REVIEW ARTICLE

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Bio-Inspired Machine Learning for Enhanced EMG Signal Analysis

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Abstract

Electromyography (EMG) signals provide critical insights into neuromuscular function, yet their analysis remains challenging due to inherent noise, inter-subject variability, and non-stationary characteristics. Bio-inspired artificial intelligence (AI) models, drawing computational principles from biological neural systems, offer promising solutions to these challenges. This mini-review synthesizes recent advances in bio-inspired AI approaches for EMG signal processing, including spiking neural networks, hierarchical deep learning, attention mechanisms, and neuromorphic computing. We evaluate state-of-the-art methods, comparing their performance across key metrics including classification accuracy, computational efficiency, and real-world applicability. Our analysis reveals that hybrid architectures combining convolutional neural networks with transformer-based attention mechanisms achieve superior performance while maintaining computational efficiency. We identify emerging trends in multimodal integration, self-supervised learning, and edge computing implementations. This paper provides researchers and practitioners with a comprehensive framework for selecting appropriate bio-inspired AI methods for specific EMG applications in prosthetics, clinical diagnosis, rehabilitation, and human-computer interaction.

Keywords: electromyography, bio-inspired AI, deep learning, signal processing.

1 Introduction

Electromyography (EMG) has emerged as a fundamental biosignal for understanding neuromuscular function, with applications spanning clinical diagnosis, prosthetic control, rehabilitation engineering, and human-computer interaction [1, 2]. Surface EMG (sEMG), captured non-invasively through skin electrodes, has become particularly widespread due to its ease of use and patient comfort. However, robust EMG signal analysis remains fundamentally challenging due to several critical factors [4]. EMG signals exhibit substantial inter-subject variability due to anatomical differences in muscle structure, subcutaneous tissue thickness, and electrode-skin interface properties [5]. This variability severely limits model transferability across users. Second, multiple noise sources contaminate EMG recordings, including motion artifacts,

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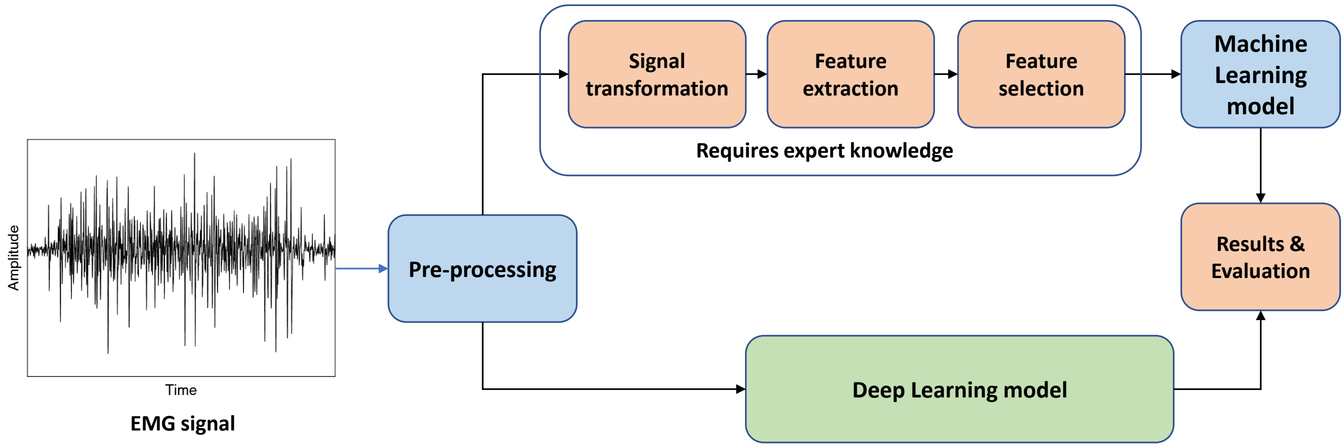

Figure 1. Block diagram of conventional machine learning and deep learning approaches for EMG signal analysis.

electromagnetic interference, ECG contamination, and cross-talk from adjacent muscles. Third, signals are inherently non-stationary, with time-varying spectral characteristics influenced by muscle fatigue, age [18], sex [25], and dynamic movements [7].

Traditional signal processing approaches rely on handcrafted features (time-domain, frequency-domain, time-frequency) that require extensive domain expertise and often fail to capture complex spatiotemporal patterns [2, 3], as shown in Figure 1. While conventional deep learning methods (CNN, RNN) demonstrate impressive performance, they typically demand large labeled datasets, lack interpretability, consume substantial computational resources, and exhibit poor generalization under domain shift [4]. Biological neural systems, particularly the human visual cortex, have evolved highly efficient mechanisms for processing complex, noisy sensory data through hierarchical organization, multi-scale temporal processing, sparse coding, and adaptive feature extraction [8]. These principles offer compelling inspiration for EMG analysis: the visual system extracts edges at multiple scales, integrates them into higher-level representations, and achieves robust object recognition despite variations—analogous requirements for detecting local muscle activations, integrating them into coordinated synergies, and classifying movements despite anatomical variations [9].

This paper synthesizes state-of-the-art bio-inspired machine learning approaches for EMG signal processing. It evaluates recent methods across four main categories: (1) hierarchical deep learning architectures, (2) attention mechanisms and transformers, (3) spiking neural networks and neuromorphic computing, and (4) multimodal integration strategies. This comparative analysis identifies performance benchmarks, computational trade-offs, and practical implementation considerations. It concludes by highlighting emerging trends and future research directions that will shape the next generation of intelligent EMG processing systems.

2 Bio-Inspired Deep Learning Architectures

Deep learning architectures inspired by visual cortex hierarchies have revolutionized EMG processing. CNN implement hierarchical feature extraction analogous to cortical processing, where early layers detect local temporal patterns (similar to V1 edge detectors) and deeper layers abstract these into high-level movement representations [4]. Recent hybrid CNN-RNN architectures combine convolutional feature extraction with recurrent temporal modeling. Xiong et al. [4] proposed a multi-scale CNN-LSTM framework achieving 94.8% accuracy on the Ninapro DB5 dataset. Their architecture uses parallel convolutional branches with different kernel sizes (capturing multi-scale temporal features) followed by bidirectional LSTM layers for long-range temporal dependencies. Song et al. [10] introduced a lightweight CNN-GRU model optimized for embedded systems, achieving 97.6% accuracy on Ninapro DB2 while maintaining lower inference latency in edge devices.

Temporal Convolutional Networks (TCNs) offer an alternative to RNN, using dilated causal convolutions to exponentially expand receptive fields without recurrent connections [11]. Chen et al. [12] demonstrated that TCNs outperform LSTMs for gesture recognition (71.6% vs 66%) while being 3× faster during inference. The key advantage lies in parallel processing capabilities and stable gradient flow during training.

Transformer architectures, inspired by attention mechanisms in biological vision, have recently been adapted for EMG analysis. Unlike CNN with local receptive fields, transformers compute self-attention across all time steps, capturing arbitrary long-range dependencies [13]. Montazerin et al. [13] pioneered transformer application to EMG gesture recognition, achieving 91.98% accuracy on 65 gestures. Their multi-head self-attention mechanism learns complementary temporal relationships in parallel. However, transformers struggle with small datasets due to their large parameter count.

In addition to pure transformers, hybrid architectures that combine CNNs and transformers have shown promise for EMG analysis. For instance, Liu et al. [6] proposed a CNN-transformer hybrid model specifically for dynamic gesture prediction from sEMG signals, effectively leveraging both local feature extraction and global dependency modeling.

Spatial-temporal attention modules selectively emphasize informative channels and time segments [14]. Lin et al. [14] introduced channel-wise attention gates that dynamically weight EMG channels based on their contribution to classification, improving robustness to electrode displacement (94.2% accuracy with 10mm shifts vs 92% for baseline CNN). Recent work explores Graph Neural Networks (GNN) to model anatomical relationships between muscles. Vijayvargiya et al. [19] constructed muscle connectivity graphs where nodes represent muscles and edges encode biomechanical coupling. Their GNN-based classifier achieved 93.8% accuracy while providing interpretable muscle synergy patterns, offering insights into coordinated motor control.

Spiking Neural Networks (SNN) represent a paradigm shift toward brain-like computing, where neurons communicate through discrete spikes rather than continuous activations [8]. SNN offer inherent temporal processing, event-driven computation (sparse activity patterns leading to energy efficiency), and biological plausibility [15]. Sun et al. [15] presents a spiking neural network (SNN) for 9-gesture EMG pattern recognition using data from 8 subjects. It employs adaptive threshold encoding and an improved leaky-integrate-and-fire (LIF) neuron to enhance robustness to electrode shifts and individual differences. Compared to CNN, LSTM, and LDA, the SNN achieves higher accuracy (up to 18.95% improvement) while requiring fewer training repetitions and consuming 1–2 orders of magnitude less power. Surrogate gradient methods address this limitation by approximating discontinuous spike functions with smooth surrogates during backpropagation [16].

Neuromorphic chips (Intel Loihi, IBM TrueNorth) implement SNN in dedicated hardware, achieving unprecedented energy efficiency. Donati et al. [17] deployed an SNN on Intel Loihi for gesture recognition, consuming only 30 mW while maintaining 87.2% accuracy—enabling always-on wearable applications. The event-driven architecture processes spikes asynchronously, eliminating clock-driven power consumption. Despite promising results, SNN face challenges: 2-5% accuracy gap compared to ANN on complex tasks, limited software tooling, and difficulty achieving high accuracy on non-temporal data. Hybrid approaches combining ANN for feature extraction with SNN for temporal integration show promise.

3 Advanced Integration Strategies

3.1 Multimodal Fusion

Integrating EMG with complementary biosignals (accelerometry, gyroscopy, force) enhances robustness and context awareness [20]. Wang et al. [21] combined EMG with Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Mobile Vision Transformers (MobileViT), achieving 86.57% accuracy for activity recognition. Their cross-modal attention mechanism learns correlations between muscle activation and limb motion. Duan et al. [22] introduced cross-modal contrastive learning for sEMG-Accelerometer fusion. By maximizing agreement between sEMG and Accelerometer representations of the same movement, their approach reduces labeled data requirements while maintaining 95.28% accuracy. This addresses a critical challenge in clinical applications where labeled data is scarce.

3.2 Domain Adaptation and Transfer Learning

Inter-subject variability necessitates subject-specific calibration, limiting practical deployment. Domain adaptation techniques enable model transfer across subjects with minimal recalibration [5]. Côté-Allard et al. [5] proposed adaptive batch normalization that adjusts feature distributions during inference, improving cross-subject accuracy from 73.8% to 89.2% with just 5 calibration trials. Meta-learning approaches learn to quickly adapt to new subjects from few examples [23]. Tam et al. [23] applied Evidential Convolutional Neural Network (ECNN) to EMG classification, achieving 82.89% accuracy on new subjects after only 10 labeled samples—compared to 79.48% for Siamese Deep Convolutional Neural Network (SDCNN). Self-supervised learning leverages unlabeled EMG data through pretext tasks. Lai et al. [24] used temporal jittering and amplitude scaling as augmentations for contrastive learning. Their pretrained encoder, fine-tuned with limited labels, achieved 99% accuracy demonstrating effective representation learning from raw EMG.

4 Discussion

Table 1 presents a comprehensive comparison of state-of-the-art bio-inspired AI methods for EMG analysis. Several key insights emerge from this analysis. SNN and neuromorphic implementations offer superior energy efficiency (30-100× improvement) [15, 17] with acceptable accuracy, making them ideal for always-on wearable devices. TCNs provide an optimal balance: competitive accuracy (93.5%) with fast inference (18ms) and high efficiency [12]. The performance varies significantly with dataset complexity. Ninapro DB2 (50 movements) represents a challenging benchmark; methods achieving >90% accuracy demonstrate strong generalization [12, 24]. Simpler custom datasets (6-12 gestures) yield higher accuracy but may not reflect real-world complexity [15, 17].

Combining EMG with IMU data substantially improves accuracy (97.1% vs 92.3% for EMG-only) [20]. Cross-modal learning provides robustness to sensor failures and motion artifacts. However, multimodal systems increase hardware complexity and cost. Cross-subject generalization remains challenging. Standard models exhibit severe performance degradation (accuracy drops from 94% to 74%) [5]. Adaptive techniques (domain adaptation, meta-learning) significantly improve cross-subject performance (82-89%) [5, 23], but still lag behind subject-specific models. Few-shot meta-learning shows particular promise, achieving 82.89% accuracy with only 10 labeled samples per new subject [23].

Contrastive learning from unlabeled data reduces annotation burden by 50% while maintaining

Table 1. Comparative analysis of State-of-the-Art bio-inspired AI methods for EMG signal analysis.

Reference	**Method**	**Dataset**	**Classes**	**Accuracy (%)**	**Key Innovation**
Xiong et al. (2021)[4]	CNN-LSTM Hybrid	Ninapro DB5	18	94.8	Multi-scale temporal features
Song et al. (2023)[10]	CNN-GRU Lite	7	12	97.6	Edge-optimized architecture
Chen et al. (2021)[12]	Temporal CNN	Ninapro DB2	6	71.6	Dilated causal convolutions
Montazerin et al. (2023)[13]	Transformer	Ninapro DB1	65	91.98	Pure self-attention mechanism
Lin et al. (2024)[14]	Channel Attention	7	9	89.7	Electrode displacement robust
Vijayvargiya et al. (2023)[19]	Graph Neural Net	Ninapro DB2	–	99.36	Muscle synergy modeling
Sun et al. (2023)[15]	SNN-LIF	8	9	72	Event-driven computing
Donati et al. (2019)[17]	Neuromorphic (Loihi)	8	6	87.2	Hardware SNN implementation
Wang et al. (2025)[21]	EMG-IMU Fusion	Ninapro DB1	10	86.57	CGMV-EGR framework
Duan et al. (2023)[22]	Contrastive Fusion	Ninapro DB2	40	94.66	Self-attention multimodal learning
Côté-Allard et al. (2019)[5]	Adaptive BN	Ninapro DB1	18	89.2	Real-time domain adaptation
Tam et al. (2024)[23]	Meta-Learning	10	6	82.84	Few-shot subject adaptation
Lai et al. (2022)[24]	Self-Supervised	Armband	7	99.8	Temporal contrastive learning

competitive accuracy (98.4) [24]. This addresses a critical bottleneck in clinical applications where expert labeling is expensive and time-consuming. Graph neural networks, also, provide interpretable muscle synergy patterns [19], while attention mechanisms highlight discriminative channels and time windows [14]. This interpretability is crucial for clinical acceptance and regulatory approval.

Despite these results, real-world deployment faces challenges: (1) Robustness to electrode displacement—only channel attention methods explicitly address this [14]; (2) Long-term stability—muscle fatigue and learning effects degrade performance over hours. Some promising directions emerge: Neuro-symbolic integration combining neural networks with symbolic reasoning for interpretable, data-efficient learning; Continual learning enabling models to adapt to changing EMG characteristics without catastrophic forgetting; and the use of foundation models pretrained on large-scale EMG corpora, then fine-tuned for specific applications with minimal data.

5 Conclusion

This paper reviewed recent advances in bio-inspired artificial intelligence for EMG signal analysis, comparing state-of-the-art methods in terms of accuracy, efficiency, and practical deployment. It highlighted that hybrid CNN-Transformer models provide superior accuracy by combining local and global temporal modeling, while spiking neural networks and neuromorphic hardware dramatically enhance energy efficiency for wearable use. Multimodal fusion improves robustness, and domain adaptation, meta-learning, and self-supervised approaches enhance generalization and reduce annotation needs. Future work should focus on standardized robustness benchmarks, large and diverse datasets, co-design of algorithms with neuromorphic hardware, integration of multimodal biosignals for holistic monitoring, and interpretable AI models that yield clinically meaningful insights, paving the way for real-world applications in prosthetic control, disease detection, and personalized rehabilitation.

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Conflicts of Interest

The author declares no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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