sEMG biceps and triceps effort signals classification using 1D-CNN convolution

Classificação de sinais de esforço de bíceps e tríceps sEMG usando convolução 1D-CNN

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ABSTRACT
In this paper, we present a system for acquiring and classifying surface physiological muscles signals (sEMG) for the biceps and triceps muscles during movement or work, as normal or aggressive effort in order to control and command the aid prostheses to intervene only during aggressive efforts. Thus, the main objective of our work is to developing and improving the performance of the hand prostheses for daily life tasks for elderly persons or for persons who have hand muscle failure. Our contribution consists of detecting and classifying physiological signals of biceps and triceps muscles hand as normal and aggressive efforts, for that we proposed a technique based on a 1D Convolutional Neural Network (CNN-1D) using the Wavelet Scattering Transform as the sEMG feature extraction technique. Our methodology is carried out in two steps: the first step is crucial to build a database for deep learning network for sEMG signals classification based on fifty-five volunteers spanning various ages and genders. The second step achieves the sEMG signals effort classification as normal or aggressive efforts based on the classification network produced based on sEMG signal sequences treated by the WST. The obtained results for the training and validation sets indicate perfect performance of the proposed technique, with an accuracy, precision, sensitivity, and specificity of 100% for the training process, and 99.3%, 98.6%, 100% and 98.7% for the accuracy, precision, sensibility and specificity respectively. It is important to note that while perfect metrics on the training and the test set might suggest excellent model learning.
Keywords: deep learning, 1D-CNN, wavelet scattering transform, sEMG biceps signals effort classification, sEMG triceps signals effort classification.

RESUMO
Neste artigo, apresentamos um sistema para aquisição e classificação de sinais musculares fisiológicos de superfície (sEMG) para os músculos bíceps e tríceps durante movimento ou trabalho, como esforço normal ou agressivo, a fim de controlar e comandar as próteses de auxílio para intervir apenas durante esforços agressivos. Assim, o principal objetivo do nosso trabalho é desenvolver e melhorar o desempenho das próteses de mão para tarefas da vida diária de idosos ou de pessoas com insuficiência muscular da mão. Nossa contribuição consiste em detectar e classificar os sinais fisiológicos da mão em esforços normais e agressivos, para isso propusemos uma técnica baseada em uma Rede Neural Convolucional 1D (CNN-1D) utilizando a Transformada de Espalhamento Wavelet como técnica de extração de características sEMG. Nossa metodologia é realizada em duas etapas: a primeira etapa é crucial para construir um banco de dados para um modelo profundo para classificação de sEMG com base em cinquenta e cinco voluntários de diversas idades e gêneros. A segunda etapa alcança a classificação do esforço manual sEMG com esforços normais ou agressivos com base na rede de classificação produzida com base nas sequências de sinais sEMG tratadas pelo WST. Os resultados obtidos para os conjuntos de treinamento e validação indicam desempenho perfeito da técnica proposta, com exatidão, precisão, sensibilidade e especificidade de 100% para o processo de treinamento e 99,3%, 98,6%, 100% e 98,7% para a acurácia, precisão, sensibilidade e especificidade, respectivamente. É importante observar que, embora métricas perfeitas no conjunto de treinamento e teste possam sugerir um excelente aprendizado do modelo.

Palavras-chave: deep learning, 1D-CNN, transformada de espalhamento Wavelet, classificação de esforço de sinais de bíceps sEMG, classificação de esforço de sinais de tríceps sEMG.

1 INTRODUCTION
In human life, most movements and gestures are driven by muscle activities, where movements and locomotion are initiated by the electrophysiological excitation of a group of motor units (MU) so that the muscle contracts voluntarily or involuntarily. The electrophysiological signal generated during arousal and contraction can be detected and used to study muscle function[1] [2]. This process is known as an electromyogram (EMG). This latter consists of the study of muscle functions through the analysis and synthesis of electrical signals generated during muscular activities [3] [4] [5].

Nowadays, electromyography (EMG) plays a crucial role in a wide range of clinical research and life applications, where the main objective of human activity
recognition (HAR) is to identify the work and physical effort provided based on physiological EMG signals generated by a specific person [6]. These signals are widely used to diagnose neuromuscular diseases, for rehabilitation, in the control of prostheses, and even in the human-machine interface, allowing more intuitive interaction between users and technological devices. For example, in the field of rehabilitation, sEMG is used to assess the level of muscle activity and to guide personalized treatment programs. However, the use of EMG signals presents challenges and limitations. One of the main challenges lies in signal quality, which can be affected by various factors, such as electrical noise, interference from other muscles, and intra/inter-individual variability. These issues can make it difficult to accurately interpret signals and, therefore, limit their applicability in certain situations [7]. Additionally, acquiring high-quality EMG signals often requires expensive equipment and technical expertise for setup and analysis, which may limit their use in resource-limited settings. The need to place the electrodes precisely on the skin may also pose comfort and practicality issues for long-term users.

Hand gesture recognition based on surface electromyographic signals (sEMG) is a promising approach for the development of naturally controlled human-machine interfaces (HMIs), such as intuitive robotic interfaces or poly-articulated prostheses. However, this area of research remains open due to some practical limitations and real problems linked to the identification and recognition of human hand movements from physiological signals, notably EMG, as well as movement artifacts depending on postural variability and time and repositioning of sensors. In the literature, several research studies have been proposed in order to identify and classify sEMG signals from the human hand. In [8], authors proposed a Hand Gesture Classification algorithm based on surface EMG Hand signals for controlling myoelectric prosthetic hands. Utilizing transfer learning and a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architectures, the main step is based on the use of an algorithmic pipeline that leverages Continuous Wavelet Transform (CWT) to convert sEMG signals into images, which are then classified using deep learning models. This approach outperforms traditional machine learning techniques, with obtained accuracy results of 99.72% and 99.83% for two different datasets respectively. The work signifies a significant advancement in developing cost-effective, high-
performance control schemes for sEMG prosthetic hands. Another research work presented in [9] presents a novel deep learning approach for EMG hand gesture recognition, employing a 50-layer Convolutional Neural Network based on Residual Networks (ResNet) architecture. The proposed method involves measuring 4-channel surface EMG signals from 30 participants simulating seven distinct hand gestures, with the signals converted into spectrogram images via Short-Time Fourier Transform (STFT) for training. The obtained results achieved an accuracy of classification around 99.59% for both training and test stages respectively across seven hand gesture classifications, demonstrating significant potential for enhancing noninvasive sEMG-controlled biomedical systems through improved accuracy and prediction speed. Authors in [10] proposed a Hand Posture and Force Estimation using sEMG and an Artificial Neural Network, focusing on developing a method to estimate hand posture and exertion force. This proposed research work addresses the challenge of accurately quantifying hand exertions, which are significant factors in upper extremity disorders. Through experiments involving twelve participants, the study demonstrates the potential of sEMG combined with ANNs to predict hand posture and force, showing varying levels of accuracy influenced by hand posture, duty cycle, and repetition rate. The findings suggest that applying more sophisticated deep learning models could further improve prediction accuracy. A new methodology for hand gesture recognition using Deep Learning techniques is presented in [11]. It highlights the challenges posed by signal variability due to factors like muscle fatigue, electrode repositioning, and individual differences. Employing a one-dimensional Convolutional Neural Network (1D-CNN), the study explores the effectiveness of various training strategies to enhance intersession, inter-posture, and inter-day classification accuracy. The obtained experimental results on the used dataset demonstrate the potential of deep learning models to improve gesture recognition performances, despite the inherent challenges of sEMG signal analysis.

Authors in [12] present a new method for recognizing hand movements using a multi-feature fusion-based LSTM convolutional neural network (MFFCNN-LSTM), applying time-domain and time-frequency-spectrum analysis of forearm sEMG signals. This technique successfully identifies ten basic hand movements, including a rest action, with notable accuracy. Based on the NinaPro db8 dataset,
the proposed model achieved a recognition accuracy of 98.5%, with sensitivity and specificity rates of 95.25% and 95.5%, respectively. These results underscore its superior performance over traditional methods such as SVM, CNN, and LSTM across multiple public datasets.

Motivated by making a contribution to improving and developing hand prostheses for daily life tasks for elderly persons or for persons who have hand muscle failure, in this article we present a system for acquiring and classifying surface physiological signals for the biceps and triceps muscles during movement or work as normal or aggressive effort in order to control and command the aid prostheses to intervene only during aggressive efforts. The paper is organized as follows: In Section 2, we present the developed sEMG system and describe all the important components. In Section 3, we describe the proposed methodology and its implementation. More specifically, in the first part, we illustrate the constructed hand sEMG database. Then, we describe the proposed methodology to classify sEMG hand signals as normal or aggressive efforts. In Section 4, the evaluation and results validation of the proposed methodology are explained. Finally, conclusions are given in Section 5.

2 THE DEVELOPED SEMG SYSTEM AND THE MATERIALS USED

To achieve our objective of precisely classifying hand signals, specifically from the biceps and triceps muscles, we propose a system for the acquisition and processing of electromyographic (EMG) signals. This system is designed for use in mechanical systems, either as a prosthesis or as a medically aided tool. The acquisition system captures EMG signals, which are the electrical activities produced by muscles during their contraction and relaxation phases. These signals are recorded using electrodes placed on the surface of the skin over the muscles of interest. The collected data can then be utilized in various applications, including the control of prosthetic devices.

The main components of our proposed EMG signal acquisition system include:
2.1 RASPBERRY PI

The Raspberry Pi is a compact and powerful computing device, approximately the size of a credit card. It has gained popularity in fields such as the Internet of Things (IoT), data acquisition, real-time sensor monitoring, robotics, and home automation, thanks to its low cost, small size, and excellent performance. Equipped with an ARM processor, the Raspberry Pi’s specifications vary by model, offering between 256 MB and 8 GB of RAM. It features full connectivity, including WiFi, Bluetooth, and Ethernet ports, along with multiple USB ports and HDMI video outputs that support up to 4K resolution. Storage is facilitated via a microSD card, and GPIO pins enable the connection to various external devices. The device is powered via USB-C or micro-USB, depending on the model, and can run a variety of operating systems, including Raspberry Pi OS. Its compact and lightweight design makes it ideal for embedded computing applications [13].

![Raspberry Pi B+ model](image)

Source: Authors

2.2 EMG DETECTOR

The EMG detector serves as a bridge between the human body and electrical devices. This sensor captures small muscle signals, which are then amplified and filtered [14]. The output signal increases from a standby voltage of 1.5V to a maximum of 3.3V upon muscle activation, making it compatible with both 3.3V and 5V systems. The features of the EMG sensors used in this research are as follows:

- grove compatible;
• 3.5mm connector;
• 6 disposable surface electrodes;
• power supply voltage: 3.3V-5V;
• 1000mm cable leads;
• no additional power supply required.

Figure 2. EMG sensor.

2.3 ANALOG-DIGITAL CONVERTER (ADC)

The ADS1115 Analog-Digital Converter offers 16-bit precision and can be configured as four single-ended input channels or two differential channels. It includes a programmable gain amplifier, which can amplify signals up to x16, enabling smaller signals to utilize the full input range. This ADC operates between 2V to 5V for both power and logic, accommodating a wide range of signals with ease. Its compact size, low power consumption, and ease of use make it an excellent choice for a variety of applications.
The ADS1115 features include a delta-sigma ($\Delta\Sigma$) analog-to-digital core with adjustable gain, an internal voltage reference, a clock oscillator, and an I2C interface. Additionally, a programmable digital comparator provides an alert function via a dedicated pin, reducing the need for external circuitry and enhancing performance.

3 TYPICAL ELECTRONIC CONNECTIONS

Our proposed EMG system incorporates four EMG sensors connected to the ADS1115 ADC, which then interfaces with the Raspberry Pi via the I2C bus using SCL and SDA lines. As the Raspberry Pi lacks analog inputs, the ADS1115 ADC is utilized to convert the analog signals from the EMG detectors into 16-bit digital signals. These signals are subsequently sent to the Raspberry Pi, as illustrated in the following figure 4 and 5.

Figure 4. Typical connections of the proposed EMG signal acquisition system.
4 THE PROPOSED sEMG CLASSIFICATION METHODOLOGY

4.1 EMG HAND DATASETS CONSTRUCTION

Techniques and applications that based on artificial intelligence, particularly those using supervised learning methods, having a comprehensive database is crucial for the training phase. To this end, we developed a new database utilizing the acquisition system described in section , which is adequately meets our research and development needs. The developed sEMG biceps and triceps signals database encompasses fifty-five volunteers spanning various ages and genders. It includes 15 volunteers aged over sixty years old (comprising 8 men and 7 women), 26 volunteers aged between thirty-five and sixty years old (13 men and 13 women), and 14 volunteers aged between 17 and thirty five years old (8 men and 6 women). The acquired Emg signals are focus is on the triceps and biceps muscles of each volunteer’s hands (right and left hands) with four different repititifs movements: two simple Free hand movements with a minimal effort, and two intense hand movements requiring significant effort using some different kinds of heavy charges according to the age and the physical stat of volunteers. Finally, for each volunteer, we obtained 8 recorded hand EMG signals that contain four EMG signals for normal and four EMG signals for agressive hand effort, focussing on biceps and triceps muscles respectively. All the acquired and recorded Emg hand signals are lasting for 50 seconds. The volunteers repeat the basic acquisition exercise five times, alternating between their right and left hands.
The first and last acquisitions occur in the morning and evening, respectively, while the other acquisitions take place during daily activities throughout the day.

4.2 CLASSIFICATION METHOD

To achieve the detection and classification of hand physiological signals as normal and aggressive efforts, we proposed a technique based on a 1D Convolutional Neural Network (CNN-1D) using the Wavelet Scattering Transform as the EMG feature extraction technique. The overarching principle of the proposed methodology is illustrated by the flowchart below:

4.2.1 Step 1

As with all artificial intelligence methods, this step is crucial to build a deep learning network for EMG hand classification. In this stage, two approaches are used:

- Wavelet scattering transform;
- construction of a 1D Deep Learning Network.

4.2.2 Step 2

This step achieves the EMG hand effort classification as normal or aggressive efforts based on the classification network produced in the first step, using EMG signal sequences treated by the WST.

Figure 6: Flowchart of the proposed EMG hand classification methodology.
4.3 WAVELET SCATTERING TRANSFORM

Authors in [15] have proposed a new mathematical technique named the Wavelet Scattering Transform (WST) for signal representation based on an iterative wavelet transform with two additional essential steps. It is found to be more precise for variant signals and more accurate in capturing short or small variations and deformations in signal representation by extracting significant features for signals at different levels or scales of representation.

We notice that the Wavelet Transform (WT) is one of the most powerful techniques in signal processing [16] [17] [18]. It is characterized by the use of well-localized mathematical functions (Wavelets) in both physical and spectral spaces, generated from one to another by translation and expansion. The wavelet transform realizes a decomposition of a signal at different scales and ensures well-resolution properties in the time-scale plane.

The wavelets transform of the function $x(t)$ is a set of coefficients obtained by the following equation:

$$CWT_{x(t)}(\psi, a, b) = \int_{\mathbb{R}} x(t)\psi_{a,b}^*(t)dt$$

(1)

where:

• $a \in \mathbb{R}^+$ and $b \in \mathbb{R}$,
• $\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi \left(\frac{t-b}{a}\right)$: it is an atom of the mother wavelet defined at the position $b$ in the scale $a$.

The main application of wavelet transformation in the signal processing field leads to multi-resolution signal representation using analytic wavelets at different scales. It is therefore considered that our original signal corresponds to the space $(D1, D2, D3,...)$. The approximation space will allow us to extract the low frequencies from our original image. The space of details will serve us to extract the high frequencies from the analyzed signals. To move from one scale to the next scale, the operation is performed recursively on the approximation spaces, see the following Figure 7.
The Wavelet Scattering transform process is based on the Wavelet transform depicted in previous paragraph followed by Nonlinearity and Averaging steps respectively as shown in the figure bellow:

Figure 8. Flowchart of wavelet scattering transform

for signal \( x(n) \) as an input, three successive process are required:

4.3.1 Convolution (Wavelet Transform)

The first step in the WST is the application of the Wavelet Transform. Given a signal \( x(t) \), its CWT at scale \( a \) and translation \( b \) using a mother wavelet \( \psi(t) \) is defined as [19]:

\[
\text{CWT}_{x(t)}(\psi, a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \cdot \psi^*\left(\frac{t-b}{a}\right) dt
\]  

(2)

For discrete signals, the Discrete Wavelet transform DWT for a discrete signal \( x(n) \) is defined by mathematics formula (equ.3). Contrary to the continuous transform in which the wavelet is dilated and translated in a continuous manner,
the discrete wavelet transform translates and dilates the wavelet according to
discrete values. The coefficients $a$ and $b$ are discretized as follows:

$$a = a_0^m, \ b = k b_0 a_0^m$$

Where:

$a_0 > 1$ and $b_0 > 0$, fixed and belonging to $\mathbb{Z}$.

The transformation is given by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a_0^m}} \psi\left(\frac{t - (k b_0)}{a_0^m}\right)$$

Thus, we obtain:

$$CWT_{x(t)}(\psi, a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^*(t) dt$$

If the signal $x(t)$ is discretized, then the discrete wavelet transform is
defined by:

$$DWT_{x(nT_e)}(\psi, a = a_0^m, b = n b_0 a_0^m) = \frac{1}{\sqrt{a_0^m}} \sum_{n=-\infty}^{\infty} x(nT_e) \psi^*\left(n T_e - \frac{(k b_0)}{a_0^m}\right)$$

Assuming a sampling period equal to 1 for simplicity, the equation is then
written as:

$$DWT_{x(n)}(\psi, a = a_0^m, b = n b_0 a_0^m) = \frac{1}{\sqrt{a_0^m}} \sum_{n=-\infty}^{\infty} x(n) \psi^*\left(n - \frac{(k b_0)}{a_0^m}\right) \quad (3)$$

Both Continuous and discrete wavelet transform can be written in the form
of filtering by convolution between a signal $x$ and wavelet $\psi$ in the vicinity of point
$b$ and at scale $a$ as written in equation bellow:
\[ WT_x(\psi, a, b) = x * \psi_{a,b} \] (4)

### 4.3.2 Scattering Transform (Modulus)

The scattering transform iteratively applies wavelet transforms and modulus operators to decompose signals into coefficients that capture their structure at multiple scales.

#### 4.3.2.1 First order scattering

For the first order, the scattering coefficient \( S_1(x) \) for scale \( a_1 \) and translation \( b \) is given by:

\[ S_1(a_1) = |WT_x(a_1, b)| \] (5)

where:

\[ |\cdot| \] denotes taking the absolute value (modulus).

#### 4.3.2.2 Second order scattering

For the second order, the process involves taking the CWT of the first order scattering coefficients:

\[ S_2(a_1, a_2) = |WT_{S_1(a_1)}(a_2, b)| \] (6)

And so on for higher orders, applying the CWT to the previous scattering coefficients and taking the modulus.

Continuing with the same process we can define all the scattering coefficients at multiple scales.

### 4.3.3 Low-pass filtering and downsampling

After obtaining the modulus, the result is usually passed through a low-pass filter \( \phi \) and downsampled to achieve translation invariance and reduce the dimensionality of the output:

\[ S_x = S_x * \phi \] (7)
Where:

* denotes convolution, and $\phi$ is the low-pass filter.

The final scattering coefficients, obtained at various orders, are aggregated to provide a new representation of the original EMG signal. These coefficients are invariant to translations and stable in the face of deformations, rendering them highly effective for a range of signal processing and machine learning applications. The coefficients derived from the Wavelet Scattering Transform hold significant value as a representation of the original EMG signal, facilitating the identification of hand EMG signals as either normal or aggressive effort.

4.4 DEEP LEARNING NETWORK FOR EMG HAND CLASSIFICATION

The input of proposed deep learning architecture is based on the coefficients obtained by the wavelet scattering transform of EMG hand signals, this coefficients appears as invariant signals contrary to their original EMG signals that were naturally variant signals. In literature many architecture of deep learning network are proposed to achieve the classification of human EMG signals [21] [22] [23] [24] [25]. The proposed configuration network was based on height level of filters to select the appropriate features. The proposed CNN network steps are detailed as follows:

- sequence input with 104 dimensions, this dimension represent the main features extracted by WST;
- 256 6x104 convolutions with stride 1 and padding 'causal';
- rectified Linear Unit;
- layer normalization with 256 channels;
- 256 12x256 convolutions with stride 1 and padding 'causal';
- rectified Linear Unit;
- layer normalization with 256 channels;
- 256 6x256 convolutions with stride 1 and padding 'causal';
- rectified Linear Unit;
- layer normalization with 256 channels;
- 1-D global average pooling
2 fully connected layer;
- softmax;
- cross-entropy with classes 'Agressive' and 'Normal'.

The proposed deep learning network for sEMG biceps and triceps muscles classification is trained with mini batches of 64 for 250 epochs.

4.5 CLASSIFICATION EVALUATION CRITERIA

The various evaluation metrics used to validate the performance of the proposed methodology for the identification and classification of EMG signals are as follows [26]:

Accuracy is a commonly used metric to assess the performance of a model, especially when all classes are of equal importance. It is determined by dividing the number of correct predictions by the total number of predictions made by the model. This metric provides insight into the model’s overall performance across all classes, rather than concentrating on a single class. Accuracy is a crucial metric in the development and evaluation of machine learning models as it offers a measure of the model’s capacity to generalize to unseen data.

\[
Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{8}
\]

Sensitivity, also known as recall, true positive rate (TPR), or hit rate, pertains to the model’s ability to correctly predict positive instances. It measures the model’s efficacy in identifying all positive instances. The term "detection rate" is also associated with this metric, indicating the capability to accurately identify relevant instances for a specific task. This criteria parameter is defined by the equation bellow:

\[
Sensitivity = \frac{TP}{TP+FN} \tag{9}
\]

Specificity, is another criteria to evaluate the machine and deep learning methods, relates to the model’s ability to correctly predict negative instances. It is also referred to as selectivity or true negative rate (TNR). This metric is important for understanding how well the model can identify all negative instances. The appropriate equation for specificity is:
Specificity = \frac{TN}{TN+FP} \quad (10)

Precision is another performance metric that measures the proportion of actual positives among instances classified as positive by the model. This metric is crucial for scenarios where the cost of false positives is high. The Precision criteria can be defined by the equation below:

Precision = \frac{TP}{TP+FP} \quad (11)

With this classification metrics: accuracy, sensitivity, specificity and precision, a correct and precise evaluation can be achieved for the adapted methodology of EMG hand classification based on 1D Deep learning technique as normal or aggressive hand actions.

5 OBTAINED RESULTS AND DISCUSSION

Based on the developed EMG signal acquisition and the constructed database depicted in the section 4.1, in this research work 2/3 of the content of the database is used for training tasks and 1/3 of the constructed database is used for test tasks or validation step. The obtained results are presented in the figures 9, 10 for deep learning network training and validation process respectively:

Figure 9. Confusion Matrix results of training process

<table>
<thead>
<tr>
<th>True Class</th>
<th>Train</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggressive</td>
<td>742</td>
</tr>
<tr>
<td>Normal</td>
<td>725</td>
</tr>
<tr>
<td>Aggressive</td>
<td>100.0%</td>
</tr>
<tr>
<td>Normal</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Source: Authors
According to the obtained results for the training process, we notice that the number of aggressive instances predicted correctly (True Positives (TP)) is 742 signals, the number of normal instances correctly predicted correctly (True Negatives (TN)) is 725 signals. In addition with an empty number of normal and aggressive signals incorrectly predicted.

These results indicate perfect performance of the model on the training set and leads to an accuracy, precision, sensitivity, and specificity of 100%. It is important to note that while perfect metrics on the training set might suggest excellent model learning.

The figure 10 show the obtained results of test or validation task based on 1/3 of the global contents of the constructed hand EMG database, we notice that the number of aggressive signals correctly predicted is 353 signals (True Positives (TP)=353) and the number of normal signals correctly predicted as normal is 375(True Negatives (TN)=375). Furthermore, five aggressive signals are predicted as normal signals effort(False Positives (FP)=5) and an empty number of aggressive signals incorrectly predicted as normal signal(False Negatives (FN)=0). This results leads to an:

Figure 10. Confusion Matrix results of validation process

<table>
<thead>
<tr>
<th>Predicted Class</th>
<th>Normal</th>
<th>Aggressive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test True Class</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>375</td>
<td>353</td>
</tr>
<tr>
<td>Aggressive</td>
<td>5</td>
<td>98.6%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Source: Authors
Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{353 + 375}{353 + 375 + 5 + 0} \approx 0.993.

Precision = \frac{TP}{TP + FP} = \frac{353}{353 + 5} \approx 0.986.

Sensitivity = \frac{TP}{TP + FN} = \frac{353}{353 + 0} = 1.

Specificity = \frac{TN}{TN + FP} = \frac{375}{375 + 5} \approx 0.987.

These results indicate that the model has high accuracy, precision, sensitivity, and specificity on the test set, suggesting it performs well in distinguishing between aggressive and normal instances.

In the test results, we can see that the model still performs very well, but not as perfectly as in the training results, which is normal. The small number of false positives indicates that the model is slightly more prone to incorrectly predicting the "Normal" class as "Aggressive" than the other way around, as there are no false negatives.

The high values of accuracy, precision, sensitivity, and specificity suggest that the model is performing well on the test set and is likely to be a good predictor for unseen data, assuming the test set is representative of the real-world data the model is expected to work with. However, the presence of false positives (albeit a small number) indicates that there is still room for improvement, possibly by further tuning the model or by gathering more representative training.

6 CONCLUSION

In this work, our primary interests is to propose a methodology and system design for acquiring and classifying surface physiological signals for the biceps and triceps muscles during movement or work, in order to control and command the aid prostheses to intervene only during aggressive efforts. Our methodology is based mainly on a 1D Convolutional Neural Network (CNN-1D) using the Wavelet Scattering Transform as an sEMG feature extraction technique. This latest technique (WST) is one of the most powerful techniques in signal processing. It is
characterized by the use of well-localized mathematical functions (Wavelets) in both physical and spectral spaces, generated from one to another by translation and expansion. The wavelet transform realizes a decomposition of a signal at different scales and ensures well resolution properties in the time-scale plane. The obtained results for the training and the test set indicate perfect performance of the model and leads to an accuracy, precision, sensitivity, and specificity of 100% for training process, and 99.3%, 98.6%, 100% and 98.7% for the accuracy, precision, sensibility and specificity respectively. According to obtained results. The proposed system and the methodology adopted in this research hold significant potential for benefiting healthcare by enhancing the field of hand prosthetic control systems where an accurate classification of sEMG signals can improve the functionality and effectiveness of aid prostheses during specific muscle efforts, this study contributes to advancements in assistive technology for individuals with limb impairments. Moreover, highlighting the utilization of the Wavelet Scattering Transform as an important and innovative approach in signal processing and convolutional neural network for Artificial intelligence applications.

However, it is important to note that while perfect metrics on the training and test set might suggest excellent model to classify sEMG signals of the biceps and triceps muscles as normal of aggressive effort needed, it is necessary to acknowledge the minor limitations presented by the validation process results. Future work should consider conducting further validation studies with larger and more diverse datasets to assess the model's robustness across different scenarios and individuals.

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