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Deep Learning Classification of Simulated Surface EMG Signals across Maximum Voluntary Contraction Levels

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Abstract: *Electromyography (EMG) is a fundamental tool in diagnosing neuromuscular disorders (NMD). Due to the complex nature of EMG signals, different approaches, based on artificial intelligence and machine learning, were developed for EMG signal analysis and NMD diagnosis. Considering the critical role of maximum voluntary contraction (MVC) as a fundamental metric in assessing muscle fatigue, in this work, classification of simulated surface EMG (sEMG) into MVC levels is performed. Unlike previous studies, which focus primarily on binary classification of fatigue and non-fatigue states, our approach employs a deep convolutional neural network for the classification of sEMG signals into ten MVC levels, where the model outputs categorical predictions, with each class representing a specific MVC level. sEMG signals were generated using a computer muscle model that we developed using MATLAB, which allows for greater control over variability, ensuring robustness and generalizability of the model. The obtained results demonstrate that the model achieved high performance in differentiating between the ten classes (MVC levels), with an accuracy, F1-score, recall, and precision of 88.88%, 88.75%, 88.80% and 88.86%, respectively. These findings reveal that the model can accurately differentiate across MVC levels, indicating a potential method for accurate assessment of muscle fatigue intensity.*

Keywords: *Artificial intelligence (AI), Diagnosis, Electromyography (EMG), Muscle fatigue.*

Introduction

Electromyography (EMG) signals are used for diagnosing patients with neuromuscular disorders (NMD) [31]. EMG data can also help guide therapy decisions and provide crucial information about the course of various disorders [31, 32]. Along with visual analysis of EMG signals by an experienced electrophysiologist to detect abnormalities, attempts are being made to develop algorithms for automated recognition of neuromuscular diseases [32].

Muscle fatigue is one of the common symptoms of NMD that can have serious consequences in a person's life. The maximal voluntary contraction (MVC) test is a general way to detect this symptom [11], where the maximum force or force generated over a voluntary contraction is measured. Practitioners can assess the level of muscle fatigue and the severity of the symptom by analyzing EMG signals during MVC. Therefore, EMG signals are an important tool for identifying and monitoring the muscle fatigue in NMD patients, as well as guiding treatment decisions to improve their quality of life [11, 34].

Accurate medical diagnosis is essential for effective treatment and avoiding major repercussions. Analyzing data from different sources using expert systems can help reduce human error and enhance outcomes [14, 15]. Due to the growth of medical practice and the difficulty of diagnosis, artificial intelligence (AI) and machine learning (ML) algorithms have attracted a lot of attention in the field of healthcare. Development of a framework using these algorithms can predict early disease diagnosis [10]. These algorithms have the ability to aid in disease diagnosis and risk estimate through analyzing huge amounts of data and identifying patterns [6, 14]. The rapid growth of AI and the growing availability of massive datasets should change health and life in general [23].

Recently, the applications of EMG classification using AI include those working on different NMDs diagnoses such as amyotrophic lateral sclerosis [8], traumatic spinal cord injury [17], neuropathy and myopathy [32] and Parkinson's disease [1]; and those who work on movement simulation and detection like hand motions [7, 28], and finger movements [30]. Many approaches were proposed to classify EMG data, in particular support vector machine (SVM) [1, 29, 30], neural networks [8, 32], tunable Q-factor wavelet transform [28] and deep learning (DL) models [7, 17]. For the muscle fatigue diagnoses, Song et al. [27] proposed a wireless device that uses wearable EMG sensors and a frequency domain-based approach to detect muscle fatigue in real time. ML algorithms were widely used for muscle fatigue detection. Where different ML techniques were employed by Karthick et al. [13] and Zhao et al. [35], SVM by Ramos et al. [25] and Liu et al. [16], and artificial neural network (ANN) by Hickman et al. [11]. DL models were also used, either for the fatigue detection as Moniri et al. did [22], or for the fatigue level determination through the detection of muscle contraction intensity as in the works of Bu and Morita [4] and Hajian et al. [9].

MVC levels of EMG signals were used in many biomedical applications [3], particularly in the assessment of muscle fatigue [5, 21]. Although ML models have claimed decent performance for surface EMG (sEMG) signal classification, DL algorithms have recently gained popularity in the literature [4, 7, 9, 17, 22]. Because they automatically learn crucial features, they tend to perform better [12]. In this study, we develop a robust classification system for simulated sEMG signals, capable of accurately quantifying and distinguishing different levels of MVC. sEMG signals used in this study were simulated for contraction levels of 10% to 100% MVC by a step of 10% using a MATLAB program that we previously developed [19]. The classification was performed using a convolutional neural network (CNN) based DL algorithm to ensure the accuracy of the predictions. This study aims to contribute to the field of muscle fatigue assessment by providing a robust automated method to differentiate between different levels of contraction, enhancing the ability of clinicians to assess muscle fatigue and monitor changes in real time, by providing an objective and accurate method instead of relying on subjective assessments and traditional electromyography techniques. Understanding MVC levels is crucial because they serve as benchmarks for muscle performance; monitoring changes in MVC can indicate the progression of fatigue and recovery states. This may facilitate early detection of fatigue, address current limitations in clinical practice, and improve patient management and treatment strategies, by providing a valuable diagnostic tool to determine the severity of the condition and enhance our understanding of muscular health.

Materials and methods

Simulation model

In this study, a MATLAB model, we previously developed in [19] and provided in [36], was used to generate sEMG signals. The model simulates the detection of sEMG above an elliptical muscle within a cylindrical limb, namely bone, muscle, fat, and skin (Fig. 1). The generated simulated signals were sampled at a frequency of 2048 Hz and had a duration of 5 s. The fundamental model parameters comprised an elliptical muscle with a cross section of 30 mm by 20 mm that contained 120 motor units (MUs) uniformly distributed. The number of muscle fibers within each MU was linked to its size: the diameters of the MUs were distributed according to Poisson's law in the range of 2-8 mm, with an average of 6 mm. The smallest MU innervated 63 fibers, while the largest innervated 1005 fibers. The conduction velocity of all MUs ranged between 2.5 m/s and 5.5 m/s, with an average of 4 m/s and a standard deviation of 0.75 m/s [19].

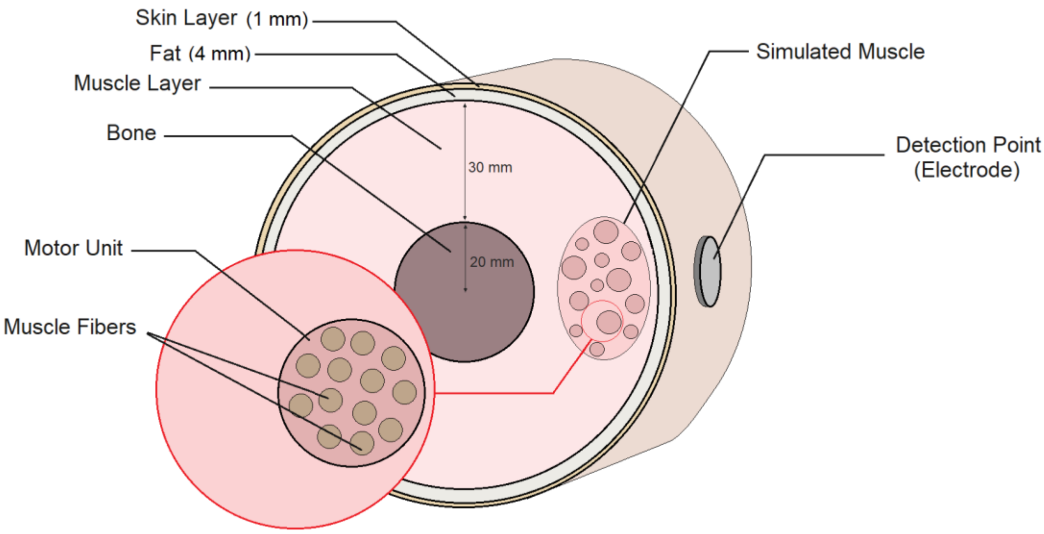


Fig. 1 The model used to simulate the sEMG signals

During the signals generation, longitudinal single differential (LSD), longitudinal double differential (LDD), and normal double differential (NDD) spatial filters were used. According to the literature, non-invasive recording of sEMG signals is based on electrodes configured in spatial filters that improves selectivity in sEMG signal detection by reducing detection volume and limiting interference from surrounding muscles. These filters use various aspects of spatial filtering, such as transverse, depth, and longitudinal selectivity, to boost crucial sEMG signal features while attenuating undesirable noise, resulting in improved muscle activity detection accuracy [20]. The electrodes were placed halfway between the innervations zone and the distal tendon, and different electrode shapes and inter-electrode distances were used. Two forms of electrodes were considered for the LSD and LDD filters: a rectangular shape of 1 mm wide and 10 mm long, with inter-electrode distances (IED) of 5 and 10 mm, and a circular shape of 1 mm diameter, with IED of 5 and 10 mm. For the NDD filter, circular electrodes with a diameter of 1 mm and IED of 5 and 8 mm were used. To show the effects of different filters and electrodes on the simulated sEMG signal for a same parameters combination, we present Fig. 2, which illustrates both the time-domain representation (1 s segment) and the frequency spectrum of the same simulated sEMG signal recorded with various spatial filters. The frequency spectra demonstrate how changes in spatial filtering affect not just the morphology of signals but also their frequency characteristics. Furthermore, Fig. 3 depicts the time-domain and spectrum representations of a sEMG signal obtained with various electrode configurations.

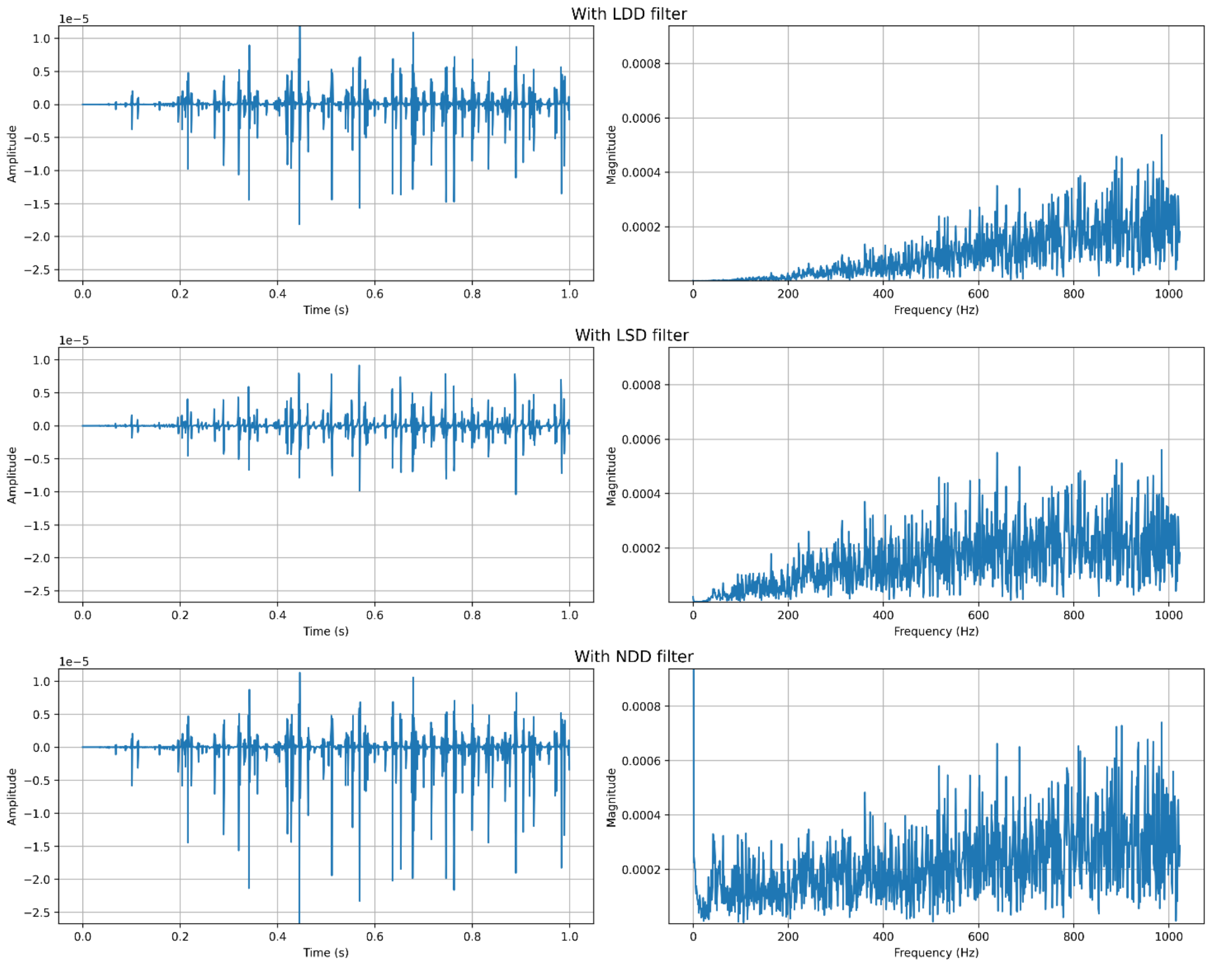


Fig. 2 Time-domain (on the left) and their frequency spectra (on the right) representations for a sEMG signal recorded using different spatial filters

The force generated by a muscle during contraction depends on the number of MUs that are activated and their firing rates. In this study, two ranges of recruitment thresholds (RR) within each MU were selected: a narrow range set at RR = 30% and a wide range set at RR = 70%, both in a pool of 120 motor neurons. Two types of MU firing rate (FR) strategies were also considered: the first strategy (FR1), termed "onion skin", involved larger firing rates of low-threshold MUs compared to high-threshold MUs, while the second strategy (FR2), called "reverse onion skin", involved smaller firing rates of low-threshold MUs compared to high-threshold MUs. In both strategies, the peak firing rate (PFR) was set at 20, 25, and 30 Hz.

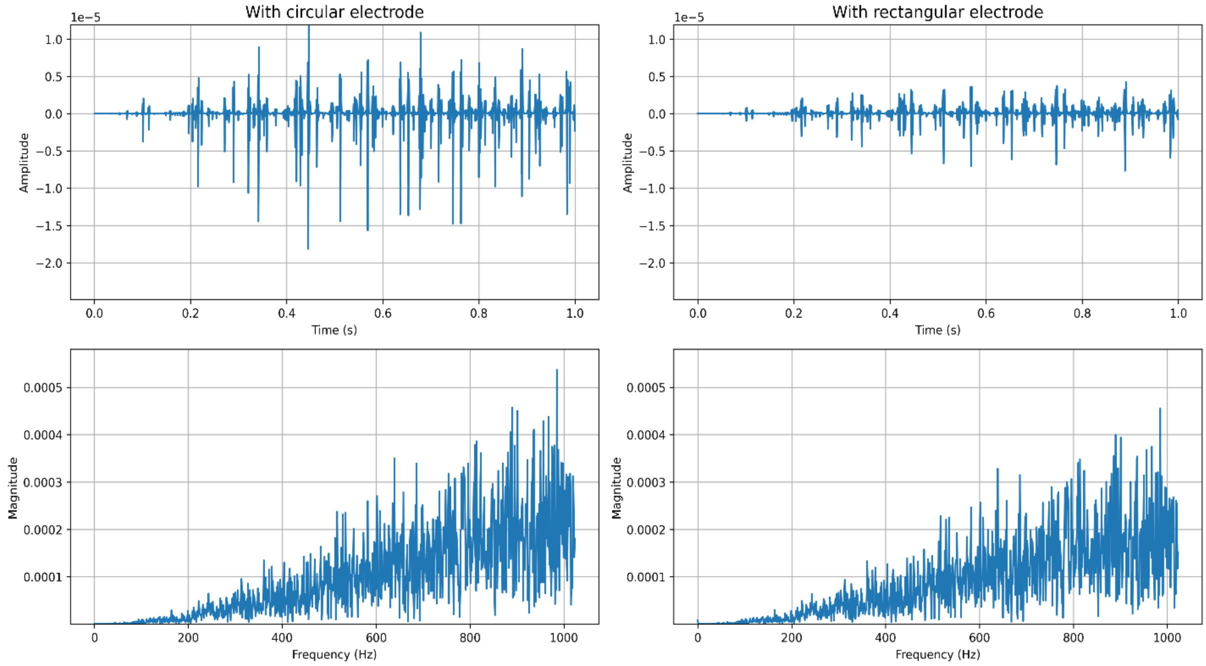


Fig. 3 Time-domain (on the top) and their frequency spectra (on the bottom) representations for a sEMG signal recorded using different electrode shapes

Dataset acquisition and preprocessing

The sEMG signals were generated for each of the parameter combinations mentioned above to create the dataset. Table 1 provides an overview of the settings used for generating the simulated sEMG signals. Ten different MVC percentages were used, ranging from 10% to 100% with a 10% increment. The use of the three spatial filter configurations, the two electrode shapes, the two inter-electrode distances, the seven values of MU recruitment (two RR, two FR strategies, and three PFR), and the ten MVC levels, allowed to obtain a total of 1200 simulated sEMG signals (720 signals generated using the circular electrode and 480 signals generated using the rectangular electrode). Fig. 4 represents an example of sEMG signal generated across the 10 MVC levels.

Table 1. Summary of simulated sEMG signal generation settings

Electrodes shapes	**FR strategies**	**Filters**	**RR**	**PFR, Hz**	**Inter-electrode distances, mm**	**MVC, %**	**Number of signals**
Circular	FR1 FR2	LDD LSD NDD	30% 70%	20 25 30	5 10 (for LDD and LSD) 8 (for NDD)	10 to 100	720
Rectangular	FR1 FR2	LSD LDD	30% 70%	20 25 30	5 10	10 to 100	480

The distributions outlined in the previous subsection, including the uniform distribution of MU recruitment time, Gaussian distribution of motor unit force lengths, neuromuscular junctions, and ending tendons, as well as the Poisson distribution of all MU firing rates, enabled the generation of diverse EMG signals following each execution, even when using the same parameter settings. The process was repeated five times to generate 6 000 different sEMG signals in total, each with 5 s length (10 240 data points).

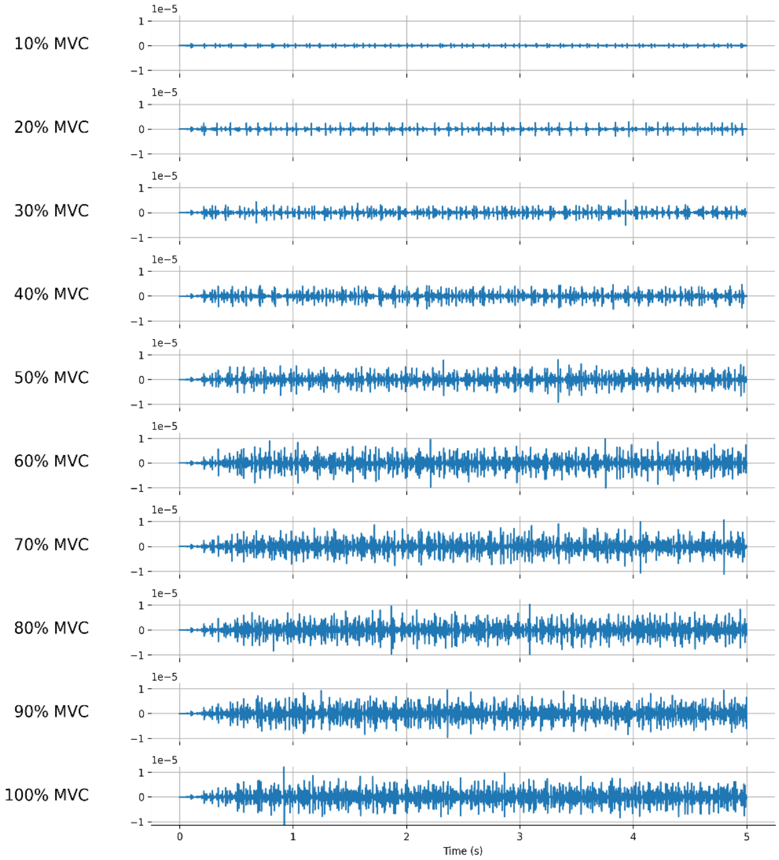


Fig. 4 sEMG signal generated with the 10 MVC levels

Preprocessing data is an important step in machine learning and deep learning workflows. It refers to a set of techniques to prepare raw data for analysis or modeling. Preprocessing is often necessary because raw data may contain inconsistencies, noise (in case of real data), or other issues that may affect model performance. Therefore, in this section, we expose the preparation steps for our sEMG dataset to train a DL model.

We first appended to each signal a numerical value ranging from 0 to 9, corresponding to the MVC level with which the signal was generated (Table 2). This step allowed us to label the data so that it can be used for supervised learning. The labeled signals were then saved in a 2D array of size (6 000, 10 241). Since 6 000 signals may be insufficient to get promising results when training a DL model, we used an augmentation technique to increase the dataset size.

Table 2. MVC levels with the corresponding labels

% MVC	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Label	0	1	2	3	4	5	6	7	8	9

To augment our dataset, we used *ImageDataGenerator*, a Python function commonly used for generating augmented data from existing samples. Each signal was subjected to four types of transformations, which were adapted to suit the temporal nature of the signals. These transformations included random rotation; which can be interpreted as a random perturbation or distortion; in the range -0.1 to 0.1 degrees, random horizontal and vertical shifts up to 20% of the original width and height, horizontal flipping, and filling in empty values with the nearest one. Using this procedure, we produced two augmented samples for every original sample, giving a total of 18 000 signals.

To improve the performance of our DL model, we normalized each EMG signal. The signals have a wide dynamic range, meaning they have both low and high amplitude components. Normalization scales the values in the signal to a common range, preventing extreme values from dominating the model's performance. We used the following equation:

$$X_{norm} = \frac{(X - X_{mean})}{X_{std}} \quad (1)$$

where, X_{norm} is the normalized signal of X – the row input of our dataset (sEMG signal), X_{mean} is the average value, and X_{std} is the standard deviation of X.

In summary, the preprocessing steps consisted in labeling the signals, augmenting the dataset with *ImageDataGenerator*, and normalizing each signal. The signals were saved in a 2D array of size (18 000, 10 241), and stored in a .csv file. This complete set of data was used to train and evaluate the performance of a DL model for the classification of sEMG signals.

Deep learning classifier

The model was built using Google Collaboratory with GPU and Python 3.10 programming language, a cloud-based platform that offers free access to computing resources. We used the convolutional neural network to build our classifier. The model has a sequential architecture, with layers organized linearly, with each layer feeding its output directly to the next layer. This sequential structure is a key feature of Keras' sequential model, which allows for straightforward layer stacking to build the neural network (Fig. 5).

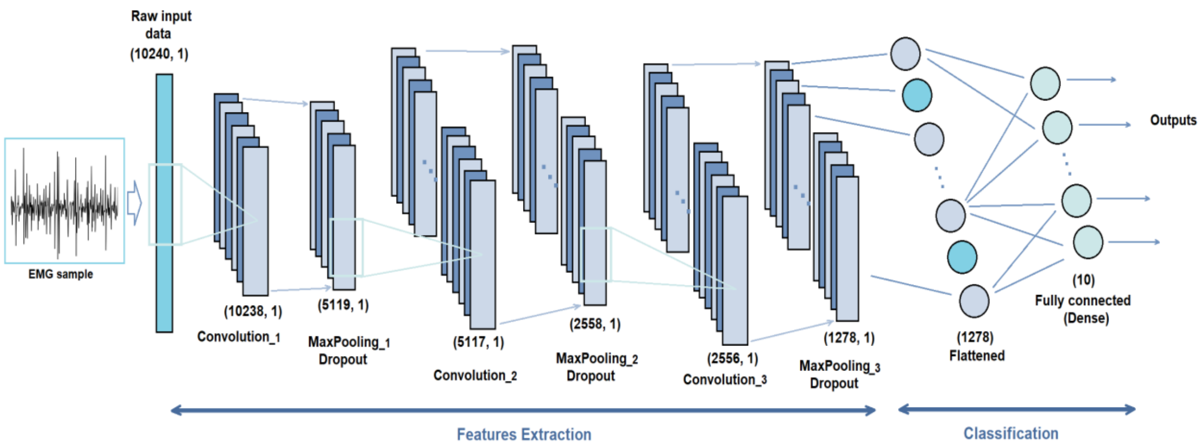


Fig. 5 Overall architecture of the CNN-based model

The first layer is a 1D convolutional layer, which performs convolution operation on the signal. It uses 128 filters with a kernel size of 3, and activated with rectified linear unit (ReLU) function to introduce non-linearity into the model, which is defined as:

$$ReLU(X) = \max(X, 0) \quad (2)$$

The convolution operation is represented mathematically as [2]:

$$(X * K)(t) = \sum_a X(a)K(t - a) \quad (3)$$

here, t is the current output position, a is the position in the input X, and K is the kernel.

The second layer is a 1D MaxPooling layer, which performs a max-pooling operation on the output of the previous convolutional layer, with a pool size of 2, allowing the maximum value within every two consecutive values to be taken. This is a form of down-sampling or sub-sampling the input signal to the layer, mathematically defined as:

$$MaxPooling(X)_a = \max\big(X(a),\ X(a+1)\big) \tag{4}$$

where $X(a)$ is the a^{th} element in the input and $MaxPooling(X)_a$ is the output of the MaxPooling layer at the a^{th} position [26].

To prevent the model from over-fitting during training, a Dropout Layer was added at a rate of 0.25. During training, this layer allows a portion of the connections between the previous layer and the next layer (0.25% of the total connections in this case) to be randomly eliminated, preventing the model from relying heavily on specific neurons and improving its generalizability [33]. With a dropout rate of p we can represent this as:

$$Dropout(X,p)_i = \begin{cases} X_i\ with\ probability\ 1-p \\ 0\ with\ probability\ p \end{cases} \tag{5}$$

A second 1D convolutional layer was afterwards added with 64 filters, a kernel size of 3, and ReLU activation. Then a similar 1D MaxPooling Layer to the previous one follows the second convolutional layer. Another Dropout Layer with a rate of 0.25 was added again, before a third 1D convolutional layer with 32 filters, the same kernel size, activation function, and a similar 1D MaxPooling and Dropout Layers with a rate of 0.5.

Finally, a Flatten layer flattens the output from the previous layer into a 1D vector. This vector is passed to a fully connected Dense layer with 10 units and a Softmax activation function, which converts the previous layer's output into a probability distribution over the ten output classes, using the following equation:

$$f(X)_i = \frac{e^{X_i}}{\sum_j e^{X_j}} \tag{6}$$

where X_i is the row score for the i^{th} class, and $f(X)_i$ is the probability of the i^{th} class. All the layers' details are represented in Table 3.

Table 3. The CNN model's layers

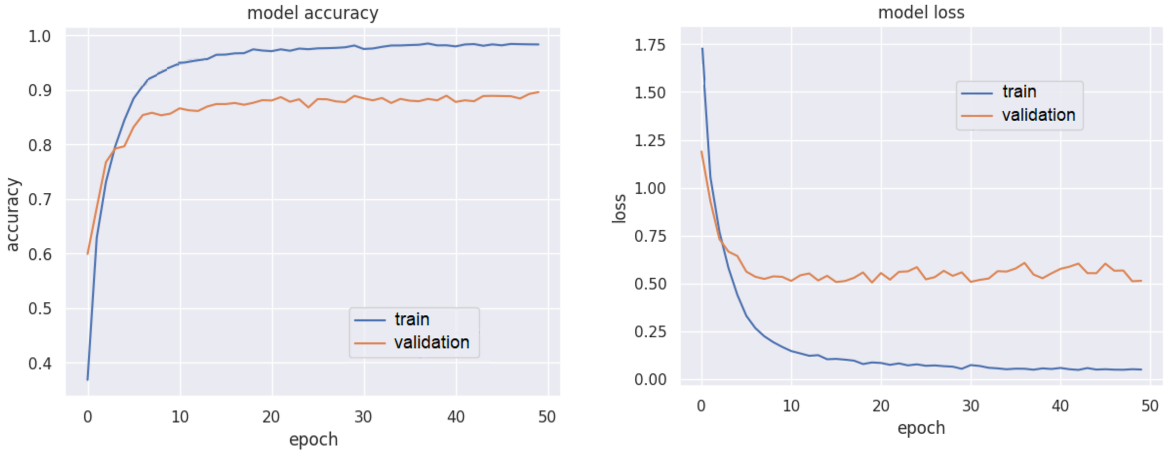
Layers	Filters	Size / Rate	Activation
1D-Convolution_1	128	3	ReLU
1D-MaxPooling_1	-	2	-
Dropout	-	0.25	-
1D-Convolution_2	64	3	ReLU
1D-MaxPooling_2	-	2	-
Dropout	-	0.25	-
1D-Convolution_3	32	3	ReLU
1D-MaxPooling_3	-	2	-
Dropout	-	0.5	-
Flatten layer	-	-	-
Dense layer	10	-	Softmax

Before compiling the model, *train_test_split* function is used to split our normalized dataset into training data (85%) and testing data (15%) with a random seed of 42. Another split is performed on training data to extract the validation data (20% of the training data), which plays a crucial role in preventing overfitting and evaluating the model's generalizability and monitoring performance during training for each epoch.

The model was compiled and trained for 50 epochs with a batch size of 80, using training data. Categorical cross-entropy is used as a loss function, which compares the Softmax output probabilities to the one-hot encoded labels. The network's parameters are adjusted to minimize the loss using the Adam optimizer, while the testing data is used later to evaluate the model performance.

Results

The line chart in Fig. 6 illustrates the DL model accuracy and loss across epochs for training and validation data. It shows the progress of the model learning, observations on its convergence, and performance. Model accuracy increased gradually over the first 10 epochs and stabilized around epoch 45, while the model loss decreased. Thus, the model progressively improved its ability to minimize errors as the number of epochs increased.

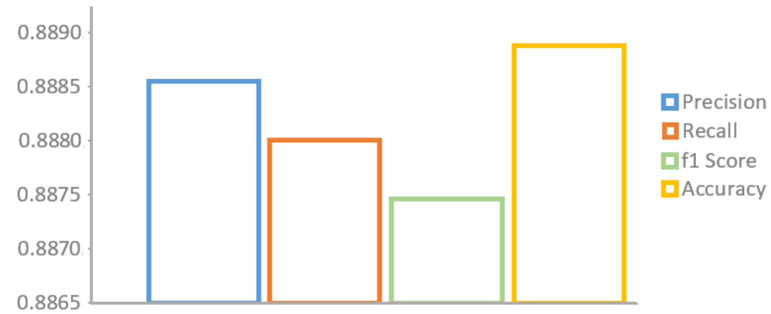


(A) (B)

Fig. 6 The DL model: accuracy (A) and loss (B) versus training epochs

Next, we calculated the four performance metrics (precision, recall, F1-scores, and accuracy) using the test dataset. The results are shown in Fig. 7. These statistical metrics offer a comprehensive evaluation of the model's classification capability, and allow us to determine its efficiency in differentiating between different classes.

The confusion matrix, a 2D matrix whose size is equal to the number of classes, is another way to assess model performance. Confusion matrix is extracted and plotted for our model to show the percentage of sEMG signals that were correctly classified and those that were misclassified. The higher the diagonal values of a confusion matrix, the better performance of the classifier. Fig. 8 shows that the CNN model obtained high performance results where the 10% MVC class achieved the highest accuracy of 97.64%.



Precision	88.86 %
Recall	88.80 %
f1-Score	88.75 %
Accuracy	88.88 %

Fig. 7 Performance metrics of the trained model

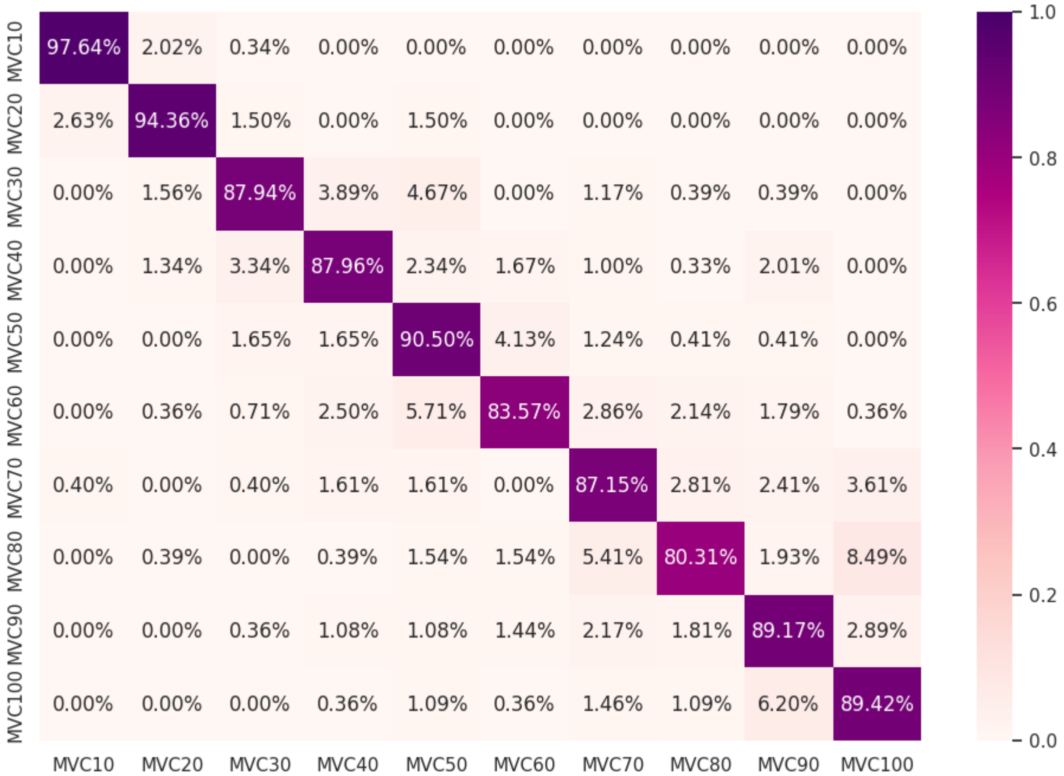


Fig. 8 Confusion matrix for the trained CNN model

Fig. 9A shows the number of correctly classified and misclassified sEMG signals in each MVC level. As an example, the second row indicates that 251 out of 266 signals with 20% MVC of the test data were correctly classified into their corresponding class, 7 signals were misclassified into 10% MVC class, 4 signals into each of 30% MVC and 50% MVC classes. The precision, recall and F1-score performance metrics for each class, along with their macro and weighted averages, are shown in Fig. 9B.

```
[[290   6   1   0   0   0   0   0   0   0]
 [  7 251   4   0   4   0   0   0   0   0]
 [  0   4 226  10  12   0   3   1   1   0]
 [  0   4  10 263   7   5   3   1   6   0]
 [  0   0   4   4 219  10   3   1   1   0]
 [  0   1   2   7  16 234   8   6   5   1]
 [  1   0   1   4   4   0 217   7   6   9]
 [  0   1   0   1   4   4  14 208   5  22]
 [  0   0   1   3   3   4   6   5 247   8]
 [  0   0   0   1   3   1   4   3  17 245]]
```

(A)

	precision	recall	f1-score	support
0	0.973	0.976	0.975	297
1	0.940	0.944	0.942	266
2	0.908	0.879	0.893	257
3	0.898	0.880	0.889	299
4	0.805	0.905	0.852	242
5	0.907	0.836	0.870	280
6	0.841	0.871	0.856	249
7	0.897	0.803	0.847	259
8	0.858	0.892	0.874	277
9	0.860	0.894	0.877	274
accuracy			0.889	2700
macro avg	0.889	0.888	0.887	2700
weighted avg	0.890	0.889	0.889	2700

(B)

Fig. 9 Number of correctly classified and misclassified signals per class (A), and performance metrics per class (B)

Discussion

Since deep CNNs have been proven to be able to extract complex patterns and features from complex signals, they were used in this work to classify the simulated sEMG signals, into the different MVC levels, overcoming the constraints of earlier studies' use of typical ML approaches [11, 13, 16, 25, 27, 35]. The results indicate strong performance of the model in distinguishing between classes, with an accuracy, F1-score, recall and precision of 88.88%, 88.75%, 88.80% and 88.86%, respectively. Most of the classes also achieved high classification accuracy, especially the first two classes which exceeded the 94.00% accuracy. We used a MATLAB model to produce sEMG signals with different filter types, electrode shapes, and other randomly distributed parameters. This allowed us to test the robustness of our method in a variety of settings and conditions by simulating a wide range of scenarios for sEMG [18]. Our findings indicate the efficiency and generalization of our approach by including such heterogeneity.

When generating the dataset, we used two ranges of recruitment thresholds within each MU (RR = 30% and RR = 70%). In the case of a narrow range for example (RR = 30%), this implied that the muscle recruited all MUs at an average of 30% of its maximum voluntary contraction. That is, even when the contraction level increases, there will be no significant increase in signal amplitude starting from 30% MVC, since most MUs were already recruited. Consequently, the classification accuracy for classes ranging from 30% to 100% was slightly lower than the first two levels. In this range, the change in the MVC level may affect more the frequency components of the sEMG signals than the amplitudes that depend on the number of recruited MUs. Hence, the amplitude contributed more to the classification of the first two classes. This, along with our prior findings in [19], aligns with the results of the muscle force production model presented in the research of Raikova et al. [24], in which the motor unit set generated muscle force estimates in both the time frame and frequency domains. In both models, motor unit firing principles influence force generation, with frequency features becoming increasingly important as the number of motor units recruited increases. These analogies emphasize the importance of frequency characteristics in effective classification, particularly when a narrow recruitment range is used.

Diverse methodologies and conclusions emerge from a collective investigation into muscle fatigue assessment using sEMG signal classification. Table 4 shows a brief summary of previous studies related to muscle fatigue detection and classification, in comparison with our work. Previous research works were mainly based on binary classification (fatigue and non-fatigue) [13, 16, 25, 27], or limited fatigue levels classification [22, 35]. In the present work, the sEMG signals were classified into ten different MVC levels. With this, we can monitor changes in muscle strength over time and identify when a muscle is getting tired. This allows clinicians and practitioners to access a more comprehensive assessment of muscle fatigue and its severity, and therefore make correct diagnoses and more appropriate decisions regarding patient management and treatment.

Table 4. Comparisons of our work with previous studies related to muscle fatigue detection and classification

Ref.	Objectives	Methodology	Results	Limitations / future work
[11]	Using the ANN for the classification of EMG signals.	3 input features: root mean square, average rectified value and mean frequency were extracted from simulated EMG signals using a computer muscle model. The scaled conjugate gradient algorithm was used to train the 16 neurons' hidden layer ANN.	Successfully classified the percentage of MVC using the input features.	No information about the size or diversity of the dataset. And no discussion of the classification system's applicability to other muscle groups or individuals.
[27]	A wireless system for monitoring and detecting muscle fatigue in real-time.	Database created from 3.4 hours of data from 10 people using wireless wearable EMG sensors. A fatigue evaluation algorithm based on time-frequency feature analysis was proposed. Isometric contraction and dynamic muscle fatigue trials were used for validation.	The mean power spectrum frequency was a more effective measure of muscle fatigue than time-domain features. It decreases as experimental time increases.	The small sample size of 10 subjects in the muscle fatigue database.

[13]	Distinguish between non-fatigue and fatigue conditions of dynamic muscle contractions using sEMG.	Nonstationary and multicomponent variations of sEMG signals recorded from the biceps brachii muscle during dynamic fatigue contractions of 52 healthy volunteers, were analyzed using time-frequency methods. For classification, nave Bayes, SVM, random forest, and rotation forests were used.	The proposed time-frequency distributions captured the nonstationary variations of sEMG signals. The majority of the characteristics differ between muscle fatigue and non-fatigue. Extended modified B-distribution with SVM achieved the highest accuracy of 91%.	–
[35]	A fatigue state classification system.	The k-nearest neighbor was used to classify sEMG from the lower limb muscles of 5 healthy subjects, into 3 categories.	The algorithm's accuracy was improved by combining time and frequency domain eigenvalues.	More data must be collected for greater accuracy.
[25]	ML system to classify fatigue regimes from EMG and heart rate variability data.	EMG and heart rate variability measurements were obtained from 14 subjects during a constant work rate test. Significant parameters were identified. A binary classification system was implemented.	The system achieved classification performances of 0.82 ± 0.24. Fourier median frequency was the best fatigue descriptor.	Fatigue-related values may vary according to the subject and experimental conditions, making a quantitative approach less appropriate.
[16]	Detect and improve the accuracy of dynamic muscle fatigue classification.	Multi-domain sEMG features were extracted and fused. An improved SVM with a differential evolution-based whale optimization algorithm was proposed.	Average accuracy of 85.50% in ankle dorsiflexion and 84.75% in ankle plantarflexion for dynamic muscle fatigue prediction.	Too many features may lead to classifier redundancy and affect recognition efficiency.
[22]	A wearable device to predict trunk muscle fatigue and prevent low back pain using CNN	Shallow models and a deep CNN were used to learn and forecast 5 common extracted time-domain and frequency-domain features of sEMG records obtained from 13 healthy male subjects.	The CNN outperformed the best shallow model by at least 30% in terms of a figure of merit combining accuracy and precision. It reduced the disparity between frequency and time domain features.	The study focused on healthy male subjects and may not generalize to other populations.

[4]	Estimate muscle contraction force from sEMG signals during biceps curl movements.	EMG signals of 8 participants used in two CNN branches for estimation: one branch for time domain characteristics from raw signal time series, and the other for frequency information.	The proposed model shows an average coefficient of determination of 0.9.	Large deviations between subjects and trials indicate limitations in estimating muscle contraction force. Testing more structural configurations of the model was suggested.
[9]	Develop a model for EMG-based force estimation, particularly during isometric elbow flexion contractions.	Deep CNN was created by fusing representations learned from high-density sEMG records from the long head and short head of biceps brachii and the brachioradialis muscles, in the time and frequency domains.	In terms of estimating force, the model with optimized hyper-parameters outperforms all other methods, with a normalized mean squared error of 1.63%.	Future research should look into other sensor types, according to the authors. More experiments under different conditions are recommended.
Our work	Asses the muscle fatigue and severity of the condition through the analysis and classification of sEMG signals into MVC levels.	A CNN-based deep learning algorithm was used for the classification of simulated sEMG signals recorded using 3 spatial filters, Different electrode shapes and various muscle parameters distributions.	The classification model achieved an accuracy, F1-score, recall, and precision of 88.88%, 88.75%, 88.80% and 88.86%, respectively.	Future work involves the use of real EMG data and explainable artificial intelligence to interpret the outcomes of the DL model for more trustworthy.

Hickman et al. [11] created an innovative ANN for EMG signal classification, achieving promising results in predicting MVC levels based on root mean square, average rectified value, and mean frequency features, but they overlook dataset diversity and applicability beyond muscle types. Song et al.'s wireless fatigue monitoring system [27], which includes time-frequency feature analysis, demonstrates the efficacy of mean power spectrum frequency in fatigue assessment, however, the limited sample size restricts generalizability. Meanwhile, Zhao et al.'s fatigue state classification system [35] encounters data scarcity, which reduces accuracy, whereas Ramos et al.'s wearable fatigue prediction device [25], although superior in performance, has limited demographic applicability. Our study provides a CNN-based DL algorithm for sEMG signal classification, which achieves respectable accuracy; however, further research in explainable artificial intelligence is required for improved interpretability. While each work improves sEMG signal classification, addressing dataset diversity, methodological validation, and demographic inclusivity are still crucial for wider clinical use and greater efficacy.

Conclusion

In this work, a convolutional neural network based deep learning algorithm was designed to classify simulated surface electromyography signals during different maximal voluntary contraction levels. The set of parameters and different distributions in the muscle model utilized in the generation of sEMG signals has shown the effectiveness and generalizability of our method.

The results of this innovative approach show that the model successfully distinguished between the ten MVC level classes, with an accuracy, F1-score of 88.88%, 88.75%, a recall of 88.80%, and a precision of 88.86%. This work holds great promise for assessing the disease, where it may allow clinicians for real-time monitoring of muscle fatigue, providing a more accurate understanding of the condition severity across different MVC levels.

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