Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6, 925-938
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i6.7976

Modeling local muscle fatigue phases from EMG: A comparative study of classification and regression approaches

Ahmed Ali DIDI[1*], Fethi Bereksi Reguig[2]
[1,2]Biomedical engineering research laboratory, University of Tlemcen, Algeria; ahmedali.didi@univ-tlemcen.dz (A.A.D.) fethi.bereksi-reguig@univ-tlemcen.dz (F.B.R.).

Abstract: Identifying local muscle fatigue phases through surface electromyography (sEMG) is essential for developing real-time, non-invasive monitoring systems. This study compares two modeling strategies—classification and regression—for detecting three fatigue phases (non-fatigue, transition, fatigue) using sEMG signals alone. Data were collected during sustained handgrip tasks from healthy subjects, and eleven EMG features were extracted. Labels were assigned based on observed force decline thresholds: upper than 90%, between 70–90% and lower than 70% of Maximum voluntary contraction (MVC), serving as ground truth during training. Three classification models: SVM (Support Vector Machine), LDA (Linear Discriminant Analysis), QDA (Quadratic Discriminant Analysis) and a Multiple Linear Regression (MLR) model were trained and tested. With classifiers, QDA yielded the highest accuracy of 82% and the most consistent phase mapping. However, MLR achieved higher performance in reconstructing continuous force output with r = 0.96, enabling smoother and more physiologically realistic phase segmentation. Visual comparisons showed that classification outputs tended to be fragmented, particularly in the transition phase while regression maintained temporal coherence. These results research show that regression provides a more robust and interpretable framework for modeling fatigue progression from EMG signals, although classification models may still be useful in applications requiring discrete outputs.

Keywords: *Classification, Multivariate linear regression, Predictive modeling, Signal processing, Surface electromyography (sEMG).*

1. Introduction

Muscle fatigue, that transient waning of a muscle's capacity to summon force or power amid voluntary striving, emerges not from one isolated cause but from a tangled weave of influences—some physiological, others psychological—that shape the neuromuscular system's output and one's sense of exertion. The task's demands mold this interplay, where constraints within the body meet perceptions in the mind. Such a dual lens, encompassing what is felt and what is performed, affords a fuller grasp of fatigue's presence in real-world endeavours [1].

Surface electromyography (sEMG) is a non-invasive method which gives the electrical potentials information generated by muscle fibres during voluntary contraction. It has been widely adopted for monitoring muscle performance over time since it provides valuable insight into neuromuscular activity. As fatigue develops, the sEMG signal reflects corresponding physiological changes, making it a useful tool for tracking fatigue progression in both clinical and experimental settings [2].

Have reported that during isometric contraction, the EMG signal reflects muscle activation and provides an indirect but reliable estimate of neuromuscular activity during maximal voluntary contractions, indicating the motor unit recruitment's level and force production.

Different sEMG features have been described and used in the domain literature to quantify fatigue-related changes, each reflecting specific aspects of neuromuscular behavior. In the time domain, simple

History: Received: 11 April 2025; Revised: 3 June 2025; Accepted: 6 June 2025; Published: 11 June 2025
* Correspondence: ahmedali.didi@univ-tlemcen.dz

amplitude-based descriptors for example as mean absolute value (MAV), root mean square (RMS), integrated EMG (IEMG) [3] and variance have demonstrated effectiveness in characterizing muscle activation during sustained effort. Waveform length and amplitude range have also been shown to capture temporal complexity and variability in the signal, making them suitable indicators of neuromuscular efficiency and fatigue progression in time-domain analysis [4, 5]. Additionally, energy-based operators such as the Teager–Kaiser Energy Operator have been shown to improve sensitivity to subtle signal modulations during muscle activation, making them valuable for enhancing fatigue detection in the time domain [6].

In addition to temporal descriptors, time-frequency features have been proven useful for analysing the non-stationary behaviour of EMG signals. Techniques as for example the Wigner-Ville distribution and the S-transform allow for localized tracking of spectral changes over time, offering insight into how frequency components evolve during fatigue [7, 8].

Complementing these, nonlinear descriptors such as Shannon entropy and Hilbert-Huang-based variance provide measures of signal complexity and irregularity, which typically increase as fatigue develops [9, 10].

Together, when used collectively, these multi-domain features offer a more comprehensive understanding of the physiological transitions associated with fatigue. These have been widely used in EMG-based modelling frameworks.

In a reported study, Atzori, et al. [11] proposed a hybrid framework. This framework combines regression and classification to ensure simultaneous and scaled force control at the wrist using EMG signals. Their method employs a multi-kernel learning classifier to identify movement classes, followed by class-specific neural network regressors to estimate the corresponding force outputs. This two-stage approach improved the accuracy of force prediction, particularly in complex degrees of freedom such as pronation and supination.

Isa and Aris [12] employed genetic programming (GP) to assess localized muscular fatigue during isometric exercises using surface EMG measurements. Their approach distinguished between non-fatigue, transition-to-fatigue, and fatigue phases by evolving a population of classifiers trained on statistical features such as RMS, entropy, kurtosis, and skewness. Of particular note, the model's explicit identification of the transition phase underscores the value of interpretable EMG models in monitoring fatigue development, and, without requiring force measurements, revealed promising classification accuracy across multiple individuals.

Marri and Swaminathan [13] developed a method for detecting muscle fatigue using features extracted from surface EMG signals. Their approach focused on distinguishing between non-fatigue and fatigue states during dynamic contractions. Using classifiers such as kNN, logistic regression and Naive Bayes, they achieved up to 86% accuracy, reinforcing the viability of machine learning techniques in binary fatigue detection based on EMG signals.

Li, et al. [14] present a comprehensive review of non-invasive muscle fatigue monitoring techniques, focusing on surface sEMG, mechanomyography (MMG), and near-infrared spectroscopy (NIRS). The survey details acquisition methods, signal processing, and machine learning applications. It highlights sEMG as the most reliable and widely adopted technique for real-time fatigue detection in wearable systems due to its non-invasiveness and strong physiological relevance.

In this study, the emphasis falls on surface electromyography (sEMG)—a modality both non-invasive and capable of continuous, real-time monitoring—not as an afterthought, but as the central means through which fatigue-induced variations in muscle behaviour are traced.

The primary goal is to characterize fatigue phases - non-fatigue, transition from non fatigue to fatigue and fatigue- using only sEMG features. However, since sEMG does not inherently include absolute force information, simultaneous recording of grip force was used during the training step to label fatigue states. These labels were based on relative reductions in maximum voluntary contraction (10% and 30%), thresholds that are consistent with physiological transitions observed in sustained isometric tasks.

A platform was developed to record sEMG signals. After preprocessing and segmentation, eleven features were extracted from each EMG segment across time, time-frequency, and nonlinear domains. Three classification models mainly (SVM, LDA, QDA) were trained to distinguish the three fatigue phases. In parallel, a multiple linear regression model (MLR) was implemented to predict force directly from EMG. This dual approach enables a comparative evaluation of classification versus regression in mapping EMG-derived neuromuscular activity to fatigue progression. The different steps of the proposed study are illustrated through the flowchart given in Figure 1.

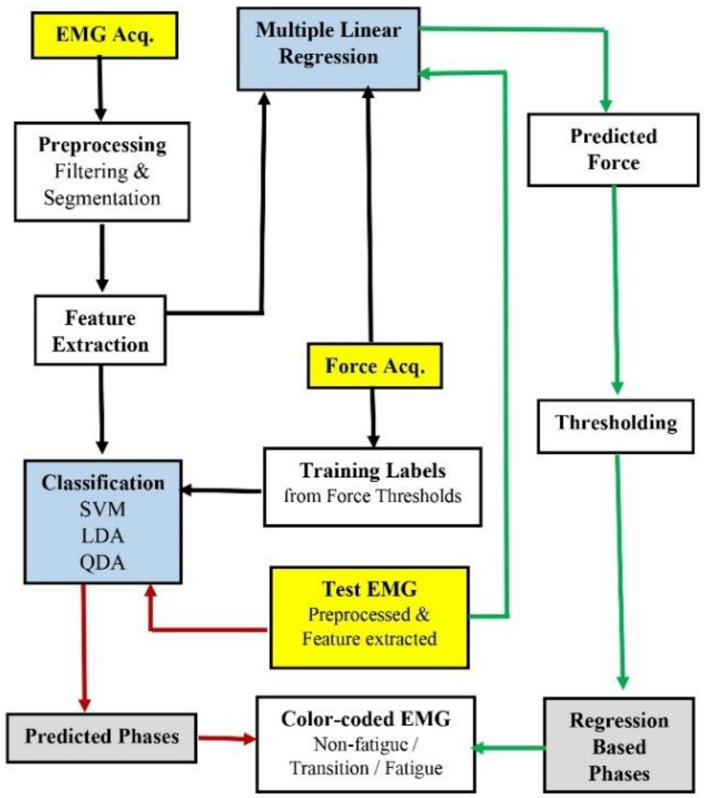

Figure 1.
Flow chart of the EMG-Based Fatigue Phase Detection and classification.

2. Materials and Methods

2.1. Experimental Setup

To carry out the study, nineteen healthy adults (13 males and 6 females), aged 22 to 38 years, with an average weight of 79 ± 8 kg for males and 68 ± 5 kg for females, were keen to participate. All subjects were right-handed and informed no history of neuromuscular disorders.

Each subject performed a sustained isometric handgrip contraction using a digital dynamometer until voluntary fatigue. Surface electromyographic (sEMG) signals were recorded from the flexor carpi radialis (FCR) muscle using standard Ag/AgCl surface electrodes [15]. The electrode's placement and the skin's preparation followed standard EMG acquisition guidelines to ensure signal quality and reproducibility.

Participants were comfortably seated, and no specific constraint was applied to the joint angle beyond maintaining a stable posture throughout the recording. They received verbal encouragement to sustain their grip for the maximum duration possible, until a visible and self-reported decline in force indicated the onset of fatigue. Simultaneous acquisition of EMG and grip force data allowed for accurate alignment of neuromuscular activity with muscular performance over time

2.2. Data Acquisition and Signal Preprocessing

sEMG signals were recorded from the flexor carpi radialis (FCR) muscle using standard Ag/AgCl electrodes placed over the muscle belly. Acquisition was performed with an ESP32 Wroom microcontroller, which provided a 12-bit analog-to-digital conversion with a 2 kHz sampling frequency [16]. This configuration ensured sufficient resolution and temporal accuracy for detecting subtle variations in neuromuscular activation associated with fatigue. The recorded sEMG signals are buried in noise. Consequently, a bandpass filter with cut-off frequencies 5Hz up to 500Hz was applied to suppress movement artifacts and high-frequency noise, while a 50 Hz notch filter eliminate powerline interference [17] (see Figure. 2). Each filtered signal was segmented into 50 equal-length non-overlapping windows, allowing for local analysis of fatigue progression over time. Importantly, the EMG and grip force signals (see Figure 3) were acquired simultaneously and time-aligned, enabling each EMG segment to be associated with a corresponding force value.

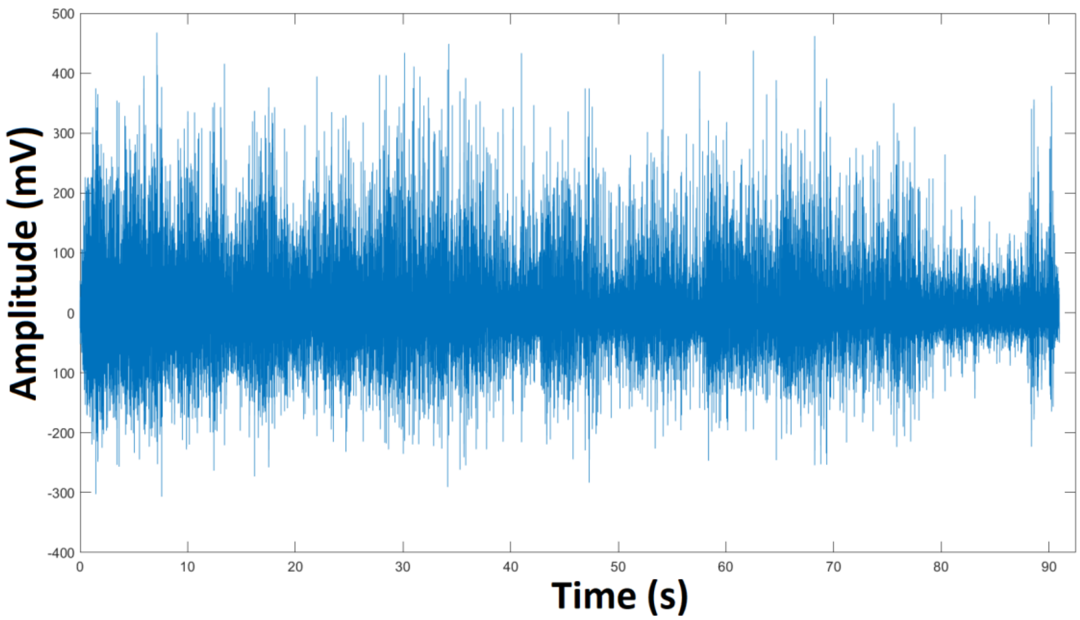

Figure 2.
Filtered EMG Signal Acquired During Sustained Contraction.

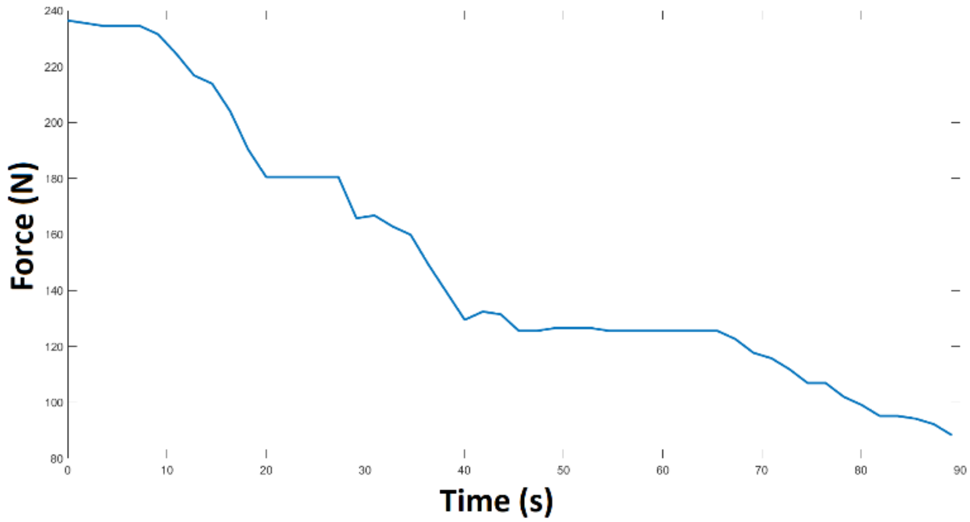

Figure 3.
Observed Grip Force Evolution Over Time.

2.3. Feature Extraction

Eleven features were computed for each EMG segment to capture signal characteristics across time, time-frequency, and nonlinear domains. The selected features included Mean Absolute Value (MAV), Integrated EMG (IEMG) [3] Root Mean Square (RMS), Amplitude Range, Variance, and Waveform Length for the time domain. In the time-frequency domain, the S-transform and Wigner-Ville distribution were used. Entropy and Hilbert-Huang transform variance were computed as nonlinear descriptors. These features were chosen based on their strong correlation with force and their frequent appearance in fatigue-related EMG studies. These are used as input to the classification and regression models after being normalized.

2.4. Classification Models

Three supervised classification algorithms were employed in this study to identify muscle fatigue phases based solely on EMG features: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Support Vector Machine (SVM) with a linear kernel. Each of these models was trained using a matrix of 11 features extracted from EMG signal segments, with corresponding labels representing one of three fatigue states: non-fatigue, transition, or fatigue. The selection of these models was motivated by their complementary strengths in handling different data distributions and decision boundary complexities.

Linear Discriminant Analysis (LDA), assuming that each class's data are normally distributed with matching covariance matrices, Linear Discriminant Analysis (LDA) stands as a traditional classifier; it projects features from a high-dimensional space into a lower one, seeking to increase the gap between class means and reduce variance within classes. Widely employed in EMG-based fatigue detection, LDA owes its frequent use to simplicity and interpretability—particularly when data separate linearly.

The linear decision boundaries produced by LDA are computationally efficient, making it particularly suitable for real-time applications where quick inference is required. Although LDA performs well when the class distributions overlap moderately and are roughly Gaussian, its performance may decline when the true class boundaries are nonlinear or when the class covariances differ significantly.

Quadratic Discriminant Analysis (QDA) extends LDA by allowing each class to have its own covariance matrix, thus relaxing the assumption of homoscedasticity. This enables QDA to model more complex, curved decision boundaries, which can better fit data exhibiting nonlinearity in the feature space. In the case of EMG signals, where the feature distributions across different fatigue states may vary in both shape and spread, QDA can provide enhanced discrimination performance compared to LDA. However, this flexibility comes at the cost of increased model complexity and a higher number of parameters to estimate, making QDA more sensitive to overfitting, particularly when the training dataset is limited or imbalanced. Nevertheless, when the class-specific distributions are distinct, QDA can significantly outperform linear models.

Support Vector Machine (SVM) with a linear kernel was also utilized due to its robustness and strong theoretical foundations in maximizing the margin between classes. SVM aims to find the optimal hyperplane that separates the data classes with the largest possible margin, leading to better generalization performance. The use of a linear kernel assumes that the classes can be effectively separated in the original feature space without the need for nonlinear transformation. This assumption is consistent with prior findings suggesting that well-selected EMG features may form linearly separable clusters for different fatigue stages. SVMs are particularly powerful in high-dimensional spaces and are less prone to overfitting when the number of features exceeds the number of observations.

Their insensitivity to outliers and strong performance on small datasets make them well-suited for biomedical applications such as fatigue phase classification.

Across the board, the three classifiers—LDA, QDA, and linear SVM—were selected due to a balance struck among interpretability, computational efficiency, and classification strength; their relative effectiveness was assessed to identify the best fit for fatigue phase classification using EMG-derived features.

Drawing on Demura, et al. [18] the fatigue phase onset linked to force falling beneath 30% of maximum voluntary contraction (MVC)—a pattern notably observed in males. Their findings showed that men's sustained force decreased to about 26% MVC, reinforcing that such a threshold marks a clear fatigue condition. Here, segments registering force ≥90% MVC were classified as non-fatigue; those ranging from 70–90% as transition; and segments at or below 70% as fatigue. This method of thresholding enabled a segmentation of muscle performance during sustained contraction that aligns with physiological expectations.

2.5. Regression Approach

A multiple linear regression (MLR) model was implemented to estimate continuous muscle force values directly from the EMG-derived feature matrix. Unlike classification models, which assign discrete class labels to predefined fatigue phases (non-fatigue, transition, fatigue), the regression approach retains the continuous nature of the underlying physiological signal. MLR is a statistical method that models the relationship between one dependent variable—in this case, the observed muscular force—and multiple independent variables, represented by the eleven EMG features extracted from each signal segment.

The MLR model was trained using paired EMG and force data obtained during voluntary isometric contraction tasks. By learning the optimal weights that link each feature to the output force, the model becomes capable of predicting continuous force levels from previously unseen EMG data without requiring any information about class labels. This characteristic is particularly advantageous, as it avoids the need for manual or automated labelling of fatigue phases during the test phase—thus enhancing applicability in real-world, real-time settings.

Once the predicted force signal had been obtained, processing followed using thresholds predetermined by the subject's Maximum Voluntary Contraction (MVC)—namely, at 90% and 70% MVC. This procedure divided the predicted force into three segments, each reflecting the fatigue phases applied in the classification models. Segments with predicted force above 90% MVC received the non-fatigue label; those between 70% and 90% were classified as transition; values under 70% were associated with fatigue. By means of this post-processing step, continuous force outputs were effectively reclassified into discrete fatigue stages, which enabled a straightforward comparison of classification versus regression methods.

This method drew on EMG data to estimate fatigue in a way that mirrored how muscle force typically diminishes—gradually, not in steps. Instead of relying on discrete class labels that often jump from one state to another without nuance, the regression-based model traced changes more fluidly; no sharp transitions were imposed. Because it didn't require predefined fatigue markers at the point of inference, it proved useful in capturing the subtle and continuous decline in muscular output. As a result, the approach created a functional middle ground—merging the detail of continuous signal modelling with the structure of categorical fatigue staging.

2.6. Performance Evaluation Metrics

Classification and regression metrics were used for Model performance evaluation. For classification, accuracy, precision, recall, F1-score, and specificity were calculated based on confusion matrices. For the regression model, the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and Pearson correlation coefficient (r) were employed to evaluate force prediction accuracy and its consistency with observed values.

3. Results

3.1. Correlation Between EMG Features and Force

To evaluate the physiological relevance of each extracted EMG feature in relation to muscle output, Pearson correlation coefficients were calculated between each feature and the corresponding observed force values across all segments. As reported in Table 1, the results indicate that most features exhibit strong linear relationships with muscular force, thereby confirming their suitability for both regression and fatigue classification tasks.

Within the time domain, features such as Mean Absolute Value (MAV), Waveform Length, Root Mean Square (RMS), Integrated EMG (IEMG), and Teager-Kaiser Energy (TKEO) all demonstrated high positive correlations ($r \geq 0.96$). These features reflect the amplitude and energy content of the EMG signal, which naturally increase with muscle contraction intensity. Notably, MAV, WL, and IEMG each achieved a correlation coefficient of 0.97, highlighting their robustness as predictors of force. Variance also showed a strong correlation ($r = 0.95$), indicating that fluctuations in signal consistency track well with changes in force output. Amplitude Range, although positively correlated ($r = 0.86$), yielded slightly lower values, possibly due to its sensitivity to noise and transient spikes.

In the time-frequency domain, both the S-Transform (Mean) and Wigner-Ville Distribution (Mean) achieved high correlations of 0.97 and 0.95, respectively. These results validate the usefulness of spectral information in characterizing force-dependent EMG changes, particularly as muscle fatigue induces shifts in frequency content.

Interestingly, in the nonlinear domain, Hilbert-Huang transform (variance) showed a solid positive correlation ($r = 0.94$), while Shannon Entropy displayed a negative correlation ($r = -0.89$). This inverse relationship supports the notion that as muscle fatigue increases, EMG signals become more chaotic and less predictable.

Altogether, the observed correlation patterns demonstrate that the selected 11 features capture essential neuromuscular dynamics and are physiologically aligned with force production and fatigue evolution.

Table 1.
Pearson Correlation between EMG Features and Observed Force.

No.	EMG Feature	Domain	r (Pearson)
1	Mean Absolute Value	Time	0.97
2	Waveform Length		0.97
3	Amplitude Range		0.86
4	Root Mean Square		0.96
5	Variance		0.95
6	Integrated EMG		0.97
7	Teager-Kaiser Energy		0.96
8	S-Transform	Time-Frequency	0.97
9	Wigner-Ville Distribution		0.95
10	Shannon Entropy	Nonlinear	-0.89
11	Hilbert-Huang transform		0.94

3.2. Classification Model Performance

As resumed in Table 2, three supervised classification models—Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA)—were compared based on their ability to assign EMG segments to one of three fatigue phases: Non-fatigue, transition, or fatigue. Among them, QDA achieved the highest overall classification performance, with an accuracy of 82%, a precision of 81%, a recall (sensitivity) of 75%, and a specificity of 90%. This indicates that QDA not only captured a large proportion of correctly classified instances but also minimized false positives and negatives, making it the most physiologically consistent classifier among the three.

Table 2.
Classification Model Performance.

Classifier	*SVM*	*LDA*	*QDA*
Accuracy (%)	65	71	82
Precision (%)	24	58	81
sensitivity (%)	33	50	75
F1-score (%)	28	54	78
Specificity (%)	73	75	90

LDA came next with an accuracy of 71%, showing strong results for precision and specificity—58% and 85%, respectively. Its recall, slightly lower at 70%, points to occasional misses in identifying some true transition or fatigue instances. Still, even with its more basic linear framework, LDA managed to strike a reasonable trade-off between detecting actual fatigue and avoiding false positives, producing a mapping of fatigue progression that remained fairly consistent.

In contrast, SVM with a linear kernel demonstrated the weakest performance, with 65% accuracy, only 24% precision, and a low F1-score of 28%, revealing a tendency to produce both false positives and negatives, especially during ambiguous states. Although SVM maintained reasonable specificity (73%), its sensitivity (33%) and low F1-score indicate that it struggled particularly with detecting the intermediate transition phase.

These quantitative findings are highly consistent with the visual comparison presented in Figure 4, which displays the EMG signal color-coded according to the fatigue phase labels assigned by each model (green: non-fatigue, blue: transition, red: fatigue). QDA exhibited smooth and continuous phase boundaries, effectively capturing the gradual shift from non-fatigue to fatigue, including a well-delineated transition zone. The transitions identified by QDA align closely with the expected physiological decay in force and EMG patterns, reflecting its superior ability to model non-linear boundaries across the feature space.

LDA, while slightly less precise, also produced interpretable segmentation with fairly consistent regions. However, some misassignments were observed, particularly at the boundaries between transition and fatigue phases. These brief classification errors may result from the linear decision surface's inability to fully capture the overlap between feature distributions.

SVM, by comparison, generated more fragmented and noisy segmentation, with frequent oscillations between transition and fatigue labels, even within stable signal regions. This suggests poor generalization and an inability to model nuanced class boundaries in the EMG feature space.

The models were generally effective at tracking fatigue development, yet their accuracy in pinpointing the middle phase differed considerably—likely because muscular activation patterns overlap in this stage. QDA's capacity to handle separate covariance structures for each class enabled segmentation that appeared more consistent with physiological behavior. This highlights that choosing the right model depends not only on statistical metrics but also on how well the results can be interpreted in clinical or biomechanical terms, particularly when dealing with gradual shifts like muscle fatigue.

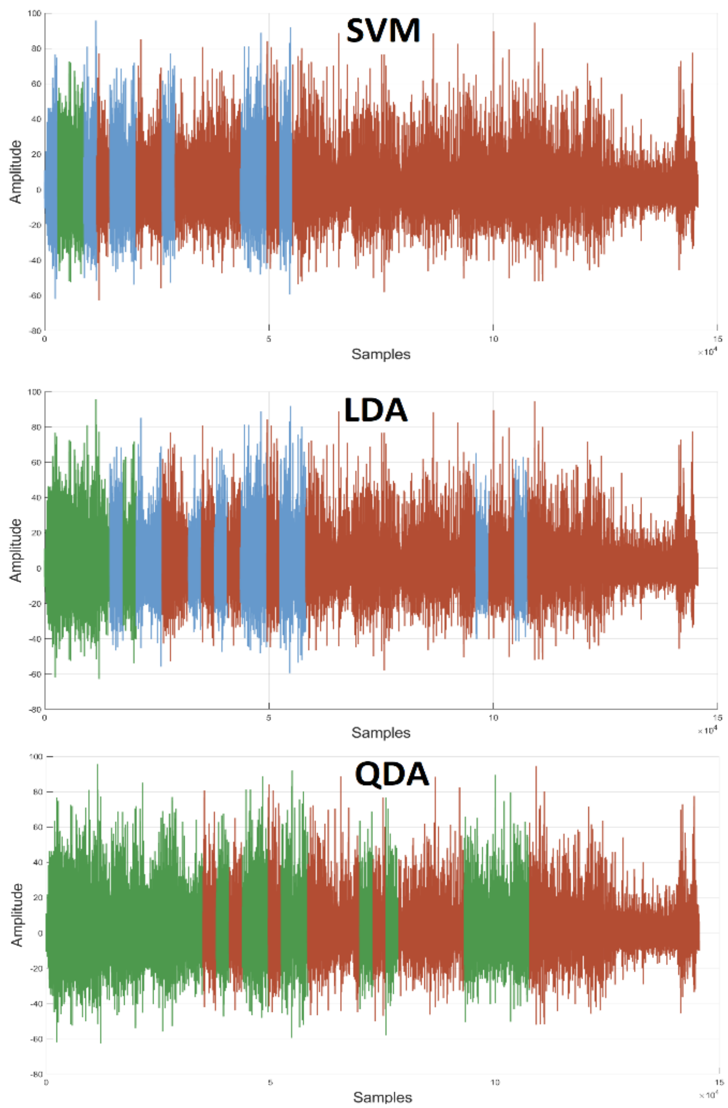

Figure 4.
Color-coded EMG Signal Segmentation Based on SVM, LDA, and QDA Classification Models (Non-Fatigue : Green, Transition : Blue, Fatigue : Red).

3.3. Regression-Based Estimation of Force

To deepen the analysis beyond discrete classification, a Multiple Linear Regression (MLR) model was implemented to predict continuous force values directly from the same EMG feature matrix. Unlike classification, which forces each segment into a fixed label, this regression-based approach preserves the continuity of muscular effort. The resulting predicted force signal was then segmented into three fatigue phases using the same MVC-based thresholds applied to the observed force. This ensured direct comparability between both approaches.

As shown in Figure 5, the predicted force trajectory closely followed the observed force curve across the entire contraction period. The model achieved a Pearson correlation coefficient of 0.96, demonstrating strong agreement between predicted and actual values. Minor discrepancies appeared primarily during the early contraction phase and in late fatigue, where EMG signal quality tends to decline due to physiological and measurement factors.

The MLR model, overall, demonstrated strong capability in recreating force output from EMG signals, providing a fluid and physiologically plausible view of how fatigue advances. Steering clear of sudden jumps between categories, this approach to continuous force estimation reveals nuanced shifts, aligning more closely with the slow progression typical of neuromuscular deterioration, thus presenting a valuable option beyond strictly discrete classification methods.

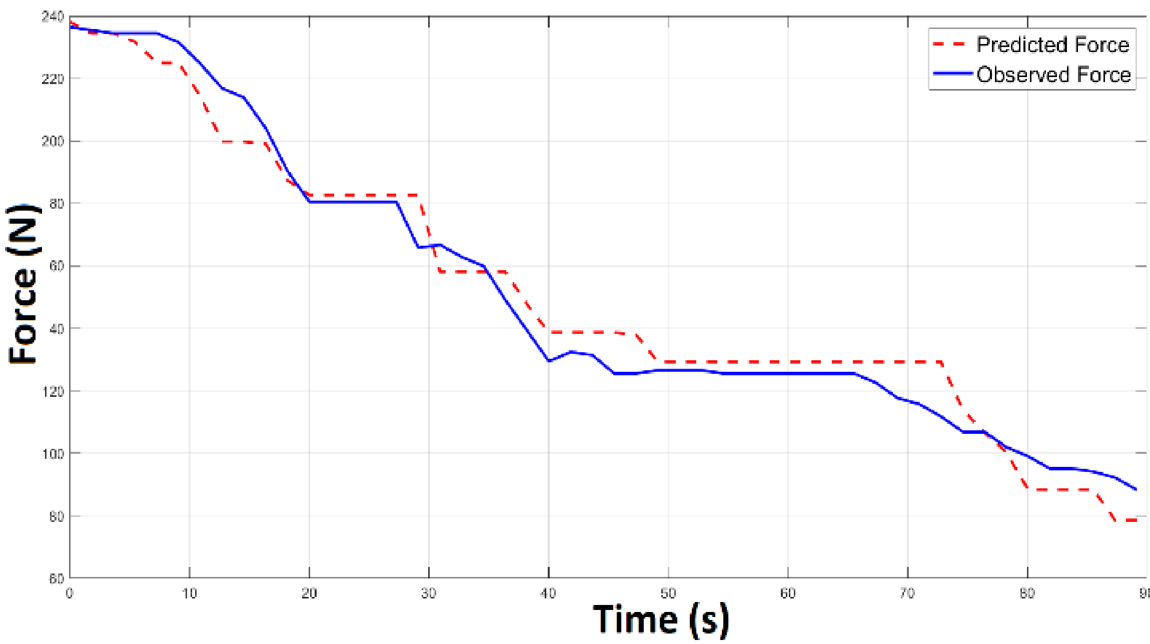

Figure 5.
Comparison Between Observed and Predicted Force Using the Multiple Linear Regression Model.

3.4. Comparison Between Observed and Predicted Force Using the Multiple Linear Regression Model

To visualize how fatigue phases unfold over time, the raw EMG signal of the test subject was segmented and color-coded on the actual observed force trajectory basis. As seen in Figure. 6, the EMG signal was segmented into green (non-fatigue), orange (transition), and red (fatigue) zones using the predefined force thresholds. The segmentation revealed a clear and physiologically coherent evolution of fatigue, with increased amplitude and signal density accompanying the decline in force.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6: 925-938, 2025
DOI: 10.55214/25768484.v9i6.7976

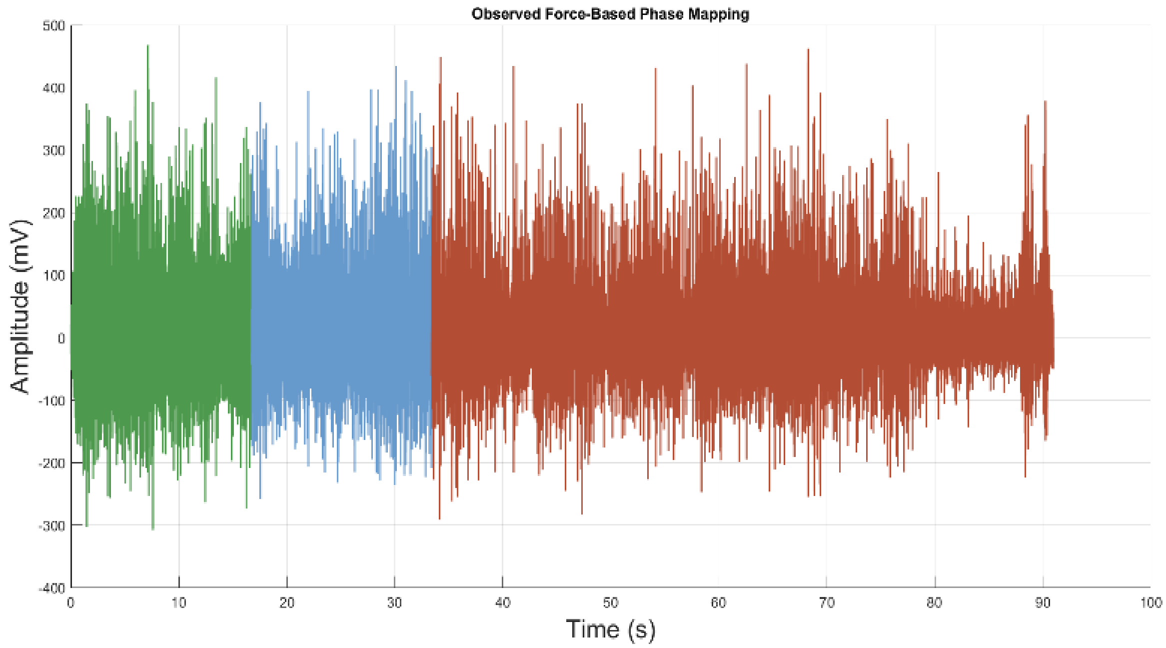

Figure 6.
Reference Fatigue Phase Mapping Based on Observed Force Thresholds.

This representation served as the reference for comparison with both classification and regression-based mappings. It confirmed that fatigue onset is not abrupt but follows a gradual and progressive transition, reinforcing the awareness of adopting continuous or flexible models.

3.5. EMG Phase Mapping Based on Regression Output

Finally, the fatigue phases inferred from the MLR-predicted force were mapped back onto the EMG signal. The resulting visualization (Figure 6), displays color-coded EMG segments based on regression-derived force thresholds. The mapping closely aligns with the ground truth as can be seen in Figure 5, emphasizing the regression model's capacity to reconstruct fatigue phases accurately.

The resulting segmentation offered a smooth representation of fatigue evolution and aligned closely with the reference force-based mapping (see Figure 7).

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 6: 925-938, 2025
DOI: 10.55214/25768484.v9i6.7976

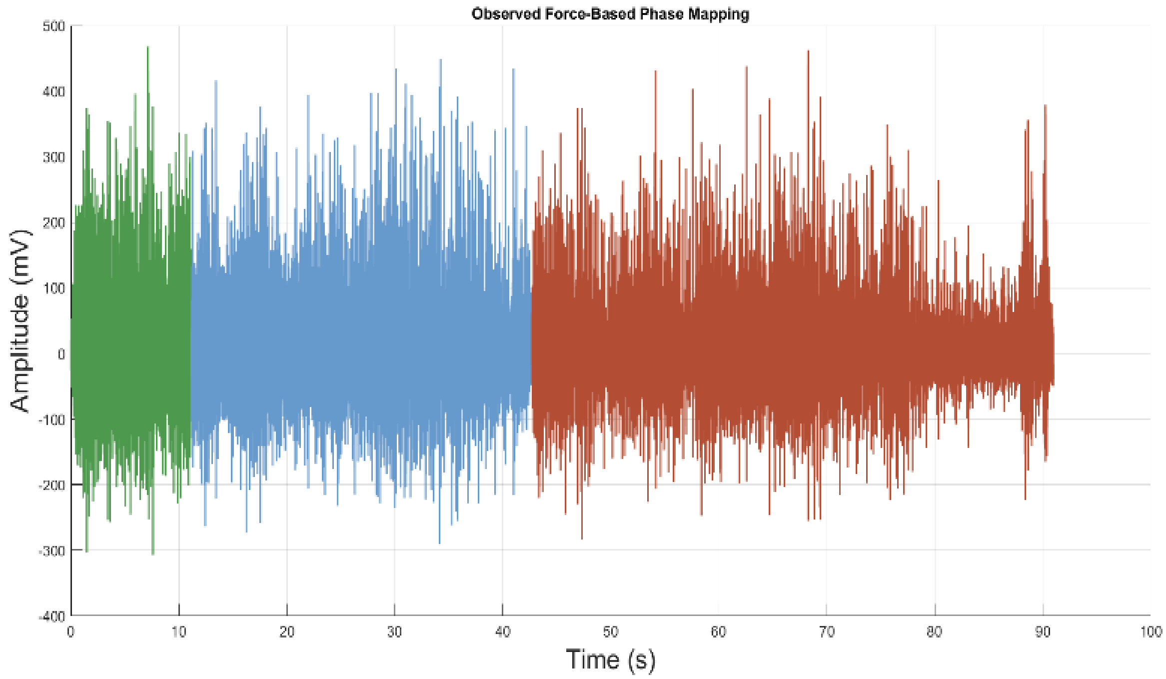

Figure 7.
Fatigue Phase Mapping Based on Regression-Predicted Force.

4. Discussion

4.1. Comparative Evaluation of Classification and Regression Strategies

Here, two fundamentally different approaches—classification and regression—were tested to describe local muscle fatigue using features derived from surface electromyography (sEMG). QDA and LDA, among the classifiers, managed to separate non-fatigue and fatigue states with reasonable success; however, all classifiers, including SVM, struggled—especially in the transition phase, where muscular activity patterns overlap and boundaries blur. On the other hand, the MLR model provided a continuous estimate of force, which—once physiological thresholds were applied—permitted a segmentation that avoided rigid classification lines; this better represents the slow, ongoing progression typical of neuromuscular fatigue. This contrast in outcomes highlights how challenging it is to model gradual fatigue transitions and suggests that continuous models, despite their complexity, might capture the nuances that discrete classes miss.

4.2. Reliability of EMG-Based Fatigue Detection Without Force Input

The regression approach, on another side, provided a continuous representation of muscle performance by estimating force directly from EMG features. This allowed for the identification of fatigue phases through force-based segmentation without rigid categorical boundaries. The regression model demonstrated strong correlation with observed force values and showed improved temporal consistency in phase mapping, which may better reflect the physiological progression of fatigue.

Overall, while classification enables rapid decision-making and discrete labelling, regression captures the gradual and evolving nature of fatigue more effectively, highlighting the complementary strengths of both approaches and justifying their comparative evaluation.

5. Conclusion

This study investigated the modelling of local muscle fatigue phases from surface EMG signals using both classification and regression approaches. By analysing a reduced set of eleven EMG features across time, time-frequency, and nonlinear domains, we trained and evaluated three classification models (SVM, LDA, QDA) and a Multiple Linear Regression (MLR) model. The different phases of fatigue were labelled based on thresholds derived from observed force levels, using criteria supported in the literature.

While all models were able to capture key transitions in muscle activity, the regression model (MLR) provided the best alignment with the reference force trajectory. It delivered continuous outputs that enabled smooth phase segmentation and greater temporal coherence, particularly in the transition phase, which is often poorly captured by classifiers. Among classification models, QDA showed the optimal performance in both numerical metrics and phase mapping.

Regression showed clear benefits by delivering fatigue evaluations that align closely with physiological patterns and offer smooth, consistent visual results — classification, on the other hand, proves useful when quick, distinct state recognition is essential; moving forward, exploring hybrid frameworks or leveraging deep learning could open new paths to boost both accuracy and robustness in tracking muscle fatigue through sEMG signals.

Institutional Review Board Statement:

Ethical review and approval were waived for this study due to its non-invasive nature and adherence to standard academic protocols for human experimentation. All procedures were carried out in accordance with the Declaration of Helsinki, and informed consent was obtained from all participants.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] R. M. Enoka and J. Duchateau, "Translating fatigue to human performance," *Medicine & Science in Sports & Exercise*, vol. 48, no. 11, p. 2228, 2016.

[2] M. Gazzoni, A. Farina, and D. Merletti, "Surface EMG and muscle fatigue: Multi-channel approaches to the study of myoelectric manifestations of muscle fatigue," *Journal of Electromyography and Kinesiology*, vol. 28, pp. 10–18, 2017.

[3] M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, "Electromygraphy (EMG) signal based hand gesture recognition using artificial neural network (ANN)," presented at the 2011 4th International Conference on Mechatronics (ICOM), 2011.

[4] F. Hug, G. Bendahan, and D. Maton, "Interpretation of EMG integral or RMS and estimates of "neuromuscular efficiency" can be misleading in fatiguing contraction," *Journal of Electromyography and Kinesiology*, vol. 20, no. 2, pp. 223–232, 2009. https://doi.org/10.1016/j.jelekin.2009.01.008

[5] A. Phinyomark, S. Hirunviriya, C. Limsakul, and P. Phukpattaranont, "Evaluation of EMG feature extraction for hand movement recognition based on Euclidean distance and standard deviation," presented at the ECTI-CON2010: The 2010 ECTI International Confernce on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 2010.

[6] S. Solnik, P. DeVita, P. Rider, B. Long, and T. Hortobágyi, "Teager–Kaiser operator improves the accuracy of EMG onset detection independent of signal-to-noise ratio," *Acta of Bioengineering and Biomechanics*, vol. 10, no. 2, pp. 65–68, 2008.

[7] R. Swaminathan and B. K. Panigrahi, "An inventive quadratic time-frequency scheme based on Wigner–Ville distribution for classification of sEMG signals," in *Proceedings of the 2007 IEEE Region 10 Conference (TENCON). Taipei, Taiwan: IEEE*, 2007.

[8] M. Ahmad, A. M. Bhatti, S. Khan, and A. Iqbal, "EMG processing-based measures of fatigue assessment during manual lifting," in *Proceedings of the 2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT). Karachi, Pakistan: IEEE*, 2017.

[9] K. Hara, T. Nishimoto, and Y. Kuroda, "Decoding of facial muscle–brain relation by information-based analysis of electromyogram (EMG) and electroencephalogram (EEG) signals," *Biomedical Signal Processing and Control*, vol. 68, p. 102665, 2021.

[10] M. U. Ahmed, S. U. Amin, A. H. Mollah, and S. H. M. Amin, "Neuromuscular disorders detection through time-frequency analysis and classification of multi-muscular EMG signals using Hilbert–Huang transform," *Biomedical Signal Processing and Control*, vol. 71, p. 103155, 2022.

[11] M. Atzori, J. Müller, A. F. Cognolato, G. Gijsberts, and H. Müller, "Combined classification and regression for simultaneous and proportional EMG control of wrist forces," in *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). Milan, Italy*, 2015, pp. 2917–2920.

[12] M. M. N. M. Isa and M. S. M. Aris, "Classification of localized muscle fatigue with genetic programming on sEMG during isometric contraction," in *Proceedings of the 2009 International Conference on Signal Processing Systems. Singapore*, 2009, pp. 401–405.

[13] R. Marri and R. Swaminathan, "Classification of muscle fatigue using surface electromyography signals and multifractals," *Engineering, Technology & Applied Science Research*, vol. 5, no. 1, pp. 739–743, 2015.

[14] N. Li *et al.*, "Non-invasive techniques for muscle fatigue monitoring: A comprehensive survey," *ACM Computing Surveys*, vol. 56, no. 9, pp. 1–40, 2024. https://doi.org/10.1145/3648679

[15] L. A. Green, J. McGuire, and D. A. Gabriel, "Flexor carpi radialis surface electromyography electrode placement for evoked and voluntary measures," *Muscle & Nerve*, vol. 52, no. 6, pp. 818–825, 2015. https://doi.org/10.1002/mus.24631

[16] A. González-Mendoza, A. I. Pérez-SanPablo, R. López-Gutiérrez, and I. Quiñones-Urióstegui, "Validation of an EMG sensor for Internet of things and robotics," presented at the 2018 15th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE) Mexico City, Mexico, 2018.

[17] Q. Zhang and Z. Luo, "Wavelet denoising of electromyography," presented at the 2006 IEEE International Conference on Mechatronics and Automation (ICMA). Luoyang, China, 2006.

[18] S. Demura, M. Nakada, and Y. Nagasawa, "Gender difference in subjective muscle-fatigue sensation during sustained muscle force exertion," *Tohoku Journal of Experimental Medicine*, vol. 215, no. 3, pp. 287–294, 2008. https://doi.org/10.1620/tjem.215.287