A Review on the Recent use of Machine Learning for Gesture Recognition using Myoelectric Signals

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Abstract. *Gesture recognition using myoelectric signals (sEMG) is a powerful tool for Human-Machine Interfaces (HMIs). While significant progress has been made with various machine learning algorithms, more recent and robust solutions in the sEMG pipeline must be explored. This study reviews recent gesture recognition research to identify gaps and analyze standard classification and feature extraction approaches from sEMG signals. We performed a review considering studies published between 2018 and 2024. Our findings reveal a prevalence of public datasets and time-domain features. We highlight the need for further research on feature engineering, algorithm exploration beyond traditional choices, and integration of DL for feature extraction.*

1. Introduction

Gesture recognition has been widely explored due to its relevance in human-machine interface applications, especially in the control of prostheses and orthotics [Bi et al. 2019]. This task uses myoelectric signals, which are representations of the electrical activity of muscles and can be captured by electrodes placed on the skin's surface. However, it is still difficult to achieve highly accurate models that can identify a large number of movements, which is fundamental when using this type of device in real life. An initiative to spread and develop the research area was presented by [Atzori et al. 2014], where the authors created the Ninapro (Non-Invasive Adaptive Prosthetics) database, enabling research groups around the world to have access to a scientific reference database to carry out tests and develop increasingly accurate algorithms.

In this context, many studies exploring Machine Learning (ML) tasks have been proposed to extract complex features from Electromyography (EMG) signals and identify movement patterns. Two alternatives are commonly explored: classical ML algorithms or Deep Learning (DL). However, there is no standard for a definitive method to perform gesture classification and feature extraction from EMG signals [Jia et al. 2020]. In the gesture recognition scenario, the signal feature extraction appears to be one of the most critical steps of the pipeline. It directly affects the results of the induced models for good or bad. Literature has complete studies benchmarking traditional feature extraction techniques for EMG signals [Phinyomark et al. 2012], but only recently DL has been investigated [Huang and Chen 2019], leaving open avenues for research in the area.

Thus, this study performs a recent review of gesture recognition studies to identify gaps in the application of more recent and robust Machine Learning (ML) algorithms in the EMG pipeline, as well as provide an analysis of the most frequently used approaches for both classification and feature extraction from EMG signals. This study aims to provide insights for researchers and practitioners, highlighting new directions for future research with gesture recognition using myoelectric signals. This paper is organized as follows: Section 2 presents some of the necessary concepts related to EMG and ML. Section 3 presents the methodology conducted to review relevant studies for EMG signal classification, while the analysis and discussions are presented in Section 4.

2. Background

2.1. Surface Electromyography

Surface Electromyography (sEMG) is a non-invasive technique widely employed to capture muscle bio-potentials, facilitating the extraction of information to monitor muscle activity [Ghaffar Nia et al. 2023]. This technique finds diverse applications, notably in pattern recognition for prosthetic control [Huang and Chen 2019]. Understanding the techniques for acquiring EMG signals is crucial for extracting pertinent features in gesture recognition through surface EMG (sEMG) signals.

Publicly available databases, such as NINAPRO, are pivotal in advancing research in this field. NINAPRO offers various datasets employing different signal acquisition methods. For instance, NINAPRO-DB5 utilizes Thalmic Myo Armbands with a 200 Hz sampling rate, while NINAPRO-DB4 employs Comet electrodes with a sampling rate of 2 kHz. The choice of sampling rate is essential, as it directly impacts signal accuracy and detail capture [Phinyomark et al. 2018].

Feature extraction is crucial in the pattern recognition of EMG signals. It involves uncovering hidden information about the signal to represent it through features capturing specific patterns [Krishnan and Athavale 2018]. This process often incorporates dimensionality reduction to produce a smaller set of representative data for precise signal description. Techniques for feature extraction in biomedical signals can be categorized into four generations: Time Domain (TD), Frequency Domain (FD), Joint time-frequency Domain (TFD), and Signal decomposition and sparse domains [Krishnan and Athavale 2018].

2.2. Machine Learning

With the expansion of data generation, Machine Learning (ML) has achieved high popularity in recent years. Progress in this area allowed a significant uptake of ML solutions by the industry, solving complex problems and providing predictions, recommendations, and classifications [Janiesch et al. 2021].

In general, ML encompasses a set of algorithms that allow programs to learn intrinsic patterns in data and perform specific tasks without the need for explicit instructions [Somvanshi et al. 2016]. Regarding this aspect, learning can be supervised, unsupervised, or by reinforcement, the most common being supervised learning. In supervised learning, the specialists provide the algorithms with the desired outputs (labels) according to their respective inputs in a training set. After the training (model induction), the algorithm (model) generates the correct outputs from any possible inputs. It can be subdivided into two sub-tasks: classification, when the model learns to assign a class or category to each input; and regression, a task where the model predicts a continuous value.

In the context of gesture recognition using myoelectric signals, the use of supervised learning is far superior to other approaches. This approach has stood out for its wide application and for presenting better performance compared to reinforcement learning.

3. Research Methodology

We performed a traditional literature review, extracting meta-information from the selected papers. Although it is not a systematic review or mapping, we explored some of their insights to list valuable information and gaps for future research in gesture classification using EMG.

3.1. Selection of the Studies

The studies included in this review were selected following specific criteria. The search used three databases: IEEE Xplore, MDPI, and Science Direct. They were selected due to their reputation, reliability, and breadth of content relevant to the scope of this study. The next step defined the keywords desired to be presented in the title or abstract of the studies of gesture classification using EMG. These keywords are detailed in Table 1.

Table 1. Search String and Keywords

Primary Search String	Keywords in Abstract
EMG Hand Gesture Classification	EMG, Classification, Recognition, Machine Learning, Deep Learning

3.2. Screening

A total of 1,577 works were returned considering the three databases. These studies were subjected to a screening process to ensure their relevance. This screening has three steps:

- **date filtering**: we selected studies published between 2018 and 2024, aiming for the most recent and relevant studies, considering only publications in conferences and journals. A total of 527 studies were removed since they did not meet the criteria;
- **title screening**: a total of 907 studies were removed, not presenting all the primary search string words contained in their titles;
- **abstract screening**: the remaining 143 studies had their abstract content analyzed considering the keywords described in Table 1, resulting in the removal of 105 works

After these steps, there were 38 remaining studies. In the final selection step, we performed a guided reading of the abstract, introduction, and conclusion sections to determine which studies would fit the review. Due to the space restrictions and the ongoing status of this research, we reported just the 23 most relevant studies in the detailed review. The entire screening process and the number of studies available in each stage are detailed in Table 2.

3.3. Metadata Extraction

For each study, we list: 1) the reference id; 2) the year of publication; 3) its title; 4) the type of study (classification or comparative); 5) datasets used in the study; 5) ML and/or DL algorithms used to classify gestures; and 6) feature extraction methods used to process EMG signals.

Table 2. Research Methodology for Article Selection

Database	Primary Search	Data Filtering	Screening by Title	Screening by Abstract	Final Selection
IEEE Xplore Access	388	300	65	12	10
MDPI	36	35	35	9	5
Elsevier	1.153	715	43	17	8
Total	1.577	1.050	143	38	23

4. Results and Discussion

Table 3 lists all the metadata extracted from the 23 selected studies, which will be discussed in more detail below. During the analysis, all studies on the classification of gestures presented a similar pipeline, with the same steps included in their solutions. This pipeline contains four main steps: data acquisition, data preparation, classification, and model evaluation. This general pipeline is depicted in Figure 1.

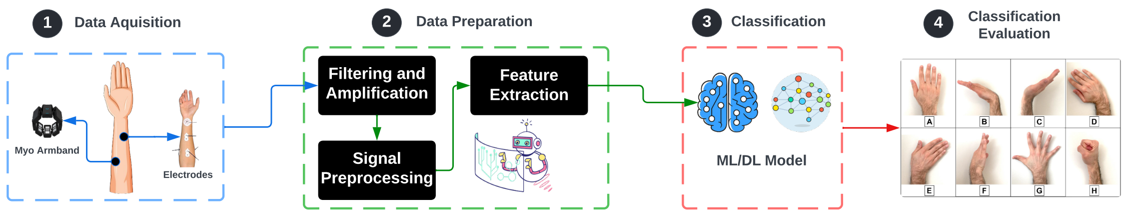

Figure 1. Gesture classification process through sEMG

The pipeline starts with a data acquisition step, generating a dataset with information from different individuals. The second step is data preparation, which involves signal preprocessing procedures and feature extraction. It aims to extract relevant features from the raw EMG signal. The third step is model induction, where a classifier is trained with the preprocessed data and extracted features. To achieve satisfactory performance, the classifier must have adequate speed and be able to handle variation in feature values. Finally, there is a model evaluation step where the induced model is evaluated according to its predictions, and gestures identified.

4.1. Overview of the studies

Different Deep Learning (DL) algorithms have been evaluated for EMG signals. In [Samadani 2018], the authors presented a comparative analysis of different Recurrent Neural Networks (RNNs) for hand gesture classification based on EMG. More specifically, LSTM and GRU architectures are considered. Additionally, the effects of an attention mechanism and varied learning rates are evaluated. Similarly, [Côté-Allard et al. 2019] introduced three new ConvNet architectures and compared them with traditional sEMG-based classifiers. A novelty was a Transfer Learning scheme that enhanced the performance of the proposed ConvNet models. [Ozdemir et al. 2022] also applied Transfer Learning (TL) for hand gesture classification using time-frequency (TF) images of sEMG signals.

In [Yoo et al. 2019], the authors investigated the most effective method for classifying myoelectric signals with a small number of electrodes. Twenty-three individuals and fourteen different hand movements were employed in the study. Furthermore, the article compared the models' accuracy of sEMG data using Discriminative Feature-Oriented Dictionary Learning (DFDL).

A different approach for classifying hand gestures with sEMG without dividing data into static and dynamic segments is proposed by [Simão et al. 2019]. It employed RNNs for sequential classification. Compared to different neural network architectures, the results showed that static and dynamic models achieved high accuracies, but dynamic models were more efficient in time.

In [Huang and Chen 2019], it was demonstrated that features with specific physical meaning, such as spectrograms, are less effective than combining such features with neural networks. The authors combined Spectrogram, CNN, and LSTM to utilize the spatial local physical and temporal sequence information fully. On the other hand, in [Sun et al. 2019], using a Generative Flow Model (GFM) alongside a SoftMax classifier is suggested to overcome the limitations of conventional classification methods in understanding the features learned by the model. The GFM achieved an accuracy of 63.86% across 53 different gestures, with the learned features appearing to be related to muscular synergy.

The study [Chen et al. 2020] proposed a new compact CNN architecture with four convolutional and single MaxPooling layers. Experiments were conducted on two public datasets (Myo Dataset and NinaPRO DB5) and using various combinations of algorithms for feature extraction and classification. The study of [Jia et al. 2020] employed ML algorithms to classify ten hand gestures based on EMG signals. It preprocessed the data by applying normalization, feature extraction, and windowing methods. Subsequently, the data is fed into multiple algorithms, and results are compared through statistical analysis. Ultimately, the study demonstrated that the proposed model, consisting of CAE+CNN using windowing and majority voting, outperformed the baselines.

The research developed by [Fajardo et al. 2021] presented a method combining CNN deep features with handcrafted values derived from a discrete spectral analysis in time. Time features extracted were MAV, SSC, and Peak Frequencies. The combined features fed a MLP classifiers to recognize signals recorded from a single-channel device. A similar benchmark is proposed by [Javaid et al. 2021]. The same structure is explored in [Javaid et al. 2021].

In the [Zhang et al. 2022] study, the authors addressed the development of ML pipeline for detecting hand movements considering gender differences to identify movement patterns. Results indicated significant differences between genders in muscle pairs during movements. The ANN algorithm benefited greatly from this method, achieving 98% accuracy. Similarly, in [Vásconez et al. 2023], the authors compared supervised learning and reinforcement learning methods for recognizing hand gestures based on EMG signals. The results suggest that supervised learning methods are more effective for EMG-based HGR systems. A similar benchmark is also conducted by [Ghaffar Nia et al. 2023], where the authors applied different ML/DL algorithms to classify four hand gestures. The results demonstrate that the ANN model achieved the best performance, reaching an accuracy of 93%.

The study by [Triwiyanto et al. 2024] develops a DL classifier based on a DNN architecture to enhance hand gesture classification and explores the impact of force variations on gesture accuracy in amputees. The classifier, which can recognize six gestures, demonstrated robustness across different strength levels (18 combinations) and achieved an average accuracy of 92%. Similarly, [Ozdemir et al. 2020] propose a deep learning approach utilizing a 50-layer CNN based on the ResNet architecture to improve prediction accuracy for hand movements, attaining 99.59% accuracy and an F1-Score of 99.57% for seven hand gestures.

[Tavakoli et al. 2018] introduce a minimalist model that classifies four gestures using only two EMG channels installed on the forearm's flexor and extensor muscles. Employing a high-dimensional feature space and SVM classifier, the system also includes methods to reject unsolicited gestures during body movement, achieving recognition accuracy between 95% and 100% for a single user. [Tepe and Demir 2022] focus on the real-time and "not real-time" classification performance of sEMG signals using SVM, comparing custom and generalized training data. The study finds that the highest accuracy for "non-real-time" classification was 96.38%, while real-time accuracy reached 95.83% for custom data and 91.79% for generalized data.

In [Khan et al. 2021], the authors employ Cubic-SVMs trained on spectral domain characteristics to classify four different hand gestures, achieving a cumulative classification accuracy of 98.9%. [Sayin et al. 2018] also focus on hand movement classification using an ANN, extracting data from five individuals with Myo Armbands. The study achieved an average classification accuracy of 88.4% using features such as MAV, SSC, WL, Willison Amp, and Mean Frequency.

[Challa et al. 2023] propose using individual EMG sensors placed on various hand parts to capture signals related to three hand gestures. The study extracted eight time-domain features and used Random Forest (RF) and Logistic Regression (LR) algorithms, achieving average accuracies of 96.66% and 94%, respectively. [Oh and Jo 2019] utilize a CNN to classify three hand gestures and three sign language gestures, finding that combining CNN with Wavelet Transform improved accuracy up to 94% for selected hand gestures.

[Esaa et al. 2022] present a method for analyzing DB5 Myo signals, focusing on segmenting long-term signals into short-term segments representing single gesture muscle activities. The method achieved high performance, with average accuracy, sensitivity, and F1-score of 86.5%, 83%, and 82.2%, respectively, for 17 gestures.

4.2. Which datasets are used?

Naturally, there are some questions we would like to answer. The first one is related to data quality and availability. If data is inadequate, it can influence the development of an unreliable and biased model. Considering the studies reported in Table 3, some of them were developed with only public datasets. Twelve studies were conducted with private datasets, and just two of them [Côté-Allard et al. 2019, Yoo et al. 2019] with both private and public data.

Considering public data, the most used was the NINAPRO-DB5 dataset, which appeared in five studies. NINAPRO-DB5 has sEMG and kinematic data from 10 intact subjects with 52 hand movements plus resting position and uses two Thalmic Myo Armbands for data acquisition with a sampling rate of 200 Hz. Seven of the studies with

Table 3. Metadata extracted from the selected studies

Ref	Title	Type	Dataset(s)	Algorithm(s)	Feature(s)
[Samadani 2018]	Gated Recurrent Neural Networks for EMG-Based Hand Gesture Classification: A Comparative Study	Comparative	NinaPRO DB2	LSTM, GRU	Not Indicated
[Sayin et al. 2018]	Hand Gesture Recognition by Using sEMG Signals for Human Machine Interaction Applications	Classification	Self Data	ANN	MAV, SSC, WL, WAMP, Mean Frequency
[Tavakoli et al. 2018]	Robust hand gesture recognition with a double channel surface EMG wearable armband and SVM classifier	Classification	Self Data	SVM	MEAN
[Côté-Allard et al. 2019]	Deep Learning for Electromyographic Hand Gesture Signal Classification Using Transfer Learning	Classification	Self Data, NinaPRO DB5	SVM, ANN, RF, KNN, LDA, ConvNet	MAV, ZC, SSC, WL, RMS, iEMG, AR, Hjorth, mDWT, SE, CEPSTRAL
[Oh and Jo 2019]	EMG-based hand gesture classification by scale average wavelet transform and CNN	Classification	Self Data	CNN	WT, STFT
[Yoo et al. 2019]	Myoelectric Signal Classification of Targeted Muscles Using Dictionary Learning	Classification	Self Data, NinaPRO DB3	DFDL, SVM, LDA, NB, RF, KNN	WT
[Simão et al. 2019]	EMG-based online classification of gestures with recurrent neural networks	Classification	UC2018DualMyo, NinaPRO DB5	FFNN, RNN, LSTM, GRU	STD
[Huang and Chen 2019]	Surface EMG Decoding for Hand Gestures Based on Spectrogram and CNN-LSTM	Classification	NinaPRO DB2	CNN, RNN, LSTM	SPECTROGRAM, CNN, RNN
[Sun et al. 2019]	sEMG-Based Hand-Gesture Classification Using a Generative Flow Model	Classification	NinaPRO DB5	GFM	GFM
[Chen et al. 2020]	Hand Gesture Recognition Using Compact CNN via Surface Electromyography Signals	Classification	Myo Dataset, NinaPRO DB5	DT, LDA, SVM, LCNN, CNN, LSTM	MAV, ZC, SSC, WL, RMS, CA, SE
[Jia et al. 2020]	Classification of electromyographic hand gesture signals using machine learning techniques	Classification	Self Data	CNN, NN, RF, DT, KNN, NB, SVM, LR, CAE+CNN	SAV, STD
[Ozdemir et al. 2020]	EMG based Hand Gesture Recognition using Deep Learning	Classification	Self Data	CNN	STFT
[Fajardo et al. 2021]	EMG hand gesture classification using handcrafted and deep features	Classification	Self Data	LDAC, SVM, MLPC, CNN	FT, WT, ZC, SSC, Mean, VAR, SKEWNESS, KURTOSIS, RMS

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Table 3. Metadata extracted from the selected studies (Continued)

Ref	Title	Type	Dataset(s)	Algorithm(s)	Feature(s)
[Javaid et al. 2021]	Classification of Hand Movements Using MYO Armband on an Embedded Platform	Classification	Self Data	QDA, SVM, RF, Gradient Boost(Tree), Subspace KNN, Bagged Tree	MAV, VAR, SD, SE, MAD, SKEWNESS, KURTOSIS, MEAN FREQUENCY, MF, THD, SNR, PSD
[Khan et al. 2021]	Supervised Machine Learning based Fast Hand Gesture Recognition and Classification Using Electromyography (EMG) Signals	Classification	Kaggle Repository	SVM	Spectral Roll off point,Spectral Flatness, Spectral Crust, Spectral Decrease, Spectral Slope, Spectral Spread
[Zhang et al. 2022]	sEMG Signals Characterization and Identification of Hand Movements by Machine Learning Considering Sex Differences	Classification	Self Data	KNN, SVM, ANN	iEMG, MAV, ICRi, VAR
[Ozdemir et al. 2022]	Hand gesture classification using time–frequency images and transfer learning based on CNN	Classification	Self Data	CNN	STFT, CWT, HHT
[Tepe and Demir 2022]	Real-Time Classification of EMG Myo Armband Data Using Support Vector Machine	Classification	Self Data	SVM	RMS, MAV, ZC, SSC, VAR, WAMP, SSI, iEMG, PKF, MNP, TTP, MNF, SM1, SM2
[Esaa et al. 2022]	Hand movements classification based on Myo armband signals	Classification	NinaPRO DB5	SVM	RMS, MAV, VAR, ZC, SSC
[Vásconez et al. 2023]	A comparison of EMG-based hand gesture recognition systems based on supervised and reinforcement learning	Comparative	EMG-EPN-612	CNN Deep Q-Network	CNN
[Ghaffar Nia et al. 2023]	EMG-Based Hand Gestures Classification Using Machine Learning Algorithms	Classification	Self Data	ANN, LSTM, KNN, SVM, RF	ANN
[Challa et al. 2023]	EMG-Based Hand Gesture Recognition Using Individual Sensors on Different Muscle Groups	Classification	Self Data	RF, LR	iEMG, MAV, SSI, RMS, WL, WAMP, WAMPV
[Triwiyanto et al. 2024]	Deep learning approach to improve the recognition of hand gesture with multi force variation using electromyography signal from amputees	Classification	Public dataset	DNN, SVM, LDA, KNN, DT	RMS, WL, AR

private datasets used only electrodes to acquire the EMG signal, using a sampling rate of 4000 Hz, 400 Hz, 2000 Hz, 1000 Hz, 2000 Hz, 2000 Hz and 2000 Hz, respectively. The other five studies used the Myo armband to perform signal acquisition with a sampling rate of 200 Hz. Finally, in the studies with both data sources, [Yoo et al. 2019] used electrodes to collect private data at a sampling rate of 500 Hz and used the public database NINAPRO-DB3, which also used electrodes, however with samples from data at a rate of 2000 Hz. The other study [Côté-Allard et al. 2019] used the Myo armband to collect data and used the NINAPRO-DB5 database.

4.3. Which feature extraction methods are being explored?

Feature extraction is an important process where the raw EMG signal is converted to a reduced set of numerical features. Selecting an appropriate feature can directly impact the performance of the induced classifiers. However, it is essential to note that no specific set of features suits all problems. Each problem may require a unique optimal set of features [Mendes Junior et al. 2020].

Considering the filtered studies, six of them explored only Time Domain (TD) features. Four studies explored Time Domain (TD) and Frequency Domain (FD). [Khan et al. 2021] explored the Spectral Domain features. However, mostly of the researches explored TD and Time-Frequency Domain features. The most investigated feature extraction method was the Average Absolute Value Amplitude (MAV), appearing in 8 studies [Chen et al. 2020, Côté-Allard et al. 2019, Zhang et al. 2022, Javaid et al. 2021, Tepe and Demir 2022, Sayin et al. 2018, Challa et al. 2023, Esaa et al. 2022], followed by the: Root Mean Square (RMS), Slope Sign Change (SSC), Zero Crossing (ZC) Wavelength (WL) and Variance (VAR). All of them are TD features.

Studies have been conducted to analyze DL techniques for feature extraction, as exemplified by [Fajardo et al. 2021], which employs a combination of features obtained through discrete spectral analysis in time and deep features extracted from a CNN. The study concludes that experimental results consistently demonstrate the superiority of the combined approach over feature extraction solely via time-spectral analysis or CNN-based extraction. The study [Huang and Chen 2019] also utilizes DL algorithms (CNN, LSTM) to extract features from the sEMG signal and concludes that the combination of traditional data preprocessing methods and deep learning positively contributes to classification accuracy.

4.4. Which are the most common ML/DL algorithms used for model induction?

Considering the algorithms used to perform sEMG signal classification, there is a wide set of solutions including: i) traditional ML - Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (kNN), Artificial Neural Network (ANN); or ii) Deep Learning (DL) architectures - Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM). In our review, just two of them explored only traditional algorithms [Yoo et al. 2019, Javaid et al. 2021], four explored only DL models [Vásconez et al. 2023, Samadani 2018, Huang and Chen 2019, Sun et al. 2019] and mostly of them evaluated both. The most traditional algorithm used was SVM, appearing in 13 of 23 studies [Chen et al. 2020, Jia et al. 2020, Ghaffar Nia et al. 2023, Côté-Allard et al. 2019, Yoo et al. 2019, Fajardo et al. 2021, Zhang et al. 2022, Javaid et al. 2021, Triwiyanto et al. 2024, Tavakoli et al. 2018, Tepe and Demir 2022, Khan et al. 2021, Esaa et al. 2022]. The DL algorithms with the highest occurrence are both: CNN (8 studies), and LSTMs (5 studies).

Even though SVMs present accurate results, the use of DL has been increasing. The study [Chen et al. 2020] presented a competitive CNN architecture for sEMG signal classification. Also, in [Jia et al. 2020], the authors proposed a CAE+CNN, reducing dimensionality, redundancy, and computational costs for EMG signal processing, achieving a classification accuracy of 99.38%.

4.5. Final Thoughts

The review of recent study literature reveals a growing trend in using DL for gesture recognition through sEMG signals. DL models have demonstrated efficiency in both characteristics extraction and classification. In addition, there is a tendency to combine handcrafted features with those extracted by deep models, which can improve classification performance. Some techniques applied in conjunction with DL algorithms, such as Transfer Learning, also improved the final performance of the induced models.

It is also noted that most studies only use accuracy as the evaluation measure, indicating an opportunity to explore other metrics, such as recall and F1 score, especially in imbalanced datasets. Another gap identified is the need for more hyperparameter tuning, which could be solved using standard ML or AutoML (Automated Machine Learning) techniques. Most of the studies covered in this review explored less than ten gestures in their proposals. Those studies that employed a larger number of gestures performed less than those that used few. The more gestures are included, the more classes need to be recognized, which raises the difficulty of differentiating them with reasonable accuracy.

Finally, it is important to point out some directions for future work. First, we intend to perform a regular, systematic review with all the required steps. Although not explicitly used, many studies listed in this work were taken from the ACM and Scopus databases. However, in a future version, we intend to explicitly include them as data sources during the initial phases of the review. Lastly, Table 3 presents studies carried out in the last five years that address the use of ML for gesture recognition by myoelectric signals, excluding studies that only present some of the methodological details we extracted. Thus, we can better describe inclusion and exclusion criteria, clarifying why these studies were described or not.

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