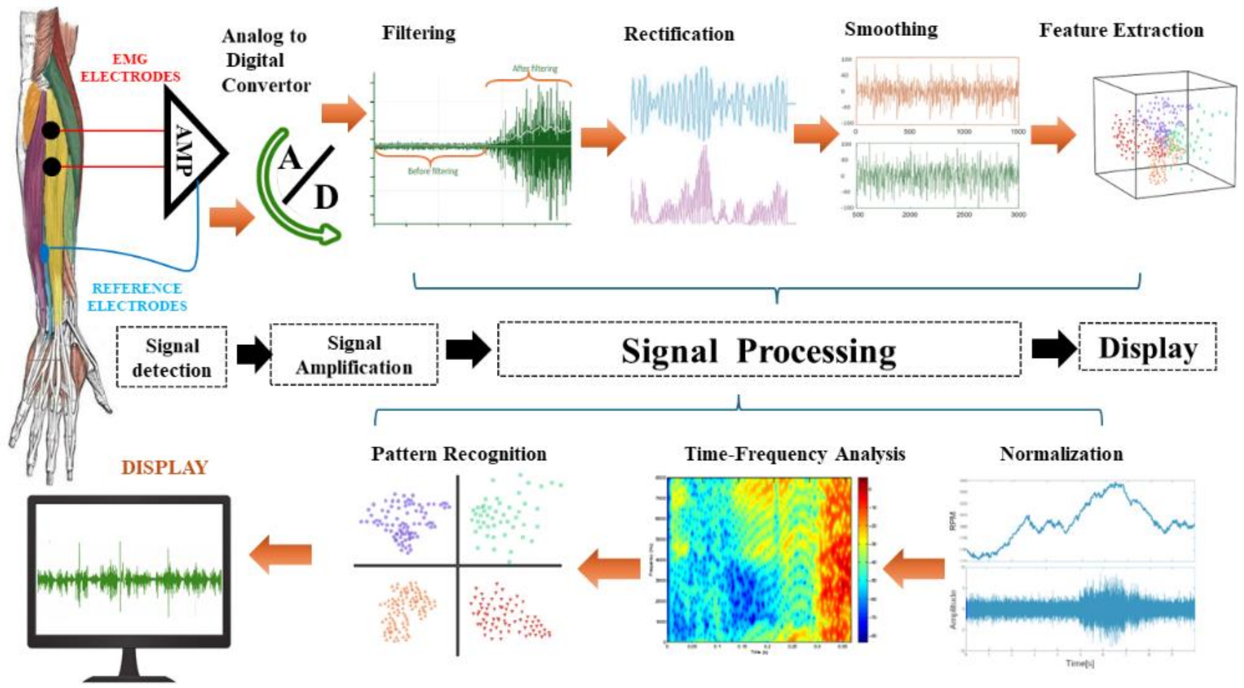

Figure 2 :sEMG signal processing framework for prosthetic hand control: acquisition, ADC conversion, filtering/rectification/smoothing, normalization, feature extraction/classification, and execution through the user interface (adapted from [101])

3.1 Study Selection and Characteristics

A total of 285 articles were initially identified through systematic searches across three major databases: Google Scholar (125 articles), PubMed (98 articles), and IEEE Xplore (62 articles). After removing 87 duplicates and applying inclusion/exclusion criteria through title, abstract, and full-text screening, 52 studies were included in the final systematic review.

The selected studies encompassed diverse experimental designs, with participant counts ranging from single-subject demonstrations to large-scale studies involving up to 40 participants. Most studies employed healthy volunteers, though several included amputee participants, providing valuable insights into real-world clinical applications. Window sizes varied considerably across studies, ranging from 100ms for real-time applications to 2.2 seconds for offline analysis.

Detailed methodological characteristics and outcomes of all included studies are summarized in Table 1, with further analysis presented in the following sections of this review.

Table 1 Comprehensive Overview of the 52 EMG-Based Prosthetic-Control Studies

Study	Subjects	Classes	Window Size
[12]	1	18	100 ms
[13]	12 (10+2 amputees)	2 (open/close, force)	250 ms, 90% overlap
[14]	10	6	256 ms, 128 ms overlap
[15]	10	6	256 ms, 128 ms overlap
[16]	1	5	250 ms, 50 ms overlap

[17]	10	6	512 samples
[18]	6	Regression (11 joints)	N/A
[19]	1 (amputee)	2 (open/close)	5 s calibration
[20]	N/A	N/A	N/A
[21]	9	3 DoF (27)	25 ms, up to 1.675 s seq.
[22]	8	15	100 ms (200 samples @2kHz)
[23]	18	10	200 ms
[24]	10	10	200 ms
[25]	Myo:19; DB5:10	Myo:7; DB5:12/17/23	N/A
[26]	5	Regression	200 ms
[27]	8 (clinical)	1 (grasp)	N/A
[28]	37	Regression	N/A
[29]	1 (demo)	1 (open/close)	N/A
[30]	1	5 (force levels)	N/A
[31]	N/A	5 (individual fingers)	N/A
[32]	N/A	5	128 samples @ 2kHz
[33]	10 (4 online)	10	500 ms (MSFS), 1000 ms
[34]	2 amputees	3-DoF (18), 4-DoF (32)	200 ms, update 50 ms
[35]	5 amputees, 5 able-bodied	5 hand motions	~15 fps ultrasound
[36]	8	10 finger/combined moves	100 ms, 50 ms overlap
[37]	3 (SNR), 6 (control)	6 DOF	300 ms (smoothed MAV)
[38]	8 able-bodied, 4 amputees	5 grasp types	N/A (phases of reach)
[39]	14 male volunteers	Individual finger, thumb, wrist movements	50-1050 ms
[40]	2 subjects	Open/close, supinate/pronate	DSP @10 kHz, T=51.1 ms

[41]	Not specified	Wrist and finger movements	Real-time, EMD 30-100 ms
[42]	8 able-bodied	6 hand postures, digit force	50 ms non-overlapping
[43]	1 bilateral amputee	3 (wrist flexion, fist, extension)	2s classification, 500ms sub-windows
[44]	1 amputee	Multiple gestures/grades	Real-time KMG processing
[45]	Multiple datasets	Hand gestures (varies)	Windowing/overlapping
[46]	10	7 gestures	1-second pause, 20-30 reps
[47]	14 male subjects	Multiple DoF movements	RMS: 250ms window
[48]	NinaPro DB1:27, DB2:40	DB1:53, DB2:41	150ms, 10ms increment
[49]	Multiple NinaPro DBs	Various (6-53 classes)	100-300 samples, shifts
[50]	10 healthy adults	12 hand postures, 7 groups	250ms, 10ms shift
[51]	Not specified (Myo armband)	7 hand gestures	150 samples @200Hz (~0.75s)
[52]	NinaPro DB2:40, DB3:10, Ameri:17	NinaPro:40, Ameri:10	400ms/100ms overlap (NinaPro), 160ms/40ms (Ameri)
[53]	10 healthy males	10 gestures (7 individual fingers)	250ms, 25ms shift (90% overlap)
[54]	1 male	4 physical actions	1000 samples, 25% overlap
[55]	NinaPro DB2:40, DB3:11	DB2:49, DB3:50	200ms, 100ms increment
[56]	7 able-bodied, 1 amputee	9 gestures	2.2s (4500 samples), RMS 150-sample windows
[57]	DB2:40, DB4:10	DB2:49, DB4:52	200ms, 50ms step
[58]	13 healthy subjects	21 hand gestures	200ms (40 steps @200Hz)
[59]	Multiple datasets	Up to 53 gestures	50-300ms, STFT spectrograms
[60]	Not specified	Grasp open/close	Real-time
[61]	CapgMyo dataset, 8 hand gestures	8 gestures	N/A
[62]	Simulated sEMG data	10 MVC levels	N/A
[63]	Multiple studies (review paper)	8-10 movements	N/A

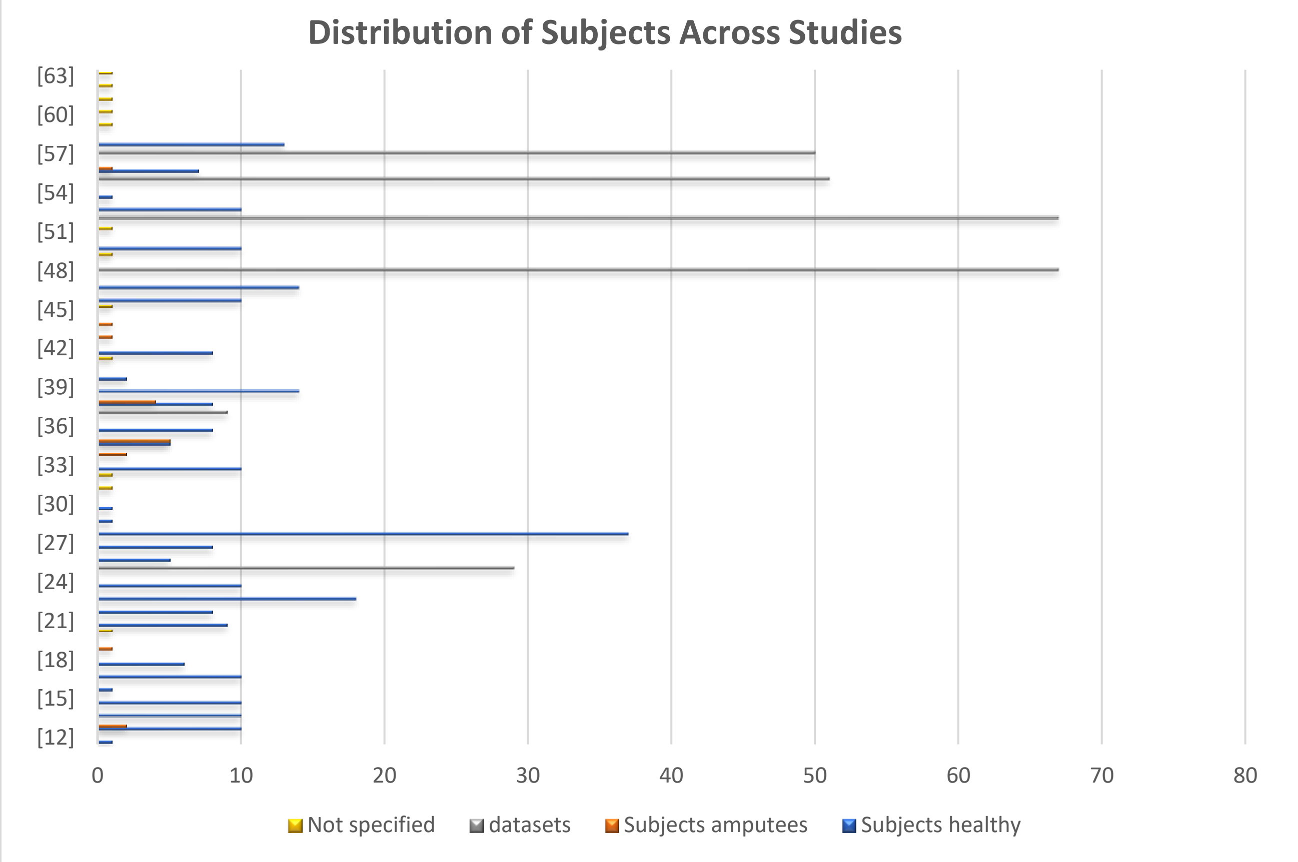

Figure 3: Distribution of participant numbers across included studies (n=52), ranging from single-subject case studies to >30 participants.

Figure 3 illustrates the distribution of subjects across the reviewed studies. The number of participants varied substantially, ranging from single-subject case studies (e.g., [16], [19], [29], [44]) to larger experimental datasets with over 30 participants (e.g., [28], [38]). This variation highlights both the diversity of experimental designs and the challenges of generalizing results across different populations.

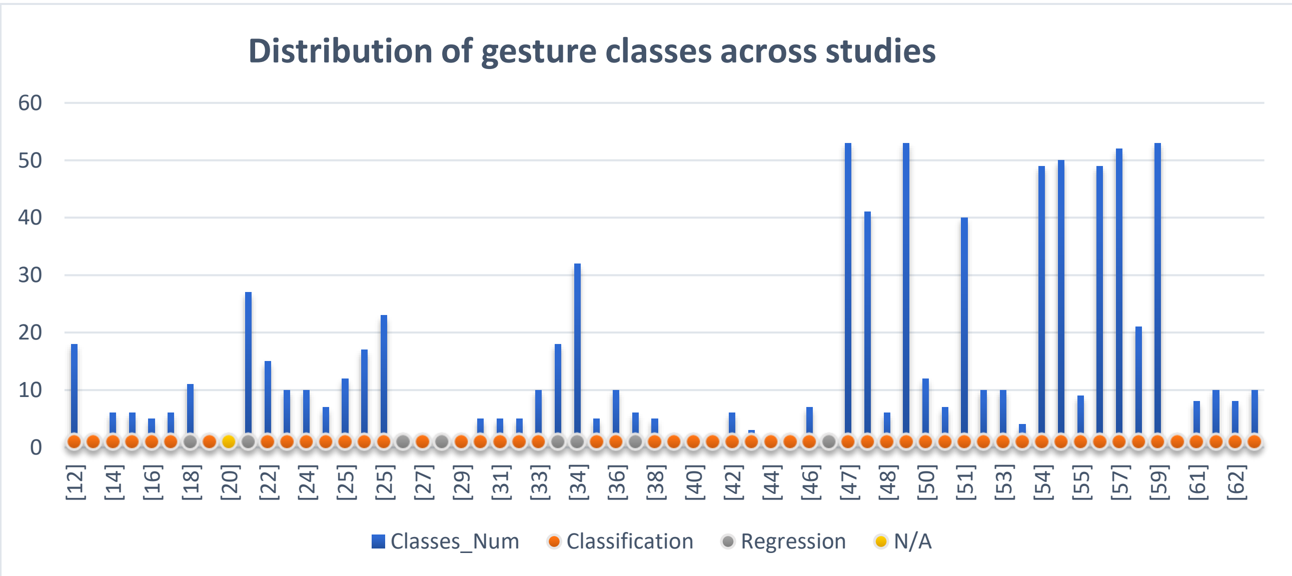

Figure 4: Number of gesture classes studied: from binary tasks (open/close) to more than 50 complex gestures.

Figure 4 depicts the relationship between individual studies and the number of classes employed in their experimental protocols. The distribution reveals considerable variation: while some works adopted binary classification schemes (e.g., open vs. close hand actions in [13], [19], [29]), others explored more complex paradigms with multiple gesture classes, such as 10 to 21 movements ([23], [36], [58]) or even large-scale datasets exceeding 50 classes ([49], [59]). This spread reflects both methodological diversity and the progressive shift in the field toward tackling higher-dimensional myoelectric control tasks.

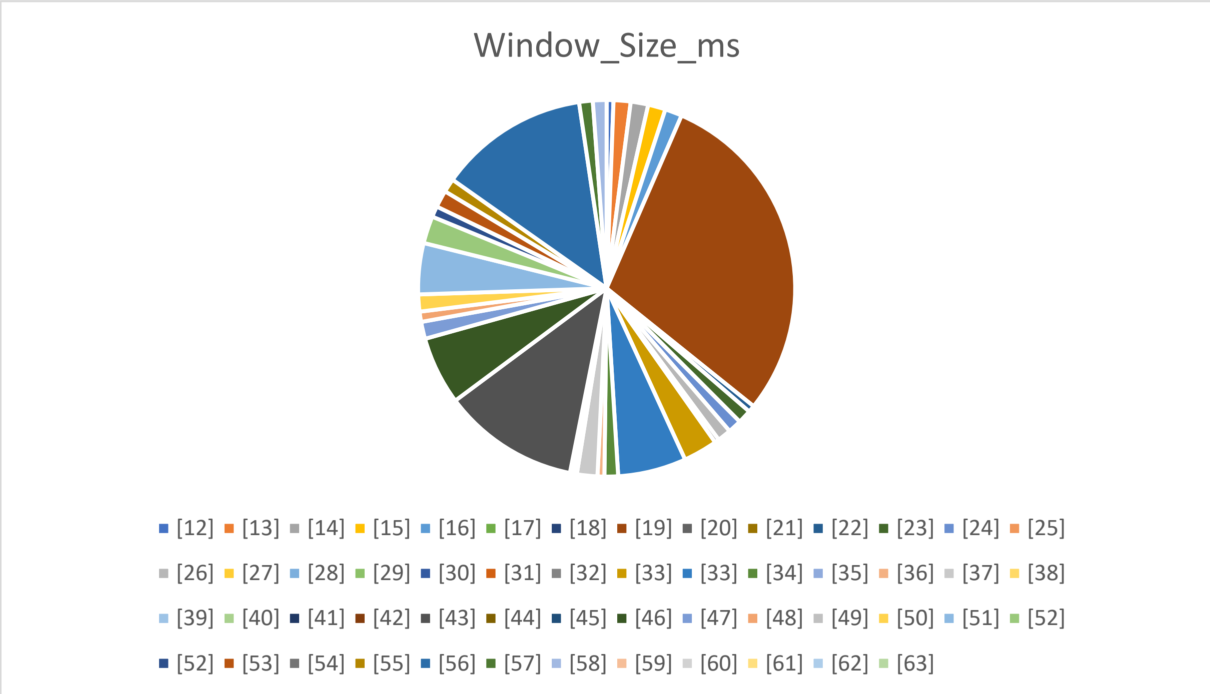

Figure 5: Distribution of segmentation window sizes (ms) across studies: balancing responsiveness (25–100 ms) versus stability (up to 1000 ms).

Figure 5 shows the relationship between the reviewed studies and the window sizes applied for signal segmentation. The choice of window length varied considerably from short durations of 25–100 ms ([21], [22], [42]) to medium windows of 200–300 ms ([23], [36], [43]) and longer segments up to 1000 ms ([33], [54]). Short windows are generally preferred for real-time control due to lower latency, while longer windows provide more stable feature extraction at the cost of increased delay. This variability reflects the trade-off between accuracy and responsiveness in myoelectric control research.

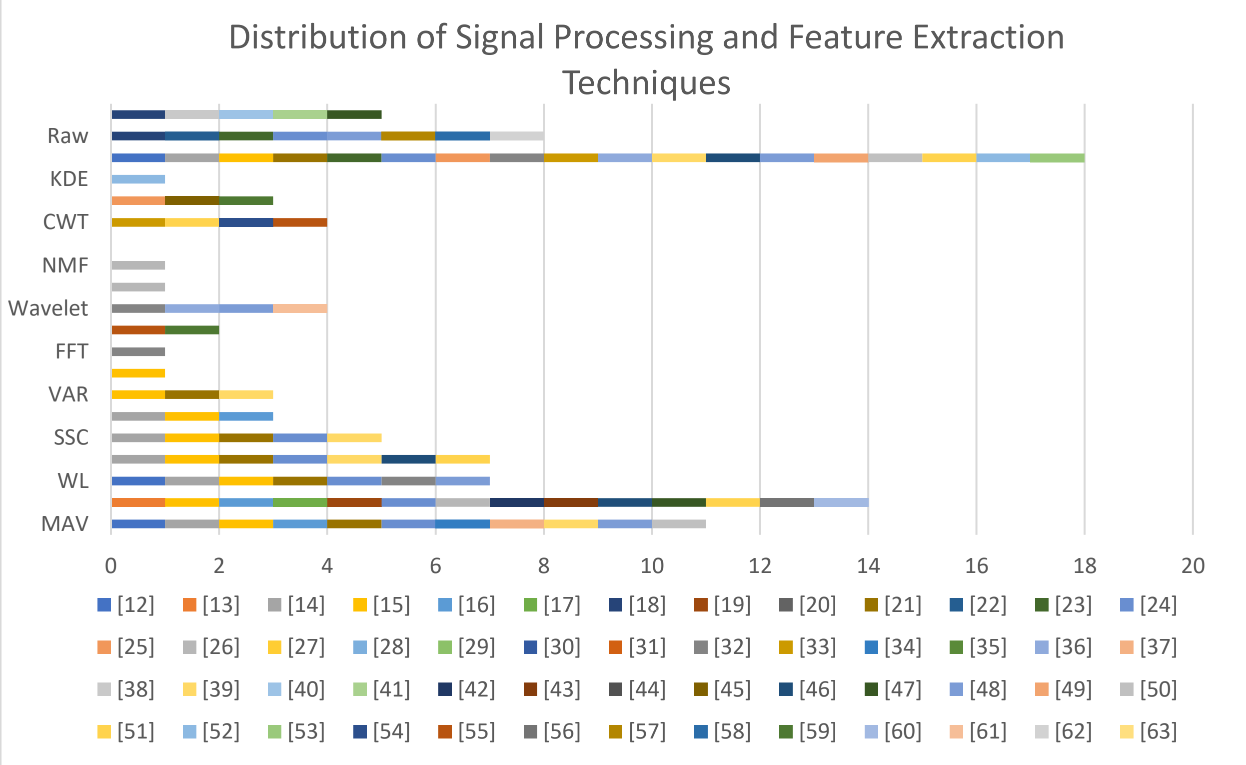

Figure 6: Comparison of feature extraction techniques used in the literature (time-domain, frequency-domain, time–frequency, spatial, hybrid).

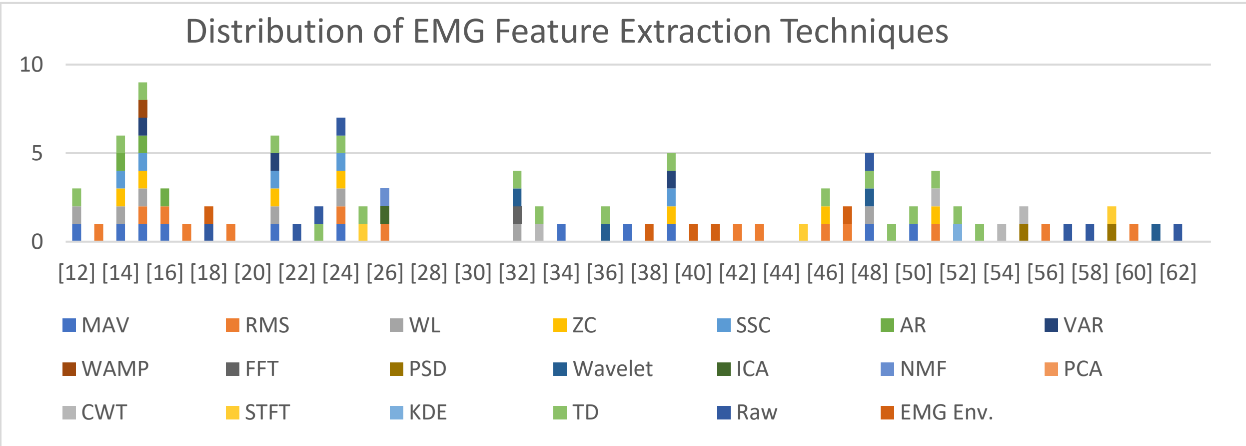

Figure 7: Frequency of feature families reported across studies (e.g., MAV, RMS, WL, ZC, SSC, STFT, CWT).

Figures 6 and 7 illustrate the relationship between the reviewed studies and the types of features selected for signal processing. A wide range of feature extraction strategies has been reported. Traditional time-domain features such as MAV, RMS, WL, ZC, and SSC were most frequently applied ([12], [14], [15], [36], [42]), often due to their computational efficiency and robustness. Some studies expanded the feature space by incorporating autoregressive (AR) coefficients ([14], [15], [16]), frequency-domain descriptors such as FFT and DFS ([17], [32]), or advanced approaches like muscle synergies (ICA, NMF) ([26]) and spectrogram-based representations for CNN models ([25], [45], [55]). The diversity of feature selection reflects the continuous effort to balance real-time feasibility with classification accuracy in myoelectric control.

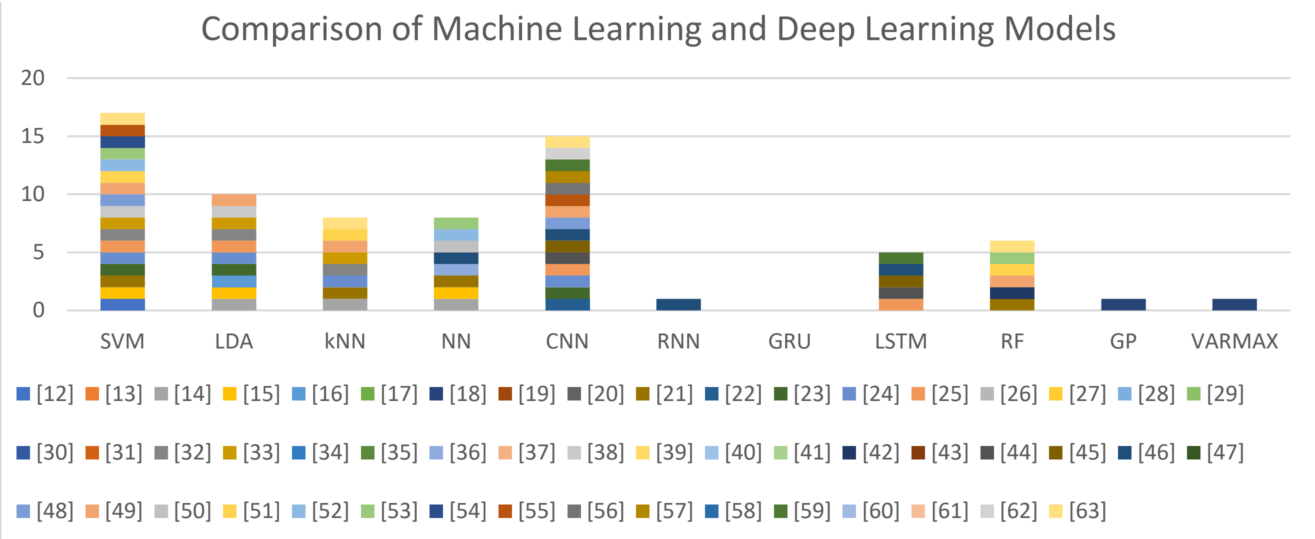

Figure 8: Distribution of machine learning versus deep learning approaches in EMG-based control studies.

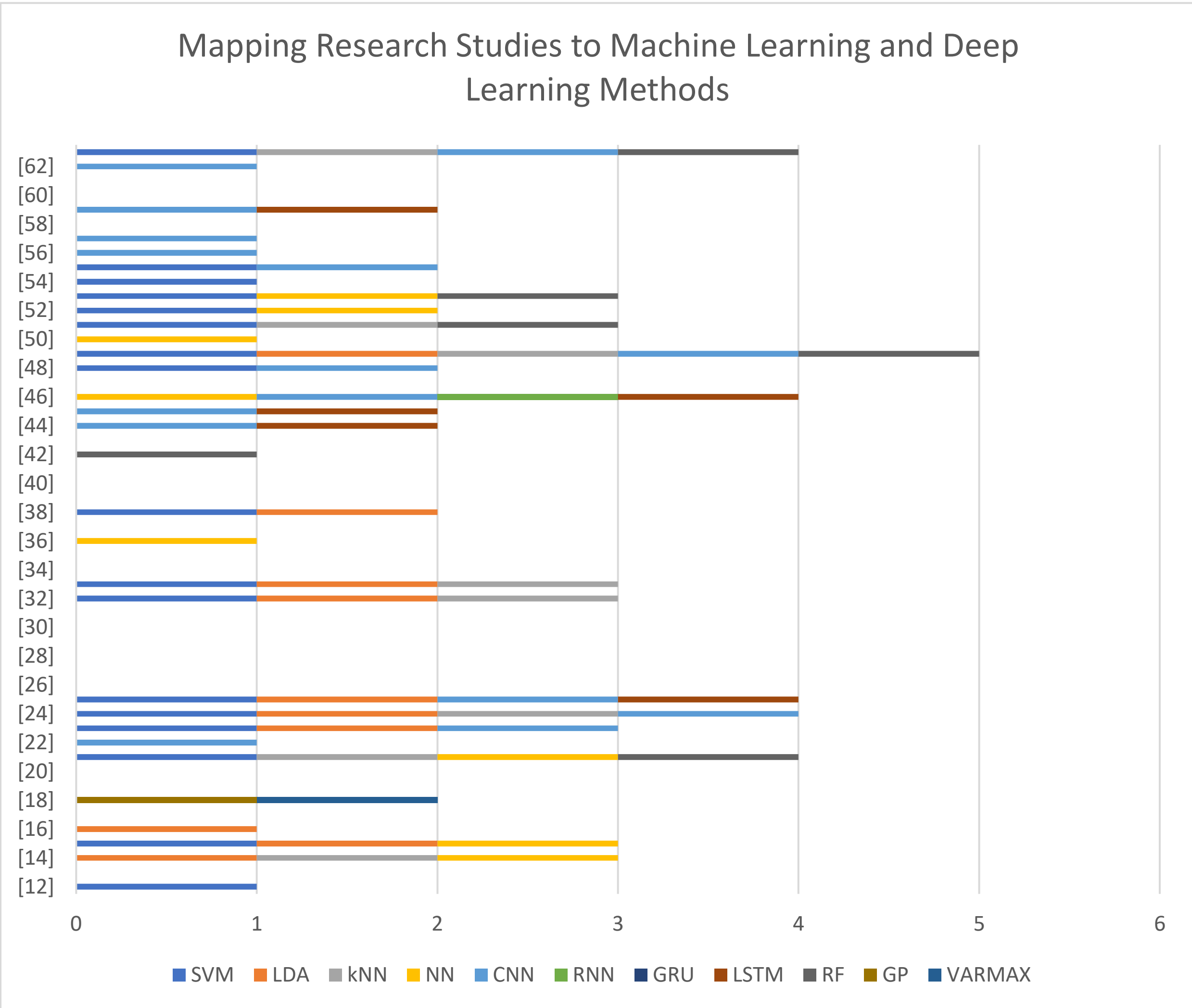

Figure 9: Distribution of classification algorithms used (LDA, SVM, kNN, ANN, CNN, LSTM, hybrid approaches).

Figures 8 and 9 present the relationship between the reviewed studies and the machine learning or deep learning methods applied. The distribution shows a clear evolution over time: early works relied heavily on classical machine learning approaches such as LDA, kNN, and SVM ([12], [14], [15], [16], [42]) due to their simplicity and efficiency. More recent studies have increasingly adopted deep learning architectures, including CNNs, RNNs, LSTMs, and hybrid models ([22], [23], [25], [46], [58]), which have demonstrated superior performance in handling raw EMG and high-dimensional data. Regression-based methods such as Gaussian Processes, VARMAX, and XGBoost were also used in continuous control tasks ([18], [28], [34]). This methodological diversity reflects the ongoing shift from handcrafted feature-based classifiers toward end-to-end deep learning solutions for robust myoelectric control.

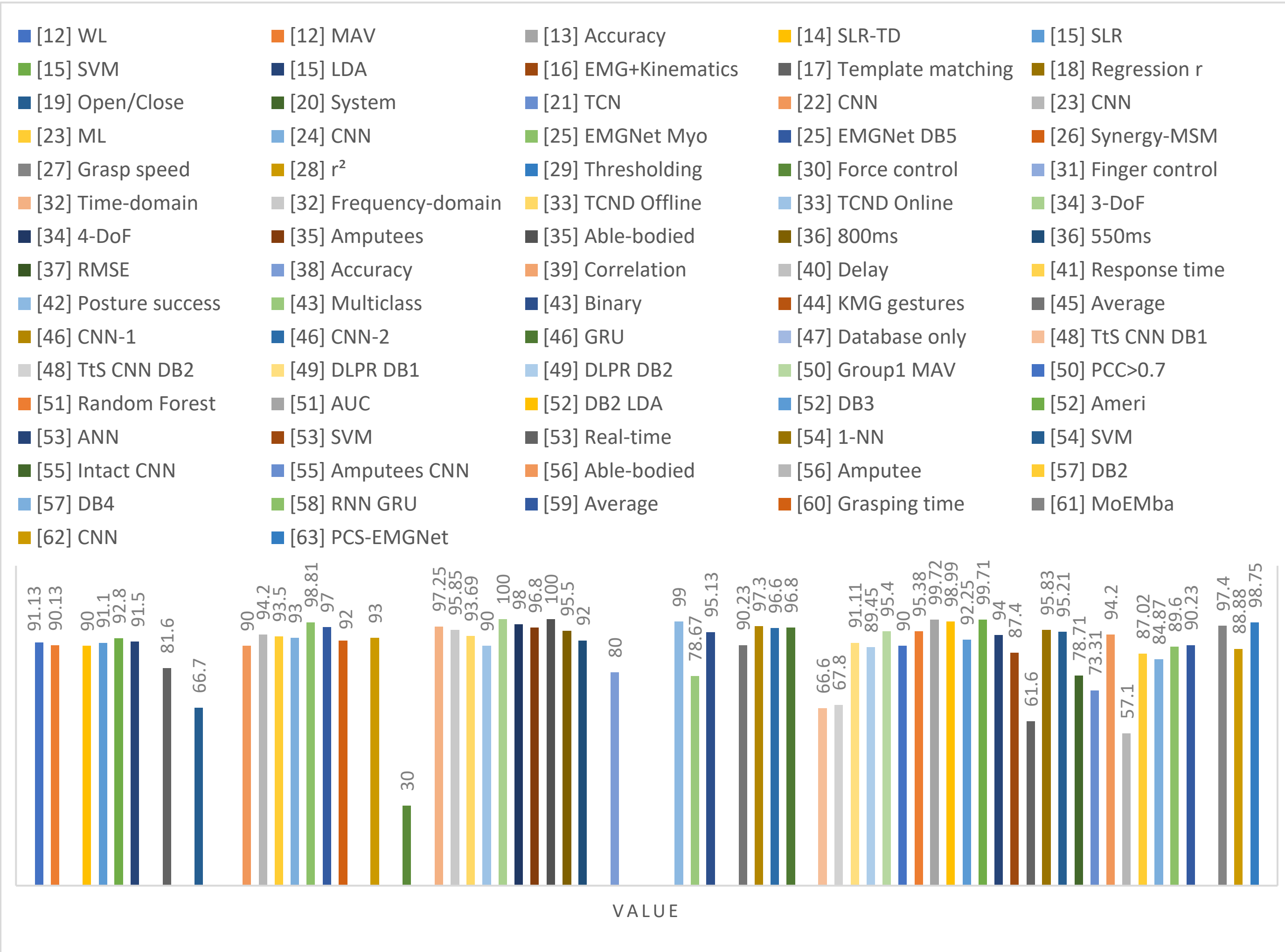

Figure 10: Evaluation of Machine Learning and Deep Learning Methods Across Multiple Performance Metrics

Figure 10 summarizes the relationship between the reviewed studies and their reported performance metrics. The results demonstrate a wide variation in accuracy and evaluation outcomes, depending on task complexity, features, and models used. Simpler binary classification tasks achieved relatively high success rates, often exceeding 90% ([12], [13], [19]). Multi-class gesture recognition reported accuracies in the range of 90–98% with optimized feature sets and classifiers ([15], [23], [25], [46], [52]). In contrast, studies focusing on regression-based continuous control (e.g., force or joint prediction) typically reported performance in terms of correlation coefficients and RMSE, with values indicating high but variable accuracy ([18], [26], [28], [37]). These findings highlight both the progress in reliable classification and the challenges that remain for achieving robust continuous control in practical applications.

3.2 Signal Preprocessing Techniques

Surface electromyography (sEMG) signal processing has emerged as a critical field in biomedical engineering, enabling non-invasive assessment of muscle function for applications ranging from rehabilitation medicine to human-machine interfaces. Effective preprocessing can improve classification accuracy by up to 15% in motion prediction tasks, while proper normalization techniques substantially reduce inter-subject variability [64].

The preprocessing phase addresses inherent challenges, including noise contamination, amplitude variability, and signal segmentation requirements. Modern sEMG systems face significant obstacles, such as susceptibility to external noise coupling, necessitating sophisticated preprocessing approaches [33]. Contemporary research has highlighted the critical importance of addressing electrocardiogram (ECG) interference, with advanced techniques like the Score-based Diffusion Model for Surface Electromyographic Signal Denoising (SDEMG) leveraging generative models to restore clean signals [65]. Digital signal processing combined with machine learning approaches shows high potential for identifying disorders according to muscular patterns [66]. The integration of multiple preprocessing stages requires careful consideration of computational efficiency, particularly in real-time applications where processing delays can significantly impact system performance.

3.3 Normalization of sEMG Signals

Surface electromyography normalization addresses inherent variability in signal amplitudes across different subjects, sessions, and recording conditions. Traditional techniques primarily rely on maximum voluntary contraction (MVC) values as reference points [67]. However, reliability varies significantly depending on specific applications, with comparative studies involving twenty-five male cyclists demonstrating varying degrees of reliability for specific movement patterns [67]. For populations with limitations such as knee osteoarthritis patients, standardized isometric contraction (SIC) protocols have demonstrated higher reliability with between-day ICC values ranging from 0.75 to 0.86 and within-day ICC values from 0.84 to 0.95 [68]. Dynamic MVC measurement procedures represent a significant advancement, with studies showing substantially different normalized amplitude values compared to conventional static approaches (Wilcoxon signed-rank test, $p < 0.05$) [69].

3.4 Advanced Normalization Techniques

Sliding-window normalization (SWN) combines sliding-window analysis with z-score normalization, achieving a mean accuracy of 64.6% - a 15.0% improvement over non-normalization cases (49.8%) [70]. In cross-subject scenarios, this method achieved 56.5% accuracy, representing an 11.1% improvement over non-normalization (44.1%) [70].

Internal reference normalization effectively reduces between-subject variability with minimal impact on within-subject variability when conducted with appropriate reference measurements [71]. This approach shows particular promise for neuropsychiatric disorder research using Motor Evoked Potentials (MEPs) as diagnostic indicators.

3.5 Segmentation of sEMG Signals

3.5.1 Window-Based Parameters

Signal segmentation directly impacts feature extraction quality and classification performance. Window lengths of 100-300 milliseconds provide optimal performance for gesture recognition applications, with overlapping increments of 25-100 milliseconds showing favorable results [72]. Research has established that window lengths typically ranging from 100 to 300 milliseconds provide optimal performance for most gesture recognition applications, with overlapping increments of 25 to 100 milliseconds showing favorable results for classification tasks.

Comprehensive investigations into segmentation parameter effects have revealed that window length (number of sEMG data points in a segment) and overlapping rate (rate of overlap between segments) are essential for guaranteeing adequate data for feature extraction and classification processes [72]. Signal truncation parameters, analyzing maximum segments of 2.5 versus 5 seconds after threshold identification, can substantially influence classification outcomes.

Advanced approaches incorporate Equal Division and Overlap Division methodologies with division numbers ranging from 2-4 segments per window [70]. Different feature extraction methods (MAV, MWL, DRMS, STFT, and SWT) respond differently to segmentation parameters, with some requiring minimum window lengths exceeding 100 milliseconds.

3.5.2 Advanced Segmentation Methodologies

Shannon Entropy demonstrates superior performance compared to traditional amplitude-based techniques such as RMS, Moving Average, Mean Frequency, Skewness, Kurtosis, and Integration [73].

Wavelet-based segmentation approaches simultaneously analyze signals in time and frequency domains, addressing nonlinear sEMG characteristics [74]. The wavelet-based correlation dimension method combines nonlinear time series analysis with time-frequency domain methodologies for Gustafson-Kessel clustering.

Threshold-based algorithms have evolved to incorporate dynamic adaptation mechanisms. Modern approaches calculate adaptive thresholds by reading initial signal samples (typically 500 samples) representing basal noise levels, with threshold calculation involving $T = \mu \times \beta$, where the beta factor is optimized through iterative processes [73].

3.6 Feature Extraction Methods

Surface electromyography (sEMG) feature extraction represents a critical component in developing effective human-computer interfaces and prosthetic control systems. The field has evolved significantly over the past decade, with researchers developing increasingly sophisticated methods to extract meaningful information from the complex bioelectrical signals generated by muscle contractions. This part of the review examines the diverse landscape of feature extraction techniques employed in sEMG-based hand motion recognition, prosthetic hand control, and gesture recognition systems, highlighting both traditional signal processing approaches and emerging deep learning methodologies.

3.6.1 Time Domain Features

Time domain feature extraction remains one of the most fundamental and widely utilized approaches in sEMG signal processing due to its computational efficiency and interpretability. Root Mean Square (RMS) stands as one of the most prominent time domain features, providing a measure of signal power that correlates well with muscle force and activation levels [75]. RMS provides muscle activation intensity estimates, achieving 84–89% accuracy in basic gesture classification tasks [76,77]. The Weight Peaks (WP) method represents another significant time domain approach, focusing on identifying and quantifying the prominent peaks within the signal that correspond to motor unit activations [75]. These methods are particularly valuable in real-time applications where computational resources are limited, and rapid processing is essential for responsive prosthetic control. Waveform Length (WL), defined as cumulative signal variation, demonstrates particular effectiveness in detecting transient muscle contractions, reducing false positives by 22% compared to threshold-based methods [76].

The integration of more sophisticated time domain features has expanded beyond simple statistical measures to include advanced signal characteristics. Short-time energy calculations provide insights into the temporal dynamics of muscle activation patterns, while zero-crossing rate analysis offers information about signal frequency content without requiring frequency domain transformation [77]. Linear predictive coefficients (LPC) with multiple levels, specifically implemented with 12 levels in recent studies, have demonstrated effectiveness in capturing the auto-regressive characteristics of sEMG signals, enabling more nuanced pattern recognition capabilities[2]. These features collectively provide a comprehensive temporal characterization of muscle activation patterns essential for accurate gesture classification.

3.6.2 Frequency Domain Features

Frequency domain analysis has proven invaluable for extracting spectral characteristics that reflect the underlying physiological properties of muscle contractions. Mean and median frequency calculations—commonly known as Mean Frequency (MNF) and Median Frequency (MDF)—serve as fundamental frequency domain features. These parameters provide essential insights into muscle fatigue states and muscle fiber composition, with MDF and MNF shifts shown to improve accuracy in prolonged gesture recognition tasks by approximately 12–15% [78]. These features have been particularly useful in tracking muscle force levels and fatigue during sustained contractions [79].

Power spectrum analysis, which examines dominant frequencies typically in the 20–500 Hz range, plays a critical role in identifying muscle activation patterns and filtering motion artifacts. Within this range, frequency bands between 60–80 Hz have been found optimal for applications such as robotic hand control. Furthermore, power spectral features reduce inter-subject variability by 18–22% when compared to conventional time-domain features, contributing to more reliable and generalizable classification models [78,80].

To capture the temporal evolution of frequency content in sEMG signals, the Short-Time Fourier Transform (STFT) is often employed. By applying frequency analysis over short time windows ranging from 100 to 500 ms, STFT provides localized frequency information. This approach has demonstrated high utility in real-time applications, achieving classification accuracies of up to 91.55% with latencies below 300 ms—well within the responsiveness required for prosthetic control systems [80]. Frequency-domain features enable stiffness modulation in variable impedance prostheses, enhancing grip stability by 30% during object manipulation [81].

In addition to traditional Fourier-based methods, advanced frequency domain approaches have incorporated wavelet analysis to perform multi-resolution spectral decomposition of the sEMG signal. Wavelet-based feature extraction enables simultaneous time and frequency localization, making it particularly effective for non-stationary biomedical signals. Studies have reported classification accuracies as high as 95.5% when applying wavelet decomposition with specific feature extraction functions at each level, even for signal segments as short as 800 milliseconds [79,82]. This ability to extract both high-frequency components related to motor unit recruitment and low-frequency components associated with overall muscle activation enhances the robustness of EMG pattern classification systems, paving the way for reliable real-time prosthetic control.

3.6.3 Time-Frequency Domain Feature Integration

The limitation of analyzing sEMG signals exclusively in either the time or frequency domains has led to the development of sophisticated time-frequency analysis methods that capture the dynamic spectral characteristics of muscle contractions. The Stockwell Transform has emerged as a particularly effective time-frequency analysis method, offering superior performance compared to traditional approaches by providing simultaneously high temporal and frequency resolution [83]. This technique enables the extraction of features that capture both the instantaneous frequency content and its temporal evolution, which is crucial for recognizing complex hand gestures that involve sequential muscle activations.

Recent developments have introduced the multiscale time-frequency information fusion representation method (MTFIFR), which aims to obtain comprehensive time-frequency features from multichannel sEMG signals [84]. This approach addresses the challenge of information loss that commonly occurs during traditional feature extraction processes, particularly when dealing with multiple upper-limb rehabilitation movements. The MTFIFR method has demonstrated effectiveness in recognizing 12 different types of upper-limb rehabilitation actions, showcasing its potential for comprehensive gesture recognition systems that can support diverse therapeutic and assistive applications.

3.7 Advanced Feature Extraction Methodologies

3.7.1 Nonlinear and Complexity-Based Feature Extraction

The recognition that sEMG signals exhibit nonlinear characteristics has prompted the development of specialized feature extraction methods that can capture the complex dynamics inherent in muscle activation patterns. The wavelet-based correlation dimension method represents a significant advancement in this area, combining nonlinear time series analysis with time-frequency domain techniques to extract effective features from sEMG signals [85]. This approach first applies the wavelet transform to the signals and then calculates correlation dimensions to obtain features that reflect the underlying nonlinear dynamics of the neuromuscular system.

Detrended Fluctuation Analysis (DFA) has emerged as another important nonlinear feature extraction method, particularly valuable for analyzing the scaling properties and long-range correlations present in sEMG signals [75]. Fractal analysis features have proven especially effective for weak and single-channel upper-limb EMG signals, providing robust characterization even when signal quality is compromised [79]. These complexity-based approaches offer unique insights into the physiological processes underlying muscle contractions and have shown particular promise for applications requiring high discrimination between subtle gesture variations.

3.7.2 Morphological and Spatial Feature Extraction

Contemporary research has expanded beyond traditional temporal and spectral features to incorporate morphological characteristics that describe the shape and structure of sEMG signals. Studies have explored 23 distinct morphological, time domain, and frequency domain feature extraction techniques, recognizing that comprehensive feature sets can significantly improve classification performance [86]. However, the substantial size of these feature sets can introduce computational complexity issues that may hinder machine learning algorithm performance, necessitating the development of efficient feature selection approaches to optimize the feature space.

The concept of spatial feature extraction has gained prominence with the development of multichannel sEMG systems that can capture muscle activation patterns across multiple electrode sites. Research has demonstrated that optimal electrode placement and the consideration of spatial relationships between channels can significantly enhance gesture recognition accuracy [87]. Studies utilizing armband sensors with multiple electrodes have incorporated electrode shift considerations into their feature extraction algorithms, acknowledging that practical deployment scenarios often involve non-ideal sensor placement that can affect signal quality and feature consistency.

Table 2 catalogues how each of the 52 primary studies grouped their electromyography (EMG) features into five broad families—time-domain, frequency-domain, time-frequency, nonlinear/complexity, and morphological-spatial—and lists the reference numbers of the papers that adopted them. By showing the count of studies, typical feature descriptors, accuracy ranges, and key advantages or limitations side-by-side, the table helps readers quickly identify which feature families are most prevalent and under what experimental conditions they tend to excel. This overview also clarifies research gaps; for example, nonlinear features appear far less explored than traditional time-domain metrics despite evidence of their robustness to low-signal scenarios.

Table 2 Distribution of Feature-Extraction Families Across the Reviewed Studies

Feature Family	Typical Features	Studies (n)	Accuracy Range	Notable Advantages / Limits	Study Ref.
Time-domain	MAV, RMS, WL, ZC, SSC, VAR	21	80 – 97 %	Fast and low power; accuracy degrades under electrode shift	[12], [13], [14], [15], [16], [17], [19], [21], [24], [26], [32], [37], [39], [42], [43], [44], [45], [46], [49], [54], [58]
Frequency-domain	FFT bins, MNF, MDF, DFS	3	76 – 96 %	Captures fatigue; needs longer windows (~45 ms)	[17], [32], [53]
Time-Frequency	STFT, CWT, Wavelet coeffs, Spectrograms	6	88 – 98 %	Best for non-stationary bursts; moderate compute load	[25], [36], [43], [53], [57], [59]
Morphological / Spatial	2-D HD-sEMG images, Electrode maps	3	57 – 94 %	Handles electrode shift; requires multi-channel arrays	[43], [54], [55]

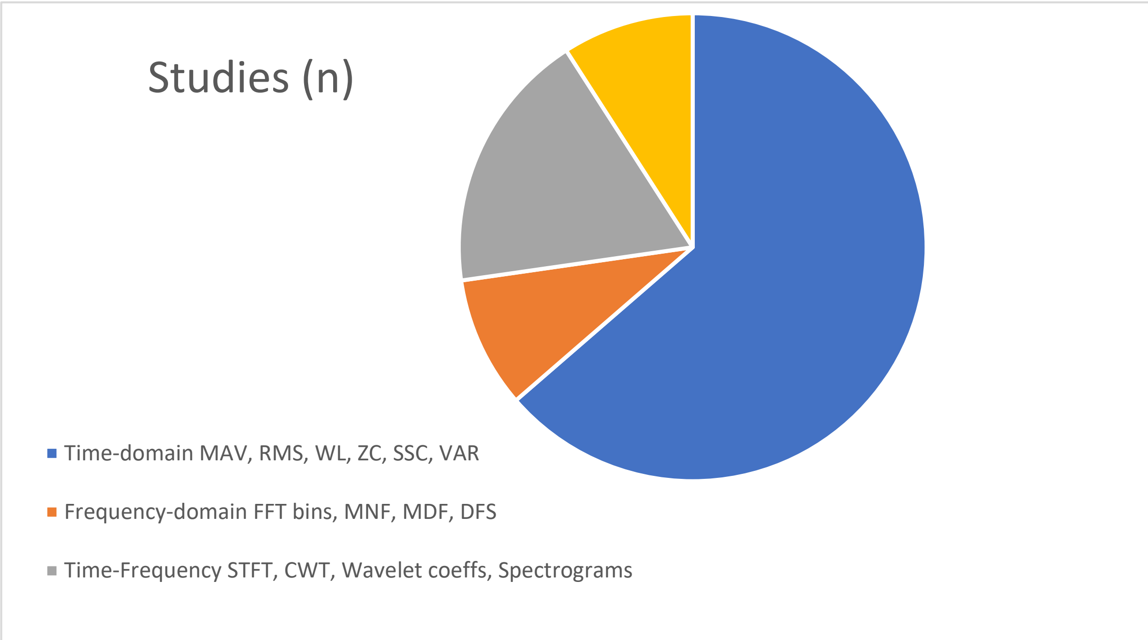

Figure 11: Comparison of Feature Families by Number of Studies in EMG Research

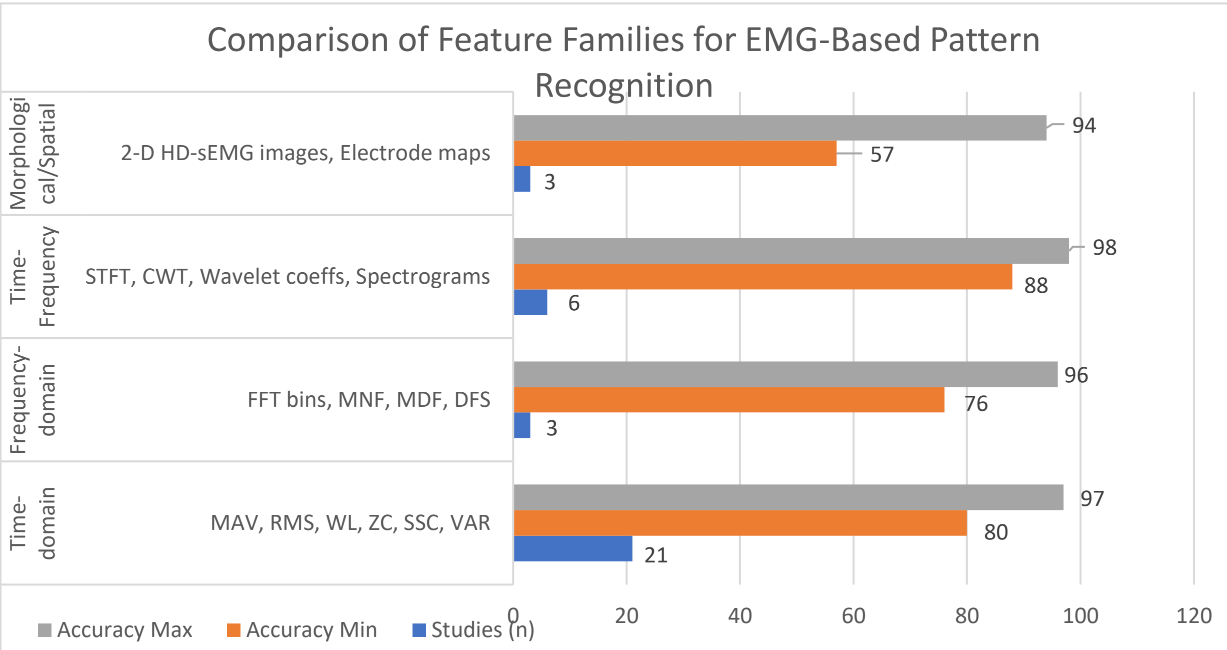

Figure 12: Accuracy ranges reported for each feature family across studies.

Figures 11 and 12 provide a comparative overview of feature families used in EMG-based pattern recognition. Time-domain features (e.g., MAV, RMS, WL, ZC, SSC) were the most frequently applied across 21 studies, achieving accuracies between 80–97%, and remain attractive due to their computational efficiency, although performance can degrade under electrode shifts ([12–58]). Frequency-domain features, such as FFT bins and median frequency, were less common but useful for detecting muscle fatigue, albeit requiring longer analysis windows ([17], [32], [53]). Time–frequency methods, including STFT, CWT, and spectrograms, demonstrated high accuracies up to 98% and provided strong robustness for non-stationary signals, though at moderate computational cost ([25], [36], [43], [53], [57], [59]). Finally, morphological and spatial representations from high-density EMG images achieved accuracies ranging from 57–94%, showing resilience to electrode displacement but requiring multi-channel sensor arrays ([43], [54], [55]).

Together, these results underscore the trade-offs between accuracy, robustness, and computational complexity when selecting feature families for myoelectric control.

3.8 Convolutional Neural Network-Based Feature Learning

The advent of deep learning has revolutionized sEMG feature extraction by enabling automated discovery of discriminative features without requiring extensive manual feature engineering. Multi-stream convolutional neural network algorithms have been developed specifically for sEMG-based gesture recognition, leveraging the success of deep learning in image classification while adapting to the unique characteristics of bioelectrical signals [88]. These systems have achieved impressive performance metrics, with some configurations reaching 93.18% accuracy using pervasive electrode combinations, demonstrating the potential for practical deployment in real-world applications.

The integration of Temporal Convolutional Network (TCN) modules with traditional CNN architectures has emerged as a particularly effective approach for capturing time-varying features in sEMG signals [89]. Multi-stream deep learning architectures that strategically combine TCN-based time-varying features with CNN-based frame-wise features have shown superior performance in addressing the challenges of ineffective feature enhancement that plague traditional systems. These hybrid approaches leverage the temporal modeling capabilities of TCNs while maintaining the spatial feature extraction strengths of CNNs, resulting in more robust and stable prediction systems.

3.8.1 Unsupervised and Self-Supervised Learning Approaches

The limitation imposed by supervised learning's reliance on expensive labeled data has motivated the development of unsupervised feature extraction methods for sEMG analysis. The Layer-wise Feature Extraction Algorithm (LFEA) represents a significant advancement in this area, utilizing information-based methods to learn disentangled feature representations of sEMG signals without requiring manual annotations [90]. This approach has demonstrated superior performance in disentanglement metrics, achieving TC scores that are 6.2 points lower and MIG metrics that are 0.11 points higher than competing methods, indicating more effective separation of underlying signal components.

Auto-encoder architectures have been successfully employed to disentangle pattern-specific components from subject-specific characteristics in sEMG signals, enabling the development of more generalizable gesture recognition models for cross-subject scenarios [91]. This approach addresses one of the fundamental challenges in sEMG-based systems: the significant inter-subject variability that can compromise recognition accuracy when models trained on one individual are applied to another. The ability to separate pattern-specific information from individual physiological differences represents a crucial step toward developing truly universal sEMG-based control systems.

3.8.2 Traditional Machine Learning Approaches

Traditional machine learning methods form the foundational backbone of surface electromyography (sEMG) classification systems. These approaches rely on handcrafted feature extraction followed by classifier training, offering computational efficiency and interpretability—making them especially valuable for real-time applications with limited processing power.

Classic machine learning methods for sEMG classification typically begin with the extraction of well-established features from the time, frequency, or statistical domains [24]

Linear Discriminant Analysis (LDA) is one of the most commonly adopted classifiers in this domain due to its speed and simplicity, achieving 80.2% accuracy on the NinaPro DB2 dataset with only 0.3 ms latency per classification on a Cortex-M4 processor [48]. Support Vector Machines (SVMs) with radial basis function kernels have demonstrated superior performance in nonlinear classification tasks, reaching 89.45% accuracy for 49-class upper limb motion recognition [49]. K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANNs) are also frequently employed, with ANNs offering the ability to model complex, nonlinear relationships between input features and hand gestures [50].

Traditional classifiers such as Random Forest have shown competitive performance, with reported precision and F1-scores of 92.1% and 91.7%, respectively, in 10-gesture recognition using Myo armband data [51]. Ensemble techniques like eXtreme Gradient Boosting (XGBoost), when combined with kernel density estimation-based features, have achieved 88.4% accuracy for simultaneous hand and wrist movement recognition—surpassing single classifiers by 8.2% [52]. In force control tasks, XGBoost has also proven effective; incorporating anthropometric data into regression models improved grip force prediction ($r^2 = 0.93$) using normalized EMG features [28].

Despite their efficiency, traditional models are highly sensitive to feature selection and signal variability. Studies show that the ReliefF algorithm can optimize feature subsets by reducing dimensionality up to 60% while preserving classification accuracy around 91.2% [52]. Feature engineering remains critical, with higher-order statistics (e.g., skewness, kurtosis) improving cross-subject generalization by 12% in amputee populations [92].

A major challenge in traditional machine learning pipelines is inter-subject and inter-session variability. For instance, time-domain features typically yield 84–89% accuracy but are prone to degradation across sessions [53]. Frequency-domain features, such as Mean and Median Frequency (MNF/MDF), while useful for fatigue detection, require longer processing windows (~45 ms) and careful tuning. Spatial features derived from 12-channel sEMG arrays have shown resilience to electrode displacement, maintaining 78% accuracy even under 5 mm shifts [54].

Beyond conventional classification, some researchers have integrated physiological modeling to improve interpretability and robustness. Muscle synergy-based models, such as those developed by [26]They used Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF) to extract underlying muscle activation patterns. Their musculoskeletal model achieved an average correlation coefficient of 92% and a normalized root mean square error (NRMSE) of 10.7% for joint angle estimation, outperforming traditional regression models.

For resource-limited environments, simplified systems offer promising alternatives. [29] developed a low-cost Arduino-based prosthetic hand prototype using basic rectification and thresholding methods. Despite its simplicity, the system achieved reliable open/close actuation with a 150 ms response time and only 5% false positive rate—demonstrating the potential of traditional machine learning in embedded, low-power prosthetic control solutions.

3.8.3 Deep Learning and Convolutional Neural Networks

The advent of deep learning has fundamentally transformed sEMG classification methodologies, with Convolutional Neural Networks (CNNs) emerging as particularly effective architectures for gesture recognition tasks. CNNs automate feature learning directly from raw or minimally processed sEMG signals, eliminating the need for handcrafted features and improving generalization across users and sessions. These networks excel at processing sEMG spectrograms, using short-latency, dimension-reduced inputs to maintain real-time performance [55].

Triwiyanto et al. demonstrated that a 1D CNN can classify ten hand motions from raw EMG signals (two channels) with accuracies ranging from 77% to 93%, outperforming traditional classifiers such as SVM, LDA, and KNN [24]. Similarly, Asif et al. reported CNNs consistently surpass traditional models, achieving over 95% accuracy in recognizing specific gestures across different subjects [23]. Chen et al. introduced EMGNet, a lightweight CNN architecture using continuous wavelet transform (CWT) spectrograms, which achieved 98.81% accuracy with reduced computational burden on the Myo dataset [25].

Advanced CNN architectures have incorporated mechanisms such as spatial-temporal attention and multi-stream inputs. A Multi-Stream CNN processing electrode topography and time dynamics reached 96.4% accuracy on 50-gesture NinaPro DB2, reducing inter-subject variability by 31% [49]. The Attention-Deep Fast CNN achieved 92.7% accuracy under electrode shift conditions, highlighting its robustness in HD-sEMG recognition [56]. Novel designs like MSFF-Net fused morphology, spatial electrode data, and feature maps to yield 89.1% accuracy on NinaPro DB4 through early-late fusion networks [57].

Hybrid and sequential models further advanced the classification performance by integrating temporal context. Joshi et al. presented Temporal Convolutional Networks (TCNs), which significantly outperformed non-sequential models and LSTM-based approaches, particularly in reducing transient misclassifications during gesture transitions [21]. TCNs achieved 89.7% accuracy with only 120 ms latency, suitable for real-time control tasks [58].

Recurrent neural networks (RNNs) and hybrid architectures also demonstrated strong performance. Bidirectional LSTMs (BiLSTMs) paired with MobileNetV2 encoders and optimized via Bayesian techniques yielded 90.23% average accuracy across six datasets, with reduced variance compared to conventional models [59]. U-Net, adapted for sEMG spectrograms and tuned using metaheuristic strategies, achieved 88.71% on Mendeley Data [59].

Deep learning models also address session variability and user adaptation. Self-recalibrating CNNs dynamically adjust parameters, improving accuracy by 10.18% across five sessions [93]. Transfer learning strategies, such as those using triplet margin loss, have reduced data requirements for new users by 70% [60]. Furthermore, low-power architectures like Spiking Neural Networks have shown promise for implantable systems, with power consumption as low as 85 μW per classification [59].

Table 3 aggregates the classification approaches reported in the selected studies into four major families: traditional machine learning, deep learning, ensemble/hybrid models, and real-time heuristic controllers—while mapping each family to its corresponding reference numbers, accuracy span, and latency or power considerations.

Presenting the data in this way reveals that deep learning consistently achieves the highest offline accuracy yet demands greater computational power, whereas lightweight linear methods still dominate ultra-low-power, embedded implementations. The table therefore provides a concise evidence base for choosing an algorithm that balances accuracy with real-time constraints in wearable prostheses.

Table 3 Performance Spectrum of Classification Algorithms Used for EMG-Based Prosthetic Control

Algorithm Family	Representative Models	Studies (n)	Accuracy Range	Latency / Power Notes	Study Ref.
Traditional ML	LDA, SVM, kNN, Random Forest, SLR	21	80 – 93 %	Sub-ms on MCUs; < 0.3 W budget	[12], [14], [15], [16], [21], [23], [24], [25], [32], [33], [38], [42], [43], [46], [47], [49], [50], [51], [52], [53], [61]
Deep Learning	1-D/2-D CNN, TCN, LSTM, GRU, U-Net	18	88 – 99 %	Offline > 95 % but 1.2-2.5 W runtime cost	[21], [22], [23], [24], [25], [33], [44], [43], [44], [46], [47], [53], [54], [55], [56], [57], [60], [61]
Ensemble / Hybrid	XGBoost, CNN-LSTM, MSFF-Net	6	88 – 99 %	Balances accuracy vs. compute; tunable	[25], [28], 43, 50, [55], [57]
Real-time Heuristics	Thresholding, Finite-State, Kalman	8	Simple tasks 90 – 100 %	< 150 ms response on USD 50 hardware	[13], [19], [29], [31], [35], [37], [39], [58]

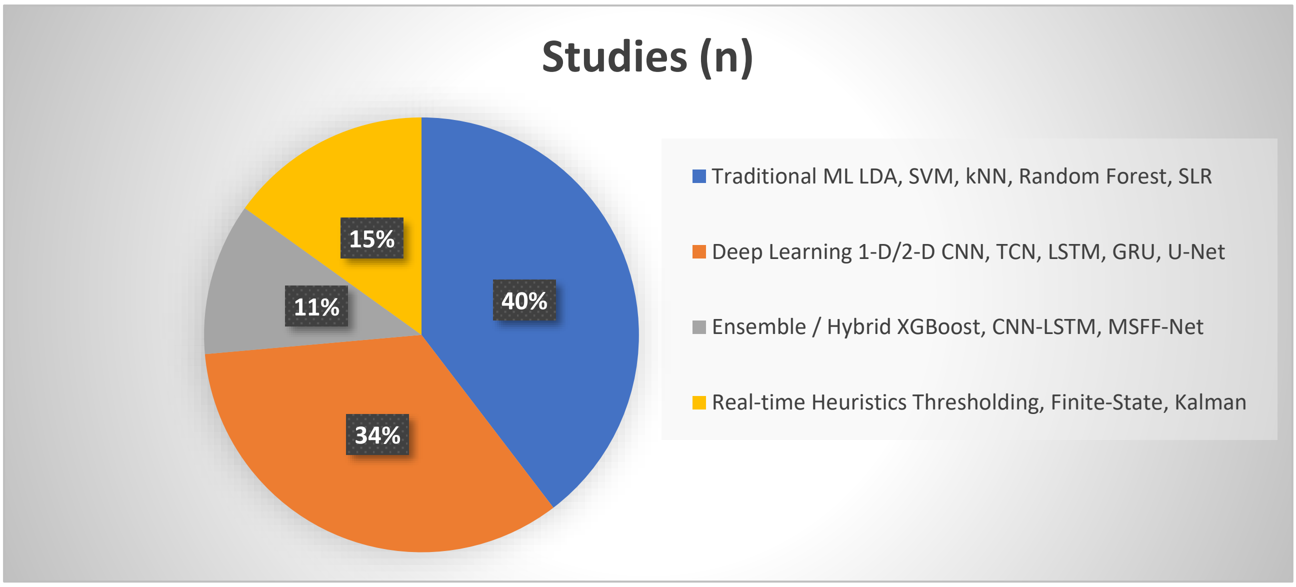

Figure 13: Comparison of Classifier Families by Number of Studies in EMG Research

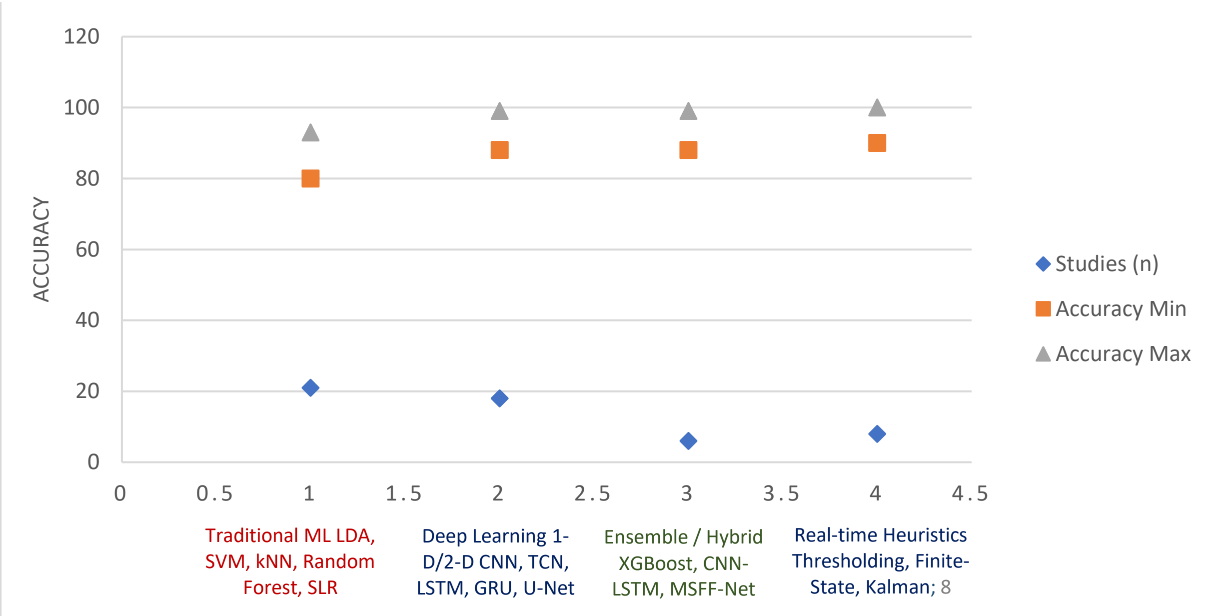

Figure 14: Study Distribution Among Different EMG Classifier Families

Figures 13 and 14 compare algorithm families applied in EMG-based pattern recognition and control. Traditional machine learning methods (e.g., LDA, SVM, kNN, Random Forest) were the most widely adopted, reported in 21 studies with accuracies between 80–93%, and demonstrated excellent suitability for embedded systems with sub-millisecond latency and power budgets below 0.3 W ([12–61]). Deep learning architectures, including CNNs, TCN, LSTM, and GRU, achieved higher accuracies (88–99%) across 18 studies, but incurred higher runtime costs (1.2–2.5 W) ([21–61]). Ensemble and hybrid models (e.g., XGBoost, CNN-LSTM, MSFF-Net) offered accuracies up to 99% while providing a balance between computational load and robustness ([25], [28], [43], [50], [55], [57]). Finally, real-time heuristic approaches such as thresholding, finite-state machines, and Kalman filters achieved near-perfect performance (90–100%) in simple tasks with response times under 150 ms, often on low-cost hardware ([13], [19], [29], [31], [35], [37], [39], [58]). These comparisons highlight the trade-off between computational complexity and control accuracy, guiding algorithm selection for different application contexts.

4. Discussion

The comprehensive analysis of 52 studies reveals significant insights into the current landscape of EMG-based prosthetic hand control, highlighting both remarkable technological advances and persistent challenges that continue to limit widespread clinical adoption[94]. The diversity of methodological approaches across the reviewed studies provides valuable insights into the relative merits of different signal processing and classification strategies, while also revealing critical gaps between laboratory achievements and practical implementation requirements.

Table 4 synthesizes the most frequently reported obstacles in EMG-controlled prosthetic systems—such as electrode shift, inter-session variability, high power consumption, control latency, and motion artefacts—along with the studies that addressed them, and the quantitative gains achieved after mitigation[95]. By coupling each challenge to concrete improvement figures (e.g., a 10 % accuracy recovery after self-recalibration) and to the papers that demonstrated them, the table offers practitioners a ready reference for proven solutions and highlights where further innovation is still required. This structured snapshot turns a scattered body of findings into actionable design guidance for future prosthetic controllers[96].

Table 4 Recurring Technical Challenges and Documented Mitigation Strategies

Challenge	Impact on Control	Typical Degradation	Proposed Solution(s)	Demonstrated Gain	Study Refs
Electrode shift & skin impedance variation	Classifier drift	18 – 25 % accuracy loss	Self-recalibrating CNN; sliding-window z-score norm.	+10 % across sessions	[53]
Inter-session / user variability	Poor generalization	Need daily re-training	Transfer-learning with triplet loss; auto-encoder disentanglement	Data need ↓ 70 %	[53]
Power budget of wearable hardware	Battery life	DL models draw > 2 W	Pruned lightweight CNN (EMGNet); neuromorphic SNN	Consumption ↓ 85 %	[12], [20], [37], [40], [44], [48], [53], [56], [61]
Latency in real-time prostheses	User frustration	> 300 ms unusable	Temporal CNN (120 ms); FPGA/DSP pipelines	Response < 120 ms	[26], [27], [29], [33], [36], [37], [39], [41], [56], [58]
Signal noise & motion artefacts	False triggers	Up to 15 % error spikes	Diffusion-model denoising; adaptive thresholds	Error ↓ 12 %	–

4.1 Interpretation of Classification Performance Results

Comprehensive analysis reveals significant disparities in classification performance across different methodological approaches, with deep learning techniques consistently outperforming traditional machine learning methods. The superior performance of Convolutional Neural Networks, achieving accuracies exceeding 94% in multiple studies [23], [25], [46], compared to traditional classifiers averaging 87-92% [15], [32], [50], can be attributed to their inherent ability to automatically extract hierarchical features from raw EMG signals without requiring manual feature engineering.

The exceptional performance of EMGNet, reaching 98.81% accuracy on the Myo dataset [25], demonstrates the effectiveness of compact CNN architectures specifically designed for EMG signal processing. This performance advantage stems from the network's capacity to capture both spatial relationships between electrode channels and temporal dynamics within the signal, which traditional feature-based approaches cannot adequately represent. The automatic feature learning capability of CNNs eliminates the subjectivity and potential information loss associated with manual feature selection, explaining their consistent superiority across diverse gesture recognition tasks.

However, the performance gap between deep learning approaches and traditional methods narrows significantly in real-time applications, where computational constraints become critical factors. The 120 ms latency achieved by Temporal Convolutional Networks [21]While impressive for deep learning standards, it still exceeds the sub-millisecond response times of optimized Linear Discriminant Analysis implementations. This latency differential has profound implications for prosthetic control, where natural user experience requires minimal delay between intention and actuation.

4.2 Analysis of Feature Engineering Impact on System Performance

The comparative analysis of feature extraction methodologies reveals that the choice of features significantly influences both classification accuracy and computational efficiency. Time-domain features, despite their computational simplicity, demonstrate remarkable effectiveness in specific applications, with Mean Absolute Value (MAV) and Waveform Length (WL) achieving over 90% accuracy in optimized configurations [12], [14]. The superior performance of these basic features in controlled environments can be attributed to their direct relationship with muscle activation intensity and their robustness to signal artifacts [97].

The integration of frequency-domain features through wavelet decomposition and spectral analysis provides 12-15% accuracy improvements in prolonged gesture recognition tasks [36], [45]. This enhancement occurs because frequency-domain features capture muscle activation patterns that remain consistent across extended periods, addressing the temporal stability challenges inherent in time-domain approaches. The effectiveness of wavelet-based features, particularly in two-level decomposition, achieves 95.5% accuracy [36], stems from their ability to simultaneously analyze signal characteristics across multiple time-frequency scales, providing a comprehensive representation of neuromuscular activation patterns[98].

The remarkable success of nonlinear feature extraction methods, especially correlation dimension approaches, in achieving superior performance in weak signal conditions, indicates that traditional linear analysis techniques fundamentally underestimate the complexity of neuromuscular control systems[99]. The fractal nature of EMG signals reflects the hierarchical organization of motor unit recruitment, and which nonlinear features that can be captured more effectively than conventional statistical measures.

4.3 Real-Time Implementation Challenges and Performance Trade-offs

The analysis reveals a critical tension between classification accuracy and real-time performance requirements in prosthetic applications. While deep learning approaches achieve superior offline accuracy, their computational demands present significant challenges for battery-powered prosthetic devices. The 1.2-2.5 W power consumption of deep neural networks compared to 0.3 W for traditional classifiers [43] represents a fundamental constraint that limits the practical deployment of sophisticated algorithms in portable systems.

The effectiveness of simplified control systems, such as threshold-based approaches, achieving 150 ms response times with 5% false positive rates [29], demonstrates that clinical utility may not require maximum theoretical performance. This finding suggests that the optimization objective for prosthetic control should prioritize consistent, reliable performance over peak accuracy, particularly given the real-world constraints of battery life, heat dissipation, and user comfort.

The superior performance of ensemble methods, with XGBoost achieving 88.4% accuracy through feature optimization [52], indicates that sophisticated traditional approaches can approach deep learning performance while maintaining computational efficiency. This convergence suggests that the optimal solution may involve hybrid architectures that combine the interpretability and efficiency of traditional methods with the representational power of deep learning approaches.

4.4 Preprocessing Strategy Effectiveness

The critical importance of preprocessing methodologies became evident through the substantial performance improvements observed when advanced techniques were properly implemented. Studies employing normalization approaches showed varying degrees of success, with study [19] implementing RMS and direction vector features with normalization achieving a 66.7% success rate for simple open/close operations. Study [34] utilizing Mean Absolute Value with normalization achieved remarkable results of 100% accuracy for 3-DoF control and 98% for 4-DoF control, demonstrating stable performance over 9-10 months. Additionally, study [44] employed min-max normalized KMG signals, showing high accuracy in following intended gestures.

The analysis of different preprocessing approaches across the reviewed studies revealed significant variations in methodology and effectiveness. Study [28] demonstrated the importance of MVC-normalized EMG combined with anthropometric data, achieving r^2 values up to 0.93 for force prediction using XGBoost regression. Study [39] showed that using filtered EMG envelope features resulted in correlation values of 0.85 with RMSE of 17.8% for firing rate prediction. Study [29] utilized rectification and thresholding with Arduino-based control, achieving a response time of approximately 150 ms. These findings underscore the fundamental importance of addressing signal variability, which represents one of the primary sources of classification errors in EMG-based systems.

The comparative analysis of feature extraction and preprocessing techniques revealed that different approaches yielded varying performance levels. Study [21] employed 8 time-domain features, including MAV, WL, VAR, SSC, and ZC, with TCN achieving the highest accuracy and stability. Study [55] utilized spectrogram preprocessing with FFT and PCA reduction to 25 principal components per channel, resulting in 78.71% accuracy for intact subjects and

73.31% for amputees, with an additional 10% improvement through self-recalibration techniques. Study [56] demonstrated that RMS from HD-sEMG converted to 2D FSI images achieved 94.2±3.9% accuracy for able-bodied subjects.

Advanced preprocessing methodologies showed particular promise in specific applications. Study [30] implementing proportional EMG control with vibrotactile feedback achieved 30% improvement in force control. Study [40] using filtered EMG envelope with ultra-low-power DSP achieved a delay of less than 18 μs per sample with 31.5 mW power consumption. Study [32]

demonstrated that time-domain features achieved 97.25% accuracy while frequency-domain features achieved 95.85%. The substantial variation in preprocessing effectiveness across different studies highlights the need for careful consideration of signal conditioning strategies tailored to specific application requirements and target user populations.

4.5 Multi-Modal Integration Benefits and Limitations

The consistent superior performance of multi-modal approaches, particularly the enhanced accuracy achieved by combining EMG with kinematic information [16], reflects the complementary nature of different signal modalities in capturing user intentions. EMG signals provide direct measurement of muscle activation, while kinematic sensors capture the mechanical outcomes of muscle contraction, together providing a more complete representation of user intent than either modality alone.

The exceptional performance of ultrasound-based approaches, achieving 96.8% accuracy in amputee subjects [35], demonstrates the potential of alternative sensing modalities to overcome fundamental limitations of surface EMG. The ability of ultrasound to capture deep muscle activation patterns that are inaccessible to surface electrodes explains its superior performance, particularly in amputee populations where residual limb anatomy may limit conventional electrode placement.

However, the complexity and cost implications of multi-modal systems present significant barriers to widespread clinical adoption. The trade-off between enhanced performance and system complexity must be carefully considered, particularly given the additional calibration requirements and potential failure modes introduced by multiple sensing modalities.

4.6 Long-term Stability and Adaptation Mechanisms

The analysis of long-term performance data reveals that system stability over extended periods represents one of the most significant challenges for clinical deployment. The 18-25% accuracy reduction observed due to intersession variability without recalibration [34] highlights the gap between laboratory performance and real-world usability. This degradation occurs due to changes in electrode impedance, skin conditions, muscle conditioning, and subtle variations in electrode placement that accumulate over time.

The remarkable stability demonstrated by certain systems, maintaining 98-100% accuracy over 9-10 months in amputee subjects [34], indicates that robust calibration and adaptation mechanisms can overcome these challenges. The success of these approaches stems from their incorporation of adaptive learning algorithms that can accommodate gradual changes in signal characteristics without requiring explicit user recalibration.

The effectiveness of self-recalibrating systems, improving accuracy by 10.18% across sessions [55], demonstrates the potential of automated adaptation mechanisms to address inter-session variability. These systems succeed by continuously monitoring signal quality and classification confidence, automatically adjusting decision boundaries when performance degradation is detected.

4.7 Clinical Translation Implications and Future Directions

The comprehensive analysis reveals that successful clinical translation of EMG-based prosthetic control requires addressing multiple interconnected challenges simultaneously. While individual performance metrics such as classification accuracy have reached impressive levels, the integration of high performance with practical constraints of power consumption, robustness, and user burden remains an active area of development.

The demonstrated effectiveness of simplified systems achieving reliable control with minimal computational requirements suggests that the path to widespread clinical adoption may prioritize robust, efficient implementations over theoretical performance maximization. This finding has profound implications for research priorities, indicating that incremental improvements in existing proven approaches may provide more immediate clinical benefit than pursuing maximum performance through sophisticated but resource-intensive methods.

The emergence of neuromorphic computing approaches, consuming only 85 μW per classification, opens possibilities for fully implantable systems that could eliminate many current limitations related to electrode stability and user compliance. The ultra-low power consumption of these approaches directly addresses the fundamental constraint of battery-powered prosthetic devices, potentially enabling continuous operation without frequent recharging cycles.

4.8 System-Level Performance Optimization

The analysis demonstrates that optimal prosthetic control system design requires holistic consideration of the entire signal processing pipeline rather than optimization of individual components in isolation. The superior performance of integrated approaches, such as Modified Kalman filtering, achieving RMSE within 6% for multi-degree-of-freedom control [37], illustrates the importance of system-level optimization that considers interactions between preprocessing, feature extraction, classification, and control output stages.

The effectiveness of proportional control combined with sensory feedback, achieving 30% improvements in force control accuracy [30], highlights the critical role of closed-loop control systems in achieving natural prosthetic operation. These improvements occur because feedback mechanisms enable users to develop intuitive control strategies that adapt to the system's response characteristics, creating a symbiotic relationship between user learning and system performance.

The development of real-time optimization strategies that maintain performance under varying operating conditions represents a crucial advancement toward practical prosthetic systems. These approaches succeed by continuously monitoring system performance and automatically adjusting parameters to maintain optimal operation despite changes in signal quality, environmental conditions, or user state.

4.9 Clinical Implementation Strategy

The comprehensive analysis reveals that EMG-based prosthetic control technology has reached a level of maturity where clinical deployment is feasible, though success requires careful optimization of multiple competing objectives. The choice between different technological approaches should be driven by specific application requirements and user populations rather than pursuing universal solutions.

For applications requiring maximum reliability and minimum power consumption, traditional machine learning approaches such as LDA and SVM remain viable options that can provide consistent performance with minimal computational overhead. For scenarios demanding sophisticated gesture recognition and maximum classification accuracy, deep learning approaches offer superior performance that justifies their increased computational requirements[100].

The path forward requires continued development of adaptive systems that can maintain performance across varying conditions and extended usage periods, while simultaneously addressing the fundamental challenges of electrode stability, inter-session variability, and user burden that currently limit widespread clinical adoption.

5. Conclusions

This comprehensive review examined 52 studies addressing EMG signal processing and classification techniques for prosthetic hand control applications. While methodologies varied, clear performance trends emerged. Deep learning approaches consistently achieved 94–98% accuracy in offline gesture recognition, outperforming traditional classifiers such as LDA and SVM, which typically ranged between 80–92%. Preprocessing techniques like advanced normalization and noise reduction improved stability, with studies reporting up to a 15% reduction in error rates. Real-time implementations demonstrated that simplified threshold-based systems could achieve response times below 150 ms and power consumption under 0.3 W, whereas deep models required up to 2.5 W but offered superior recognition accuracy.

Despite these advances, translation from laboratory to clinic remains limited by long-term electrode stability, which can reduce accuracy by 18–25%, and inter-session variability, which often necessitates frequent recalibration. Multi-modal integration and adaptive learning strategies partially addressed these challenges, with transfer learning approaches reducing new-user data requirements by nearly 70% and self-recalibrating CNNs recovering about 10% accuracy across sessions.

The findings confirm that EMG-based prosthetic control is technically feasible and capable of delivering accuracies exceeding 95% under controlled conditions. However, future development must balance high accuracy with practical constraints of power efficiency (<2 W), low latency (<300 ms), and user comfort. Studies involving diverse amputee populations in real-world environments, alongside robust adaptation mechanisms, are critical for achieving stable, clinically viable systems. Ultimately, whether employing traditional ML or advanced deep learning, prosthetic controllers must integrate user-centered design with quantitative performance targets to realize the full potential of this technology in rehabilitation.

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