Artificial Intelligence-based Muscle Motor Control and Recuperation using Surface Electromyography (sEMG): A Review on Datasets, Methods, Applications, and Future Directions

Dilliraj Ekambaram[1][0000-0002-9245-2746], Vijayakumar Ponnusamy[1][0000-0002-3929-8495], and Emilija Kisić[2][0000-0003-3059-2353]

[1] Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Kattankulathur – 603203, Tamil Nadu, India
[2] Faculty of Information Technology, Belgrade Metropolitan University, Tadeuša Košćuška 63, 11000, Belgrade, Serbia
de0642@srmist.edu.in, vijayakp@srmist.edu.in
emilija.kisic@metropolitan.ac.rs

Abstract. Advancements in human-machine interaction are enabling prosthetic hand control for people with physical disabilities, achieved through surface electromyography (sEMG). The sEMG is an emerging, non-invasive, and versatile technique for recuperation and prosthetic applications. For classifying both discrete and continuous muscle movements on the human body, carried through advanced non-invasive sensors, high-density sEMG (HD-sEMG), and Artificial Intelligence (AI) learning models. The combination of sensors with AI models enables the recognition of precise hand gestures and body postures by extracting key signal features for muscle motor activities through the placement of electrodes on the skin surface. This systematic review outlines English-language articles from 2020 to 2025, focusing on the process of signal acquisition and processing for deep learning or machine learning models, in line with time and frequency methods for decomposing motor units. Surveyed challenges in the real-world applications, such as healthcare, artificial replacement of body parts, and sports medicine. To highlight the need for reproducibility and analyze the performance of various AI models, we discussed the open-source datasets and toolboxes used for software development with standardized benchmark datasets. Experimental challenges related to sEMG hardware, including electrode displacement on the skin surface, inter-individual variability, and cross-talk, were discussed. Ultimately, the pathway for future directions in the development of AI-based sEMG models, with a focus on explainable AI, multimodal systems, and diverse federated data, aims to bridge the gap between laboratory research and clinical impact.

Keywords: Surface Electromyography · Gesture Analysis · Prosthetic Control · Artificial Intelligence · Gait Analysis · Signal Processing

Review Paper
DOI: https://doi.org/10.46793/BISEC25.358E
Part of ISBN: 978-86-89755-40-4

1 Introduction

Muscle motor control is one of the important nervous systems that interacts with other body parts through the spinal cord of the human body [1]. The prevalence of muscular disorders, such as neuromuscular disorders, carpal tunnel syndrome, low back pain, limb amputations, injuries in the spinal cord, stroke, and many more, creates a global economic loss of four to six percent every year, which is also an important cause of their reduced quality of life [2, 3]. The restoration and recovery of these disorders is not an easy process in practice. The ability of traditional therapeutic systems for the rehabilitation of the mentioned disorders was minimal [4]. Improving the effectiveness and providing personalized, scalable, and reliable services for long-term muscle motor recovery for humans requires the integration of computational intelligence systems with multimodal sensory support. These systems offer robust monitoring and augment human control (Prosthetic hand control) [5]. To monitor sports performance, analysis of biomechanical movements using wearable technologies provides valuable insights into the improvement of mechanical actions in sportspeople to avoid the risk of muscle injuries [6].

The non-invasive method of acquiring the muscle movement signals is done through surface electromyography (sEMG). The signal from the sEMG sums up the voltage potentials on muscle contraction by placing the electrodes on the skin surface of the human body [7]. It is useful for a wide range of applications, such as gesture recognition [8–11], gait analysis [12–15], exercise-based human recuperation [16–20], and prosthetic hand control [21–24]. Advancements in AI with modern machine learning approaches provide more precise outcomes for recognizing, classifying, and augmenting control of muscle motor functions. Our review showcases the recent updates in AI-based muscle motor control action recognition and classification, also highlights its progress and limitations.

We addressed the following questions:

- What are the suitable machine learning models for classifying the muscle motor activities through sEMG and HD-sEMG?
- What is the impact of electrode placements on the muscles and the configuration of sensors to achieve a high degree of accuracy and generalizability on EMG-based activity recognition models?
- How far do the EMG-driven AI models support clinical recuperation applications, such as gesture, prosthetic control, gait analysis, and stroke rehabilitation?

This review work is organized as follows: Section 2 deliberates the literature review and its searching strategies on various muscle motor functions that imply AI models. Section 3 describes the advancements in wearable technologies, signal processing, motor unit decomposition, and clinical applications for recuperation. Section 4 discusses the key findings and various datasets available for muscle motor activity from sEMG. Section 5 summarizes the limitations of various proposed approaches and the future research directions. Lastly, Section 6 comprises the conclusion of this review work.

This section deliberates the methodology used for the literature review of the works discussing the AI-based sEMG signal analysis for the muscle movements and its applicability in clinical trials. Initial screening of literature starts with a PubMed search engine for the articles, and it is organized into three divisions: (i) Gait analysis, (ii) Gesture analysis, and (iii) Prosthetic hand control from the muscle motor control unit.

1.1 Literature Search

A primary literature search was conducted for English-language manuscripts from 2020 to July 2025 across five online databases: PubMed, ACM Digital Library, Scopus, and IEEE Xplore. Using a systematic review web app, Rayyan, the duplicate articles from the searched articles were removed, and full-text screening was also conducted. The filtering of eligible articles for the title, "Muscle motor control signal processing" with full-text was done through the following eight words: "classification", recognition", "signal processing", "muscle motor unit", "analysis", "muscle signal sensors", "sEMG", and "HD-sEMG". This search ended up with 28 articles. Further search was applied using, "machine learning" and "deep learning". The selection of articles was then assessed with the following expression: "(Muscle*) AND (Gestur*) AND (Gait*) AND ((classifi*) OR (recog*) OR (signal pro*) OR (sEMG*))." The process of including selected articles from the search analysis is discussed in the next section.

The manuscripts were included in this review based on the following criteria: (i) studies that utilize sEMG and HD-sEMG bio signals acquisition for muscle movement analysis, (ii) studies that include human participants with amputees, muscular disease patients, stroke patients, and healthy individuals, (iii) studies that investigate functional activities such as, hand gesture recognition, micro-gestures, grasping, walking, lifting, gait analysis, post-stroke rehabilitation, and upper and lower body joint movement analysis, (iv) research studies which employs various machine learning and deep learning algorithms such as, CNN, LSTM, ANN, SVM, DTW, TinyML, Transformers, and explainable AI for classification and recognition of human functional activities. (v) studies included that provide quantitative performance metrics such as classification accuracy, recognition rate, and error reduction models from the various custom datasets or online available benchmark datasets (NinoPro, UCI datasets, and Kaggle datasets, etc.), (vi) studies written in the English language only included. All the studies included in this review have full-text articles, excluding editorial letters, magazines, short papers, and comments.

Further analysis on inclusive of articles was performed to avoid redundancy and eliminate duplicates. The following terms were used to assess the inclusion and exclusion criteria i.e., title of the article, publishing year, purpose of the study, study population, activity performed, electrode configuration, and types of EMGs. Methods and their outcomes include the error reduction, classification accuracy of ML and DL techniques, the techniques for signal processing and feature extraction that are relevant to movement classification, prosthetic controls, and rehabilitation. Recent studies from 2025 were manually searched, and the extracted information from the searched articles was used.

A total of 1,862 records were initially identified from IEEE Xplore (367), Scopus (268), ACM Digital Library (460), and PubMed (767). After removing 54 duplicates, 764 records were excluded by the Rayyan web app, and 62 records were excluded for being unrelated to the scope of this review, such as studies focusing only on electrode signal analysis, hardware systems without ML/DL evaluation, or applications beyond motor control (e.g., facial recognition). This process resulted in 982 records for screening. Among these, 818 were excluded during the screening stage, leaving 164 reports for retrieval. Of these, 94 could not be retrieved, and 70 were assessed for eligibility. Further exclusions were made due to duplication (n=12), unavailability of full text (n=31), editorial letters (n=3), and non-English full texts (n=2). Finally, 22 studies met the inclusion criteria and were analyzed in this review. Figure 1 shows the article inclusion criteria process for this review.

Thus, a total of 22 studies were finally included in this review, providing the evidence base for analysing AI-driven approaches to muscle motor control and recuperation using sEMG.

2 Discussion

Non-invasive methods of extracting signal from sEMG have to follow a set of procedures. When extracting the sEMG signal for the forearm extensor/flexor, the subject must sit stably, and the forearm must be at rest. The surface of the skin must be wiped with alcohol (or shaved if needed) and then dried to reduce skin impedance (or noise). Then, the high-quality Ag/AgCl electrodes are placed along the muscle fibres longitudinally with an inter-electrode distance of 1-2 cm. To minimize the crosstalk and signal distortion, determining the muscle belly for the particular muscle to place the electrode at the center of the muscle belly and end plate of the motor muscle. The reference (or) ground electrode is placed on the bone's region of the body part. During the acquisition of the signals, the sampling rate for the system is set to more than or equal to 1000Hz with a band-pass filter (BPF). The BPF is used to remove the motion artifacts and other noises, and the notch filter suppresses the interferences. Then the subject is asked to perform the forearm flexor/extensor to acquire the signals from the sEMG. Observe the difference between baseline muscle signals and movement muscle signals. The smoothening of acquired signals was performed by using the normalization of maximum voluntary contraction (MVC), taking the RMS/ linear envelope methods. These are the features used for the classification or recognition of muscle movements that should feed into the machine learning (ML) or deep learning (DL) models. Figure 2 depicts the process flow of feature extraction and feeds it to ML or DL techniques.

This section describes the key findings of this review article from various existing methodologies for muscle motor control with sEMG and HD-sEMG. The publicly available benchmark datasets and technological translation on clinical

Table 1: Comparative Analysis of Existing Muscle Movement Activity Monitoring Systems

References	Muscle Selected	Activity	Data	Methodology	Models Classification Result	Type of EMG
Han et al., 2025 [28]	Wrist muscles and bones	Micro Gesture activity (Thumb up/right/down/left movement)	Two datasets were collected. The first dataset comprises 28 subjects gathered using eight EMG sensors, while the second dataset has 43 subjects with data from three electrode EMG sensors.	Deep Compressed Spiking Neural Network (DCSNN)	Achieved recognition accuracy of 88.55% for dataset 1 and 95.76% for dataset 2	8-channel and 3-channel sEMG
Wang et al., 2025 [34]	Upper Arm	Post-stroke Rehabilitation	Motion Analysis Data was collected from five volunteers and gathered 300 movements	Improved Dynamic Time Wrapping (DTW) Algorithm	Compared to the traditional DTW algorithm, the Improved DTW algorithm achieved an increased accuracy of 15.99%.	sEMG
Hodossy et al., 2024 [35]	Four leg Muscles	Gait Analysis	Data collected from five subjects with no history of neurological conditions	Temporal Convolutional Network (TCN)	The model achieved 70% less error prediction than traditional location-specific models.	High-Density sEMG (HD-sEMG)
Li et al., 2024 [36]	Forearm extensor and flexor, biceps brachii	Elbow extension and flexion with fingers closed and opened	Data collected from 50 male and 50 female to analyze the cohort study	Recurrent Neural Network (RNN) and Representative Visual Transformers (RepVIT) deployed with STM32F429 microcontrollers	Achieved recognition accuracy of 95%	Adaptive Transcutaneous Electrical Nerve Simulation device utilizing sEMG
Lim et al., 2024 [37]	Lower limb amputees	Hip leg flexion, and leg upward and downward extension	Data were acquired from five amputees and ten non-amputees with MR rehabilitation simulation conducted over twelve weeks. Totally 300 seconds per subject were collected in this study	Mixed Reality (MR) with Gated Recurrent Unit (GRU) for motion classification is proposed in this work	This model achieves a classification accuracy of 92.81%	sEMG
Buteau et al., 2024 [38]	Forearm and wrist	Gesture Recognition	Six hand gestures, such as hand open, finger flexion, index finger extension, Thumb finger extension, Pinch, and relaxed hand, from 12 users with two different sessions.	TinyML enabled with Coral Tensor Processing Unit (TPU)	TPU with 8 bits achieved 92% accuracy	HD-sEMG with 64-channel sensor
Salerno and Sylvain Barraud, 2024 [39]	Forearm	Gesture Recognition	Ninapro Benchmark Dataset Utilized	High Dimensional Computing (HDC) algorithm with spatial-temporal encoder	The HDC model achieved a maximum accuracy of 92%.	HD-sEMG

Chaves, Vieira and Markus, 2024 [40]	Forearm Muscle	Gesture activities (Hand Fist, Rest, Wave-in, Wave-out, open, and pinch)	Collected six hand gestures from ten healthy subjects, with 400 training samples and 150 testing samples	Feedforward Neural Network (FNN) for the classification of gesture actions.	The best-trained FNN model achieved a mean accuracy of 97.2%	8-channel sEMG
Jiang et al., 2024 [41]	FLow back muscles	FStoop lifting with varying weights	FTen healthy subjects were recruited to perform the stoop lifting activity.	FArtificial Neural Network (ANN) classifier	FThe classifier model achieved a classification accuracy of 96%	F3x7 electrode array sEMG
Akhil et al., 2023 [42]	Hamstring and Gastrocnemius muscles	Walking activity	The data were acquired from twenty-one male subjects with healthy conditions to perform various walking actions, such as even forward, even backward, uneven forward, and backward actions.	Scattering transform (ST) features with the SVM classifier method were used in this study	ST-SVM classifier achieved an accuracy of 99.42%	sEMG
Zou et al., 2023 [43]	Forearm Muscle	Seven hand gesture activities	Recruited twelve subjects to perform seven hand gestures, each gesture segmented with a 160-ms window.	Feature Extraction of sEMG with Multiple Sub-CNN models	Model achieves within-session 99.26%, cross-subject accuracy of 53.52%, and cross-time accuracy of 78.47%.	8-channel sEMG
Erazo and Ko, 2023 [44]	Forearm Muscle	Grasping Activity (cylindrical, hook, lateral, palmar, spherical, and tip)	UC Irvine repository EMG Dataset for gesture	2D-Long Short-Term Memory (LSTM) Model	Achieved an accuracy of 99.12%.	sEMG
Zhang et al., 2023 [45]	Forearm Muscle	Gesture Recognition	NinaPro DB5E3, DB2E2, and CapgMyo DB-c	Long Short-Term EMG Feature Fusion Network (LST-EMG-Net)	The model achieves 88.24%, 81.47%, and 98.95% accuracies for the mentioned databases	sEMG and HD-sEMG
Nafe Muhtasim Hye et al., 2023 [46]	Forearm Muscle	Hand Movement	NinaPro Database1	K-Nearest Neighbors (KNN) ML algorithm	For inter-subjects achieved 89.844% and for intra-subjects achieved 95.04%	sEMG
Li et al., 2022 [47]	Forearm Muscle	Continuous Hand Movement Action	NinaPro db8 dataset	Multi-Features Fusion-based Convolution Neural Network Long Short-Term Memory (MFFCNN-LSTM)	The accuracy achieved by this model is 98.5%	sEMG
Ankit Vijayvargiya et al., 2022 [48]	Lower limb muscle	Jumping, sit-ups, Stairdown, Stairup, and Walking	Five healthy subjects with three male and two female, were recruited for the collection of data. 8000 samples collected per subject.	Explainable AI utilizes various ML classifiers such as decision tree, bagging, gradient boosting, and extra tree	Among various classifiers Extra Tree classifier achieved 96.83% mean accuracy on various activities.	sEMG

Abdolahnezhad et al., 2021 [49]	Tibialis anterior, Gastrocnemius, and Soleus muscles	Treadmill Walking	Nine healthy individuals insisted on walking on a treadmill for 3 minutes at 2-4 kmph. Features such as root mean square, waveform length, mean absolute value, zero crossing, and variance were gathered from the data	Multi-layer Perceptron (MLP)	MLP with ADAM optimizer achieved activity recognition accuracy of 99.29%.	8-channel sEMG
Coskun et al., 2021 [50]	Two forearm muscles	Grasping things through a prosthetic hand	Dataset collected from five healthy subjects, two male and three female, with a sample length of 3000 for database1 and 2500 for database2.	One-dimensional Convolution Neural Network (1D-CNN)	The model achieved 94.94% accuracy on the grasping activity	sEMG
Su et al., 2020 [51]	Tibialis anterior, gastrocnemius, peroneus longus, extensor halluces longus, and digitorum longus muscles were utilized in this study	ankle eversion and inversion	Features such as, RMSE, normalized RMSE, and cross-correlation coefficients from five healthy subjects and three patients were acquired for analysis	ANN and Support Vector Regression (SVR) were proposed for predicting joint ankle movement	The SVR algorithm achieved a prediction accuracy of 96.6%.	sEMG
Roland, 2020 [52]	Forearm Muscle	Muscle artifact suppression	Collected motion contraction and artifact signal with 16008 samples	Recurrent Neural Network (RNN)	The RNN model achieves classification accuracy of 99.91%.	Flexible insulated EMG sensors
Tam et al., 2020 [53]	Forearm Muscle	Grasping activity	NinaPro Database	Convolutional Neural Network (CNN)	This model achieved an accuracy of 98.15%.	8x4 Array (32 electrodes) HD-sEMG
Secciani et al., 2020 [54]	Forearm posterior muscle	Forearm muscular activity (Open, close, and rest)	The dataset collected from exoskeleton-based sEMG at a frequency of 50Hz, and the sample size of 5736 samples.	Point-in-polygon model used for the classification of extensor activity	The point-in-polygon model achieved a classification accuracy of 94.4%.	sEMG with exoskeleton system

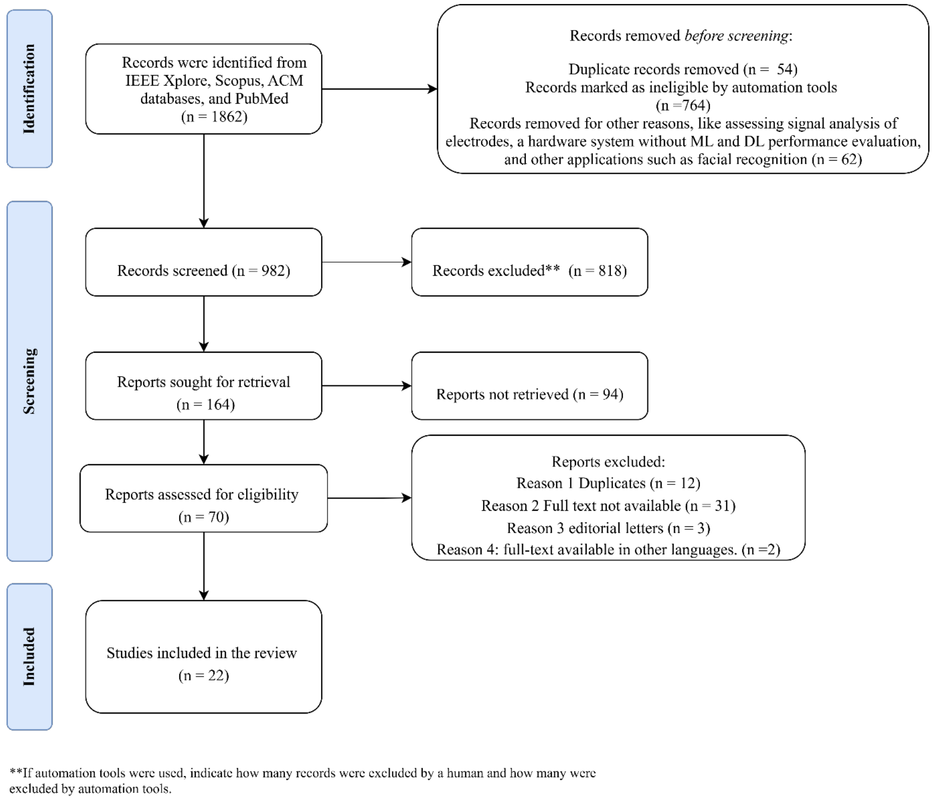

Fig. 1. Flow chart of the Articles' inclusion process for the review.

aspects. Table 1 represents a comparative analysis of a muscle movement activity monitoring system using conventional machine learning and deep learning techniques.

Recent technological developments in applications such as prosthetic hand control, human-machine interaction, and wearable devices have utilized the sEMG motor function recognition system. These systems are concentrated on improving their accuracy, efficiency, and generalizability by researchers around the globe. One of the recent studies uses eight muscle-specific index EMG electrodes to recognize the hand gestures. The signal-to-noise ratio, signal-to-motion artifacts were assessed by placing the electrodes in the elbow and mid-arm to improve the quality of the signal. The hand gesture orientation performance for the forearm was evaluated using ML classifiers such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and k-Nearest Neighbours (KNN). Furthermore, more evaluation has been done with DL techniques such as 1D CNN, LSTM, RNN, and hybrid architectures [25], a sliding voting random forest classifier was included to achieve the classification accuracy of 94.23%, whereas LDA

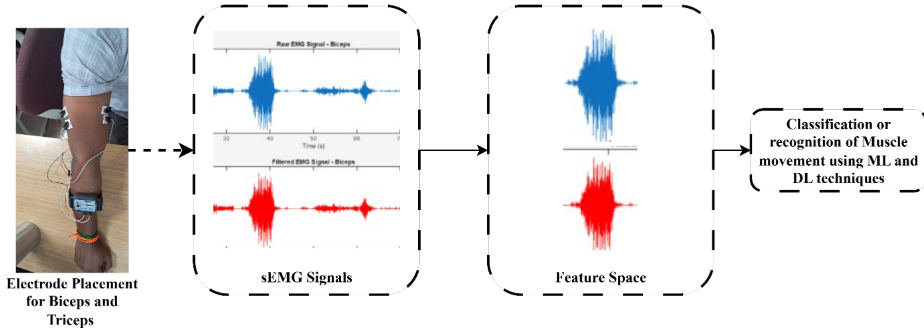

Fig. 2. Flow diagram of Feature Extraction from the sEMG signals.

achieves 76.67%. This study uses the NinaPro database to train the model for recognizing hand gestures [26]. Spatial Temporal Graph Convolution Network (STGCN) is one of the significant deep learning models for the classification of hand gestures. One of the recent studies uses STGCN with HD-sEMG signals for classifying hand gestures. The human-machine interaction with HD-sEMG achieved 91.07% of classification accuracy and was able to classify 65 different hand gestures by this system [27]. Another study developed a Binarized Neural Network (BNN) that contains one dry sEMG sensor to acquire signals of nine dynamic gestures, which achieves 95.4% accuracy with low latency and low power [28].

To evaluate the impact on classification accuracy for various feature selection algorithms, extracted features from the time and frequency domains have to be analysed. The recursive feature elimination mechanism is well-suited for achieving higher classification accuracy in gesture and gait analysis through sEMG [29].

3 Challenges and Future Directions

This section describes the various clinical and technical challenges of AI-based muscle motor control and rehabilitation using sEMG that persist in real-world implementation.

Despite standardized protocols for sEMG electrode placement, individual variations in skin properties and potential signal contamination from non-intended muscles necessitate person-specific adjustments [30]. These anatomical and biological variations complicate cross-person muscle activity recognition, rendering model generalization a persistent fundamental challenge [31]. This issue is further compounded by a lack of demographic, configuration, and task diversity within common benchmark datasets such as NinaPro, CapgMyo, and the UCI EMG archives. Furthermore, the high computational cost of deep learning models hinders real-time inference on resource-constrained hardware; while architectures like Binary Neural Networks (BNN) and TinyML have been explored, they often struggle with accuracy trade-offs and critical latency [32]. Ultimately, the gap between research prototypes and clinical utility remains wide, as most AI-driven systems require frequent user recalibration for long-term rehabilitation tasks [33].

3.1 Future Directions

Future research should focus on advancing signal processing algorithms, sophisticated electrode designs, and wearable system enhancements to mitigate existing placement challenges [55]. Specifically, the development of flexible and stretchable electrodes can significantly reduce skin-surface barriers and minimize mediolateral placement errors [56]. To bolster core machine learning performance, further optimization of cross-subject gesture recognition is required to account for variations in muscle geometry, electrode positioning, and signal normalization [57]. Privacy-preserving frameworks like the FedAssist system also offer a path forward by utilizing federated learning to tackle non-IID challenges among users [58]. Additionally, the field must prioritize lightweight deep learning architectures optimized for low-power embedded hardware, such as microcontrollers and TPUs; techniques like quantization and pruning are essential for achieving real-time, adaptive control in wearable prosthetics [32]. Finally, establishing large, globally accessible benchmark datasets that encompass diverse demographics and medical conditions, paired with standardized data collection and labeling protocols, will be critical for ensuring reproducibility and fair algorithmic comparison [33].

4 Conclusions

This review emphasizes the recent advancement of Artificial Intelligence-driven systems for muscle motor control and rehabilitation utilizing surface electromyography (sEMG). The combination of powerful machine learning and deep learning models has made gesture recognition, gait analysis, and prosthetic control much more accurate. The field has made great strides in identifying complicated muscular activity and deciphering motion intent, moving from classical models like SVM, LDA, and ANN to more advanced neural frameworks like CNN, LSTM, and ST-GCN. The review also points up big problems with hardware consistency, differences across subjects, dataset diversity, and clinical usefulness.

Future research should concentrate on developing resilient, interpretable, and energy-efficient AI models capable of generalization across varied users and contexts. The present gap between laboratory prototypes and clinical rehabilitation systems can be closed by combining multimodal biosignals, federated learning, and embedded AI approaches. The combination of wearable sensor technologies, AI, and rehabilitation research will eventually make human-machine interactions more natural and flexible. This will give people with muscular disorders or limb loss the tools they need to restore their independence and improve their quality of life.

References

1. Poppler, L.H., Mackinnon, S.E.: The role of the peripheral nerve surgeon in the treatment of pain. Neurotherapeutics **16**(1), 9–25 (2019)
2. Debenham, M.I., Franz, C.K., Berger, M.J.: Neuromuscular consequences of spinal cord injury: New mechanistic insights and clinical considerations. Muscle & nerve **70**(1), 12–27 (2024)
3. Zhou, J., Xie, S., Xu, S., Zhang, Y., Li, Y., Sun, Q., Zhang, J., Zhao, T.: From pain to progress: comprehensive analysis of musculoskeletal disorders worldwide. Journal of Pain Research pp. 3455–3472 (2024)
4. Gill, T.K., Mittinty, M.M., March, L.M., Steinmetz, J.D., Culbreth, G.T., Cross, M., Kopec, J.A., Woolf, A.D., Haile, L.M., Hagins, H., et al.: Global, regional, and national burden of other musculoskeletal disorders, 1990–2020, and projections to 2050: a systematic analysis of the global burden of disease study 2021. The Lancet Rheumatology **5**(11), e670–e682 (2023)
5. Rasa, A.R.: Artificial intelligence and its revolutionary role in physical and mental rehabilitation: a review of recent advancements. BioMed Research International **2024**(1), 9554590 (2024)
6. Alzahrani, A., Ullah, A.: Advanced biomechanical analytics: Wearable technologies for precision health monitoring in sports performance. Digital health **10**, 20552076241256745 (2024)
7. Farago, E., MacIsaac, D., Suk, M., Chan, A.D.: A review of techniques for surface electromyography signal quality analysis. IEEE Reviews in Biomedical Engineering **16**, 472–486 (2022)
8. Shin, J., Miah, A.S.M., Konnai, S., Takahashi, I., Hirooka, K.: Hand gesture recognition using semg signals with a multi-stream time-varying feature enhancement approach. Scientific Reports **14**(1), 22061 (2024)
9. Xia, Y., Qiu, D., Zhang, C., Liu, J.: semg-based gesture recognition using multi-stream adaptive cnns with integrated residual modules. Frontiers in Bioengineering and Biotechnology **13**, 1487020 (2025)
10. Gan, Z., Bai, Y., Wu, P., Xiong, B., Zeng, N., Zou, F., Li, J., Guo, F., He, D.: Sgrn: Semg-based gesture recognition network with multi-dimensional feature extraction and multi-branch information fusion. Expert Systems with Applications **259**, 125302 (2025)
11. Zhang, M., Qu, L., Wu, W., Han, G., Zhu, W.: semg-based gesture recognition using sigimg-gadf-mtf and multi-stream convolutional neural network. Sensors **25**(11), 3506 (2025)
12. Sharma, A.K., Liu, S.H., Zhu, X., Chen, W.: Predicting gait parameters of leg movement with semg and accelerometer using catboost machine learning. Electronics **13**(9), 1791 (2024)
13. Pradon, D., Tong, L., Chalitsios, C., Roche, N.: Development of surface emg for gait analysis and rehabilitation of hemiparetic patients. Sensors **24**(18), 5954 (2024)
14. Alegria, M., Gomez-Correa, M., Cruz-Ortiz, D., Ballesteros, M.: Design of a wearable system for gait analysis based on imu, semg and plantar load signals. In: 2024 12th International Conference on Control, Mechatronics and Automation (ICCMA). pp. 205–210. IEEE (2024)
15. Liu, S.H., Sharma, A.K., Wu, B.Y., Zhu, X., Chang, C.J., Wang, J.J.: Estimating gait parameters from semg signals using machine learning techniques under different power capacity of muscle. Scientific Reports **15**(1), 12575 (2025)

16. Blanco-Giménez, P., Vicente-Mampel, J., Gargallo, P., Maroto-Izquierdo, S., Martín-Ruíz, J., Jaenada-Carrilero, E., Barrios, C.: Effect of exercise and manual therapy or kinesiotaping on semg and pain perception in chronic low back pain: a randomized trial. BMC musculoskeletal disorders **25**(1), 583 (2024)
17. Chatragadda, L., Fletcher, A., Zhong, S., Vargas, F.A., Bhagat, N., Mankodiya, K., Delmonico, M.J., Solanki, D.: Development and assessment of a soft wearable for semg-based hand grip detection and control of a virtual environment. Sensors **25**(8), 2431 (2025)
18. Alyanak, B., İnanır, M., Sade, S.I., Kablanoğlu, S.: Efficacy of game-based emg-biofeedback therapy in post-stroke dysphagia: A randomized controlled trial: B. alyanak et al. Dysphagia **40**(6), 1289–1301 (2025)
19. Marcos-Antón, S., Jardón-Huete, A., Oña-Simbaña, E.D., Blázquez-Fernández, A., Martínez-Rolando, L., Cano-de-la Cuerda, R.: semg-controlled forearm bracelet and serious game-based rehabilitation for training manual dexterity in people with multiple sclerosis: a randomised controlled trial. Journal of neuroengineering and rehabilitation **20**(1), 110 (2023)
20. Al-Ayyad, M., Owida, H.A., De Fazio, R., Al-Naami, B., Visconti, P.: Electromyography monitoring systems in rehabilitation: A review of clinical applications, wearable devices and signal acquisition methodologies. Electronics **12**(7), 1520 (2023)
21. Dunai, L., Verdú, I.S., Turcanu, D., Bostan, V.: Prosthetic hand based on human hand anatomy controlled by surface electromyography and artificial neural network. Technologies **13**(1), 21 (2025)
22. Chau, M.T., Hung, B.D.: Semg-based prosthetic hand with an integrated mobile application. In: International Conference on Computational Science and Its Applications. pp. 23–38. Springer (2024)
23. Tchimino, J., Hansen, R.L., Jørgensen, P.H., Dideriksen, J., Dosen, S.: Application of emg feedback for hand prosthesis control in high-level amputation: a case study. Scientific Reports **14**(1), 31676 (2024)
24. Rafiq, A., Talukder, Z., Hamim, A., Firdous, J., Ahmed, K.I.U.: semg signal-based prosthetic hand control using embedded machine learning with deep neural network. In: 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT). pp. 382–386. IEEE (2024)
25. Rumman, U., Ferdousi, A., Saha, B., Hossain, M.S., Islam, M.J., Ahmad, S., Reaz, M.B.I., Islam, M.R.: Fors-emg: a novel semg dataset for hand gesture recognition across multiple forearm orientations. arXiv preprint arXiv:2409.07484 (2024)
26. Zhang, M., Liu, S., Li, X., Qu, L., Zhuang, B., Han, G.: Improving semg-based hand gesture recognition through optimizing parameters and sliding voting classifiers. Electronics **13**(7), 1322 (2024)
27. Zhong, W., Zhang, Y., Fu, P., Xiong, W., Zhang, M.: A spatio-temporal graph convolutional network for gesture recognition from high-density electromyography. arXiv preprint arXiv:2312.00553 (2023)
28. Han, Y., Zhao, W., Gao, G., Chen, X., Yin, J., Wang, L., Meng, X., Yu, Y., Zhang, T.: Dcsnn: An efficient and high-speed semg-based transient-state micro-gesture recognition method on wearable devices. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies **9**(2), 1–34 (2025)
29. Hellara, H., Barioul, R., Sahnoun, S., Fakhfakh, A., Kanoun, O.: Comparative study of semg feature evaluation methods based on the hand gesture classification performance. Sensors **24**(11) (2024), https://www.mdpi.com/1424-8220/24/11/3638

30. Cheng, L., Li, J., Guo, A., Zhang, J.: Recent advances in flexible noninvasive electrodes for surface electromyography acquisition. npj Flexible Electronics **7**(1), 39 (2023)
31. Zhao, K., Zhang, Z., Wen, H., Scano, A.: Intra-subject and inter-subject movement variability quantified with muscle synergies in upper-limb reaching movements. Biomimetics **6**(4) (2021), https://www.mdpi.com/2313-7673/6/4/63
32. Chopra, S., Emran, T.B.: Advances in ai-based prosthetics development. International Journal of Surgery **110**(8), 4538–4542 (2024)
33. Chen, Z., Min, H., Wang, D., Xia, Z., Sun, F., Fang, B.: A review of myoelectric control for prosthetic hand manipulation. Biomimetics **8**(3) (2023), https://www.mdpi.com/2313-7673/8/3/328
34. Wang, S., Wu, X., Lai, W., Yao, J., Gou, X., Ye, H., Yi, J., Cao, D.: Rehabilitation evaluation method and application for upper limb post-stroke based on improved dtw. Biomedical Signal Processing and Control **106**, 107775 (2025)
35. Hodossy, B.K., Guez, A.S., Jing, S., Huo, W., Vaidyanathan, R., Farina, D.: Leveraging high-density emg to investigate bipolar electrode placement for gait prediction models. IEEE Transactions on Human-Machine Systems **54**(2), 192–201 (2024)
36. Li, Y., Ma, L., Yue, W., Chen, F.: Design of an arm posture recognition system and adaptive tens therapeutic device based on semg signals. In: 2024 8th International Conference on Electrical, Mechanical and Computer Engineering (ICEMCE). pp. 1171–1174. IEEE (2024)
37. Lim, G., Youn, H., Kim, H., Jeong, H., Cho, J., Lee, S., Pak, C., Kwon, S.: Impact of mixed reality-based rehabilitation on muscle activity in lower-limb amputees: An emg analysis. IEEE Access **12**, 106415–106431 (2024)
38. Buteau, É., Gagné, G., Bonilla, W., Boukadoum, M., Fortier, P., Gosselin, B.: Tinyml for real-time embedded hd-emg hand gesture recognition with on-device fine-tuning. In: 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). pp. 1–6. IEEE (2024)
39. Salerno, A., Barraud, S.: Evaluation and implementation of high-dimensionnal computing for gesture recognition using semg signals. In: 2024 International Conference on Control, Automation and Diagnosis (ICCAD). pp. 1–6. IEEE (2024)
40. Chaves, G.S., Vieira, A.S., Lima, M.V.: semg-based gesture classifier through dtw and enhanced muscle activity detection. IEEE Access **12**, 117595–117607 (2024)
41. Jiang, N., Wang, L., Wang, D., Fang, P., Wu, X., Li, G.: Loading recognition for lumbar exoskeleton based on multi-channel surface electromyography from low back muscles. IEEE Transactions on Biomedical Engineering **71**(7), 2154–2162 (2024)
42. Akhil, V., Satheesh, R., Ashmi, M., Tawk, C.D.: Lower limb emg signal analysis using scattering transform and support vector machine for various walking conditions. IEEE Access **11**, 129566–129575 (2023)
43. Zou, Y., Cheng, L., Han, L., Li, Z., Song, L.: Decoding electromyographic signal with multiple labels for hand gesture recognition. IEEE Signal Processing Letters **30**, 483–487 (2023)
44. Erazo, A., Ko, S.B.: A long short-term memory-based interconnected architecture for classification of grasp types using surface-electromyography signals. IEEE Transactions on Artificial Intelligence **5**(1), 434–445 (2023)
45. Zhang, W., Zhao, T., Zhang, J., Wang, Y.: Lst-emg-net: Long short-term transformer feature fusion network for semg gesture recognition. Frontiers in Neurorobotics **17**, 1127338 (2023)

46. Hye, N.M., Hany, U., Chakravarty, S., Akter, L., Ahmed, I.: Artificial intelligence for semg-based muscular movement recognition for hand prosthesis. IEEE Access **11**, 38850–38863 (2023)
47. Li, J., Wei, L., Wen, Y., Liu, X., Wang, H.: An approach to continuous hand movement recognition using semg based on features fusion. The Visual Computer **39**(5), 2065–2079 (2023)
48. Vijayvargiya, A., Singh, P., Kumar, R., Dey, N.: Hardware implementation for lower limb surface emg measurement and analysis using explainable ai for activity recognition. IEEE Transactions on Instrumentation and Measurement **71**, 1–9 (2022)
49. Abdolahnezhad, P., Yousefi-Koma, A., Zakerzadeh, M.R., Rezaeian, S., Farsad, M., Aboumasoudi, S.S.: Identification of locomotion modes based on artificial intelligence algorithms using surface electromyography signals. In: 2021 9th RSI International Conference on Robotics and Mechatronics (ICRoM). pp. 198–202. IEEE (2021)
50. Coskun, M., Yildirim, O., Demir, Y., Acharya, U.R.: Efficient deep neural network model for classification of grasp types using semg signals. Journal of ambient intelligence and humanized computing **13**(9), 4437–4450 (2022)
51. Su, C., Chen, S., Jiang, H., Chen, Y.: Ankle joint torque prediction based on surface electromyographic and angular velocity signals. IEEE access **8**, 217681–217687 (2020)
52. Roland, T.: Motion artifact suppression for insulated emg to control myoelectric prostheses. Sensors **20**(4) (2020), https://www.mdpi.com/1424-8220/20/4/1031
53. Tam, S., Boukadoum, M., Campeau-Lecours, A., Gosselin, B.: A fully embedded adaptive real-time hand gesture classifier leveraging hd-semg and deep learning. IEEE Transactions on Biomedical Circuits and Systems **14**(2), 232–243 (2020)
54. Secciani, N., Topini, A., Ridolfi, A., Meli, E., Allotta, B.: A novel point-in-polygon-based semg classifier for hand exoskeleton systems. IEEE Transactions on Neural Systems and Rehabilitation Engineering **28**(12), 3158–3166 (2020)
55. Gomez-Correa, M., Cruz-Ortiz, D., Ballesteros, M.: Wearable and wireless semg acquisition system based on the internet of medical things. Sensing and Bio-Sensing Research **49**, 100828 (2025). https://doi.org/https://doi.org/10.1016/j.sbsr.2025.100828, https://www.sciencedirect.com/science/article/pii/S2214180425000947
56. Yang, S., Cheng, J., Shang, J., Hang, C., Qi, J., Zhong, L., Rao, Q., He, L., Liu, C., Ding, L., et al.: Stretchable surface electromyography electrode array patch for tendon location and muscle injury prevention. Nature Communications **14**(1), 6494 (2023)
57. Wang, Z., Wan, H., Meng, L., Zeng, Z., Akay, M., Chen, C., Chen, W.: Optimization of inter-subject semg-based hand gesture recognition tasks using unsupervised domain adaptation techniques. Biomedical Signal Processing and Control **92**, 106086 (2024). https://doi.org/https://doi.org/10.1016/j.bspc.2024.106086, https://www.sciencedirect.com/science/article/pii/S1746809424001447
58. Lee, H., Jiang, M., Zhao, Q.: Fedassist: Federated learning in ai-powered prosthetics for sustainable and collaborative learning. In: 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). pp. 1–5 (2024). https://doi.org/10.1109/EMBC53108.2024.10781961