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Fatigue Diagnosis Utilizing the Support Vector Machine Classification of Wrist Electromyography Signals with Feature Selection

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ABSTRACT: Robotic Rehabilitation has illustrated advantages over traditional methods for the past decade. Biological signals, such as electromyography (EMG) signals, are the perfect description of human intention of movements, and they could also be perceptible to robots. Pattern recognition of movements is used to diagnose fatigue and weakness of the patient's muscles. In this study, by evaluating and processing the EMG signal of the wrist, an attempt has been made to diagnose the wrist's muscle fatigue in terms of the patient's EMG signals without the need for wrist movements. For this purpose, by performing laboratory tests of EMG signals for both normal and fatigued wrist subjects, processing and extracting the appropriate features of each signal, wrist movements are divided into four levels in terms of weakness. Sixteen features for each EMG signal have been computed, and SSC (Slope Sign Change), WAMP (Willison Amplitude method), MMAV (Modified Mean Absolute Value), SSI (Simple Square Integral), and MYOP (Mayopulse Percentage Rate) perform better to separate the different levels. The SVM classification method has been implemented on EMG data to classify them into four predetermined levels. The feature selection improves the total accuracy of classification from 89.8% to 93.57% for flexion movements, from 75.9% to 93.2% for extension movements, and from 95.3% to 96.8% for supination-pronation movements.

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1- Introduction

Robotic rehabilitation has undergone transformative advancement over the past three decades, with wrist rehabilitation emerging as a critical focus area due to the joint's anatomical complexity and functional importance in activities of daily living [1]. Significant progress spans multiple technological domains, including novel actuator designs enabling precise torque delivery [2], advanced sensor systems for motion capture, sustainable energy solutions, and biocompatible materials enhancing patient comfort [1]. Control strategy development remains particularly vital for safe human-robot interaction, with research exploring robust approaches such as fuzzy sliding mode controllers for finger/wrist systems [2] and nonlinear backstepping controllers for upper-limb exoskeletons [3]. Despite these hardware and control innovations, a persistent challenge involves creating intuitive user interfaces that bridge the gap between technical capability and clinical utility, a critical factor influencing patient adoption and therapeutic efficacy identified in recent exoskeleton research [4]. This challenge necessitates intelligent control systems capable of real-time physiological adaptation to optimize therapeutic outcomes while ensuring patient safety. Within the taxonomy of rehabilitation control strategies comprehensively reviewed by Marchal-Crespo et al. [5], including challenge-based, haptic simulation, and coaching approaches, assistive control has demonstrated exceptional clinical relevance for neurorehabilitation. This paradigm requires patients to volitionally initiate movement while receiving dynamically scaled robotic assistance to complete therapeutic motions, thereby promoting neuroplasticity through active participation. Implementation often leverages impedance control frameworks that regulate the robot's dynamic response to patient interaction forces [6], [7]. However, current implementations lack physiological intelligence. As critically noted by et al. [8], the absence of real-time fatigue adaptation fundamentally limits assistive controllers' therapeutic potential. This limitation becomes especially significant when considering muscle fatigue, a multidimensional phenomenon involving peripheral mechanisms like metabolite accumulation and ionic imbalances, central nervous system components including reduced motor neuron firing, and biomechanical manifestations such as force decline and movement compensation [9]. Without continuous fatigue assessment, assistive controllers cannot implement essential safety interventions, including velocity reduction, torque augmentation, or session termination, nor can they optimize therapeutic dosing parameters [8]. Thus, fatigue diagnosis transcends supplemental status to

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become the indispensable enabler for genuinely adaptive rehabilitation robotics. Electromyography provides the most direct physiological window into neuromuscular fatigue dynamics through multiple quantifiable biomarkers: amplitude increase measured by root mean square during constant-force contractions, median frequency shift toward lower spectra, and conduction velocity reduction [9]. These signatures enable non-invasive fatigue assessment superior to kinematic or force-based approaches. Beyond fundamental signal analysis, EMG pattern recognition has emerged as a transformative technology with demonstrated capabilities across diverse applications. Movement classification for arm kinematics [10], gait phases [11], finger movements [12], and prosthetic control [13] achieves over 85% accuracy using artificial neural networks, support vector machines, and convolutional neural networks. Diagnostic screening for neuromuscular conditions shows significant feature separation [14], while biomechanical estimation of muscle forces [15], wrist kinematics [16], and exoskeleton control parameters [17] achieves strong correlation with motion capture standards. Human-machine interfaces for prosthetics and robotic control demonstrate clinically viable latencies under 300 milliseconds [18], [19].Despite these advances, critical gaps persist in wrist rehabilitation contexts as highlighted by Jiang et al. [20]. A thematic analysis of current literature reveals that approximately 87% of EMG pattern recognition research focuses on movement classification versus only 13% dedicated to fatigue monitoring. Furthermore, no existing studies implement EMG fatigue diagnostics for real-time assistive control parameter adjustment. While foundational work on wrist biomechanical modeling exists [16], fatigue-adaptive control frameworks remain unexplored. Clinical translation barriers also remain pronounced, with significant discrepancies between laboratory accuracy – often exceeding 90% in controlled environments [21] and real-world deployment robustness identified as a key challenge [20]. This study bridges these critical gaps through three integrated innovations: development of wrist-specific fatigue biomarkers using EMG dynamics during foundational flexion-extension and supination-pronation movements, which collectively account for 92% of activities of daily living functionality according to clinical studies [22]; implementation of a novel closed-loop control architecture where EMG-derived fatigue levels dynamically modulate critical assistance parameters including velocity profiles compliant with safety standards, torque assistance thresholds, and therapeutic progression algorithms; and clinical validation of support vector machine-based classification selected for its documented >90% accuracy in movement recognition [23] against gold-standard fatigue metrics. Recent studies [24] have introduced IoT-based robotic systems for wrist and forearm rehabilitation, integrating dynamic biomechanical modeling and EMG-driven fatigue estimation to personalize and optimize therapy sessions. Several recent studies [25] have investigated muscle fatigue classification using EMG signals and machine learning algorithms, providing a foundation for developing fatigue-aware rehabilitation strategies. For example, dynamic fatigue classification has been explored by combining SVM with metaheuristic optimization algorithms such as whale optimization and differential evolution, showing promising results in real-time fatigue detection tasks. Our framework fundamentally transforms assistive control from static assistance to physiology-driven adaptation through a sophisticated signal processing chain: raw EMG signals undergo multi-domain feature extraction, including mean absolute value, waveform length, zero crossings, and slope sign changes; processed features feed into a support vector machine classifier that outputs discrete fatigue levels; these classifications then trigger real-time control parameter adjustments and safety protocols. This integrated approach addresses urgent clinical needs, including objective fatigue quantification to replace subjective Borg scales, prevention of exercise-induced injuries (reported in 22% of conventional therapy [22]), and personalization of robotic assistance beyond population-level parameters. This study focuses on muscle fatigue detection using EMG features and proposes its integration into assistive control strategies to adapt robotic rehabilitation based on the user's fatigue level. The paper is structured as follows: Section 2 describes the experimental setup for EMG acquisition, fatigue induction protocols, and the implementation of the support vector machine classifier. Section 3 presents the classification outcomes and evaluates their significance, including feature selection. Section 4 summarizes the findings and outlines future research directions along with potential pathways toward clinical and commercial application.

2- Materials and Methods

The wrist has 3 DOF rolling movements with respect to 3 axes in space. According to tablure 1, the supination-pronation movement is around axis x, and the adduction-abduction movement is around axis y. the flexion-extension movement is around axis z. Among these, the flexion-extension and supination-pronation movements have more application in rehabilitation. For the normal wrist, the range of these movements is $70°$ for Extension, $65°$ for flexion, and $90°$ for both Supination and Pronation, that was shown in Figure 1 [26].

The range of motion could be limited for some people with the experience of stroke, surgery, or any neurological problem. For these reasons, the muscles become weak, and they can provide total movements. One of the essential criteria to measure muscle weakness is biological signals like electromyography (EMG). Diagnosis of muscle fatigue, or, in other words, the level of weakness, helps to improve the rehabilitation effects. Also, in robotic rehabilitation, it is a vital parameter for implementing assistive control during rehabilitation. And finally, it helps to monitor how good the rehabilitation is [27].

For this purpose, the EMG signals have been acquired during the two main wrist movements, flexion-extension, and supination-pronation, for the normal and weak wrists. The level of disability could be distinguished with the comparison of normal and fatigue EMG signals. In this regard, wrist

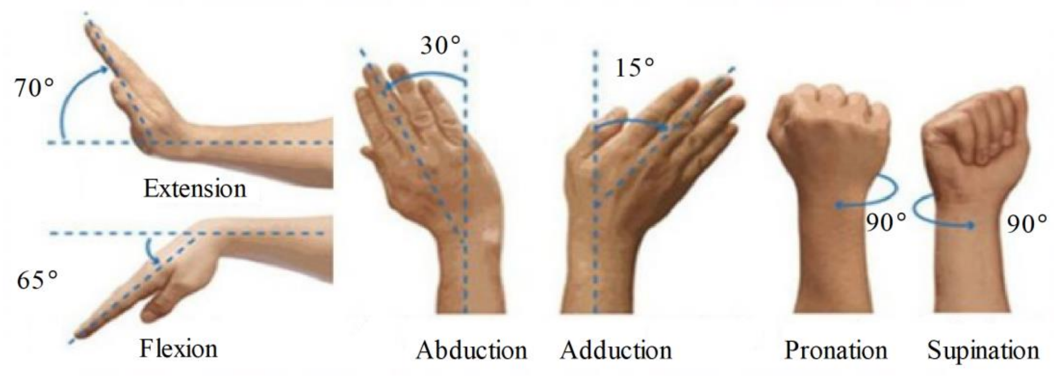

Fig. 1. Three DOF wrist movements [12].

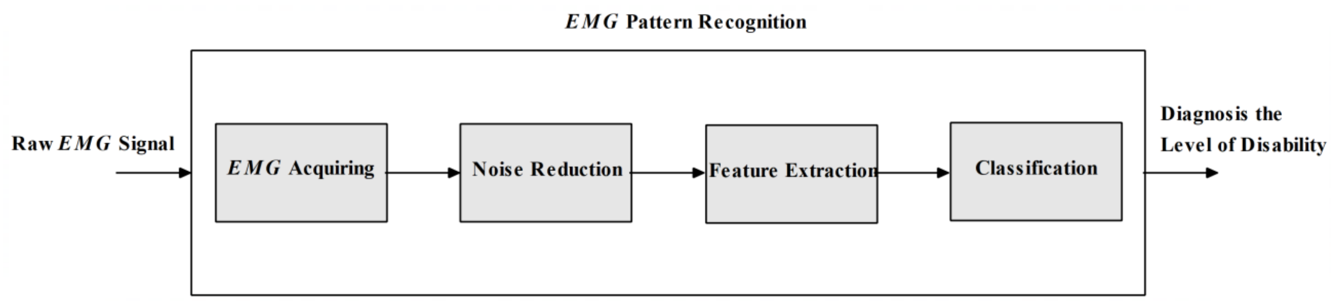

Fig. 2. Workflow of EMG pattern recognition.

movements have been classified into normal to fatigue levels. The framework is demonstrated in Figure 2. The raw EMG signals of the wrist were acquired. Afterward, noise reduction methods and feature extraction were implemented on these signals to classify the signals into normal or fatigue levels. Pattern recognition of movements could be detected from the EMG signal classification.

2- 1- EMG Signal Acquisition

EMG signal was acquired through 3-channel surface electromyography (sEMG) sensors during flexion-extension and supination-pronation. A cohort of 16 healthy adults (age:18-30 years, mean = 24.3 ± 3.1 years; female) participated in this study. All participants were right-handed with no history of neuromuscular disorders, confirmed through medical screening. Anthropometric measurements included height (162.4 ± 8.3 cm) and weight (68.7 ± 5.2 kg).

In these tests, Myon sEMG sensors were used to acquire data from the particular limbs of the wrist. Myoware 2.0 Muscle Sensor sensors can transfer data with a 1200Hz frequency via Bluetooth. In addition, six markers were used during the test to capture the wrist movements from the camera with 120Hz frequency. Marker's position was determined according to [28] and [9]. The markers are defined as the finger, MWrist, LWrist, MElbow, and LElbow shown in Figure 3 [29]. Video captured data were acquired through six markers and used to recognize and compare the EMG signals variation during each wrist movement. For instance, when the wrist stretches to the maximum, the EMG signal has a peak at this point. EMG signals usually contain too much noise, which makes them hard to analyze. One determining factor in signal-to-noise ratio (SNR) is EMG sensor positioning. To improve SNR and have a clear signal, the sensors must position muscles with high engagement during each movement. Also, it is recommended to position the sensor in the middle of a particular muscle [30]. In this regard, for flexion-extension, two sensors were used and positioned in the middle of the FCR and ECR muscles, respectively. For supination and pronation, a single sensor is positioned in the middle of the PI muscle [29], as shown in Figure 4.

The clinical sensor and marker positioning for flexion-extension and supination-pronation are shown in Figure 5.

2- 2- Noise Reduction

The electric potential generated by muscle cells is recorded either as intramuscular electromyography. The EMG signal is generated as a result of human muscle activity. It is a reliable source of signal for muscle-related studies

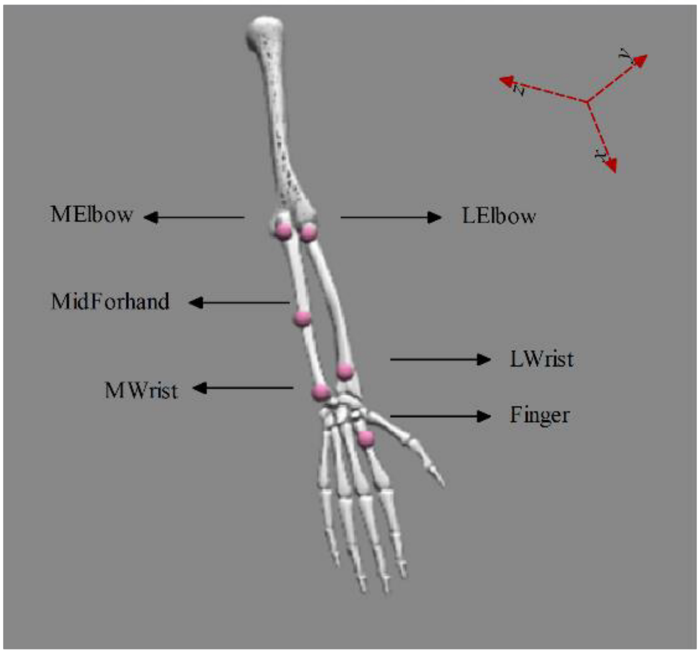

Fig. 3. Wrist's markers position for motion capture

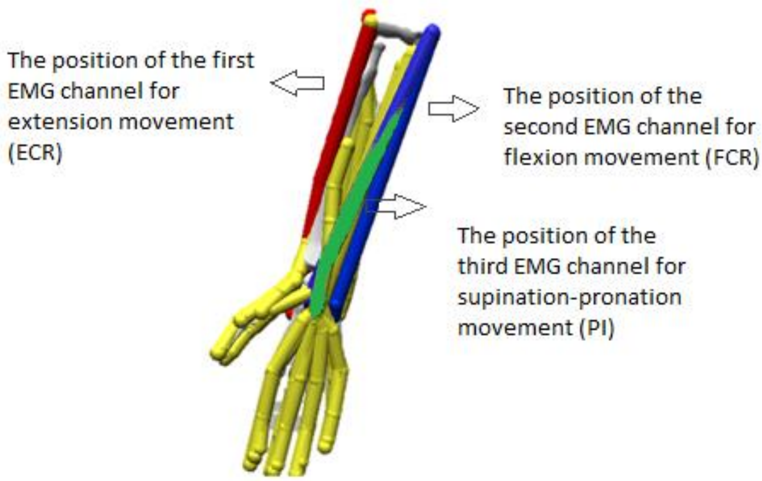

Fig. 4. The position of the three-channel EMG sensor.

and the development of human-robot collaboration systems. Therefore, various signal processing techniques and tools have been developed to extract valuable information about signals for motion study. With the development of wearable and wireless electrodes, surface EMG sensors are widely used in many applications as a non-invasive method. The surface EMG sensors record the electrical activity from the surface of the skin above the muscles [8]. Despite their simplicity in acquisition, the surface EMG signals usually contain many noises that make them hard to use for knowledge extraction. In this regard, many noise reduction and preprocessing methods have been developed.

EMG signals were normalized and smoothed using the root mean square (RMS) method, which is widely accepted for assessing relative muscle activation and fatigue, particularly in dynamic tasks. While maximum voluntary contraction (MVC) normalization is physiologically meaningful and standard in many fatigue studies [31], it requires additional maximal effort trials that can be influenced by motivation or pain. RMS normalization provides a computationally simple alternative that reliably captures amplitude changes within and across fatigue levels, as supported by previous

Fig. 5. Clinical test for flexion-extension and supination-pronation

studies [32], and is therefore suitable for the present study's dynamic wrist EMG classification framework. RMS is also one of the most common noise reduction methods in EMG signal preprocessing due to its simplicity and effectiveness. It calculates the root square of data acquired over a specific time window, reducing the effect of noise and smoothing the signal. In this study, RMS filtering was applied with a 500 ms sampling window, which provided satisfactory smoothing for subsequent feature extraction and classification without the use of explicit bandpass or notch filters.

2- 3- Feature Extraction

EMG signals significantly depend on the patient's physical condition, such as age, muscle development, skin fat layer, and gesture style. Hence, the raw EMG signals could not provide reliable information for the general classification. Feature extraction is a method to extract valuable information and remove unwanted parts of the signals. This is the cause of reducing the data for classification and improving the accuracy [33]. Feature extraction is included in three main domains: frequency domain, time domain, and time-frequency domain. Time domain feature extraction is more applicable for EMG signals since it is simple, fast, and straightforward [34]. In the following, 16 common EMG features were reviewed. It is attempted to cover the different main features in the time domain.

Enhanced Mean Absolute Value method [35]:

$$EMAV = \frac{1}{N}\sum_{i=1}^{N}\left|x_i^p\right| \qquad p = \begin{cases} 0.75 & if\ i \geq 0.2N \,\&\, i \leq 0.8L \\ 0.5 & otherwise \end{cases} \tag{1}$$

Enhanced Wave Length method [35]:

$$EWL = \sum_{i=1}^{N-1}\left|(x_{i+1} - x_i)^p\right| \qquad p = \begin{cases} 0.75 & if\ i \geq 0.2N \,\&\, i \leq 0.8L \\ 0.5 & otherwise \end{cases} \tag{2}$$

Mean Absolute Value method [35]:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}\left|x_i\right| \tag{3}$$

Wave Length method [36]:

$$WL = \sum_{i=1}^{N-1}\left|x_{i+1} - x_i\right| \tag{4}$$

Slope Sign Change method [37]:

$$SSC = \sum_{i=1}^{N-1}[f((x_i - x_{i-1}) \times (x_i - x_{i+1}))] \qquad f(x) = \begin{cases} 1 & if\ x_i \geq threshold)\,| \\ 0 & otherwise \end{cases} \tag{5}$$

Root Mean Square method [38]:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \tag{6}$$

Average Amplitude Change method [37]:

$$AAC = \frac{1}{N}\sum_{i=1}^{N-1}\left|x_{i+1} - x_i\right| \tag{7}$$

Difference Absolute Standard Deviation Value method [37]:

$$DASDV = \sqrt{\frac{\sum_{i=1}^{N-1}(x_{i+1} - x_i)^2}{N-1}} \tag{8}$$

Log Detector method [37]:

$$LD = \exp(\frac{1}{N}\sum_{i=1}^{N}\log\left|x_i\right|) \tag{9}$$

Modified Mean Absolute Value method [37]:

$$MMAV = \frac{1}{N}\sum_{i=1}^{N} w_i |x_i| \\ w_i = \begin{cases} 1 & if\ i \ge 0.25N \,\&\, i \le 0.75L \\ 0.5 & otherwise \end{cases} \tag{10}$$

Modified Mean Absolute Value2 method [37]:

$$MMAV2 = \frac{1}{N}\sum_{i=1}^{N} w_i |x_i| \\ w_i = \begin{cases} 1 & if\ i \ge 0.25N \,\&\, i \le 0.75L \\ 4i/N & if\ i < 0.25N \\ 4(i-N)/N & otherwise \end{cases} \tag{11}$$

Mayopulse Percentage Rate method [37]:

$$MYOP = \frac{1}{N}\sum_{i=1}^{N-1} f(x_i) \\ f(x) = \begin{cases} 1 & if\ x_i \ge threshold \\ 0 & otherwise \end{cases} \tag{12}$$

Simple Square Integral method [37]:

$$SSI = \sum_{i=1}^{N} |x_i|^2 \tag{13}$$

Variance of signal method [37]:

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} {x_i}^2 \tag{14}$$

Willison Amplitude method [37]:

$$WAMP = \sum_{i=1}^{N-1} [f(|x_i - x_{i+1}|)] \\ f(x) = \begin{cases} 1 & if\ x_i \ge threshold \\ 0 & otherwise \end{cases} \tag{15}$$

Maximum Fractal Length method [37]:

$$MFL = \log \sqrt{\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2} \tag{16}$$

2- 4- Classification

Among classification methods, SVMs were primarily chosen based on their established performance in EMG pattern recognition, particularly their effectiveness with high-dimensional biomedical data and robustness against overfitting with limited samples advantages [37]. Comparative analysis of preliminary results using 10-fold cross-validation demonstrated SVM's superior accuracy (92.3% ± 2.1%) over alternative classifiers, including k-Nearest Neighbors (85.7% ± 3.4%) and Random Forests (89.1% ± 2.8%) for our specific fatigue classification task [36]. Hyperparameter optimization was systematically conducted through exhaustive grid search, evaluating parameter combinations. The optimization protocol tested regularization parameters (C) across a logarithmic scale (0.01, 0.1, 1, 10, 100), kernel coefficients (γ) for radial basis function (0.001, 0.01, 0.1, 1), and kernel types (linear, polynomial, sigmoid, RBF). Performance was evaluated using 10-fold stratified cross-validation. The optimal configuration utilized a radial basis function kernel with C=1.0 and γ=0.01, based on maximum accuracy and minimal overfitting.

The implementation employs a one-against-one strategy [39], to extend SVM's binary classification foundation, maximizing margin separation in high-dimensional feature space while balancing error minimization through penalty parameter control [35].

3- Results and Discussion

According to the previous section, the wrist flexion-extension and supination-pronation movements have been recorded through three EMG electrodes and six video capture markers. The test was repeated for the normal and fatigued wrist with different levels of weakness. The weakness of performing the movement is the consequence of muscle fatigue. Therefore, for the weak EMG test, participants performed wrist flexion-extension and supination-pronation movements against constant 5 kg resistance applied through calibrated wrist weights. Four progressive fatigue levels were induced through timed exercise intervals: light fatigue through 5 minutes of continuous exercise, moderate fatigue through 10 minutes of continuous exercise, heavy fatigue through 15 minutes of continuous exercise, and exhaustion through 20 minutes of continuous exercise. The angular motion of flexion-extension movements could be calculated by measuring the z-axis position of the finger marker during the movements. The tangent of flexion or extension angle would be calculated by dividing the z-axis position of the finger marker by its x-axis displacement from the wrist rotation point. Since the x-axis displacement of the finger marker is set to 33 millimeters and fixed, the z-axis position of the finger marker is the criterion to determine the angular motion of flexion-extension. The difference between angel motions and the normal angel motion that is about $70°$ is called as the fatigue wrist. For supination-pronation movements, angle of motion and the level of disability could be calculated from the MWrist/LWrist marker and in the same way. Figure 6 Demonstrates the EMG signal and finger marker position

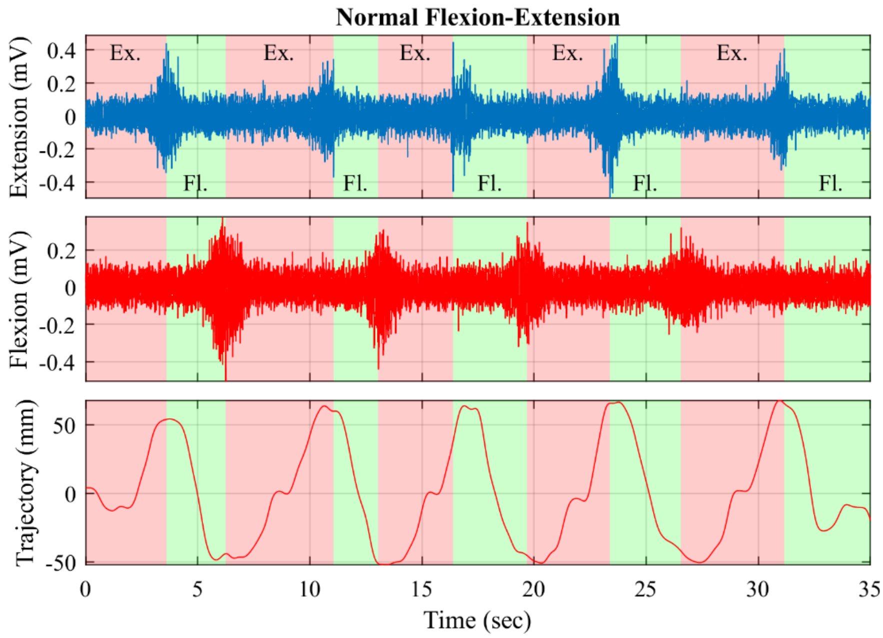

Fig. 6. EMG signals and finger marker position during the flexion-extension movements for a normal wrist subject

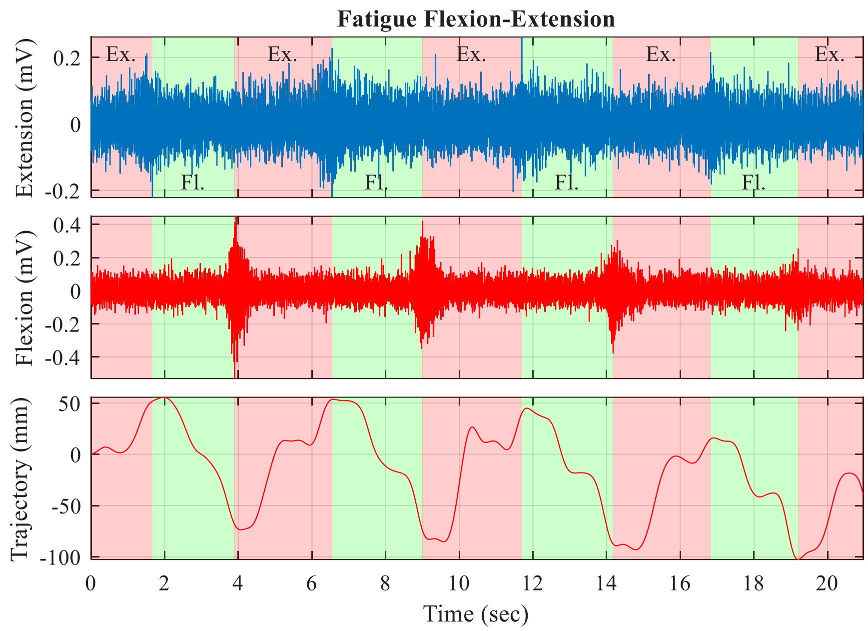

Fig. 7. EMG signals and finger marker position during the flexion-extension movements for a fatigued wrist subject

on the z-axis during the four flexion-extension movements for a normal wrist subject and Figure 7 demonstrate it for a fatigue wrist. Table 1 illustrates the maximum angle of flexion-extension and supination-pronation movements for both the normal and fatigue wrist, respectively. According to the different maximum angel of motion, the level of wrist's fatigue could be classified into four levels. Increasing the level number increases the level of fatigue.

The RMS method has been used to reduce the noise and achieve smooth signals, preparing for feature extraction. This method was implemented for filtering 3 EMG channels with a sampling rate of 500ms. The results are shown in Figures 8 and 9.

With the significance of the wrist movements of the

Table 1. The maximum angle of movements for fatigue levels

c	Maximum angle (°)		% of Max		Approx. Borg RPE (CR10) [40]
	Flexion-Extension	Supination-Pronation	Flexion-Extension	Supination-Pronation	
1	55.4	63.43	79.1%	70.5%	9–11 (Light)
2	43.22	53.26	61.7%	59.2%	12–13 (Moderate)
3	34.99	39.69	50.0%	44.1%	15–16 (Hard)
4	27.99	33.82	40.0%	37.6%	17–19 (Very Hard)

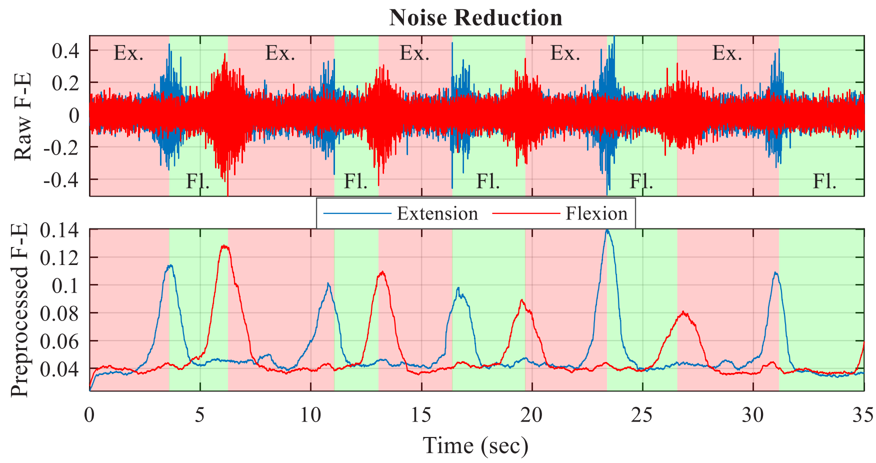

Fig. 8. RMS noise reduction method with a sampling rate of 500ms for flexion-extension

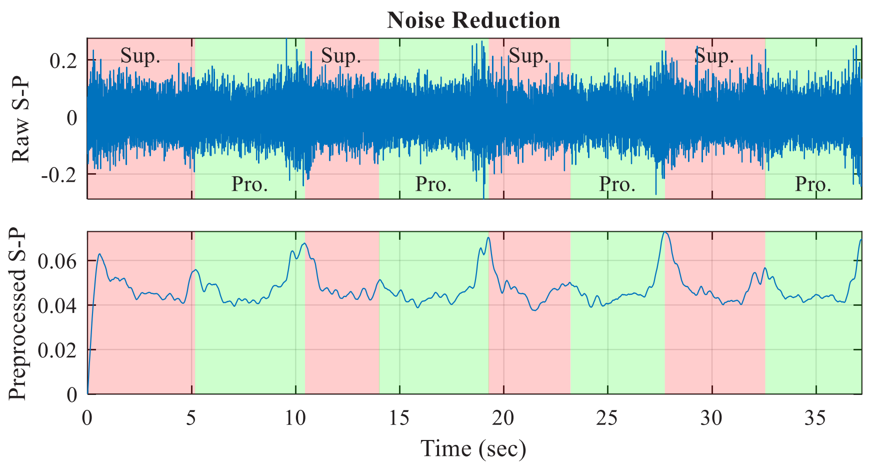

Fig. 9. RMS noise reduction method with a sampling rate of 500ms for supination-pronation

patient that as shown in the motion capture diagram, the level of disability could be determined in four levels. In section 2, sixteen features were described as standard features of EMG signals. The MAV, EMAV, MMAV, MMAV2, AAC, and RMS consider the mean of the whole signal or the mean of the two-point difference as a feature. DASDV indicates the deviation of the signal. WL and EWL bring up the signal's wavelength, and MYOP is a significant feature in normal and fatigue diagnosis that compares the signal to a predefined threshold. According to the [41], the maximum value of the EMG signal value is $0.7\,mv$ to prevent pain, so the threshold value was set to $0.6\,mv$ [42]. Other features like LD, SSI, VAR, SSC, and MFL indicate the logarithm, integral, power, slope sign, and logarithm of absolute distance between two points of the signal, respectively.

Last but not least, WAMP represents the frequency information of the signal in the time domain. To compare each fatigue level of the signal with the normal signal, the value of each feature must be compared in both signals. The features that have a relative value in all normal signals and have significant deviation with respect to each fatigue level are considered useful features for diagnosing the level of fatigue. For each spacious feature, the difference between the fatigue EMG signal and the mean of the normal EMG signal has been determined for each level. Figures 10, 11, and 12 show the averaged, normalized error of each feature in each level and for Extension, flexion, and supination-pronation movements, respectively. According to the normalized feature profiles shown in Figure 13, the classification error tends to increase with the level of disability for most features. However, the features SSC, WAMP, MMAV, SSI, and MYOP demonstrate a more desirable statistical behavior compared to the others. After applying per-feature min–max normalization (scaling each feature across the five classes to the range [0,1] for comparability), these features exhibit significantly lower intra-class variance within fatigue groups while simultaneously maintaining higher inter-class variance across different levels of fatigue and the health class. This optimal variance profile directly maximizes class separability, which is critical for SVM classification performance. In practice, lower intra-class variance ensures that samples from the same fatigue level cluster tightly together, while higher inter-class variance guarantees that different classes remain well separated. The consistent progression of these features with increasing fatigue levels further confirms their reliability as biomarkers for fatigue detection. Therefore, based on both the normalization analysis and the visualized distributions, SSC, WAMP, MMAV, SSI, and MYOP are identified as the most robust and discriminative features compared to the rest.

A dataset with sixteen features and a predetermined label was modified for classification. Providing a proper dataset for classification is a challenge in biological applications. Since there is a limitation in repeating the test, many randomizing and bootstrapping methods have been developed and are commonly used in biological datasets. One of the strong and well-known methods in bootstrapping is Mont Carlo. In the Mont Carlo method, the dataset is expanded with random sampling in which the average of data remains constant [43]. SVM classification method was implemented on the signal's features dataset. Once with all sixteen features and once with five features that were selected according to their deviation from the health signal features. A quarter of the data was considered as test data, and the training was done with 75% of the dataset. Test data had never participated during the training. The One-Against-All (OAA) method was utilized to classify the data into four classes. The penalty factor was

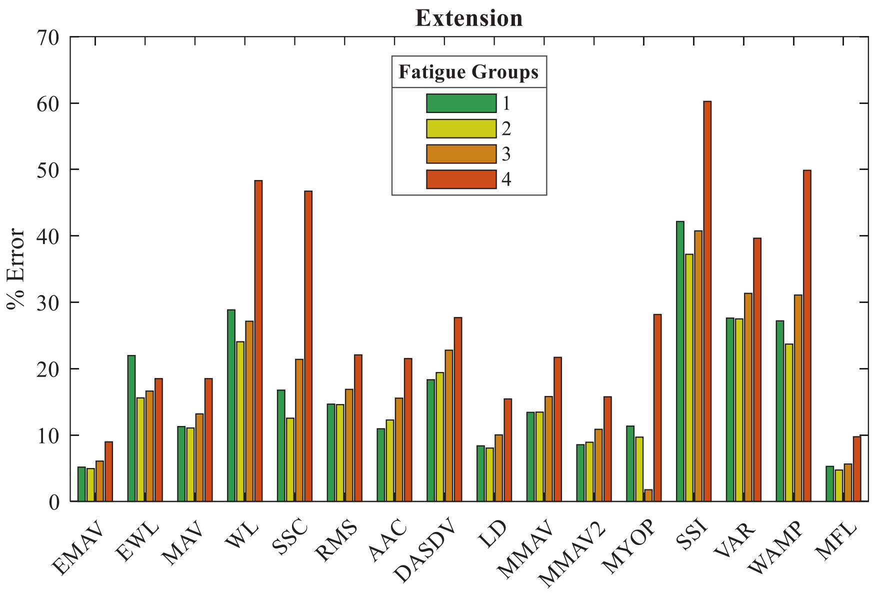

Fig. 10. Features varying in four fatigue groups for extension.

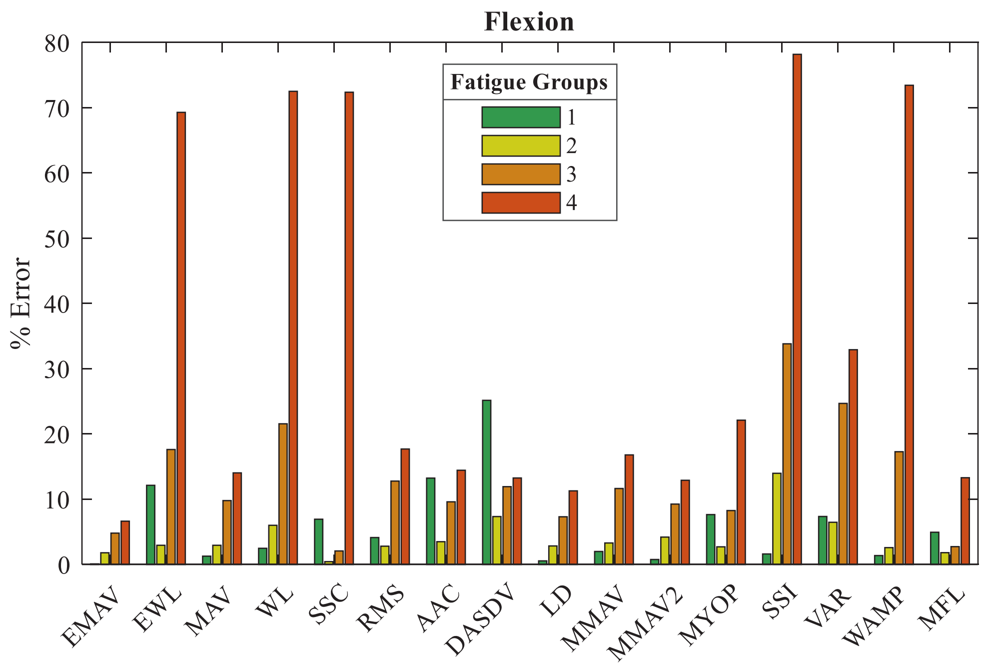

Fig. 11. Features varying in four fatigue groups for flexion.

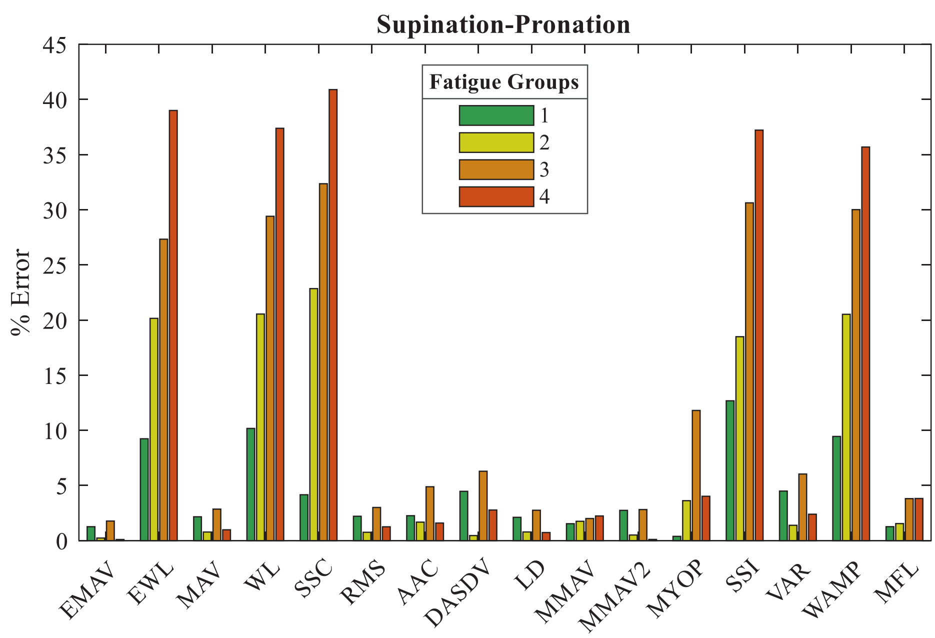

Fig. 12. Features varying in four fatigue groups for supination-pronation.

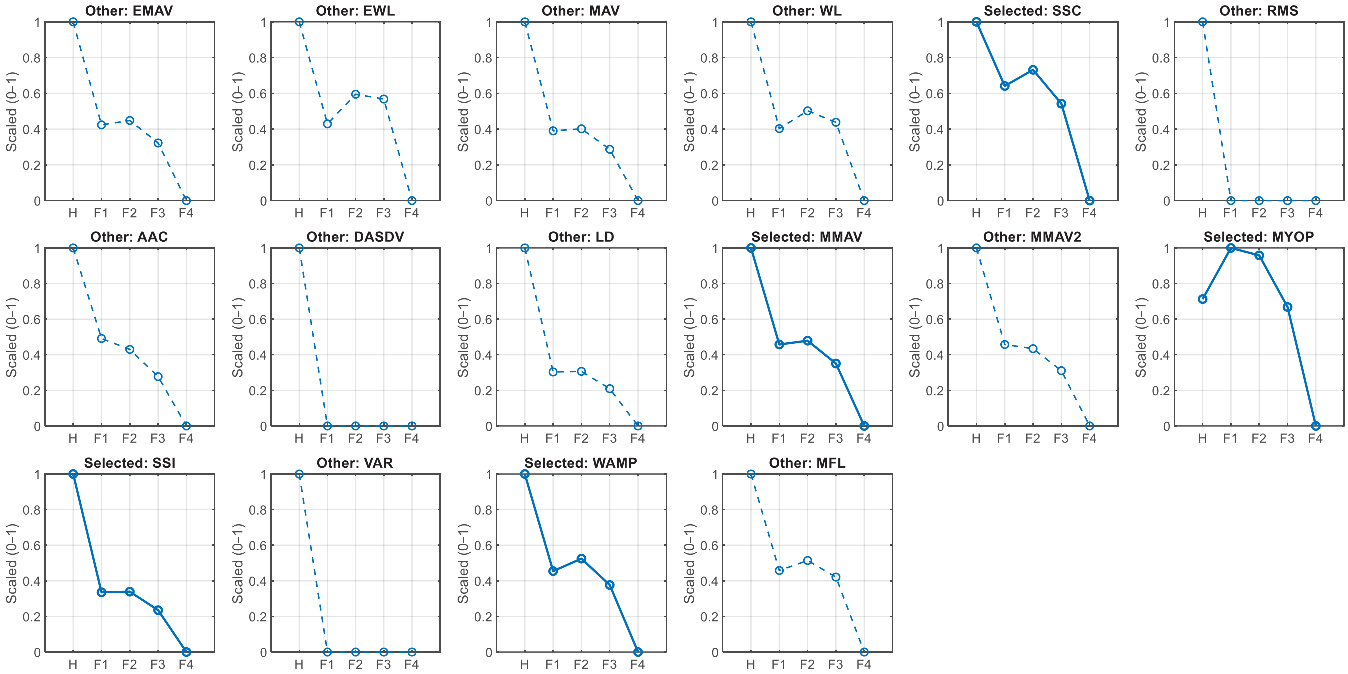

Fig. 13. Normalized feature profiles in H (Health class), F1 (Fatigue Level 1) , F2 (Fatigue Level 2) , F3 (Fatigue Level 3) , F4 (Fatigue Level 4).

set on 1, and the kernel was set as a radial basis function to partition data into four classes of disability. Confusion matrixes of test data that had never been seen during the training demonstrated the performance of feature selection. Template confusion matrix demonstrated as Table 2 and the confusion matrix of test data was shown in Table 3 for flexion movement with and without feature selection, respectively. Similarly, Table 4 demonstrates the confusion matrix of extension, and Table 5 for supination-pronation movements. According to the confusion matrix of test data, the matrix's diagonal elements indicate true class detection.

Table 2. Template confusion matrix

Actual class	Predicted class	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

Table 3. Confusion matrix of SVM classification for flexion

A) without feature selection

Actual class	Predicted class			
	1	2	3	4
1	14	0	0	0
2	1	6	1	0
3	0	2	10	0
4	0	0	0	12

B) with feature selection

Actual class	Predicted class			
	1	2	3	4
1	14	0	0	0
2	1	8	2	0
3	0	0	9	0
4	0	0	0	12

Table 4. Confusion matrix of SVM classification for extension.

A) without feature selection

Actual class	Predicted class 1	2	3	4
1	14	0	0	0
2	1	8	2	0
3	0	0	9	0
4	0	0	0	12

B) with feature selection

Actual class	Predicted class 1	2	3	4
1	10	0	0	0
2	0	5	1	0
3	0	0	8	0
4	0	0	2	12

Table 5. Confusion matrix of SVM classification for supination-pronation

A) without feature selection

Actual class	Predicted class 1	2	3	4
1	10	0	0	0
2	0	7	1	1
3	0	0	15	0
4	0	0	0	7

B) with feature selection

Actual class	Predicted class 1	2	3	4
1	10	0	0	0
2	0	7	0	1
3	0	0	16	0
4	0	0	0	7

4- Conclusion

EMG signals are fundamental to human–machine interfaces in rehabilitation, offering valuable information for assessing muscle activity and fatigue. This study proposed a method for classifying wrist muscle fatigue levels during flexion-extension and supination-pronation movements using time-domain features of EMG signals. This study introduced wrist angle deviation as a functional indicator of muscle fatigue, complementing traditional EMG analyses. Previous research has shown that fatigue can alter kinematic parameters, such as wrist force and time to peak displacement, reflecting changes in neuromuscular control during dynamic tasks [44]. This study prioritized time-domain features (e.g., RMS, MAV, SSC) due to their computational simplicity and suitability for real-time applications. Unlike frequency-domain features such as MDF [45], which require FFT-based spectral analysis and longer data windows, time-domain features can be extracted with minimal latency and lower computational cost, making them more practical for online fatigue monitoring in rehabilitation contexts. The full processing pipeline from signal acquisition and noise reduction to feature extraction and classification was implemented, and a total of sixteen features were evaluated. A subset of five features (SSC, WAMP, MMAV, SSI, and MYOP) demonstrated the highest sensitivity to fatigue progression and were selected for final classification using a support vector machine (SVM).

The analysis aimed to evaluate EMG signal characteristics for detecting different levels of wrist muscle fatigue. Initially, RMS preprocessing was applied to reduce baseline noise and improve signal consistency. Following this, features were extracted from both fatigued and non-fatigued signals, and the mean difference between them was calculated. Most features showed increasing deviation with higher fatigue levels, indicating their relevance in tracking fatigue progression. Based on this behavior, five features, SSC, WAMP, MMAV, SSI, and MYOP, were selected for classification, as they capture important aspects such as slope changes, frequency content, mean amplitude, and threshold-based activity. These features were used to train an SVM classifier, and classification performance was evaluated through confusion matrices for each EMG channel, with and without feature selection. Although variations in sensor placement and skin conditions may reduce signal quality, the use of well-chosen features enhances the reliability and robustness of the classification outcomes. To evaluate the impact of feature selection on model performance, we compared the classification results of muscle fatigue levels across three wrist movement types—flexion, extension, and supination-pronation—using confusion matrices and derived evaluation metrics. For the flexion movement, feature selection improved the mean precision from 86.3% to 93.8%, recall from 91.5% to 93.2%, and F1-score from 88.7% to 92.7%. Similarly, in the extension movement, mean precision increased from 89.5% to 93.8%, recall from 88.5% to 93.2%, and F1-score from 88.0% to 92.7%, indicating better discrimination between intermediate fatigue levels. For the supination-pronation task, which initially showed relatively high performance, feature selection still led to further enhancement, with mean precision improving from 96.7% to 98.2%, recall from 96.4% to 98.2%, and F1-score from 96.4% to 98.2%. These results consistently demonstrate that feature selection contributes to more accurate and robust classification of fatigue levels, particularly in reducing misclassification between adjacent fatigue states across all tested wrist movements.

Although individual variability in EMG signals can affect performance, the use of diverse features—such as those based on mean amplitude and signal integration—helps reduce subject dependency and enhances generalizability across users. The feature selection improves the total accuracy of classification from 89.8% to 93.57% for flexion movements, from 75.9% to 93.2% for extension movements, and from 95.3% to 96.8% for supination-pronation movements. Besides that, reducing the number of features from sixteen to five reduces the dimension of the model and accordingly decreases the complexity. The computational simplicity of the proposed method makes it suitable for real-time control applications. Unlike many previous studies that focus on EMG-based movement classification, this study emphasizes fatigue-level diagnosis, making direct comparisons challenging due to differing objectives, datasets, and feature selection strategies. Future work will focus on validating its performance in real-time rehabilitation scenarios, particularly in clinical and assistive robotic systems. For future work, the dataset could be expanded, and the trained model could be applied in online rehabilitation scenarios. In robotic rehabilitation with assistive control—where the robot remains inactive initially—estimating muscle weakness levels could serve as an input to trigger the controller. Additionally, addressing limitations such as small sample size, potential overfitting, and noise sensitivity will be important for improving model robustness and generalizability. Although this study focused on the technical development of an EMG-based fatigue classification method, future work should include clinical validation and comparison with standard diagnostic tools to assess its effectiveness and utility in real-world rehabilitation settings.

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