

Machine learning-based classification of local muscle fatigue using electromyography signals for enhanced rehabilitation outcomes

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ABSTRACT

Muscle fatigue is a key factor affecting rehabilitation progress, safety, and patient engagement. Accurate detection of fatigue during physical activity remains a challenge, particularly in clinical and remote settings. This study presents the development of an internet of things-based system for classifying local muscle fatigue using surface electromyography (EMG) signals and machine learning. A wearable device was used to collect real-time EMG data and subjective fatigue ratings from 10 healthy participants during sustained isometric grip exercises. Feature extraction was performed on-device, and the data were transmitted wirelessly for analysis. Machine learning models including logistic regression, decision tree (DT), random forest, and extreme gradient boosting (XGBoost) were trained to classify fatigue states. The DT model achieved the highest accuracy of 90.7%, with a precision of 90.7% and a recall of 90.9%. SHAP analysis revealed time under load, smoking, and alcohol use as the most influential factors in fatigue classification. These results show that wearable EMG devices combined with smart algorithms are effective for real-time fatigue monitoring during rehabilitation.

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1. INTRODUCTION

Muscle fatigue is a critical area of research in sports medicine and occupational health [1]. It is an exercise-induced decrease in the ability to produce force [2]. Measuring fatigue and fatigability is critical to understanding the impact of the disease, determining optimal levels of physical activity, tailoring rehabilitation programs, and assessing the effectiveness of therapeutic interventions, which is a central aspect of rehabilitation [3]. Effective fatigue diagnosis can prevent muscle damage, thereby increasing the safety of rehabilitation exercises. It has important practical significance for the assessment of muscle function in the field of rehabilitation medicine and the determination of fatigue in rehabilitation science [4].

Fatigue is a multidimensional phenomenon that degrades physical and cognitive performance, ultimately reducing rehabilitation efficiency and threatening patient safety. In clinical settings, it presents not

only as a subjective loss of energy but also as an objective fall in neuromuscular coordination and motor function [5]. Chronic fatigue in post-stroke syndrome or Parkinson's disease intensifies motor weakness and markedly increases fall risk, jeopardizing safety during daily activities and therapy sessions [6]. Biomechanically, fatigue reduces neuromuscular synergy and proprioceptive acuity, creating unstable movement patterns that predispose individuals to injuries such as anterior cruciate ligament rupture [5], [7]. Cognitively, it slows information processing, lengthens reaction times, and undermines decision-making during unexpected events [8], [9]. Persistent fatigue can extend rehabilitation timelines [10] and erode patient motivation [11]. Routine monitoring is therefore essential for timely adjustment of interventions and for safeguarding functional outcomes [9].

Performance fatigue is a major cause of work-related musculoskeletal disorders and understanding its impact during manual handling (MHT) is critical to preventing such problems [12]. Practical measurement remains challenging due to limitations in equipment size and cost. Invasive and cardiopulmonary methods are often inconvenient and not suitable for the daily training of patients or athletes [13]. Muscle fatigue monitoring is in demand for daily activities and exercise, including injury prevention in athletes. A wearable system is needed that not only notifies the user of the onset of fatigue but also provides information on a relaxed state to minimize the risk of injury.

The rapid proliferation of wearable sensors and Internet of things (IoT) devices has shifted the paradigm toward real-time physiological monitoring, making fatigue detection a critical application in transport, industrial safety, sport and healthcare [14]. Advances in miniaturized biosensors, low-latency wireless protocols and edge-cloud infrastructures now enable continuous data capture and processing, allowing systems to detect subtle physiological changes [15]. Several recent reviews summarise IoT-based fatigue monitoring—especially for driver drowsiness, worker safety and health management—yet highlight persistent challenges in real-time processing, privacy and algorithm adaptability across heterogeneous settings [14].

Emerging technologies such as the IoT and sensors make it possible to remotely monitor and visualize physical data [16]. Detection of muscle fatigue using EMG is valuable in a variety of applications such as sports performance, rehabilitation, occupational health and driver safety. It helps to prevent fatigue-related injuries and optimize performance. Surface electromyography (EMG) can be used in the rehabilitation of musculoskeletal disorders to assess the coordination of muscles that stabilize a joint or as an objective tool to assess muscle fatigue [17]. Machine learning models using EMG signal properties in time and frequency domains are used to differentiate muscle fatigue levels [18]. The performance of models may depend on the thresholds used to define fatigue in the reference measurements, and the choice of these thresholds influences which predictors are considered relevant [15]. Most previous research has focused on muscle fatigue during short bursts of maximal effort or alternating contraction-relaxation tasks, which don't fully capture the sustained muscle activity common in everyday rehab exercises. Also, many studies rely only on objective EMG data and don't consider how people actually feel during the task.

This study addresses the critical challenge of accurately detecting muscle fatigue—a complex, multifactorial phenomenon that impacts rehabilitation safety and effectiveness—by integrating surface EMG with machine learning in a novel IoT-based wearable system. While prior works have primarily relied on brief, high-intensity contractions and objective EMG features alone, this research uniquely combines real-time EMG signal processing with subjective fatigue ratings during sustained submaximal grip tasks, enhancing ecological validity. The proposed system, Qimyl, introduces methodological advancement by enabling on-device extraction of surface EMG features and low-latency wireless data transmission, thereby addressing key limitations of existing fatigue monitoring systems that depend on multiple external sensors and post-hoc data analysis. Its architecture accommodates the constraints of mobile and embedded environments, with a comparative evaluation of classifiers that supports intelligent deployment in adaptive rehabilitation contexts. By aligning physiological signals with user-reported fatigue in real-time, this work contributes a scalable, practical solution to longstanding challenges in fatigue classification, and sets a foundation for future telerehabilitation and personalized health monitoring systems. The remainder of the article is organized as follows. Section 1 presents the introduction and problem statement. Section 2 provides a critical literature review. Section 3 details the experimental methodology and the Qimyl device architecture. Section 4 reports and discusses the results. Section 5 concludes the paper and outlines directions for future research.

2. LITERATURE REVIEW

Muscle fatigue is the gradual decline in a muscle's ability to generate force, which is commonly observed in various conditions such as multiple sclerosis, stroke, chronic insomnia, and musculoskeletal injuries [19], [20]. Due to the subjective nature of fatigue, its precise measurement and prediction remain challenging tasks [21]. Inadequate fatigue management can lead to injuries and poorer rehabilitation

outcomes [22]. Fatigue is typically assessed using EMG signals, sometimes combined with accelerometer data and other physiological indicators, such as ECG and heart rate. Some studies utilize surface EMG during robotic movements to evaluate the impact of fatigue on joint position sense [23]. In rehabilitation systems, fatigue detection acts as a signal to modify or stop exercises in order to protect the patient [24]. Adaptive load control methods based on online fatigue detection are being developed to optimize training duration and intensity. A fatigue assessment model for virtual reality has also been developed, allowing for individualized fatigue measurement without additional sensors [25]. In addition, digital twins combined with machine learning methods are used for real-time visualization and forecasting, which can be applied in the management of rehabilitation processes [26].

EMG plays a key role in assessing muscle activity and patient condition during rehabilitation [27]. Surface EMG allows the detection of muscle activity during movements and exertion, which is important for diagnosis and evaluation of functional changes [28]. EMG is widely used in orthopedics, neurorehabilitation, sports medicine, and the study of aging processes [29]. EMG is applied in gait rehabilitation, control of knee exoskeletons and prostheses, and in the assessment of motion parameters (such as speed and slope) during robotic assistance. EMG-based biofeedback contributes to improving strength and balance in stroke patients and the elderly [30]. Combining EMG with electrical stimulation triggered by EMG signals enhances hand function in chronic stroke patients. EMG analysis helps detect motor impairments, assess coordination, and identify spasticity [31]. The theory of muscle synergies, based on EMG signal decomposition, is used for quantitative assessment of motor control disorders [32]. To improve diagnostic accuracy and control of assistive devices, multisensory integration methods are being developed, combining EMG with other biomedical signals [27].

EMG processing includes noise suppression, amplification, filtering, decomposition, and feature extraction, which allows classification and analysis of signals across different fields [33]. Machine learning is used for the automatic classification of muscle fatigue states based on surface EMG [34]. The classical and most widely used algorithm is the support vector machine (SVM), which achieves an accuracy of around 90% in distinguishing fatigued and non-fatigued states [22]. This involves extracting features from the time and frequency domains [34]. Fatigue classification during dynamic movements, such as the sit-to-stand test, has been implemented using EMG and accelerometer data [35]. In addition to SVM, recurrent neural networks such as long short-term memory (LSTM) are used to account for temporal dependencies in EMG signals, improving classification performance [34]. Machine learning is also used to analyze complex nonlinear characteristics of EMG [36], [37]. In practical applications, fatigue classification enables the creation of adaptive rehabilitation systems that automatically adjust robot and exoskeleton loads based on the patient's condition, ensuring an optimal training process [22]. A similar approach is successfully used in the oil and gas industry, where LSTM and BiLSTM models provide highly accurate predictions of operational parameters, highlighting the potential to transfer these solutions to rehabilitation settings [38].

The IoT is being actively integrated into rehabilitation technologies for remote monitoring and management of the recovery process [39]. IoT solutions are applied in wrist and forearm rehabilitation robots, as well as in knee rehabilitation systems [22]. Integrated systems have been developed that combine wearable IoT sensors with deep learning methods for personalized recognition of patient activity at home and in "smart homes" [39]. These systems enable real-time monitoring of physiological parameters and movements, ensuring connectivity between the patient and medical staff via the internet. Wearable and edge computing devices with built-in sensors and Bluetooth support play a key role in making rehabilitation more mobile and convenient. The Edge Impulse platform and Arduino Nano 33 BLE Sense devices are used to implement machine learning on edge devices in orthopedic rehabilitation [25]. IoT also enables monitoring of vital signs (ECG, blood pressure, oxygen saturation), which is important in treating chronic diseases [39]. Furthermore, IoT systems have already demonstrated high accuracy and efficiency in managing microclimate and monitoring room conditions, which may be beneficial for creating optimal environments in rehabilitation zones [40]. Despite these prospects, the widespread commercial adoption of IoT in rehabilitation remains limited and requires further research and development [41].

The detection and prediction of muscle fatigue remain challenging tasks due to the subjective nature of fatigue itself and the lack of universal evaluation methods [22]. Modern solutions often rely on external physiological data such as surface EMG and heart rate, which require additional sensors, increase costs, and complicate system use [22], [24]. Moreover, such methods may be unsuitable for patients with limited physical abilities, such as those with spinal cord injuries. Insufficient attention is given to analyzing fatigue based solely on internal system data (*e.g.*, from VR or robotic devices), which could reduce dependence on external sensors. Although a few studies use simple models such as SVMs with a limited number of features, they highlight the need for more advanced and accurate approaches [24]. The development of monitoring and rehabilitation systems is also constrained by technical and sensor-related limitations [22]. The use of stepper motors with low torque, IMU vibrations, and the need for precise sensor positioning create significant

challenges. Wired connections between sensors and embedded systems reduce mobility, while surface electromyography (sEMG) data quality is affected by artifacts related to skin contact and electrode placement. The limited availability of large, diverse, and open sensor datasets, along with the discrete interpretation of continuous movements, hinders the accuracy and adaptability of modern algorithms [25]. In this regard, intelligent sensor systems using IoT and ML for environmental monitoring demonstrate high sensitivity and real-time analysis capabilities, which could be adapted for monitoring patients' physiological parameters [42]. All of this underscores the need for a comprehensive reassessment of both sensing and analytical approaches in this field.

In this study, an experimental investigation and data-driven analysis were conducted to classify local muscle fatigue during isometric hand grip exercises using electromyographic (EMG) signals. The primary goal was to enhance rehabilitation outcomes by integrating real-time physiological monitoring with machine learning-based classification and subjective fatigue assessment.

Recognizing the challenges of accurately detecting muscle fatigue—due to its subjective and multifactorial nature—the study employed a dual approach. A custom-built IoT-enabled wearable device, the Qimyl system, was used to record and process EMG signals. Feature extraction methods were applied directly on the device to generate compact descriptors such as RMS, MAV, P2P, and MDF, which were transmitted to a cloud server for storage and analysis. During the experiment, participants performed sustained submaximal muscle contractions while periodically reporting their perceived fatigue levels, enabling alignment between objective EMG features and subjective sensations. To classify muscle states as fatigued or non-fatigued, several machine learning models—logistic regression (LR), decision tree (DT), random forest (RF), and XGBoost—were trained and evaluated. XGBoost yielded the best overall performance, while RF was identified as suitable for real-time embedded applications. The findings demonstrate the feasibility and effectiveness of combining wearable EMG sensing with intelligent classification algorithms to support adaptive rehabilitation, personalized training, and early fatigue detection. This integrated approach offers a scalable solution for modern telerehabilitation and remote patient monitoring systems.

Unlike many previous studies, which often rely solely on objective EMG data without incorporating subjective fatigue perceptions, or focus on short, maximal effort bursts rather than sustained submaximal contractions typical in rehabilitation, our work addresses these gaps by synchronizing real time physiological signals with user-reported fatigue levels during realistic task conditions. Moreover, existing solutions frequently depend on multiple external sensors, leading to increased complexity and reduced practicality for everyday use, whereas our IoT-enabled wearable platform emphasizes on-device feature extraction and efficient wireless data transmission, promoting low-power and mobile applicability. Additionally, while prior works have utilized relatively simple machine learning models or faced limitations in real time embedded implementation, our comparative analysis highlights advanced algorithms like XGBoost for accuracy and Random Forest for embedded deployment, balancing performance and operational feasibility. Thus, our study not only enhances fatigue detection accuracy but also advances practical integration into adaptive rehabilitation systems, overcoming key technical and methodological limitations identified in literature.

3. METHODOLOGY

3.1. Experiment description

Ten healthy volunteers (8 male, 2 female), aged 19–22, participated in this study. To ensure internal validity and safety, participants were recruited based on strict inclusion criteria. All were free of any known musculoskeletal, cardiovascular, or neurological conditions, had no upper limb injuries within the previous six months, and were not taking medication that could affect neuromuscular function. Each individual provided written informed consent after demonstrating a clear understanding of the experimental protocol. The primary objective of this study was to investigate the development of localized muscle fatigue during a brief, controlled isometric handgrip task. A key goal was to explore the correlation between sEMG activity and participants' self-reported sensations of fatigue. The entire procedure was conducted in a single session lasting approximately three minutes per participant, using a calibrated handgrip dynamometer to quantify force output. The experimental session involved two consecutive phases. First, to establish each individual's maximal voluntary contraction (MVC), participants performed three maximal isometric contractions with their dominant hand. Each contraction lasted three seconds, and participants were motivated with real-time visual feedback and standardized verbal encouragement. During this phase, sEMG signals were continuously recorded from the target forearm flexor muscles. The root mean square (RMS) value of the EMG signal was calculated for each trial, and the average of the three trials was used to define the baseline MVC reference, ensuring inter-participant comparability. Immediately following the MVC assessment, participants began the second phase without rest to ensure physiological continuity. In this phase, they maintained a steady isometric contraction at 50% of their individual MVC for 120 seconds. This protocol, combining maximal

effort with sustained submaximal exertion, is widely adopted in fatigue research to simulate real-world muscular demands and ensure a controlled induction of fatigue [43], [44]. Throughout the 120-second sustained contraction, EMG activity was continuously recorded to track changes in muscle activation. Simultaneously, participants provided verbal ratings of their perceived fatigue at 30-second intervals. These ratings were captured using a 0-10 numerical scale, where 0 indicated "no fatigue" and 10 represented "maximal fatigue." For analysis, these self-reports were then categorized into low (0–3), moderate (4–6), and high (7–10) levels of fatigue.

This dual-modality approach, which integrates objective electrophysiological data with subjective perceptual feedback, was chosen to provide a comprehensive and ecologically valid assessment of fatigue. The protocol's design included several intentional choices to ensure data integrity. The absence of a rest period between the two phases was critical to prevent partial muscle recovery, which could confound the fatigue profile. Likewise, forgoing a warm-up or cooldown aimed to isolate the acute muscular response to a sustained load, mirroring the demands of many real-world tasks. In summary, this framework provides a validated and practical method for assessing localized muscle fatigue. Its brief duration, minimal equipment requirements, and high reproducibility make it ideally suited for integration into mobile health platforms, wearable technologies, and remote musculoskeletal evaluation systems.

3.2. Qimyl IoT device

To ensure accurate and reproducible acquisition, processing, and analysis of surface electromyographic (sEMG) signals, we developed a three-tiered system architecture integrating hardware, firmware, and algorithmic modules. This architecture encompasses: i) an edge-level IoT device (Qimyl) for signal acquisition and preprocessing, ii) a central server for structured data storage and synchronization, and iii) a machine learning pipeline for high-level classification of muscle fatigue states, as illustrated in Figure 1.

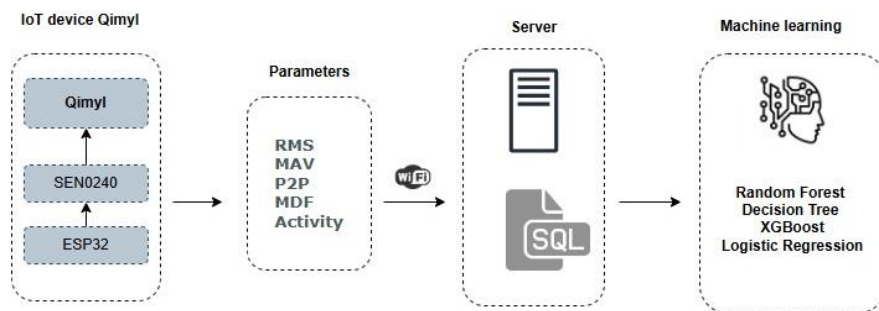


Figure 1. Architecture of the multi-level system for acquisition, processing, storage, and analysis of EMG signals

The Qimyl device constitutes the core of the sensing subsystem and is composed of a SEN0240 sEMG sensor and an ESP32 microcontroller. The SEN0240 module captures differential biopotentials from the skin surface over the target muscle group. The analog signal is routed to the high-impedance input of the ESP32, where it undergoes analog-to-digital conversion. Sampling rates between 100 Hz and 1000 Hz were empirically tested, with 500 Hz selected as the default, providing a balance between spectral fidelity (preserving the informative 20–450 Hz EMG band) and power efficiency. A digital 4th-order Butterworth band-pass filter (cut-off: 20–450 Hz) is applied in real-time to suppress motion artifacts and powerline interference (50/60 Hz). This filtering stage represents a standard but essential step in ensuring the physiological relevance of the acquired signal.

Following filtration, the signal stream is segmented into overlapping 200 ms windows with 50% overlap to retain temporal resolution. Within each window, five validated time-domain and frequency-domain features are extracted: root mean square (RMS), mean absolute value (MAV), peak-to-peak amplitude (P2P), median frequency (MDF), and a binary activity flag. RMS and MAV, commonly used in EMG analysis, reflect contraction intensity, while P2P and MDF provide insights into signal amplitude dynamics and spectral distribution. The binary activity flag is calculated using a hysteresis-based rule applied to RMS and MAV, indicating the presence of voluntary muscular activation. Rather than transmitting raw EMG signals, which are bandwidth-intensive and susceptible to loss, the system transmits only compact five-element feature vectors with timestamps via Wi-Fi. This approach, as illustrated in Figure 1, significantly reduces data load and improves energy efficiency, making it suitable for wearable, battery-operated systems.

The server backend receives these feature vectors in real-time and stores them in a structured time-series format together with metadata such as timestamps, session identifiers, and device identifiers. This design supports longitudinal analysis, time-based aggregation, and stable storage. A RESTful API interface facilitates real-time access for monitoring and visualization, as well as historical data export for offline training, annotation, or review.

The machine learning module addresses the binary classification task of detecting the onset of muscle fatigue. This constitutes a novel application of supervised learning in edge-deployed EMG systems, with labels derived from real-time user input and force decay criteria. Four classification algorithms were evaluated: logistic regression, decision tree, random forest, and XGBoost. Stratified 5-fold cross-validation was used to improve generalization and address class imbalance. Model performance was assessed using ROC-AUC, F1-score, and inference latency. XGBoost achieved the highest accuracy under limited training data, while the random forest model showed superior execution speed and was thus selected for on-device deployment. This enabled local inference directly on the ESP32, ensuring real-time classification without requiring a constant server connection.

The physical realization of the Qimyl device is depicted in Figure 2. The EMG sensor is attached over the flexor carpi radialis muscle using medical-grade adhesive, while the ESP32 microcontroller is fixed to the forearm with a lightweight strap. This arrangement reduces wire tension and movement-induced noise, while preserving comfort and mobility during use. If network connectivity is temporarily lost, feature vectors are buffered locally and automatically transmitted once the connection is restored, ensuring the continuity of the dataset. Overall, the proposed system integrates validated signal processing techniques with embedded machine learning to deliver an energy-efficient, low-latency, and intelligent EMG monitoring solution. Its design supports personalized fatigue tracking and adaptive rehabilitation in real-time, as visually summarized in Figure 1.



Figure 2. IoT device Qimyl

3.3. Data preprocessing

The dataset employed in this study was obtained through surface electromyographic (sEMG) recordings using a standardized EMG sensor over a 120-second interval for each participant. To capture subjective perceptions of fatigue, individuals were prompted every 30 seconds to self-assess their fatigue level using a 10-point Likert-type scale. For analytical purposes, these self-assessment scores were subsequently discretized into three ordinal categories: 0–3 (no fatigue, labeled as class 0), 4–6 (moderate fatigue, class 1), and 7–10 (high fatigue, class 2). This procedure aligns with recent efforts to pair subjective fatigue ratings with sEMG data to enhance model training and classification [45], and the adopted categorization scheme was specifically chosen to ensure robust class separation in supervised learning tasks, consistent with established practices in muscle fatigue research.

Unlike certain preprocessing pipelines that introduce synthetic augmentation, this study exclusively utilized original experimental data to preserve ecological validity. The raw dataset was initially screened for duplicates and missing entries; none were found, confirming data integrity. Contrary to typical normalization procedures, no scaling transformations were applied at this stage, since the selected machine learning models employed later in the pipeline demonstrated robustness to scale heterogeneity.

Additional contextual variables were incorporated to explore their potential influence on fatigue perception. These included demographic and lifestyle factors such as age, gender, regular engagement in sports, smoking status, and alcohol consumption. Categorical features were encoded numerically using the LabelEncoder function from scikit-learn, enabling seamless integration into downstream statistical and machine learning models.

A correlation analysis was conducted to evaluate inter-variable relationships and detect potential multicollinearity. The resulting Pearson correlation matrix, shown in Figure 3, served as a diagnostic tool for feature selection and dimensionality reduction. Applying a simple correlation filter significantly mitigates multicollinearity and, when combined with complementary feature-selection methods, reliably enhances both the predictive accuracy and robustness of the models [46]. As indicated in the matrix, the “fatigue” score demonstrated an extremely high positive correlation ($r = 0.95$) with the derived categorical variable “fatigue_class,” confirming redundancy. Accordingly, the “fatigue” column was excluded to prevent collinearity-induced model instability. Additionally, the “name” column, serving only as a participant identifier, was discarded due to its lack of analytical utility and potential to introduce artifacts. This rigorous preprocessing pipeline ensures that only informative and non-redundant features are retained for further analysis, thereby enhancing both the validity and reproducibility of the research. The use of domain-justified discretization, exclusion criteria based on statistical diagnostics, and standardized encoding techniques collectively support the methodological transparency required for replication.

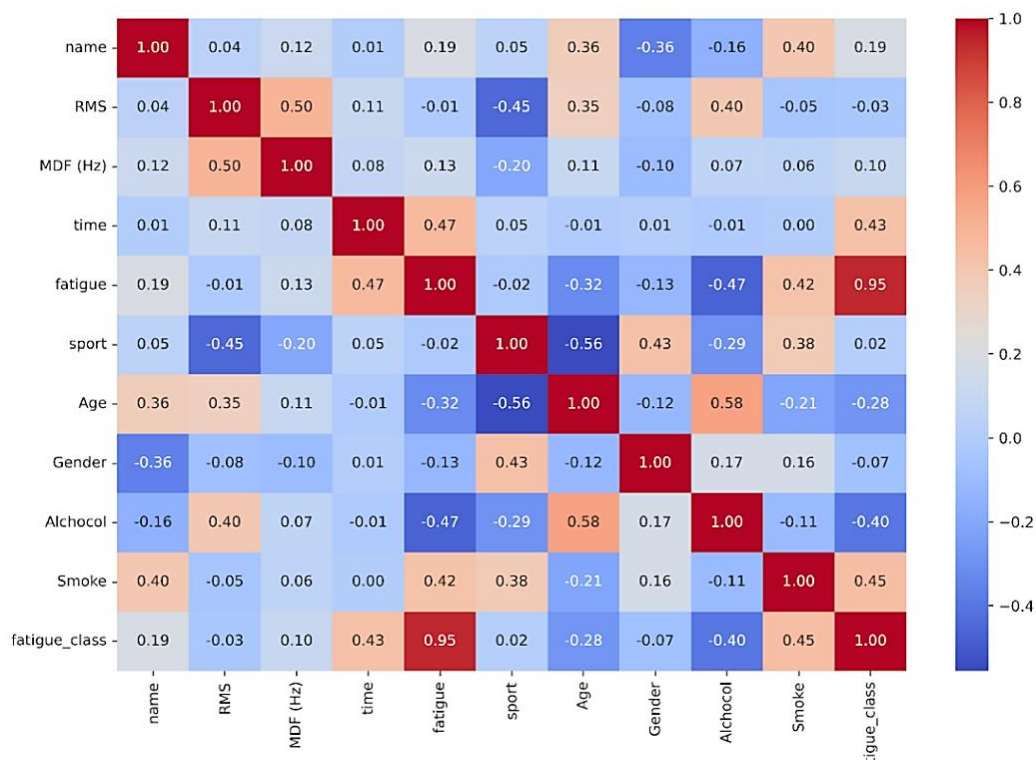


Figure 3. Correlation matrix

3.4. Machine learning classification

Supervised machine-learning techniques were employed to construct a model that quantifies participants' fatigue levels from electromyography (EMG) recordings together with additional contextual factors. Four complementary classifiers—LR, RF, XGBoost and DT—were selected because they manage complex, structured data effectively and capture potential non-linear relationships within it. Logistic regression served as an interpretable linear baseline for detecting simple associations [47], whereas RF and DT, as tree-based ensemble learners, modelled hierarchical patterns and high-order feature interactions [48], [49]. Extreme gradient boosting (XGBoost) was included for its proven capacity to represent intricate variable dependencies while maintaining strong predictive performance [50]. Hyper-parameter optimisation for every algorithm was performed with an exhaustive GridSearch, ensuring each model was tuned to the specific characteristics of the dataset. Implementation relied on the Scikit-learn and XGBoost libraries.

Model performance was assessed with four standard metrics. Accuracy—the ratio of correctly classified instances to the total number of predictions—offers an overall gauge of correctness but can mask deficiencies when classes are imbalanced. Precision, defined as the proportion of true positives among all positive predictions, highlights the model's resistance to false positives. Recall measures the share of true positives retrieved from all actual positives, indicating the model's sensitivity. The harmonic mean of

Precision and Recall, the F1-score, provides a balanced single-value summary when a trade-off exists between the two. The metrics were computed according to the expressions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Here, TP represents the number of true-positive predictions, TN the true-negative predictions, FP the false-positive predictions, and FN the false-negative predictions.

Taken together, the carefully tuned classifier set, the class-imbalance strategy, and the four complementary metrics provide a comprehensive and reproducible evaluation framework [51]. This structure not only highlights overall accuracy but also clarifies each model's tendency toward false alarms or missed detections—critical factors when assessing fatigue from EMG data—thereby ensuring that subsequent comparisons and interpretations rest on a solid, transparent foundation.

4. RESULTS AND DISCUSSION

The analysis of machine learning models for classifying participants' fatigue levels shows varying accuracy and efficiency among the tested algorithms. The DT model achieved the best results with an accuracy of 90.7%, along with high precision (90.7%) and recall (90.9%). This indicates its ability to effectively classify fatigue levels with a good balance between completeness and precision.

The RF model demonstrated an accuracy of 89.4%, precision of 89.3%, and recall of 89.9%. The classification results across classes showed high scores for all three fatigue categories, with particularly high Recall for class 0 (no fatigue) at 96%. Due to its ensemble structure, RF effectively captures complex dependencies between features, ensuring model robustness.

The XGBoost model showed comparable results with an accuracy of 89.4%, and precision and recall both at 89.4%. Class-wise classification was also stable, with precision and recall ranging from 86% to 95%. This method confirmed its effectiveness in the fatigue classification task, although it slightly lagged behind the DT in overall accuracy. Logistic regression achieved the lowest accuracy at 74.2 %. Its precision and recall were only 73.5 % and 74.3 %, respectively. The linear nature of this model limited its ability to capture nonlinear patterns in the data, which led to more errors in classifying fatigue levels.

Thus, among the tested algorithms, the Decision Tree demonstrated the best balanced performance, as shown in Table 1, followed by RF and XGBoost with very close results. Logistic regression proved to be the least effective for the classification task. All model results are presented in classification reports and metrics, enabling conclusions about the practical applicability of each model for fatigue analysis based on EMG data.

Table 1. The performance of machine learning models was evaluated for classifying muscle fatigue using EMG signals

Model	Accuracy	Precision	Recall	F1
Random forest	89%	87%	89%	89%
Decision tree	90%	90%	90%	90%
XGBoost	89%	89%	89%	89%
Logistic regression	74%	73%	74%	73%

Figure 4 shows the confusion matrix for the fatigue level classification model with three classes: low (0), medium (1), and high (2). The matrix indicates that the model correctly classified 76 instances of low fatigue level, with 1 instance misclassified as medium and 2 as high. For the medium fatigue level, 76 instances were correctly identified, while 9 were misclassified as low and 7 as high. Regarding the high fatigue level, 59 instances were correctly classified, with 2 and 4 instances misclassified as low and medium, respectively. The confusion matrix demonstrates that the model performs well, with most misclassifications occurring between adjacent fatigue levels, highlighting the challenge of precisely distinguishing closely related classes.

Figure 5 shows the feature importance of the DT model. The chart displays the relative influence of each feature on the model's predictions. The most important feature is time, followed by Smoke and Alcohol, indicating their significant impact on the prediction outcomes. Other important features include Age and sport, which also have a noticeable effect on the model.

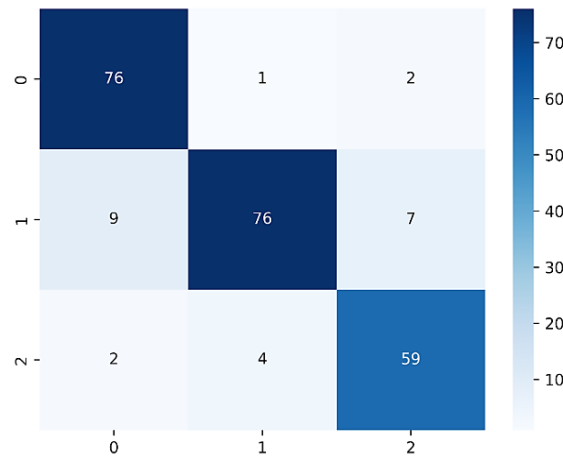


Figure 4. Confusion matrix

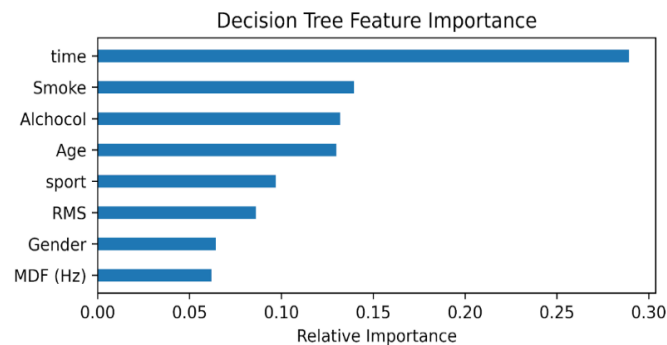


Figure 5. Feature importances

It is evident that time has a strong influence, as the longer the load is applied, the greater the fatigue experienced—an observation that aligns with the known physiological accumulation of neuromuscular fatigue during sustained exertion [52]. Behavioral factors, including smoking and alcohol consumption, also emerged as significant predictors, indicating that lifestyle habits may contribute meaningfully to the development and perception of fatigue. Less important features include RMS, Gender, and MDF (Hz), which have lower relative importance values. These results confirm that time, along with certain biological and behavioral parameters, plays a key role in the Decision Tree model's predictions. The inclusion of both physiological and behavioral variables enables the model to represent fatigue more comprehensively, offering meaningful guidance for the design of individualized rehabilitation protocols.

The study aimed to develop a real-time, IoT-enabled system for classifying local muscle fatigue using surface EMG signals, behavioral context, and subjective fatigue perception. The goal was to improve rehabilitation outcomes through more accurate and personalized fatigue detection. A key methodological innovation was the use of subjective fatigue ratings as the target variable, predicted from a combination of objective EMG signal features and behavioral factors such as smoking and alcohol consumption. These features were extracted directly on a wearable device (Qimyl) and transmitted wirelessly for analysis. Several supervised machine learning algorithms—LR, DT, RF, and XGBoost—were applied to classify fatigue states, with the DT model achieving the best performance at 90.7% accuracy. The conceptual novelty lies in synchronizing physiological and behavioral inputs to model subjective fatigue in real time, enabling efficient on-device processing and practical deployment for adaptive telerehabilitation.

Existing studies on muscle fatigue assessment have predominantly adopted objective methodologies based on surface EMG, with limited consideration of subjective perceptions. One line of research has employed continuous wavelet transforms [53] to analyze electrophysiological responses across varying exercise intensities, focusing on features such as frequency drop-offs, burst power, and area changes to infer localized fatigue, without integrating participant-reported exertion. Other investigations have used time and frequency domain features—such as median and mean frequency shifts, root mean square (RMS), and mean absolute value (MAV)—to classify fatigue states, including prolonged fatigue induced by treadmill protocols [54]. While these approaches demonstrated high classification accuracy using machine learning algorithms, they assessed fatigue solely through changes in signal properties. Robotic protocols have also been proposed [55] to objectively determine the onset of fatigue using surface EMG frequency metrics and estimated energy expenditure during resistive motor tasks. Similarly, studies analyzing isotonic contractions have quantified fatigue through spectral changes in EMG signals under varying load conditions [56]. Despite their methodological rigor, these works consistently omit real-time or structured subjective fatigue ratings.

While previous works have relied solely on objective EMG features to evaluate muscle fatigue, this study models subjective fatigue perception as the target variable, using a structured numerical rating scale collected during the task, while employing objective EMG signal features and contextual behavioral factors—such as smoking and alcohol consumption—as predictive inputs. This paradigm shift enables the model to learn how perceived fatigue correlates with physiological and behavioral indicators, offering a more personalized and psychologically informed approach to fatigue monitoring. By synchronizing EMG feature extraction with participants' real-time self-reports during sustained isometric contractions, the system enhances the ecological validity of fatigue detection. The ability to model subjective states directly—rather than infer them solely from physiological thresholds—supports more responsive and adaptive rehabilitation strategies. The platform's remote monitoring capabilities also support telerehabilitation, allowing healthcare providers to deliver customized care. Beyond its immediate utility, the proposed framework offers substantial long-term potential for the advancement of adaptive rehabilitation and personalized health monitoring.

A key innovation of this study lies in its dual-input modeling approach, which combines objective surface EMG signal features with contextual behavioral variables such as smoking and alcohol consumption. By training machine learning models to predict subjective fatigue ratings derived from participant self-assessments, the system bridges the gap between measurable physiological activity and individual perceptual experience. This modeling strategy acknowledges fatigue not merely as a biomechanical phenomenon but as a multidimensional construct influenced by both internal and external factors. As such, it facilitates the development of real-time closed-loop rehabilitation systems that can dynamically tailor exercise parameters—including intensity, duration, and recovery intervals—based on the evolving interplay between physiological load and personal tolerance. The ability to model how fatigue unfolds over time, as perceived by the individual, enables clinicians and intelligent systems to detect early warning signs of overexertion and intervene preemptively to prevent injury or disengagement. Moreover, the demonstrated feasibility of on-device feature extraction and classification using embedded ML models on ESP32 architecture paves the way for edge-AI rehabilitation systems that are portable, energy-efficient, and deployable at scale in home settings. This edge-first paradigm alleviates reliance on cloud connectivity, reduces latency, and protects patient privacy—key requirements for widespread adoption in telerehabilitation and remote elderly care applications. With such a system, real-time feedback loops can be enabled even in low-resource or offline environments, where conventional cloud-based systems may fail. It opens avenues for longitudinal analysis, where trends in fatigue progression can be analyzed over days or weeks, yielding new biomarkers for therapy effectiveness, overtraining, or risk of relapse. The presented study offers an interdisciplinary contribution at the intersection of electrical engineering, embedded systems, IoT technology, and machine learning, targeting critical needs in modern healthcare applications. The proposed low-power wearable device enables on-device EMG signal processing and fatigue classification, integrating physiological and lifestyle data for personalized monitoring. Aligned with current trends in smart health systems, this work contributes to advancing adaptive rehabilitation technologies and offers a practical framework for future research and clinical applications.

However, several limitations were encountered during the experiment that suggest further improvement. The sample size was limited to ten healthy individuals aged 19 to 22, which restricts the generalizability of the results to diverse clinical populations, such as older adults or patients with neuromuscular conditions. The exercise protocol lasted approximately three minutes to reflect typical rehabilitation sessions, yet this short duration restricted the ability to observe longer-term fatigue patterns or recovery behavior. The system also relied on subjective self-assessments of fatigue, which may vary due to differences in individual pain threshold, perception, or communication style, potentially affecting the consistency of the data.

5. CONCLUSION

The study demonstrated that a low-power single-channel wearable device based on surface EMG can reliably recognize muscle-fatigue levels in real time during prolonged submaximal hand-grip tasks. In ten healthy volunteers EMG signals and subjective fatigue ratings were recorded synchronously, and machine-learning models—Decision Tree with 90.7 % accuracy and XGBoost—clearly separated fatigue states. Time under load and behavioral factors such as smoking and alcohol consumption had a marked impact, confirming the main hypothesis that a compact energy-efficient system with one EMG sensor can serve as a dependable fatigue detector without bulky laboratory hardware. This result opens the way to move fatigue monitoring from research settings into everyday rehabilitation practice, giving patients and clinicians an affordable tool for accurate load and recovery tracking.

The findings carry three main implications. First, future studies can build larger and clinically diverse datasets, extend monitoring over weeks, and integrate inertial and heart-rate sensors together with an embedded Random Forest model on the ESP32 to explore long-term fatigue trajectories and new biomarkers of therapy effectiveness. Second, clinical practice can benefit from instant feedback that allows therapists to adjust exercise intensity, duration, and rest intervals in real time, reducing overexertion risks and improving adherence. Third, health-care policy can leverage the device's low cost, privacy-preserving edge processing, and ease of home deployment to add wearable fatigue trackers to national telerehabilitation programmers and reimbursement frameworks, lowering face-to-face visits and accelerating the move toward personalized, data-driven rehabilitation services.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data supporting the findings of this study are not publicly available due to their ongoing use in further research and related projects.

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