Deep Learning for Processing Electromyographic Signals: a Taxonomy-based Survey★

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ABSTRACT

Deep Learning (DL) has been recently employed to build smart systems that perform incredibly well in a wide range of tasks, such as image recognition, machine translation, and self-driving cars. In several fields the considerable improvement in the computing hardware and the increasing need for big data analytics has boosted DL work. In recent years physiological signal processing has strongly benefited from deep learning. In general, there is an exponential increase in the number of studies concerning the processing of electromyographic (EMG) signals using DL methods. This phenomenon is mostly explained by the current limitation of myoelectric controlled prostheses as well as the recent release of large EMG recording datasets, e.g. Ninapro. Such a growing trend has inspired us to seek and review recent papers focusing on processing EMG signals using DL methods. Referring to the Scopus database, a systematic literature search of papers published between January 2014 and March 2019 was carried out, and sixty-five papers were chosen for review after a full text analysis. The bibliometric research revealed that the reviewed papers can be grouped in four main categories according to the final application of the EMG signal analysis: Hand Gesture Classification, Speech and Emotion Classification, Sleep Stage Classification and Other Applications. The review process also confirmed the increasing trend in terms of published papers, the number of papers published in 2018 is indeed four times the amount of papers published the year before. As expected, most of the analyzed papers (≈60 %) concern the identification of hand gestures, thus supporting our hypothesis. Finally, it is worth reporting that the convolutional neural network (CNN) is the most used topology among the several involved DL architectures, in fact, the sixty percent approximately of the reviewed articles consider a CNN.

1. Introduction

In many fields surface electromyography (sEMG) is frequently used [141], such as neurophysiology [74], ergonomics and occupational medicine [122], posture analysis [46], movement and gait analysis [145], EMG-based biofeedback [57], exercise physiology and sports [26], as well as human-machine interaction/interfaces (HMI) [38, 14, 186]. In detail, electromyographic signals (EMG) are biomedical signals that provide representations of the electrical potential fields produced by the membrane depolarization of the outest muscle fibers. An EMG signal corresponds to a train of motor unit action potential (MUAPs) showing each muscle response to neural stimulation and presents a random behavior. Shapes and firing rates of MUAP in EMG signals revealed to be important source of information that can be used in several applications. In particular, EMG signal detection requires the use of intramuscular electrodes or surface ones positioned at a certain distance from sources, i.e., muscle fibers. Moreover, EMG detectors, especially surface electrodes, collect signals from different motor units at the same time thus leading to an interaction of different signals. Just before the amplification, the amplitude range of the EMG signal is $\pm$5 mV and is affected by several types of noise: a) inherent noise in electronics equipment, b) ambient noise, c) motion artifacts due to the movement of both electrode interfaces and cables. There are also other factors affecting the EMG signals, besides noise [142]: a) electrode structures and placements, b) physiological, anatomical, biochemical characteristics of muscles fibers and the amount and type of tissues between muscle surfaces and electrodes, and c) crosstalk from nearby muscles. All such factors strongly affect the characteristics of collected signals (e.g. signal amplitudes and frequency contents), thus explaining the intra-subject / inter-subject variability that may be observed when acquiring EMG signals. Clinical/HMI applications of EMG signals should clearly rely on reliability and repeatability of used techniques. The repeatability of sEMG measurements has been tested by many researchers, and a critical issue concerning features of single-channel sEMG signals, obtained in different tests and days, concerns with the repeatability of electrode positions and inter-electrode distances [73, 130, 143, 157]. It can be observed that the reproducibility of estimates of the sEMG characteristics under isometric or dynamic conditions is generally not excellent. This observation is partially caused by a persisting lack of standards in this field. A substantial contribution to this issue has been received by some researchers' effort in defining the standard

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procedures to follow for acquiring EMG signals [77], starting from the use of electrodes grids and the automatic identification of regions of interest. Besides electrode design, many researchers also started to investigate new signal processing techniques that could robustly decipher all key information encoded in the EMG signals; some of these techniques are based on artificial intelligence (AI) [139].

Researchers interested in myoelectric man-machine interfaces have long been aware of the high potential of the AI in EMG signal (pre-)processing [48, 116] and myoelectric prosthesis represent one of the most worthy application examples. In fact, thanks to the direct association between the action potential produced by the motor neurons and the electrical activity induced in the innervated muscle fibers, muscles cab be considered as biological amplifiers of efferent nerve activity in applications of man-machine interfacing. Nowadays, data-driven approaches, which are mainly based on machine learning (ML) techniques, represent the most used solution for implementing the mapping between EMG signals and the device to be driven [186, 75, 113, 40] after the model-driven approaches that use EMG signals as the input to specific physical models of the musculotendon system [38, 39, 37, 36, 43, 41].

Over the past decades the weakness of the myoelectric prosthetic hands offered by industry and the need to develop more intuitive and efficacious EMG-based human-prosthesis interfaces have clearly boosted the research on data-driven approaches [14]. Therefore, several researchers started focusing on developing new machine learning-based methods for detecting the intended hand gesture from forearm muscle activations and better controlling prosthetic devices [79]. ML techniques have demonstrated to be valid in several others domains where the quantitative EMG (or QEMG) plays an important role [204]. As an example, ML approaches have been widely used to develop intelligent systems for supporting clinicians in diagnosing and staging diseases that affects the human motor system, such as myopathy, neuropathy, amyotrophic lateral sclerosis, Parkinson's disease [85, 177, 147, 90, 204, 117, 42, 138, 45, 47].

In biomedical applications, as well as in other contexts, the increasing amount of multi-modal physiological information, together with an increased problem complexity and all subsequent difficulties concerning the extraction of meaningful hand-crafted and domain-dependent features, limit the power of the traditional shallow machine learning approaches, despite the considerable research works carried out for optimising performance of available classifiers [107, 108, 66, 133, 216, 93, 29, 44, 67]. Deep Learning (DL) overcomes these limitations allowing an increasing transformation of data into a more abstract representation.

Deep learning is actually a growing breakthrough technology in data analysis [208, 34, 134, 103, 27, 196, 194, 137, 135, 211] and it is becoming as the leading ML approach both in general image processing and computer vision domains [33, 31, 35, 201, 195, 218, 136, 62, 54]. Moreover, promising results emerge from deep learning networks in various medical fields, since deep learning can be intended as an improvement of artificial neural networks, based on more layers that enable higher abstraction levels and better predictions from data [30, 28].

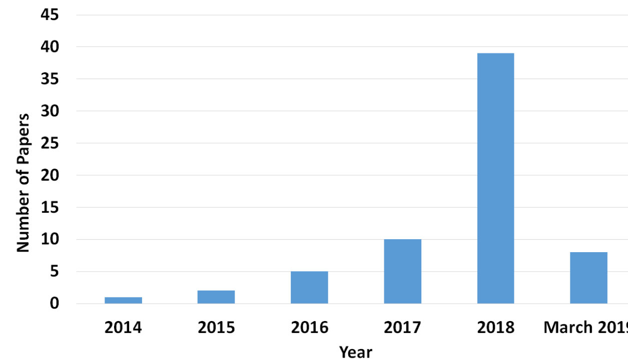

Figure 1: Number of published papers related to Deep Learning and EMG signals per year.

Researchers have therefore begun to investigate the ability of DL to process and decode sEMG data (see Figure 1), also thanks to the recent launch of several EMG recording benchmark databases, e.g. NinaPro [16], BioPatRec [152], CapgMyo [80], UCI Database [167], CSL-HDEMG [8], PhysioNet [86] and MASS-DB [151]. Such a growing trend in science also includes many other physiological signals, for instance electroencephalogram (EEG), electrocardiogram (ECG), and electrooculogram (EOG), as discussed in two recent surveys [78, 76]. Nonetheless, as these two surveys address papers published up to December 2017, the number of investigated articles related to the analysis of EMG signals using deep learning techniques is limited to fifteen. Therefore, since it seems to be an exponential growing interest on this subject (see Figure 1), an updated review is necessary to comprehend the current challenges and future perspectives.

In this work, an amount of papers about the application of DL techniques on EMG data published from 2014 till March 2019 has been analyzed and review. After selecting 65 articles on the Scopus database for the survey, the papers were reviewed and classified into four main categories according to the considered final application of the EMG signal processing: (1) Hand Gesture Classification; (2) Speech and Emotion Classification; (3) Sleep Stage Classification; (4) Other Applications. As expected, from the full text analysis, it resulted that most of the selected papers were published from the beginning of the 2018, thus supporting the rationale of this work. Moreover, it turned out that the majority of the reviewed papers are related to the hand gesture recognition and classification, but also other applications, e.g. sleep stage, speech and emotion classification, are taking advantage of DL, since they are based on the analysis of a big amount of data.

2. Deep Learning Architectures

During the last decades, deep learning techniques have faced a growing research interest because of their inherent capability of overcoming the drawbacks of traditional machine learning algorithms based on hand-crafted features [134, 127, 178, 217]. Deep learning techniques have also been found to be suitable for the analysis of big data with successful applications to computer vision, speech recognition, pattern recognition, natural language processing, and recommendation systems [134, 106, 105]. According to recent surveys on DL methods [134, 92], it can be stated that there are five main deep learning architectures: deep neural networks (DNNs), deep recurrent neural networks (RNN), convolutional neural networks (CNNs), autoencoders (AEs) and deep belief networks (DBNs). The main properties of the above cited DL techniques are herein briefly summarized.

2.1. Deep Feedforward Neural Networks

Deep neural networks or multilayer perceptrons (MLPs) can be described as extensions of shallow feedforward neural networks featuring an increased number of layers and neuron units per layer [134, 87]. A common feedforward network behaves by using a composition of several different functions; the overall length of the whole function gives the depth of the model and the deep learning definition. The complexity of this function can be easily extended by adding an increasing number of layers. These kinds of networks are called feedforward networks because the information flow is computed through the functions of each layer until outputs. There are not any feedback connections able to feed back in input the obtained outputs of the model. A deep feedforward neural network is trained by using a supervised learning procedure that provides a mapping function between general input patterns and corresponding targets. In deep neural networks learning requires computing gradients of complicated functions, and proper back-propagation algorithm and its recent generalizations can be used to effectively compute these gradients.

2.2. Deep Recurrent Neural Networks

It is well known that traditional neural network topologies can process and make decisions on the basis of the understanding of their current input space. Decisions, indeed, consider only network inputs, with neither information of previous ones nor inner states of the network itself. Feedforward neural networks that include feedback connections are called recurrent neural networks (RNN) [87]. In detail, in the RNN architecture, internal states store the values of activations generated at each time step, thus providing temporal memory properties [20]. Outputs of RNNs can depend both on the current states and previous network ones (i.e. RNNs can produce a decision on a video frame using the information of the previous ones). As a consequence, the number of previous network states to consider reveals to be an important parameter to be set. Furthermore, RNNs show their main limitations when there is the need of learning long-range time dependencies [20, 25, 156]. This important limitation has been addressed by introducing the long short-term memory (LSTM) network, which, thanks to a chain-like structure, is able to face the learn long-term dependencies problem [104, 215].

2.3. Convolutional Neural Networks

Convolutional neural networks were defined by Goodfellow et al. as artificial neural networks that use convolution in place of a general matrix multiplication in at least one of their layers [87, 55, 190, 196, 54, 96, 131, 84, 83, 165, 221, 82, 160, 173, 97, 179, 92]. A CNN makes is based on weights, biases and non-linear activation functions as an ANN but, in addition, considers a mathematical convolution operation in at least one layer. As stated in the previous paragraphs, regular fully connected networks compute a transformation of the input layer by using the weight of the fully connected hidden layers. Each neuron of each layer is connected to all the neurons of the previous one, being independent from the other neurons (i.e. there are not connection among neurons belonging to the same layer). Due to their architecture, DNNs are not suitable to process data with grid-like topology (i.e. time series, image data); in detail, due to the huge amount of involved weights, regular ANNs and DNNs do not scale well in image processing applications; the number of parameters to be learned, indeed, increases rapidly as the image resolution grows up. For this reason, the CNN architecture revealed to be particularly suitable when facing domains involving multidimensional data, such as images or volumetric data. The convolutional layer is the core of a CNN and carries out the computational reduction. For the sake of a better comprehension, convolution layers can be considered as a set of filters, whose weights are learned during the training phase. The filter shape is properly selected and, for a bi-dimensional convolution, the depth size is the same of the input space; as an example, for RGB images, the shape of filters of the first convolution layer is NxNx3, where N is an odd number lower than the input width and height (usually 3, 5 or 7) and 3 because of the images depth (or color channels). The forward computation consists of a filter convolution across width and height, i.e. filter sliding with dot product among filter weights and corresponding inputs. The corresponding output is a bi-dimensional activation map for each filter and the corresponding stack of the activation maps along the depth dimension is the output of the convolutional layer. More convolution layers could be arranged together with non-linear layers. In applications involving classification, one or more fully connected layers are used as output layers of the network to compute the class scores; an increase of depth clearly leads to an increase of the trained parameters, however the depth of CNNs and the complexity of the topology are usually linked to performance outcomes. Due to the difficulties concerning the training of deep CNNs, a technique called transfer learning (TL) is commonly used [193]. TL consists is using a pretrained CNN network on a very large dataset as initialization or as a feature extractor. The first approach is specifically used to fine tune the parameters of the pretrained network continuing the training on a new dataset, with the possibility to fine-tune the whole network or just a specific section (i.e. the first convolution layers that learn to extract generic features could have fixed weights). The latter approach considers the pretrained network as a feature extractor; in detail, the fully connected layers are removed and extracted features are then used as input of a new fully connected layer or different classifiers, such as support vector machines.

2.4. Autoencoders

Autoencoders are particular types of neural networks trained with the aim to copy input data to the corresponding output layer [87]. Hence the size of the input layer is the same as the output layer. Autoencoders are trained with an unsupervised learning technique able to leverage neural networks for a representation learning task, e.g. denoising, feature reduction, clustering, image processing [212, 202, 203, 132, 101, 214, 114, 220, 159, 88, 123, 223, 185]. An autoencoder has a hidden layer that generates a latent code that represents the input. Such a neural network is composed of two main parts: an encoder that codifies each input into the code and a decoder that produces the reconstruction. A valid autoencoder is not trained to perfectly copy inputs, but to produce outputs that resemble the training data. According to both the internal structure of the network and their training modalities, there are five main AE families [87]: under-complete AE, regularized AE, sparse AE, denoising AE and variational AE.

2.5. Deep Belief Networks

Deep belief networks were one of the first non-convolutional models to admit training of deep architectures [87, 124, 148, 125, 126, 166, 210, 209]. Before the introduction of deep belief networks, deep models were considered too difficult to optimize, but, in 2006, Hinton et al. proposed a novel efficient learning process demonstrating that deep architectures could be successful by outperforming the best approach for the MNIST dataset at that moment [100]. A deep belief network was defined as a stack of restricted Boltzmann machines (RBMs) [102, 99, 149]. Each stacked RBM layer communicates both with previous and subsequent layers, but there is no intra-layer communication – this is the restriction in an RBM. RBMs are two-layer generative stochastic neural networks that can learn a probability distribution over its set of input, thus an RBM is an unsupervised model. A deep belief network can then be used either to cluster unlabeled data in an unsupervised learning scenario or to create a classifier. Concerning the clustering problem, several works have demonstrated that applications of DBNs are more effective than ANNs [134]. When a DBN is used for a classification problem, it might end with a softmax layer. The training process is composed of two subsequent steps: pre-training and fine-tuning. The pre-training helps in optimization by better initializing the weights of all the layers. The Greedy Layer wise algorithm is used to rapidly train each layer sequentially starting from the bottom layer. Finally, a fine-tuning, that can be achieved by a wake sleep algorithm or back propagation, slightly modifies the whole network to better discriminate among different labels.

2.6. Discussion about Deep Learning

In the last years deep neural networks shown their dominating performance in many fields leading to the development of several network topologies. Regarding the theory behind the training of neural networks, it is limited to topologies with one of few hidden layers; whereas the theory behind multilayer networks remains largely unsettled [6]. Allen-Zhu et al. attempt to formalize a convergence theory behind deep learning and to explain the empirical finding by Goodfellow et al. [89], proving that stochastic gradient descent algorithm is able to find a global minima in polynomial time; the authors assess the applicability of their theory to fully connected neural networks, convolutional neural networks, and residual neural networks [6].

The problem of network convergence was faced by Ioffe et al. too. The authors focus on the difficulties of deep neural networks training due to the changing of layers distribution over the training phase, as the parameters of the previous layers change; this phenomenon, referred by the authors as internal covariate shift, slows down the training by requiring a lower learning rate. Ioffe et al. successfully addressed the problem by normalizing layer inputs and performing the normalization for each training batch; this new Batch Normalization layer allows to increase the learning rates and to reduce the effects of the initialization [111]. Nowadays, the Batch Normalization layer is widely used and considered as a standard layer in deep neural networks and convolutional neural networks.

Regarding the training time, despite the popularity of deep learning in wide application fields, there is not a well know methodology to predict the training time for a specific problem. Common applications try to infer the training time as a linear extension of the single epoch timing or from the number of operations. These approaches are usually an oversimplification because they ignore secondary aspects of the training such as data loading or non-optimal parallel execution. Starting from the definition of the training time as the product of the training time per epoch and the number of epochs which need to be performed to reach the desired level of accuracy, Justus et al. proposed an alternative approach in which a deep learning network is trained to predict the execution time for parts of a deep learning network. The combination of the individual parts provide the prediction of the whole execution time [115].

Despite the deep learning becomes a widely and largely used in many artificial intelligence problems due to its ability to outperform alternative techniques and even humans, they are not general purpose. The main drawback is the requirement of large amount of data (and annotated output data in some applications); this sometimes biases the researcher to work on specific data that lack of generalization, such as benchmarked datasets, or on tasks where annotation is easy to obtain instead of on the tasks itself. Fortunately, the research community continuously produce and share new public dataset, and there are techniques that allow to reduce the need of supervision (i.e. transfer learning, unsupervised learning, and weakly supervised learning) [205].

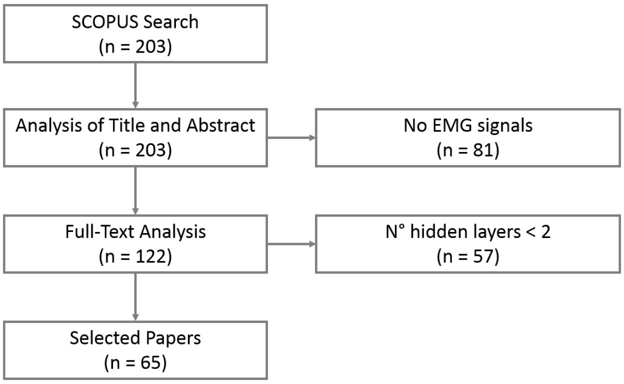

Figure 2: Paper Selection Process.

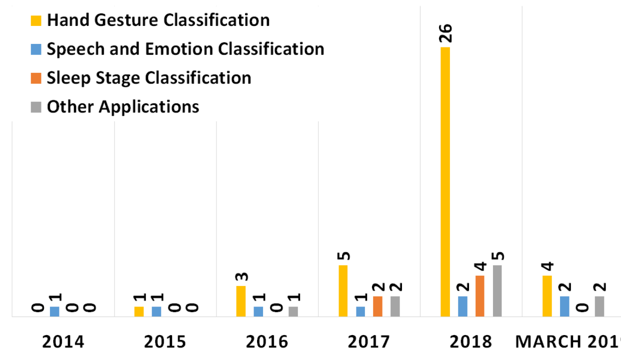

Figure 3: Number of papers of each individuated category per year.

3. Paper search methodology

The literature search was performed for articles published on Scopus until March 2019. The quest concentrated on papers written in English and included a selection of keywords covering the two main topics "Deep Learning Methods" and "Electromyographic Signals" the specific used query string is “*(TITLE-ABS-KEY ("deep learning*" OR "deep neur*" OR *cnn* OR autoencoder OR *lstm* OR *rnn* OR "recurrent neur*" OR dbn OR rbm OR "deep belief network" OR "restricted Boltzmann machine") AND TITLE-ABS-KEY (electromyo* OR *emg* OR myoelectric)) AND PUBYEAR > 2013 AND (LIMIT-TO (LANGUAGE , "English"))*”). Figure 2 reports the flow of information through the different phases of the paper selection process [144]. An amount of 203 papers was originally selected from a Scopus Bibliometric Research. Then, all findings, either based on topologies composed of only one hidden layer or related to the processing of other types of signals (such as EEG, video or photos), have been ruled out as reported in Figure 2. Among all found papers, an amount of 65 articles, published in international journals or conference proceedings, have been selected for the herein developed review.

Two out of 65 papers are survey/review articles [78, 76]. The remaining 63 papers have been then classified in four main categories according to the final goal of the EMG signal processing (see Figure 3): (1) Hand Gesture Classification; (2) Speech and Emotion Classification; (3) Sleep Stage Classification; (4) Other Applications:

- ***Hand Gesture Classification.*** Every paper in this category explores deep learning techniques for hand/finger gesture recognition and identification by examining EMG signals obtained from the main upper limb muscles. These papers reflect most of the chosen articles.
- ***Speech and Emotion Classification.*** The research papers that belong to this group use deep learning methods for identification of speech and emotion through EMG signals recorded from the facial muscles.
- ***Sleep Stage Classification.*** The papers falling within this section are researching the application of deep neural networks for sleep stage identification and rating. All these articles consider the processing physiological multi-modal signals like EMGs, EEGs, EOGs and ECGs.
- ***Other Applications.*** All the papers which could not be allocated in to one of the classes listed above were marked as "Other Applications".

4. Content review

The bibliometric research clearly revealed the existence of four classification criteria of papers according to different final aims: (1) Hand Gesture Classification (see Table 1); (2) Speech and Emotion Classification (see Table 2); (3) Sleep Stage Classification (see Table 3); (4) Other Applications (see Table 4).

4.1. Hand Gesture Classification

As clearly shown in Figure 3, most of the selected papers concern with the processing of EMG signals acquired from the muscles of upper limbs. Such finding is closely linked to many researchers' recently growing interests in applying DL methods to a myoelectric control of prosthesis and advanced natural human-machine interaction interfaces [186]. After a careful review of all papers within this class, CNNs revealed to be the most commonly used networks, followed by AEs, RNNs, and DBNs (see Figure 5). According to the increasing popularity of CNNs in several research fields due to their proven high performance, several authors proposed classifiers based on CNNs only [14, 155, 94, 183, 174, 18, 199, 161, 163, 171, 7, 64, 120, 22, 180, 192, 13, 213, 68, 56, 52, 70, 140], or on both CNNs-RNNs [81, 200, 198, 191], or on CNN-AE [219]. Some authors have alternatively developed multi-class classifiers entirely based on deep AEs [222, 110, 128, 164, 163, 3], RNNs [175, 98, 181] or DBNs [170, 169]. The reviewed papers are presented in Table 1, where, for each paper, acquisition setups or used database, number of classified classes, i.e. hand/finger gestures, and summarized results are reported.

4.2. Speech and Emotion Classification

In this section, all papers related to facial electromyography (fEMG) research have been listed. Although the number of found papers is not high (see Figure 3), a particular category is assumed for such papers due to the significant effect of speech and emotion classification in clinical applications. More in detail, four papers out of seven examine the potential of fEMG-based speech recognition techniques [189, 61, 188, 71, 146], whereas three papers out of seven focus on emotion detection and classification [118, 1, 95]. Regarding with the used methodology, the selected papers use standard deep neural MLP networks [189, 61, 188], CNNs [71, 146], and DBNs [118, 1, 95]. In Table 2 the number of classified categories, i.e. words or emotions, the summary results, the acquisition setup or the used database, are listed for each checked paper falling into this class.

4.3. Sleep Stage Classification

In addition to the two above mentioned categories, some papers often refer to sleep stage classification and rating. Current sleep medicine relies on supervised polysomnographic recording analysis, which involves electroencephalogram, electromyogram, and electrooculogram signals. This analysis explains why these particular papers suggest to process multimodal information like physiological signals, for example EEG, EMG, EOG, ECG. However, it is important noting that the role of EMG signals in the identification of sleep stage is not as primary as the contribution of the EEG signal. Nevertheless, the findings of all selected and updated studies show that the quality of classification benefits from the use of EMG signals. Many research studies in this group focused on CNNs as well as the "Hand Gesture Classification" articles [49, 51, 11, 12, 184]. Only one work relies on the integration of a DBN with an RNN [206]. Table 3 reports acquisition set-ups or used databases, number of classified classes, i.e. sleep stages, and summarized results of each article.

4.4. Other Applications

Ten papers out of 63 have not been included in any of the above presented three categories. Due to the small number of uncategorized papers, in this subsection the main objective of each of the ten papers is briefly described including the specific used deep learning technique. Su et al. have proposed a DBN to predict the onset of muscle fatigue that occurs while holding a load with the upper limbs [176]. Belo and his colleagues have developed a deep RNN to synthesize biosignals including the EMG activations [23]. Xia et al. proposed a CNN integrated with an RNN for the estimation of hand trajectory [197]. Said et al. presented a stacked autoencoder for the compression of multimodal biosignals, i.e. EMG and EEG [24]. Guo et al. developed and tested a CNN able to predict EMG signals given multi-unit neural signals recorded with multiple electrode arrays from the corticospinal tract in rats [91]. Bakiya et al. proposed a DNN to discriminate healthy subjects from patients affected by the amyotrophic lateral sclerosis or myopathy [17]. Sengur et al. presented a CNN for an efficient classification of amyotrophic lateral sclerosis and normal electromyogram signals [168]. Chen et al. implemented a DBN to extract EMG features for the estimation of the human lower limb flexion/extension joint angles [53]. Rane et al. developed a CNN for lower limb muscle force estimation during gait [158]. Finally, Akhundov et al. proposed a CNN for the rating of the EMG signal quality in terms of signal to noise ratio [4]. Table 4 reports acquisition setups or used database, main goals of each study, and summarized results of each above cited study.

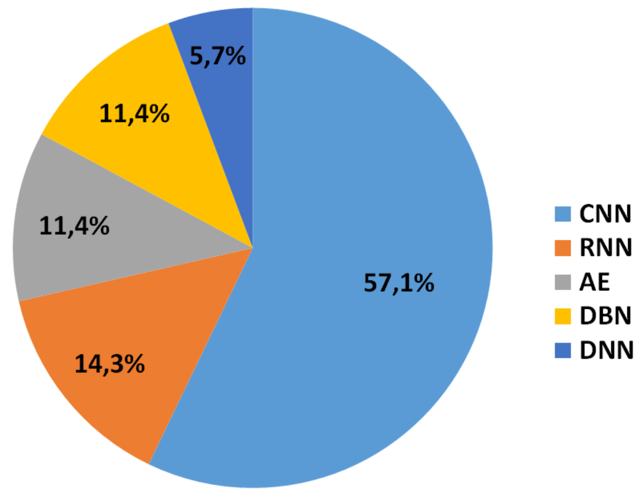

Figure 4: Frequencies of the used deep learning techniques among reviewed papers. Papers that investigate mixed approaches are accounted more times.

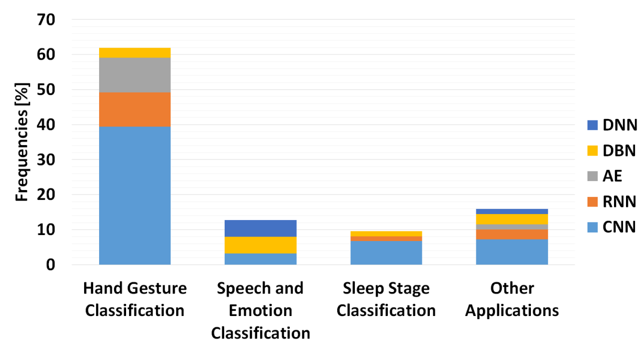

Figure 5: Frequencies of the used deep learning techniques among the reviewed papers reported for each individuated category.

5. Published Datasets

Although some of analyzed papers concerns with studies conducted on proprietary datasets generated from scratch, most of them works on publicly available benchmark datasets, aiming at a validation of new approaches comparing them with the state-of-the-art. In this section, the most used benchmark datasets that have been conveniently organized according to the clusters of applications are introduced. The summarized features of considered datasets are reported within

Reference	DL Algorithm	Data	N° of Classes	Results
Shim et al., 2015 [170]	DBN	28 Subjects. 2 Bipolar EMG signals.	5	Accuracy: 88.6 %
Atzori et al., 2016 [14]	CNN	NinaPro Database	50	Accuracy: - Dataset 1: 66.6 % - Dataset 2: 60.3 % - Dataset 3: 38.1 %
Shim et al., 2016 [169]	DBN	28 Subjects. 2 Bipolar EMG signals.	5	Accuracy: 89.3 %
Park et al., 2016 [155]	CNN	NinaPro Database	6	Accuracy: ≈93.0 %
Asai et al., 2017 [13]	CNN	8 Bipolar EMG Signals.	4	Accuracy: ≈83.0 %
Zhengyi et al., 2017 [219]	CNN-AE	NinaPro Database	23	Accuracy: 85.0 %
Zhai et al., 2017 [213]	CNN	NinaPro Database	50	Accuracy: 78.7 %
Du et al., 2017 [68]	CNN	a)NinaPro, b)CSL-HDEMG, c)CapgMyo Databases	a)12, b)12, c)27	Accuracy: a)>90 %, b)>95 %, c)>98 %
Côté-Allard et al., 2017 [56]	CNN	17 Subjects. 8 EMG Bipolar Signals.	7	Accuracy: 97.8 %
Zia-ur-Rehman et al., 2018 [222]	AE	7 Subjects. 6 Bipolar EMG Signals.	11	Accuracy: ≈98.5 %
Kim et al., 2018 [120]	CNN	NinaPro Database	6	Accuracy: >90 %
Chen et al., 2018 [52]	CNN	8 Subjects. 16 EMG Bipolar Signals.	a)5 - Wrist b)5 - Finger	Accuracy: a)73.8 %, b)49.8 %
Geng et al., 2018 [81]	CNN-RNN	a)NinaPro-DB1, b)NinaPro-DB2, c)BioPatRec, d)CapgMyo, e)CSL-HDEMG.	a)52, b)50, c)26, d)8, e)27	Accuracy: a)87.0 %, b)82.2 %, c)94.1 %, d)99.7 %, e)94.5 %
Ibrahim et al., 2018 [110]	AE	9 Subjects. 2 EMG Bipolar Signals.	10	Accuracy: 92.2 %
Duan et al., 2018 [70]	CNN	50 Subjects. 8 EMG Bipolar Signals.	10	Accuracy: 94.6 %
Hartwell et al., 2018 [94]	CNN	10 Subjects. 8 EMG Bipolar Signals.	14	Accuracy: 84.2 %
Sosin et al., 2018 [175]	RNN	5 Subjects. 8 EMG Bipolar Signals.	10	RMSE (finger angles estimation): 18.6°
Tsinganos et al., 2018 [183]	CNN	Ninapro Database - DB1	52	Accuracy: 70.5 %
Ban et al., 2018 [18]	CNN	15 Subjects. 8 EMG Bipolar Signals.	8	Accuracy: 95.0 %
Xu et al., 2018 [200]	CNN-RNN	8 Subjects. 4x16 HD Electrode array.	1	RMSE% (hand force estimation): 8.7
Xing et al., 2018 [199]	CNN	Ninapro - DB2	17	Accuracy: 83.2 %
Redrovan et al., 2018 [161]	CNN	5 Subjects. 8 EMG Bipolar Signals.	8	Accuracy: 91.3 %
Xie et al., 2018 [198]	CNN-RNN	10 Subjects. 8x24 Electrode Array.	10	Error Rate: 1.5 %
Zia-ur-Rehman et al., 2018 [162]	CNN	7 Subjects. 8 EMG Bipolar Signals.	11	Classification Error: 9.8 %
Li et al., 2018 [129]	AE	15 Subjects. 8 EMG Bipolar Signals	8	Accuracy: > 95.0 %
Zia-ur-Rehman et al., 2018 [164]	AE	8 Subjects. 6 EMG Bipolar Signals.	11	Accuracy: 98.3 %
Ameri et al., 2018 [7]	CNN	17 Subjects. 8 EMG Bipolar Signals.	8	Accuracy: 91.6 %
Teban et al., 2018 [181]	RNN	8 EMG Bipolar Signals.	1	RMSE (finger angle estimation): 8 %
Ding et al., 2018 [65]	CNN	NinaPro database (DB2)	50	Accuracy: 78.9 %
Wangshow et al., 2018 [191]	CNN-RNN	5 Subjects. 8 EMG Bipolar Signals + IMU	50	Accuracy: 87.3 %
Zia-ur-Rehman et al., 2018 [163]	AE	16 Subjects. Six sEMG and six iEMG electrodes	11	Classification error: < 1%
He et al., 2018 [98]	RNN	NinaPro Database.	52	Accuracy: 75.5 %
Ahmad et al., 2018 [2]	AE	5 EMG Bipolar Signals.	5	Accuracy: 99.3 %
Becker et al., 2018 [21]	CNN	11 Subjects. 8 EMG Bipolar Signals.	3	Accuracy: 91.2 %
Tao et al., 2018 [180]	CNN	8 Subjects. 8 EMG Bipolar Signals + IMU	6	Accuracy: 98.0 %
Maufroy et al., 2019 [140]	CNN	5 Subjects. 8 EMG Bipolar Signals.	21	Accuracy: 91.1 %
Song et al., 2019 [174]	CNN	UCI Database	6	Accuracy: 87.5 %
Shioji et al., 2019 [171]	CNN	8 Subjects. 8 EMG Bipolar Signals.	3	Accuracy: 94.6 %
Wei et al., 2019 [192]	CNN	a) NinaPro database (DB1), b) CSL-HDEMG database c) CapgMyo database (DB-a)	a) 52 b) 27 c) 8	Accuracy: a) 85.0%, b) 95.4%, c) 99.7%

Table 1
Summary of publications about Hand Gesture Classification

Reference	DL Algorithm	Objective	Data	N° of Classes	Results
Wand et al., 2014 [189]	DNN	Speech Recognition	20 Subjects. 1x8 and 4x8 electrode arrays.	a)45, b)8, c)5, d)3, e)4, f)4, g)2	Accuracy: a)15.7 %, b)45.7 %, c)38.3 %, d)60.2 %, e)41.4 %, f)38.3 %, g)70.7 %
Diener et al., 2015 [61]	DNN	Speech Synthesis	10 Subjects. a)6 EMG channels. b)4x8 EMG array.	19	DNN performs better than the Gaussian Map in utterances generation.
Wand et al., 2016 [188]	DNN	Speech Recognition	EMG-UKA Corpus	10	Word Error Rate: 19.4 %
Elmahdy et al., 2017 [72]	CNN	Speech Recognition	10 subjects. 2 EMG Channels.	20	Word Error Rate: 9.2 %
Kawde et al., 2018 [118]	DBN	Emotion Classification	DEAP database	Valence: 9 Arousal: 5 Dominance: 5	Accuracy: Valence: 75.8 % Arousal: 70.7 % Dominance: 69.1 %
Abtahi et al., 2018 [1]	DBN	Emotion Classification	12 subjects. 6 EMG channels.	7	Accuracy: 62.8 %
Morikawa et al., 2019 [146]	CNN	Speech Recognition	5 subjects. EMG Channels.	5	Accuracy: 47.6 %
Hassan et al., 2019 [95]	DBN	Emotion Classification	DEAP database	5	Accuracy: 89.5 %

Table 2
Summary of publications about Speech and Emotion Classification

Reference	DL Algorithm	Data	N° of Classes	Results
Cen et al., 2017 [50]	CNN	PhysioNet Database	5	Accuracy: 69.8 %
Yulita et al., 2017 [207]	DBN	PhysioNet Database	5	Precision: 86.1 % Recall: 72.3 %
Chambon et al., 2018 [51]	CNN	MASS Dataset - session 3	5	Accuracy: $\approx$ 80.0%
Andreotti et al., 2018 [11]	CNN	SLPEDF-DB, MASS-DB, CAPSLP-DB, RBD-DB	5	Sensitivity: $>$ 60%
Vetek et al., 2018 [184]	CNN-RNN	38 Subjects. EEG, EOG and EMG.	5	Precision: 81.7 % Recall: 78.8 %
Andreotti et al., 2018 [12]	CNN	MASS-DB	5	Accuracy: 90.0 %

Table 3
Summary of publications about Sleep Stage Classification

Table 6 and Table 7.

5.1. Hand Gesture Classification

The database of NinaPro project [15] is a publicly accessible database used for research studies on hand gesture recognition and decoding and for development of hand prostheses. NinaPro-DB1 is the first version of this database and contains sparse multi-channel sEMG samples of 52 gestures performed by 27 intact subjects. Each sample was recorded at a sampling rate of 100 Hz with 10 sparsely located electrodes placed on upper forearms. The first 8 components correspond to the equally spaced electrodes around the forearm at the height of the radiohumeral joint, where the last two components corresponded to electrodes placed on the main activity spots of the flexor digitorum superficialis and the extensor digitorum superficialis, respectively. All hand poses were recorded by a 22-sensor CyberGlove II and synchronized with all sEMG signals.

NinaPro-DB2 and NinaPro-D3 [15] are the second and the third version of the NinaPro project database, they contain tasks relating to upper-limb movement respectively performed by healthy subjects and amputees. In particular, NinaPro-DB2 contains sEMG data recordings from 40 intact subjects (12 females, 6 left handed and aged 29.9±3.4 years) who perform 49 types of hand movement (8 isometric and isotonic hand configurations, 9 basic wrist movements, 23 grasping and functional movements and 9 force patterns) relevant to the activities of daily living. NinaPro-DB3 comprises data from 11 transradial amputees with disabilities of the arm, shoulder, and hand, with a score ranging from 1.67 to 86.67 (on a scale of 0–100) for each subject's ability to perform the same hand movements as in NinaPro-DB2. Each movement is repeated 6 times with a rest period of three seconds between them. The EMG signal was recorded using 12 electrodes of a Delsys Trigno Wireless system, which provides a sampling rate of 2 kHz. Then, the recorded signal was fil-

Reference	DL Algorithm	Application	Data	Results
Su et al., 2016 [176]	DBN	Muscle Fatigue Detection	6 healthy Subjects. 1 EMG Channel.	Accuracy: >80 %
Belo et al., 2017 [23]	RNN	EMG Signal Synthesis	14 Subjects. 14 EMG signals.	Averaged RMSE: < 28.0
Ben Said et al., 2017 [24]	AE	Multimodal Data Compression	DEAP Dataset	Compression Ratio: 90 %
Xia et al., 2018 [197]	CNN-RNN	3D Hand Trajectory Reconstruction	8 Subjects. 5 Bipolar EMG signals.	R^2: 0.91
Guo et al., 2018 [91]	CNN	EMG Signal Estimation from rat Spinal Cord Signals	4 × 7 electrode array. 4 × 7 electrode array. 4 EMG channels.	R^2: > 0.2 (EMG signals reconstruction)
Bakiya et al., 2018 [17]	DNN	Amyotrophic Lateral Sclerosis detection	1 EMG signal	Accuracy: 97.7 %
Sengur et al., 2018 [168]	CNN	Amyotrophic Lateral Sclerosis detection	N2001 [99]	Accuracy: 96.7 %
Chen et al., 2018 [53]	DBN	Lower-Limb Joint Angle Estimation	6 Subjects. 10 EMG Signals.	RMSE: ≈ 3.3 deg ρ: ≈ 0.96
Rane et al., 2019 [158]	CNN	Estimation of several variables of the lower limb during gait	156 Subjects. 13 estimated signals: a) Medial knee joint reaction force, b) Forces of four major muscles, c) EMG signals of eight muscles	Averaged RMSE: a) 216 N b) 185.0 N c) 0.25
Akhundov et al., 2019 [4]	CNN	EMG Signal Quality Rating	Three EMG Datasets. 5 Quality Classes	Accuracy: 99.5 %

Table 4
Summary of publications falling into "Other Applications".

DL Algorithm	CNN	RNN	AE	DBN	DNN
Hand Gesture Classification	28	7	7	2	0
Speech and Emotion Classification	2	0	0	3	3
Sleep Stage Classification	5	1	0	1	0
Other Applications	5	2	1	2	1
Total	**40**	**10**	**8**	**8**	**4**

Table 5
Summary of the DL methods applied to the individuated paper categories. Papers that investigate mixed approaches are accounted more times.

tered with a Hampel filter to remove the 50 Hz power line interference. The electrodes were positioned to combine a dense sampling approach with a precise anatomical positioning strategy.

Moreover, the BioPatRec database [153] contains a set of EMG recording sessions from 17 intact subjects provided under the label "10mov4chUntargetedForearm". They are 4 differentially recorded myoelectric signals digitalized at 2 kHz with a 14-bits resolution. A usage of four bipolar electrodes has been proved to be sufficient for the classification of at least 10 hand/wrist movements. Ten different hand/wrist movements were repeated 3 times during 3 seconds with equal relaxation periods between repetitions. Considered movements are: open hand, close hand, flex hand, extend hand, pronation, supination, side grip, fine grip, agree or thumb up, and pointer or index extension. These movements were selected as they could be feasible in high-end commercial prostheses.

Then, the CapgMyo-DBa [80, 69] consists of high-density sEMG (HDsEMG) signals of 8 isometric and isotonic hand gestures performed by 18 subjects. The gestures in DB-a correspond to Nos. 13-20 in the NinaPro database. They were recorded at a sampling rate of 1 kHz using an electrode array with 128 electrodes that covered the upper forearm muscles (forming a grid of 8 to 16 channels). Each gesture is held for 3 to 10 seconds.

The csl-hdemg dataset [9] contains high-density sEMG (HDsEMG) data recordings of 5 subjects performing 27 finger gestures. Each subject recorded over 5 sessions where 10 trials of each gesture is performed in each session. The sEMG signals are bipolar recorded at a sampling rate of 2048 Hz using an electrode array with 192 electrodes that covered the upper forearm muscles (forming a grid of 7 to 24 channels).

5.2. Speech and Emotion Classification

The EMG-UKA Corpus database [187] is the most comprehensive publicly available corpus for EMG-based speech recognition. It consists of surface electromyographic and acoustic recordings of 8 subjects reading speech in English language, from the Broadcast News domain. Data was recorded as normal (audible) speech as well as whispered/silently mouthed speech. The recording setup consisted of 6 EMG channels capturing data from major facial muscles namely according levator anguli oris, zygomaticus major, platysma, depressor anguli oris, anterior belly of the digastric, and the tongue. Recordings were performed at 600 Hz sampling rate. The acoustic signal was recorded synchronously with a standard headset microphone. The dataset is composed by 61 sessions and each session comprises 50 sentences.

The DEAP database [121] was developed to achieve realistic human emotional states that are persuaded by music videos that were one-minute long. The database contains 32 subjects. For every subject, 40 videos were presented in 40 trials with EEG and peripheral physiological recorded signals. In each trial, 32 channels of EEG signals were recorded at 512 Hz; 4 electrodes were used to record EOG and 4 for EMG (zygomaticus major and trapezius muscles). All the physiological responses were later downsampled to 256 Hz to reduce processing time. In each of them, the current trial number was displayed for 2 seconds proceeded with 5 seconds long baseline and finally the music video is displayed for 1 minute. Later, the ratings on different dimensions (such as valence, arousal, dominance, liking and familiarity) were acquired. These ratings are subjective to user's self-assessment.

5.3. Sleep Stage Classification

The dataset UCD-DB is provided by St. Vincent's University Hospital and University College Dublin and it is available on PhysioNet platform [86]. The dataset consists of 25 recordings of EEG, EOG and EMG signals from subjects (21 males aged 50 $\pm$ 10 years, 4 females aged 28-68 years) with suspected sleep disordered breathing. Only one EMG channel was recorded by using 10-20 electrode placements system at a sampling rate 64 Hz. Five sleep stages, wakefulness, N1, N2, N3, and REM, were evaluated by a sleep expert.

The MASS-DB [151] is a large dataset comprising EMG recordings of 200 healthy subjects with ages ranging between 18 and 76 years (98 males aged 42.7 $\pm$ 19.4 years and 102 females aged 38.1$\pm$18.9 years). The database contains single nights and is divided into 5 cohorts.

The SLPEDF-DB [119, 86] comprises 38 two-night recordings from 19 healthy subjects (9 males aged 28.3 $\pm$ 2.3 years and 10 young females 29.1$\pm$3.4 years). The only EMG signals was sampled at 1 Hz EMG. The dataset also contains recordings of EEGs signals that were sampled at 100 Hz.

The CAPSLP-DB [182, 86] consists of 108 single night polysomnography recordings of 16 healthy and 92 pathological subjects (66 male aged 48.4 $\pm$ 19.2 years and 42 female aged 40.0 $\pm$ 19.4 years). Individuals with sleep disorders included periodic leg movements, insomnia, as well as 22 REM behavior disorder subjects.

The RBD-DB [10]consists of 21 two-night recordings of 21 subjects (20 male aged 61.5 $\pm$ 7.0 years and a female patient aged 69 years) all suffering from REM behavior disorder. Data were acquired by John Radcliffe hospital, Nuffield Department of Clinical Neurosciences at the University of Oxford.

5.4. Other Applications

The N2001 database contains clinical signals recorded and analyzed as a part of Nikolic M. PhD Thesis [150]. This dataset consists of EMG recordings of a normal control group, a group of patients with myopathy and a group of patients with Amyotrophic Lateral Sclerosis (ALS). The control group consists of 10 healthy subjects (aged 21-37 years). The group with myopathy consisted of 7 patients (aged 19-63 years). The ALS group consists of 8 patients (aged 35-67 years). The recordings were made at low voluntary and constant level of contraction using visual and audio feedback to monitor signal quality and a standard concentric needle electrode. The EMG signals were recorded from five places in the muscle at three levels of insertion (deep, medium, low) at a sampling frequency of 23437. The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz, respectively.

6. From raw EMG signals to deep network input

The use of different EMG signal acquisition setups, i.e. sparse and array electrodes, combined with the possibility to employ several kind of deep learning techniques enables many solutions for designing network inputs that are computed from the raw EMG signals. The first pre-processing step commonly consists in filtering any EMG signal with a digital high-pass/ band-pass filter to remove the low-frequency artifacts, e.g. movement artifact and baseline noise contamination [60, 19]. A valid alternative regards the application of the wavelet transform (WT) that is used to reconstruct the original signal with signal components without noise information [154]. The power line interference has also to be removed, and if it is not done by the EMG amplifier a specific digital filter has to be used, e.g. the spectral Hampel filter [5].

The pre-processing step is followed by a signal segmentation procedure that aims at extracting several portions of EMG signals using a time-windows. All information encoded within the time windows of avery considered EMG signals will be then used to construct a specific example used to train, validate or test an ad-hoc deep network. This means that the employed network will provide an output, i.e. a vector of class probabilities for a classification problem or a set of estimated variables in case of regression problems, for each time window. The time-window length is a crucial parameter to be subsequently set, a large window contains more temporal information but at the same time causes a delay between the event to be detected and the related network output. On the other hand, a small window is adequate for real-time applications but considers a limited amount of information. A large variability of the window length used by the authors of all reviewed papers has been observed, typical time-window length values are 30ms, 50ms, 100ms, 150ms, 200ms and 300ms. The time-window length has a particular relevance when the deep network is included in closed loop

Database	Subjects	Gestures	Sessions	Trials	Number of electrodes	Sampling rate [Hz]
NinaPro-DB1 [15]	27 (Intact Subj.)	53	1	10	10	100
NinaPro-DB2 [15]	40 (Intact Subj.)	50	1	6	12	2000
NinaPro-DB3 [15]	11 (Amputated Subj.)	50	1	6	12	2000
BioPatRec [153]	17	26	1	3	8	2000
CapgMyo-DBa [80]	18	8	1	10	128	1000
CSL-HDEMG [9]	5	27	5	10	192	2048

Table 6
Details of the main sEMG benchmark databases used for gesture recognition.

Database	Application	Subjects	Number of electrodes	Sampling rate [Hz]
EMG-UKA Corpus [187]	Speech Recognition	8	6	600
DEAP Database [121]	Emotion Classification	32	4	256
PhysioNet UCD-DB [86]	Sleep Stage Classification	25	1	64
MASS Database [151]	Sleep Stage Classification	200	1-5	256
SLPEDF-DB [86]	Sleep Stage Classification	19	1	1
CAPSLP-DB [86]	Sleep Stage Classification	108	1-2	200-256
RBD-DB [10]	Sleep Stage Classification	21	1	256
N2001	Amyotrophic Lateral Sclerosis detection	25	5	23437

Table 7
Details of the main sEMG benchmark databases used Speech Recognition, Emotion Classification, Sleep Stage Classification and Other Applications.

myoelectric controllers where the input latency is a fundamental factor to consider. As an example, a maximum time delay of 300ms can be acceptable when controlling of prostheses through EMG signals [109]. Sliding time-window are usually extracted considering an overlap (also called increment) that is defined as a percentage of window length. Another important factor that is considered to choose the window length is the sampling frequency of EMG signals [59]. It is also important notice that many authors choose a time-window length value that is equal to the value used by the authors of already published works thus allowing a robust comparison of the model performance. In fact, the possibility of comparing results plays an important role when working with public datasets. However, some authors decided not to consider the windowing approach and prefer to provide EMG signals at each sampling instant as input to the network [68]; such approach could be especially followed when dealing with high-density EMG arrays since they can provide a lot of activation data at a single time sample.

After all EMG signals have been segmented with overlapped time-windows, the process to build network inputs is clearly highly dependent on the preferred deep network architecture. Existing approaches can be mainly divided in two main groups according to the fact that the selected architecture (or its first module in case of mixed architectures, e.g. CNN-RNN) is either 1) a CNN or 2) a DNN, an AE, a DBN or a RNN. When dealing with DNNs, AEs, DBNs and RNNs networks input have vector-like shapes. In most of the cases, such vectors are composed of the values of hand-crafted features extracted by the window segment of each acquired EMG signal. All revised articles considered both the time-domain features and frequency-domain ones that are usually used in EMG processing [112].

A different approach has to be followed when a convolutional neural network is considered for EMG signal processing. CNNs that are employed for traditional image processing usually take as input either a (MxN)-size orray or a (MxNx3)-size one if they have to process a gray or an RGB image, respectively. As consequence, information contained within the EMG signals have to be arranged in a (2D or 3D)-dimensional array. More in details, the specific approach to follow depends on the used setup that can consider the acquisition of either high-density sEMG signals [80, 9] or sparse multi-channel sEMG ones [15]. A solution can intuitively consider to arrange EMG signals in a sEMG-image where each electrode can be regarded as a pixel of the image. Such solution is certainly valid when using high-density sEMG signals that are collected by a grid of sEMG electrodes [192, 68]. Then in this case the size of the sEMG image will be equal to the electrode array size. However, when considering sparse multi-channel sEMG signals, the number of electrodes is limited and their placement is sparse, thus the above presented approach cannot be directly implemented. Among all multiple solutions that have been adopted to deal with sparse electrodes, the main two used techniques consider 1) an (NxL)-dimension matrix where N is the number of electrodes and L is the time-window length, and 2) a matrix built assembling the spectrogram of each EMG signal computed on the time-window.

7. Discussion

In several research fields, such as image, video and audio processing, deep learning has already demonstrated its robustness and effectiveness [63, 62, 34, 30, 32]. As this work has shown, in recent years the scientific community has been increasingly interested in applying deep learning methods for EMG signal analysis and processing, thus confirming the same tendency that involves other physiological signals, e.g. EEG and ECG [78, 76]. The search and analysis performed in this work revealed that the major contribution to EMG signal processing in the field of deep learning comes from a research focused on myoelectric prosthesis. Such finding has two main reasons: technical limitation of available commercial products and many existing workbench databases. However, in addition to papers dealing with hand gesture classification, DL techniques have been also applied to other research fields which consider the processing of large amounts of data, e.g. works concerning the classification of sleep stage, speech or emotion. Regarding with deep learning methods, convolutional neural networks turned out to be the most commonly used networks among the five DL investigated methods: deep neural networks, convolutional neural networks, auto-encoders, deep-belief networks and deep-recurring neural networks (see Figure 4, Figure 5 and Table 5). In some other cases such specific strategies were combined to take advantage of the pros of different DL approaches.

As reported within the four tables listing all analyzed papers, a high percentage of selected papers considers the analysis of existing workbench datasets thus confirming that the availability of existing databases has actually boosted the research in this field. Summarizing outcomes, it can be concluded that: a) the most used datasets among the Hand Gesture Classification papers the Ninapro, CSL-HDEMG, and CapgMyo; b) in works related to the emotion classification the most used dataset is DEAP; c) the most used databases for the investigation of the DL techniques in sleep stage classification are PhysioNet and MASS. Furthermore, the additional significant advantage of using datasets, as is well known, is the possibility of comparing the results of different studies. Unfortunately, it mainly arises from the review of papers on *hand gesture classification*, that the comparison of results is made difficult by the broad variation among used setups, i.e., number of acquired EMG signals, adoption of different types of electrodes, that can be superficial or intramuscular, and number of classes to be classified.

Even though a large amount of EMG data is available thanks to published datasets, in the authors' opinion data augmentation is necessary to improve the both inter-subjects and inter-sessions variability. Data augmentation is a common technique to improve results, avoid overfitting and guarantee generalization. Data augmentation algorithms used in image and video processing are already well defined and consolidated over the recent years [172]. The same cannot be stated for EMG signal analysis. In-fact, only few of the herein reviewed papers consider data augmentation. In particular the authors of three articles augmented the EMG signals by adding Gaussian noise to the original set of signals and modulating the signal to noise ratio [14, 219, 183]. Only one paper dealing with high-density EMG electrodes proposes a random shift of the training images by one pixel in four directions to improve the system robustness respect to electrode array positioning [68]. Hence, a deeply investigation of data augmentation techniques in EMG signal processing represents a completely open and unexplored field. At the moment, the majority of the authors primarily focused on a continuous improvement of the classification/regression performance [192], whereas, in the authors' opinion, a big effort should be put 1) in improving the generalization ability of the proposed models by introducing new data augmentation methods and 2) in investigating compact deep topologies to shorten both learning and execution time while maintaining high performance levels [94].

8. Conclusion

Concluding, in this work recent articles concerning the processing of EMG signals with deep learning methods that were published between January 2014 and March 2019 have searched and reviewed. After a deep text analysis, 65 papers have been selected for the review. The bibliometric research showed that the selected papers could be sorted in four distinct categories focused on different applications: (1) Hand Gesture Classification; (2) Speech and Emotion Classification; (3) Sleep Stage Classification; (4) Other Applications. As expected, the review process revealed that (a) most of the papers related to DL and EMG signal processing concern with the hand gesture classification, and (b) the convolutional neural network is the most used technique. In the authors' opinion the hand gesture classification is the most studied topic for two main reasons: a) the availability of several public and easily accessible datasets and b) the big limitation of the current myoelectric controlled prosthesis in terms of usability. Moreover, research on the control of myoelectric prosthesis has a high practical value since it has a big social impact and can be easily tested on patients (sEMG is a non-invasive technique). Furthermore, the authors do not think the other presented applications have less social value than the "hand gesture classification", however they are in a research stage yet. Given the impact of both the *hand gesture classification* category and the CNN, future works could deeply study the CNN topologies used to classify hand/finger gestures by EMG signals, including a systematic comparison among the several papers. In the next future, the research community should also focus in developing ad-hoc data augmentation techniques for EMG signals. As emerged in this work, only a couple of articles employed simple data augmentation procedures involving the signal to noise ration and the electrodes shift. More studies are then needed in order to understand the impact of such augmentation techniques on the final performance and perhaps propose new methodologies. A further effort should also be put in decoding and interpreting the EMG signals features that are automatically extracted by deep architectures.

Some researchers already started to correlate the most common handcrafted features with the feature maps extracted by convolutional layers [58], however more studies should evaluate the robustness of such correlation among several application and DL techniques.

CRediT authorship contribution statement

Domenico Buongiorno: Conceptualization of this study. Methodology. Literature search, selection and review of the papers. Manuscript writing and editing (lead author). **Giacomo Donato Cascarano:** Review of the papers. Manuscript structuring, writing and reviewing. Contribution to discussion. **Irio De Feudis:** Review of the papers. Manuscript structuring, writing and reviewing. Contribution to discussion. **Antonio Brunetti:** Manuscript structuring, writing and reviewing. Contribution to discussion. **Leonarda Carnimeo:** Manuscript structuring, writing and reviewing. Contribution to discussion. **Giovanni Dimauro:** Manuscript structuring, writing and reviewing. Contribution to discussion. **Vitoantonio Bevilacqua:** Conceptualization of this study. Methodology. Manuscript writing and reviewing. Contribution to discussion. Work Supervision.

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