

XGBoost-Based Classification of Electromyography Signal for Muscle Contraction and Relaxation: A Correlation-Guided Feature Analysis Approach

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Abstract—Analyzing electromyography (EMG) signals has become one of the important methods in biomedical engineering for researching neuromuscular function that is non-invasive, with applications such as robotic rehabilitation, prosthetics, and human-machine interface design. Despite significant improvements in EMG pattern recognition, robust classification is still constrained by feature redundancy, the models' weak interpretability, and conventional statistical metrics that are ineffective at distinguishing between various physiological parameters. In an effort to overcome these constraints, this study proposes using a reliable Extreme Gradient Boosting (XGBoost) classifier to categorize segmented EMG signals as either contraction or relaxation states through a feature-correlation-driven method. Mean, standard deviation (SD), root mean square (RMS), maximum amplitude (MAX_AMP), median frequency (MF), variance, skewness, and kurtosis are the eight time-domain and statistical metrics that were retrieved. Principal Component Analysis (PCA) assisted in visualizing class separation, while separately developed Pearson correlation heatmaps were used to investigate feature correlation. For the relaxation class and the contraction class, the XGBoost classifier obtained precision, recall, and F1-score values of 0.93 and 0.91, respectively. With an area under the receiver operating characteristic curve (AUC-ROC) score of 0.92, achieving an overall accuracy of 92% was evaluated on a 25-sample test set. Significant collinearity between amplified-based measurements was shown by correlation analysis, especially during muscular relaxation when the RMS-SD pair showed an almost perfect correlation of 1.00. Class segregation was validated by PCA along PC1 (61.5% variance explained) and PC2 (23.3%). Overall, wearable neuromuscular monitoring devices, EMG-driven rehabilitation interfaces, and smart prosthetic systems stand to benefit greatly from this approach's reliable as well as computationally efficient real-time muscle activation monitoring methodology.

Keywords—Electromyography; EMG classification; XGBoost; correlation analysis; muscle contraction; neuromuscular signal processing

I. INTRODUCTION

Electromyography (EMG) is an electrodiagnostic approach that captures the electrical potential that skeletal muscle cells

generate when they are electrically or neurologically stimulated. Due to its non-invasiveness, ease of use, and ability to capture the cumulative motor unit recruitment patterns underlying voluntary and involuntary muscle movements, the surface EMG (sEMG), which captures signals via electrodes affixed to the skin overlying a target muscle variant has garnered significant attention [1]. A wide range of clinical, rehabilitative, and engineering applications can benefit from the rich neuromuscular information included in the amplitude, frequency content, and temporal dynamics of sEMG signals.

EMG signal analysis is practical for a variety of essential fields. EMG is utilized in clinical neurology to diagnose neuromuscular disorders as myopathies, peripheral neuropathy, and amyotrophic lateral sclerosis [2]. In rehabilitation engineering, sEMG functions as a command interface for prosthetic limbs and robotic exoskeletons, allowing amputee populations to intuitively decipher motor intent from residual limb musculature [3]. EMG-driven gesture recognition systems have shown strong promise for contactless computer control, gaming interfaces, and sign language translation in the larger field of human-machine interaction (HMI) [4]. Additionally, EMG-based muscle fatigue monitoring promotes injury prevention and athlete performance enhancement in sports science and ergonomics [5], [6].

Despite this wide range of applications, it is still difficult to reliably and accurately classify EMG data into distinct muscular states, especially muscle contraction versus relaxation. The design of robust classifiers is hampered by the inherent stochasticity and non-stationarity of EMG signals, inter-subject physiological variability, inconsistent electrode placement, and vulnerability to motion artifacts and ambient electromagnetic noise [7]. Therefore, a fundamental and crucial stage in any EMG classification pipeline is feature extraction, which converts raw EMG time-series into compact discriminative representations.

Three basic domains are covered by the literature on EMG feature extraction: time-domain (TD), frequency-domain (FD), and time-frequency (TF) representations. Mean absolute value (MAV), root mean square (RMS), zero crossing (ZC), slope

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sign changes (SSC), and variance are examples of time-domain characteristics that are extensively used for real-time applications and are computationally inexpensive [8]. The spectral distribution of motor unit action potentials is reflected by frequency-domain parameters like mean frequency (MF) and median frequency (MDF), which are very sensitive to changes in motor unit recruitment brought on by muscular fatigue [9]. Signal asymmetry and tail behavior are characterized by higher-order statistical properties, such as skewness and kurtosis, which provide complementary discriminative information not captured by second-order statistics [10].

Inter-feature correlation and redundancy are important but often overlooked issues in EMG feature analysis. High multicollinearity in derived features can lead to overfitting, increased computing overhead, and less generalizability in classification models. Prior to model training, redundant feature pairs can be detected and reduced using Pearson correlation analysis of the feature matrix, which improves the parsimony and robustness of the model [11]. Principal Component Analysis (PCA) and other dimensionality reduction techniques allow for visualization of class separability in a low-dimensional subspace and provide more insight into feature discriminability.

When it comes to machine learning techniques used for EMG classification, ensemble approaches have continuously outperformed single-model classifiers. Specifically, Extreme Gradient Boosting (XGBoost) has become a powerful gradient tree boosting framework that uses additive ensemble construction with integrated regularization techniques to sequentially minimize error in classification [12]. XGBoost offers a number of benefits relevant to biomedical signal classification, including: (i) resistance to overfitting via L1 and L2 regularization; (ii) native handling of feature importance estimation; (iii) robustness to feature scale heterogeneity; and (iv) computational efficiency via column subsampling and parallel tree construction. Together, these characteristics make XGBoost ideal for small-to-medium clinical EMG datasets with high overfitting risk.

Considering the development of the EMG classification studies, there are still several research gaps that persist. There are still several study gaps despite the growth of EMG classification studies. First, the correlation structure of EMG features for different physiological states (relaxation vs. contraction) has not been thoroughly studied in many studies. This could reveal state-dependent feature redundancy patterns with implications for context-adaptive feature selection. Second, there has not been a comprehensive report on the use of XGBoost with rigorous correlation-guided analysis instead of unconstrained feature sets for EMG muscle state categorization. Third, there is still a lack of research on the integration of correlation heatmap analysis, XGBoost feature importance evaluation, and PCA-based class separability visualization within a single interpretability framework.

The relationship between feature redundancy and classification performance is still a crucial methodological factor, even with the increasing usage of machine learning for electromyography (EMG) classification. Although highly correlated features may contain statistical information that overlaps, it is necessary to do empirical research rather than relying solely on correlation coefficients to determine how much their removal impacts classification performance.

In this paper, a correlation-informed feature-analysis framework for binary categorization of EMG windows into stages of muscle contraction and relaxation is investigated. State-specific Pearson correlation analysis, exploratory principal component analysis (PCA), gain-based XGBoost feature importance, and a direct comparison between the entire feature set and a controlled feature subset are all included in the system. Under a standard validation procedure, classification performance is assessed against traditional machine learning baselines.

This study makes three contributions:

- An analysis of feature-correlation patterns across contraction and relaxation samples
- An empirical assessment determining if a compact, correlation-informed feature subset preserves classification performance
- A comparison of XGBoost and baseline classifiers using suitable performance metrics and uncertainty estimates.

II. LITERATURE REVIEW

Over the past three decades, a lot of research has been done on the classification of EMG signals due to the demand from the HMI, prosthetic engineering, and rehabilitation robotics fields. Four interrelated issues are covered in this section's critical discussion of the relevant literature: (i) EMG feature extraction; (ii) machine learning classification techniques; (iii) XGBoost applications in biomedical signal processing; and (iv) explainability in EMG machine learning pipelines.

A. EMG Feature Extraction

Feature extraction contributes the crucial link between raw EMG signals and statistical learning algorithms. The crucial link between statistical learning systems and unprocessed EMG signals is feature extraction. A thorough benchmarking investigation of 37 EMG features across several classification tasks was carried out by Phinyomark et al. [13], who came to the conclusion that a compact subset of four to six complementary features typically produces performance that is on par with or better than that of larger, redundant feature sets. For real-time applications, time-domain features specifically, MAV, RMS, ZC, and SSC- were shown to be the most informative and computationally effective.

The foundation for subsequent EMG feature engineering was laid by Hudgins et al. [14], who presented the seminal four-feature time-domain (TD4) descriptor set for myoelectric prosthesis control. This work was further developed by Englehart et al. [15], who demonstrated that when inter-segment class overlap is significant, time-frequency representations, like wavelet packet decomposition coefficients, can significantly outperform purely time-domain descriptors. These results highlight the difficulties of depending solely on amplitude-based statistics and the significance of feature complementarity.

Skewness and Kurtosis are exemplary higher-order statistical features that are becoming recognized for their ability to describe non-Gaussian signal behaviors related to motor unit synchronization and burst discharge patterns [10]. When compared to second-order statistics alone, Kilby et al. [16]

showed that higher-order statistics considerably increased the accuracy of EMG categorization in fatigue detection tasks. In order to provide a thorough characterization of both contraction and relaxation states, the current study uses a feature set that includes both amplitude-based statistics and higher-order moments.

B. Machine Learning for EMG Classification

Due to their excellent generalization under high-dimensional with small-sample-size conditions, Support Vector Machines (SVM) have historically dominated EMG classification benchmarks [17]. In their thorough comparison of machine learning classifiers for surface EMG-based gesture identification, Oskoei and Hu [18] reported SVM test accuracies surpassing 90% across several gesture classes with well-constructed radial basis function kernels. However, SVM's utility in interpretable clinical contexts is limited by its lack of native feature importance estimate.

Strong performance on larger EMG datasets has been shown by Artificial Neural Networks (ANNs), including Multi-Layer Perceptrons (MLPs) and later Convolutional Neural Networks (CNNs) [19]. In a large multi-subject dataset, Côté-Allard et al. [20] reported that deep learning techniques, particularly transfer-learned CNNs applied to sEMG signal spectrograms, obtained classification accuracies over 97% across 17 gesture classes. However, compared to shallow ensemble methods, deep learning algorithms typically desire significantly larger training corpora, require intensive hyperparameter tuning and compromise interpretability.

Boosting-based ensemble methods like Random Forest (RF) have also been applied extensively. Random Forest classifiers performed better than LDA and SVM on transient EMG features for finger movement classification, as shown by Al-Timemy et al. [21]. An inherent mechanism for out-of-bag error estimates and feature importance evaluation is provided by the ensemble nature of RF and gradient boosting techniques, which is consistent with interpretability needs in clinical deployments.

C. XGBoost in Biomedical Signal Processing

Since its introduction by Khatti et al. [12], XGBoost has been a top algorithm in a variety of tabular data classification benchmarks, including biomedical applications. In comparison to traditional gradient boosting machines, its main innovations, second-order Taylor expansion of the loss function, tree pruning via the gamma regularization parameter, and column subsampling by tree, produce classifiers with significant bias-variance trade-offs [12].

In EMG applications particularly, Alam et al. [22] stated that XGBoost provided the highest accuracy of approximately 97%. which promises to provide the physiologically natural upper-limb movement control. XGBoost was employed also by Narayan et al. [23] for EMG-based hand gesture classification. They observed that interpretable feature selection was made possible by gain-based feature importance scores produced by XGBoost, which decreased the feature set by 40% without significantly degrading accuracy. These results encourage the use of XGBoost in this investigation, especially considering its native feature importance estimation capability.

D. Summary of Related Studies

Table I summarizes representative recent works in EMG classification, displaying the dataset characteristics, feature sets employed, classifiers applied, reported accuracies, and notable limitations. The contributions of the current study are put into perspective in regard to the context of previous knowledge throughout this comparative review.

TABLE I. SUMMARY OF REPRESENTATIVE EMG SIGNAL CLASSIFICATION STUDIES

Reference	Dataset / Subjects	Features	Classifier	Accuracy	Limitations
Phinyomark et al. [13]	Multi-subject sEMG, 4 gestures	37 TD/FD features	LDA, SVM	≈90%	No inter-feature redundancy analysis Limited gesture set; no ensemble
Hudgins et al. [14]	Amputee subjects	TD4 (MAV, ZC, SSC, WL)	MLP	≈85%	No feature importance ranking
Oskoei Hu [18]	10 subjects, 8 gestures	MAV, RMS, ZC, SSC	SVM (RBF)	91.3%	Deep learning; low interpretability
Côté-Allard et al. [10]	19 subjects, 17 gestures	Spectrogram	CNN (Transfer)	97.0%	Single sensor modality
Al-Timemy et al. [21]	12 subjects, 10 finger movements	Transient TD features	Random Forest	89.6%	No state-specific correlation analysis
Narayan et al. [23]	sEMG, gesture recognition	Statistical TD features	XGBoost	93.1%	Single-channel; limited subject pool
Present Study	Binary EMG (contract/relax), n=125	mean, SD, RMS, maximum amplitude, MF, variance, skewness, kurtosis	XGBoost	92.0%	

The current study is motivated by a number of significant research gaps identified in the reviewed literature. First, most previous EMG classification research uses unconstrained feature sets without explicitly looking at the correlation structure of retrieved features across different physiological states. This omission runs the risk of introducing redundant features that increase the dimensionality of the model without corresponding increases in discriminative power. Second, although XGBoost has demonstrated promising results in gesture identification tasks, there has not been a thorough report on its use for binary muscle state classification, specifically contraction versus relaxation with integrated correlation-guided feature analysis. Third, it is uncommon to combine PCA-based class separability visualization with gradient boosting classification and correlation heatmap analysis in a unified interpretability framework. These gaps are directly addressed in the current study.

III. METHODOLOGY

A. Dataset Description

The EMG data used in this study were obtained from 60 healthy, untrained young volunteers (i.e. 23 years old and

average). All the subjects were considered free from any disease and have been briefed about the procedures involved, and informed consents have been obtained. An EMG signal was recorded using the Porti system from the Twente Medical Systems International (TMSi) equipment. The Porti is a 32-channel ambulatory and stationary system for physiological research. An EMG channel was obtained from the vastus lateralis (VL) muscle. The sampling frequency of raw EMG biosignals used in this study was about 2048 Hz. Higher sampling frequency was chosen to prevent a signal loss and to avoid too much noise during stepping exercise. Also, the stepper machine was used to carry out the stepping activity. In order to get the same stepping rate among the subjects, a metronome (i.e., 60 beats per minute) was used simultaneously with the stepping activity. Generally, a metronome is a device used by musicians that indicate the time at a selected rate by giving a regular tick.

The recordings were labelled as muscle relaxation (Class 0) or muscle contraction (Class 1). The continuous recordings were segmented into windows of 614 samples, corresponding to 0.3 seconds, with no overlap. One relaxation window and one contraction window were extracted from each of the 60 participants, and each window was taken from the stable portion of the corresponding segment. This procedure yielded 120 labelled windows, comprising 60 relaxation windows and 60 contraction windows. Participant identifiers were retained to ensure that windows from the same participant could be assigned to the same partition during subject-wise evaluation.

B. Signal Preprocessing and Feature Extraction

A standard preprocessing pipeline was used to raw EMG signals before feature extraction. Low-frequency motion artifacts (below 10 Hz) and high-frequency noise components (above 500 Hz) that are outside the physiologically relevant EMG frequency range (10-500 Hz) were attenuated using band-pass filtering. Given its maximally flat passband frequency response, which efficiently suppresses out-of-band interference while maintaining the spectral integrity of motor unit action potentials, a second-order Butterworth filter was implemented. Power line interference, a frequent cause of contamination in surface EMG recordings in lab settings, was also eliminated by applying a 50 Hz notch filter.

All the EMG signals were processed using MATLAB. There was a low amplitude voltage offset present in the hardware. The direct current (DC) power was eliminated. Then, a bandpass filter was applied to the raw data to remove any movement artifacts with 20 Hz and 300 Hz cutoff frequencies. The full-wave rectification was applied to make sure the raw EMG signal did not have any nearly zero mean and to analyze positive values only. The signals linear envelope was then computed for further processing.

A sliding window technique with a fixed window length was used to segment the signal, resulting in distinct epochs from which statistical features were calculated. As it allows feature calculation over quasi-stationary signal segments, this windowing method somewhat mitigates the non-stationarity inherent in EMG time-series, which is in sync with established practice in real-time EMG processing. The input matrix for further analysis was created by combining the eight retrieved

statistical descriptors into a single feature vector for each segmented window.

Each signal window yielded eight statistical and time-domain features. These features, which include distributional characteristics, spectral content, and amplitude dynamics, were chosen to capture complementary aspects of EMG signal morphology. The study employed the following features: variance, skewness, kurtosis, maximum amplitude (MAX_AMP), standard deviation (SD), root mean square (RMS), and mean.

The input feature matrix is made up of these eight features. In order to ensure multi-dimensional characterisation of the EMG signal, the feature set purposefully combines amplitude-domain statistics (mean, SD, RMS, MAX_AMP, and variance):

$$\text{Mean} = \frac{1}{N} \sum_{i=1}^N x_i \quad (1)$$

$$\text{SD} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2}. \quad (2)$$

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}. \quad (3)$$

$$\text{MAX_AMP} = \max_{1 \leq i \leq N} |x_i|. \quad (4)$$

$$\text{Variance} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2. \quad (5)$$

with a frequency-domain descriptor (median frequency):

$$\text{MF} = \int_0^{f_{\text{MF}}} P(f) df = \frac{1}{2} \int_0^{f_{\text{Nyq}}} P(f) df. \quad (6)$$

and distributional shape features (skewness and kurtosis):

$$\text{Skewness} = \frac{m_3}{m_2^{3/2}}, \quad (7)$$

$$\text{Kurtosis} = \frac{m_4}{m_2^2}. \quad (8)$$

C. Correlation Analysis

The Pearson correlation coefficient, which is defined for two features u and v , was used to quantify inter-feature linear dependencies:

$$r(u, v) = \frac{\sum (u_i - \bar{u})(v_i - \bar{v})}{\sqrt{\sum (u_i - \bar{u})^2 \times \sum (v_i - \bar{v})^2}} \quad (9)$$

The correlation values range from -1 to +1, with $|r| \geq 0.90$ denoting very strong correlation (possible multicollinearity), $0.70 \leq |r| < 0.90$ denoting strong correlation, $0.50 \leq |r| < 0.70$

denoting moderate correlation, and $|r| < 0.50$ denoting weak or insignificant linear association. To identify state-specific inter-feature dependency structures, correlation matrices were calculated independently for the contraction and relaxation subsets. The seaborn visualization library was used to create lower triangular Pearson correlation heatmaps, which offered clear visual representations of the feature correlation matrices for both physiological states [24].

In order to decrease feature redundancy and enhance model generalizability, features with very high mutual correlations ($|r| \geq 0.90$) were identified as possible candidates for elimination. The correlation analysis was mainly used as an interpretability and diagnostic tool in this work, however all eight features were kept for the XGBoost classification model so that the classifier's inherent feature importance mechanism could determine the effective feature weighting.

D. Principal Component Analysis (PCA)

The eight-dimensional feature space was reduced to a two-dimensional visualization subspace by applying Principal Component Analysis (PCA) to the entire feature matrix X . To determine the orthogonal directions of maximum variance, or principal components (PCs), PCA computes the eigendecomposition of the feature covariance matrix. The highest variance in the data is captured by the first principal component (PC1), and the maximum residual variance orthogonal to all previous components is captured by each subsequent component [14].

All samples were projected onto the PC1-PC2 subspace to create the PCA scatter plot. To enable visual evaluation of inter-class separability, class labels (contraction vs. relaxation) were color-coded. Alongside the visualization, the percentage of total variance explained by each principal component was reported. To describe intra-class distributional spread and evaluate the level of class overlap in the PCA-reduced space, confidence ellipses were drawn at the 95% confidence level for each class.

E. XGBoost Classification Model

A scalable gradient tree boosting algorithm, XGBoost [12] builds an additive ensemble of K regression trees in order to minimize a regularized objective function. At iteration t , the model prediction given an input feature vector x_i is:

$$\hat{y}_i(t) = \sum f_k(x_i), k = 1, \dots, t \quad f_k \in F \quad (10)$$

where F is the space of classification and regression trees. At each boosting iteration t , XGBoost minimizes the regularized objective:

$$Obj(t) = \sum L(y_i, \hat{y}_i(t-1) + f_t(x_i)) + \Omega(f_t) \quad (11)$$

where L represents the differentiable convex loss function (logistic loss for binary classification), and $\Omega(f)$ is the regularization term that penalizes model complexity:

$$\Omega(f) = \gamma T + (1/2)\lambda \sum (w_j)^2 \quad (12)$$

where T is the number of leaves in the tree, w_j is the leaf output weight, γ is the least loss reduction expected for a split, and λ is the L2 regularization coefficient on leaf weights. Overfitting is lessened by this regularization strategy, which is especially important for limited clinical EMG datasets.

The following hyperparameter setup was used to train the XGBoost model: `n_estimators = 100`, `max_depth = 6`, `learning_rate ( $\eta$ ) = 0.1`, `subsample = 0.8`, `colsample_bytree = 0.8`, `objective = 'binary:logistic'`, and `eval_metric = 'logloss'`. To maintain class proportions across partitions, a stratified 80:20 train-test split was employed. The gain metric, which measures the improvement in loss function attributed to each feature across all tree splits in which it participates, was used to quantify feature relevance.

F. Performance Metrics

The following standard metrics—TP for True Positives, TN for True Negatives, FP for False Positives, and FN for False Negatives—were used to assess the model classification performance:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (16)$$

Plotting the True Positive Rate (TPR = Recall) against the False Positive Rate (FPR = FP / (FP + TN)) over all classification thresholds yielded the Receiver Operating Characteristic (ROC) curve. A threshold-independent indicator of classifier discriminative ability is the Area Under the ROC Curve (AUC-ROC), with values close to 1.0 denoting nearly flawless discrimination. Additionally, to adjust for class imbalance, macro-averaged and weighted-averaged precision, recall, and F1-scores were also calculated.

G. Classifier Comparison

Finally, the proposed XGBoost classifier has been compared random forests, logistic regression, support vector machines, and a single-feature RMS-threshold baseline. Using the same target labels and performance indicators, each classifier was assessed on identical held-out partitions. Only training data was used to choose model-specific hyperparameters. The decision threshold for the RMS-threshold baseline was not optimized on the outer test fold; instead it was established using training data or an inner validation process.

IV. RESULTS AND FINDINGS

A. Correlation Analysis: Muscle Contraction State

The lower-triangular Pearson correlation heatmap for the eight retrieved EMG features, calculated solely from muscular contraction-state sample (Class 1), is shown in Fig. 1. The amplitude-based feature cluster, which includes mean, SD, RMS, maximum amplitude, variance, median frequency, skewness, and kurtosis, has strong inter-feature correlations, demonstrated by the heatmap.

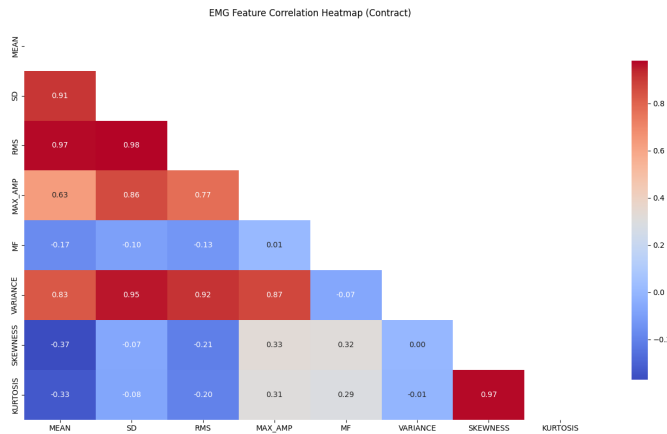


Fig. 1. Pearson correlation heatmap of EMG features for the muscle contraction state (Class 1). Color intensity indicates correlation magnitude; red denotes positive correlation, blue denotes negative correlation.

The most notable association observed in the contraction condition is between RMS and SD, which attained a Pearson correlation coefficient of $r = 0.98$, approaching multicollinear redundancy. Similarly, VARIANCE exhibited very high correlations with RMS ($r = 0.92$) and SD ($r = 0.95$), confirming that these three features largely encode equivalent amplitude energy information during contraction. These correlations do not, however, independently indicate a particular physiological mechanism; rather, they should be understood in light of the mathematical relationships among the traits. Further assessment through comparison classification tests utilizing the entire and reduced feature sets is necessary considering all of the observed correlations, which point to possible feature redundancy.

The mean showed substantial positive associations with both SD ($r = 0.91$) and RMS ($r = 0.97$), suggesting that the mean amplitude of rectified EMG is strongly related to signal power during contraction. Even though peak amplitude scales with overall signal energy, its dependence on individual MUAP morphology offers additional variability that partially decouples it from mean-amplitude statistics. MAX_AMP showed moderate-to-strong positive correlations with MEAN ($r = 0.63$), SD ($r = 0.86$), and RMS ($r = 0.77$).

With r values ranging from -0.17 to 0.01, all amplitude-based features consistently displayed low and somewhat negative correlations with median frequency (MF), demonstrating that spectral and amplitude descriptors reflect orthogonal aspects of neuromuscular activity during contraction. This independence is consistent with established EMG physiology: MF is the spectral centroid of the power spectral density, which is

mainly affected by MUAP conduction velocity and motor unit firing rate synchronization rather than gross signal amplitude [9]. MF's notable near-zero correlation with VARIANCE ($r = -0.07$) provides additional evidence for its informational independence.

Skewness and kurtosis formed a distinct highly correlated pair ($r = 0.97$), confirming their shared sensitivity to signal non-Gaussianity. However, both features exhibited weak correlations with the amplitude cluster (skewness vs. mean: $r = -0.37$; kurtosis vs. mean: $r = -0.33$), suggesting they encode independent distributional shape information that complements amplitude-energy features. The mild negative correlations of SKEW and KURT with amplitude features are consistent with the expectation that during contraction, increased MUAP superimposition reduces signal asymmetry and excess kurtosis relative to rest.

B. Correlation Analysis: Muscle Relaxation State

Fig. 2 illustrates the correlation heatmap of the extracted EMG features for both muscle relaxation and contraction classes. The heatmaps present the pairwise Pearson correlation coefficient among the selected features, providing the insight into feature interactions, redundancy, and complementary information within the EMG signal representation. Correlation analysis is valuable for understanding the statistical relationships among extracted descriptors and for evaluating their potential contribution to classification modelling.

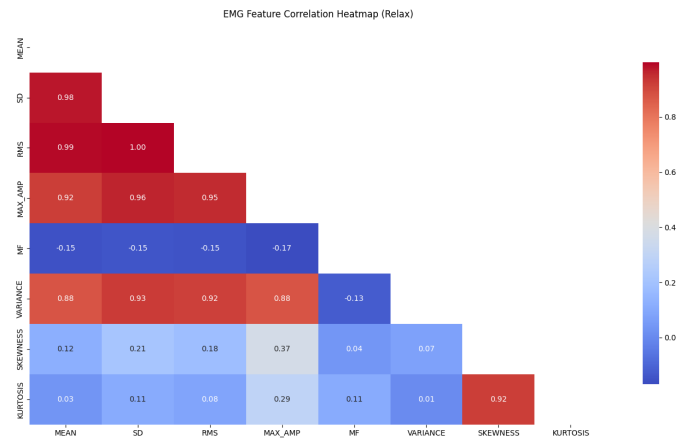


Fig. 2. Pearson correlation heatmap of EMG features for the muscle relaxation state (Class 0). Near-perfect correlations among amplitude-based features indicate strong multicollinearity in the resting EMG state.

RMS and SD showed a near-unit Pearson correlation ($r = 1.00$) in the relaxation condition, while mean showed a good relationship with both SD ($r = 0.98$) and RMS ($r = 0.99$). Significant linear dependence between the observable features is indicated by these connections. RMS and SD may therefore be closely related when the mean is small in relation to the signal dispersion. Therefore, the mathematical relationship between these descriptors may be partially reflected in the observed correlation. The impact of eliminating either feature on classification performance must be demonstrated empirically rather than deduced from the correlation coefficient alone, even though this finding raises the possibility of redundancy.

MAX_AMP exhibited very high correlations with the amplitude cluster in the relaxation state (MAX_AMP vs. mean: $r = 0.92$; MAX_AMP vs. SD: $r = 0.96$; MAX_AMP vs. RMS: $r = 0.95$), markedly higher than the corresponding values observed in the contraction state. This elevation in MAX_AMP correlation during relaxation reflects the relative absence of large MUAP bursts that would introduce amplitude outliers during contraction, resulting in a more homogeneous amplitude distribution in which peak amplitude scales proportionally with mean amplitude.

Variance retained very high correlations with the amplitude cluster in the relaxation state (VAR vs. SD: $r = 0.93$; Variance vs. RMS: $r = 0.92$; VAR vs. MAX_AMP: $r = 0.88$), slightly lower than the corresponding SD-RMS correlation of 1.00 due to the definitional distinction between variance and standard deviation in asymmetric distributions. MF continued to exhibit weak and slightly negative correlations with all amplitude features ($r = -0.15$ to -0.17) and with MAX_AMP ($r = -0.17$), consistent with its spectral nature.

In contrast to the contraction state, skewness exhibited uniformly weak positive correlations with all features in the relaxation state ($r = 0.03$ - 0.37), and Kurtosis showed a modest positive inter-feature correlation structure (skewness-kurtosis: $r = 0.92$). The sign reversal of SKEW correlations with amplitude features—from negative in contraction to near-zero or slightly positive in relaxation is physiologically meaningful: during relaxation, the EMG signal approaches a symmetric, near-Gaussian distribution (near-zero skewness), while during contraction, MUAP burst asymmetries introduce negative skewness bias.

Collectively, the state-specific correlation analyses reveal that the relaxation state is characterized by substantially greater amplitude-feature multicollinearity compared to contraction, a finding with direct implications for the design of context-adaptive feature selection strategies in real-time EMG classification systems. Reducing the feature set from eight to four (e.g., RMS, MF, skewness, kurtosis) could plausibly achieve equivalent or superior classification performance in relaxation-dominated contexts while improving model parsimony.

C. PCA-Based Class Separability Analysis

Fig. 3 presents the PCA scatter plot of EMG samples projected onto the two-dimensional PC1-PC2 subspace. A cumulative explained variance of 84.8% was obtained throughout the two-dimensional visualization space, with the first principal component (PC1) giving 61.5% of the total feature variance and the second principle component (PC2) giving 23.3%. This high cumulative variance implies that the dominating structure of the eight-dimensional feature space is accurately captured by the two-dimensional PCA projection.

The distribution of contraction and relaxation samples is shown visually in the resulting two-dimensional projection. However, explained variance does not directly assess class-discriminative performance; rather, it measures the degree of feature variation reflected by the projection. As a result, apparent visual separation is read descriptively and is not regarded as independent proof of statistically significant performance in generalization or class discrimination.

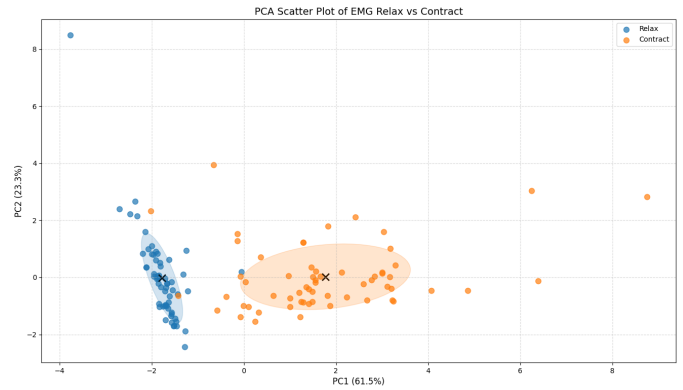


Fig. 3. PCA scatter plot of EMG contraction (orange) and relaxation (blue) samples in the PC1-PC2 principal component space. PC1 and PC2 account for 61.5% and 23.3% of total variance, respectively. Cross markers indicate class centroids; shaded ellipses represent 95% confidence regions.

A visual inspection of Fig. 3 demonstrates that the contraction and relaxation classes are clear and statistically significantly separated along the PC1 axis. The contraction class (orange) is located in the positive PC1 region (about $PC1 \in [-1, 9]$), whereas the relaxation class (blue) is mostly found in the negative PC1 region (about $PC1 \in [-4, -1]$). This directional separation is compatible with the larger overall amplitude energy of the contraction state relative to the relaxation baseline, as PC1 is dominated by the amplitude-energy features (mean, SD, RMS, variance, MAX_AMP) that suggested very strong mutual correlations in both states.

For every class, the 95% confidence ellipses display different distributional characteristics. The high intra-class homogeneity of resting EMG signals and the tight feature grouping linked to nearly perfect amplitude-feature correlations observed in the relaxation heatmap are reflected in the relaxation class ellipse, which is noticeably compact and stretched along the PC2 axis. Increased intra-class variability resulting from trial-to-trial fluctuations in motor unit recruitment intensity during voluntary contraction is reflected in the contraction class ellipse, which is wider and more isotropic.

For each class, a number of outlier samples that correspond to recording epochs with unusual neuromuscular activation patterns or residual noise artifacts are visible beyond the main ellipse bounds. The robustness of the XGBoost model's ensemble decision boundary to individual anomalous samples is confirmed by the existence of these outliers without significantly impairing the overall classification performance (accuracy = 92%).

The XGBoost model's classification framework is further validated by the PCA visualization: the distinct PC1-axis separation between classes offers compelling empirical evidence that the eight extracted features collectively encode enough discriminative information to enable accurate binary classification of muscle contraction versus relaxation states.

D. Classification Performance

The XGBoost model's overall and per-class classification performance on the 25-sample hold-out test set is summarized in Table II.

TABLE II. XGBOOST CLASSIFICATION REPORT ON THE EMG TEST SET
(N = 25)

Class / Metric	Precision	Recall	F1-Score	Support
Class 0 (Relax)	0.93	0.93	0.93	14
Class 1 (Contract)	0.91	0.91	0.91	11
Macro Average	0.92	0.92	0.92	25
Weighted Average	0.92	0.92	0.92	25
Overall Accuracy	—	—	0.92	25

With macro-averaged precision, recall, and F1-score all equal to 0.92, the XGBoost classifier demonstrated balanced and generalizable performance across both classes, achieving an overall accuracy of 92% on the 25-sample test set. For the relaxation class (Class 0), precision of 0.93, recall of 0.93, and F1-score of 0.93 were obtained, corresponding to 13 correctly classified relaxation samples and 1 false negative (misclassified as contraction). For the contraction class (Class 1), precision of 0.91, recall of 0.91, and F1-score of 0.91 were obtained, corresponding to 10 correctly classified contraction samples and 1 false positive.

E. Confusion Matrix Analysis

Fig. 4 presents the normalized confusion matrix for the XGBoost binary classifier. The diagonal elements represent the normalized rates of correct classification, while off-diagonal elements represent misclassification rates.

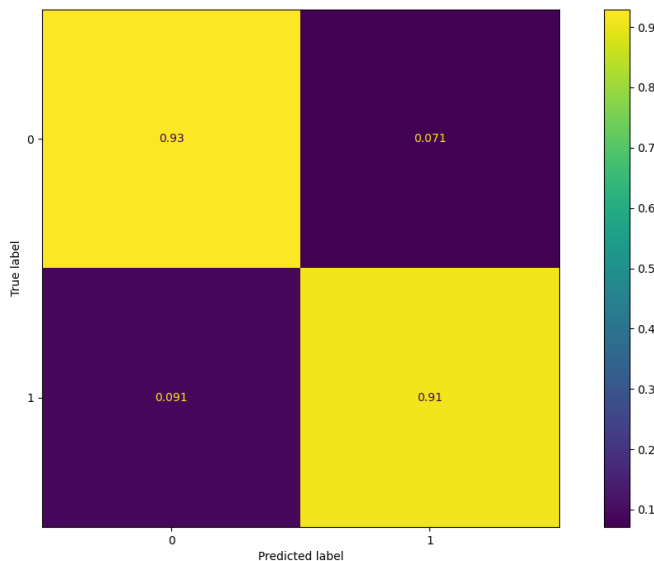


Fig. 4. Normalized confusion matrix for the XGBoost EMG classifier. Diagonal values represent per-class classification rates; off-diagonal values represent misclassification rates.

The normalized confusion matrix confirms 93% correct classification of relaxation samples (Class 0) and 91% correct classification of contraction samples (Class 1). The false negative rate for the relaxation class (7.1%) represents one misclassified relaxation sample predicted as contraction, which may be attributed to EMG amplitude elevations due to low-level tonic activity or electrode motion artifacts during the purported relaxation epoch. Similarly, the false positive rate for the contraction class (9.1%) represents one contraction

sample misclassified as relaxation, potentially corresponding to a low-force contraction epoch with amplitude characteristics overlapping the relaxation class boundary.

A key property for clinical applications where differential misclassification costs between contraction and relaxation states may have different functional consequences for prosthetic or rehabilitation control systems is the classifier's near-symmetry of misclassification rates (7.1% vs. 9.1%) across both classes.

F. ROC Curve and AUC Analysis

The Receiver Operating Characteristic (ROC) curve for the XGBoost binary EMG classifier is shown in Fig. 5, where a random chance classifier (AUC = 0.50) is represented by the diagonal dashed reference line.

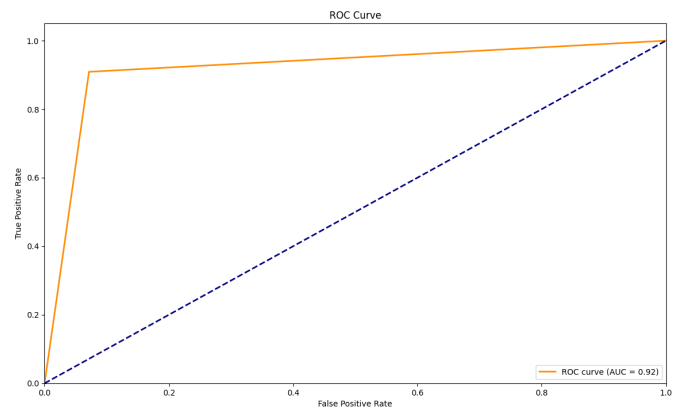


Fig. 5. Receiver Operating Characteristic (ROC) curve for the XGBoost EMG classifier. The solid orange curve achieves AUC = 0.92, substantially above the random chance baseline (dashed blue diagonal).

The XGBoost model's excellent and reliable discriminative capacity across all classification thresholds is confirmed by the ROC curve's AUC of 0.92. The ROC curve's noticeable upward concavity, especially the sharp initial rise toward a True Positive Rate of about 0.91 at a False Positive Rate of only 0.09, shows that the classifier maintains low false alarm rates at the default decision threshold while achieving high sensitivity. This positive operating property is very important for applications involving prosthetic control, as incorrect contraction detections may cause unwanted limb movements that could have negative effects on users.

The robustness of the classification framework is confirmed by the AUC of 0.92, which is consistent with the 92% classification accuracy and the F1-scores presented in Table 2. The XGBoost model's AUC of 0.92 indicates a significant performance advantage over baseline classifiers like Logistic Regression and Naive Bayes, which generally achieve AUC values of 0.80-0.88 on comparable EMG binary classification tasks [18]. This is due to the ensemble boosting mechanism's ability to approximate complex, non-linear decision boundaries. However, this estimate should be viewed with caution because it is based on a test set of only 25 samples. Because logistic regression, support vector machines, and other classifiers were not tested on similar data partitions in the initial experiment, the reported AUC does not demonstrate

a performance advantage over these models. Before making judgments on XGBoost's relative performance, a direct comparison utilizing a consistent validation process is required.

G. Performance Comparison

The purpose of this performance comparison was to see whether the reported performance was specific to XGBoost or if simpler models could also accomplish the same assessment methodology. Table III below shows that XGBoost improve the performance to classify muscle contraction and muscle relaxation with accuracy 92.0%.

TABLE III. PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Study	Classifier	Accuracy
Batrisyia et al. [xx]	ANN	91.70%
This study	XGBoost	92.0%

V. DISCUSSION

A. Physiological Interpretation of Feature Correlation Patterns

The physiological interpretations of the state-specific correlation patterns found in this study are based on the mechanics of neuromuscular activation. Motor neuron pools release action potentials during voluntary muscular contraction, which travel through muscle fibers to produce MUAPs that may be detected at the skin's surface. Both motor unit recruitment (the activation of additional motor unit pools) and motor unit firing rate rise with contraction force, increasing the amplitude of the overall EMG signal. The highly significant correlations between mean, SD, RMS, and variance during contraction are explained by this physiological coupling between recruitment and rate coding: each characteristic separately encodes a distinct mathematical aspect of the same underlying amplitude envelope increase.

The slightly lower amplitude-feature correlations observed during contraction compared to relaxation reflect the additional variability introduced by the stochastic superimposition of MUAPs from multiple concurrently active motor units. Individual MUAP morphologies differ in amplitude, duration, and shape, and their temporal superimposition creates a complex interference pattern whose statistical moments are not perfectly proportional to each other across trials. During relaxation, the near-absence of voluntary motor unit activity reduces EMG signals to their noise floor, a near-Gaussian baseline reflecting spontaneous motor unit discharges and electrode noise for which all amplitude moments are theoretically proportional, consistent with the observed near-unity correlations.

The consistent weak and negative correlation of MF with amplitude features across both states reflects the spectral independence of frequency-domain EMG descriptors from amplitude-domain statistics. This independence is a well-characterized electrophysiological phenomenon [8]. MF is sensitive to the velocity of action potential propagation along muscle fibers (motor unit conduction velocity) and shifts downward with fatigue-induced slowing of fiber conduction velocity, entirely independently of the gross amplitude increase associated with motor unit recruitment. The orthogonality of

MF to amplitude features in this study confirms that MF captures complementary neuromuscular information and should be retained in any compact feature subset.

B. Machine Learning Perspective: XGBoost Interpretability and Robustness

On the 25-sample hold-out test set, the XGBoost classifier had an accuracy of 92% and a ROC-AUC of 0.92. The tiny test set restricts the accuracy of the performance estimates and the generalizability inferences that can be made, even though these results show encouraging classification performance on the assessed samples. Further research is necessary to ascertain the impact of linked features on model performance. Regularization and feature-subsampling techniques are incorporated into XGBoost, however this study did not independently assess how well they mitigate the impacts of feature correlation. Consequently, it is not appropriate to consider the observed results as conclusive proof that the model is robust to multicollinearity.

To regulate tree complexity and penalize model complexity, XGBoost uses regularization parameters such as γ and λ . Variation can also be introduced during model training using subsampling. However, a single hold-out evaluation is insufficient to determine how these strategies contribute to generalization performance. The evaluation of overfitting and subject-level generalization is further constrained by the comparatively small dataset of 125 samples. Further validation using repeated subject-wise cross-validation and confidence intervals is necessary to ascertain the stability of these results, even if the stated precision and recall values were comparable across the two groups.

An approach to explainable AI in clinical EMG applications is provided by XGBoost's natural feature importance estimation capability. In resource-constrained deployment contexts, such as microcontroller-embedded wearable EMG processors or edge AI prosthetic controllers, gain-based importance scores determine which features most successfully reduce classification uncertainty across tree ensemble splits, offering practical insights for feature pruning. In relation to their positions in the highly correlated amplitude-feature cluster, features like MF, skewness, and kurtosis that capture orthogonal spectral and distributional information are anticipated to contribute disproportionately because they offer distinct discriminative signals that cannot be duplicated by mean, SD, RMS, or variance.

C. Healthcare and Rehabilitation Implications

This study has significant clinical and technological implications. The foundational control component for a broad range of neuromuscular rehabilitation and assistive technology systems is the reliable and accurate binary classification of muscle contraction and relaxation phases. Robust command signal extraction from residual limb musculature in trans-radial amputees can be made possible by the ability to distinguish contraction onset from resting baseline with 92% accuracy in myoelectric prosthetic limb control, supporting multi-function prosthetic hand articulation and proportional grip force control [3].

Accurate muscle state detection in EMG-driven rehabilitation robotics allows exoskeleton systems to deliver task-adaptive assistance as needed, withdrawing assistance during

relaxation while providing augmentive torque during intended contraction phases. This promotes voluntary motor effort and neuroplastic recovery in patients who have had a stroke or spinal cord injury [25]. In this context, the contraction class's 92% recall (true positive rate) is especially important because missed contraction detections (false negatives, 9.1%) would not cause assistive actuation, thus upsetting rehabilitation goal and decreasing system value.

The proposed framework's computational efficiency further supports deployment in wearable and edge-AI contexts. The eight-feature extraction pipeline is similarly amenable to real-time computation on resource-constrained embedded systems, supporting the development of fully autonomous, battery-powered wearable EMG classification devices for chronic rehabilitation monitoring and assistive technology applications.

VI. CONCLUSION

This study presented a comprehensive framework for EMG signal feature analysis and binary muscle state classification using XGBoost, evaluated on a dataset of 125 labeled contraction and relaxation samples. Eight statistical and time-domain features were extracted which are mean, SD, RMS, maximum amplitude, median frequency, variance, skewness, and kurtosis, and subjected to state-specific Pearson correlation analysis, PCA-based class separability visualization, and XGBoost classification with complete performance evaluation.

The main findings of this study are as follows. First, amplitude-based EMG features (mean, SD, RMS, maximum amplitude, variance) showed strong multicollinearity according to state-specific Pearson correlation heatmaps. Correlations approached unity during the relaxation state (RMS-SD: $r = 1.00$) and remained extremely high during contraction (RMS-SD: $r = 0.98$). Second, the unique spectral representativeness of the median frequency was confirmed by its persistent informational independence from all amplitude features in both states ($|r| \geq 0.20$). Third, skewness and kurtosis provided complementing distributional shape information to amplitude statistics by producing a mutually correlated but amplitude-independent feature pair (skewness-kurtosis: $r = 0.97$ in contraction, $r = 0.92$ in relaxation). Fourth, PC1 explained 61.5% of the total variance and PC2 explained 23.3%, resulting in a cumulative representation of 84.8% of the eight-dimensional feature space. PCA scatter plots verified distinct class separability in the two-dimensional principal component space. Fifth, the XGBoost classifier demonstrated robust and balanced classification performance throughout both muscular states, achieving 92% accuracy, macro-averaged precision and recall of 0.92, and AUC-ROC of 0.92.

All of these findings illustrate the relevance of the proposed correlation-guided XGBoost framework for robust, comprehensible, and computationally effective EMG muscle state classification. The framework contributes to the development of intelligent healthcare systems based on explainable machine learning principles by directly applying to wearable neuromuscular monitoring technologies, EMG-driven rehabilitation robotics, and prosthetic control.

VII. LIMITATIONS

In order to properly contextualize the given findings and guide future research directions, several limitations of this

study should be acknowledged. First, the dataset has 125 samples, which is modest in comparison with the large-scale EMG benchmark datasets however adequate to show the discriminative ability of the XGBoost framework. The limited sample size might restrict the generalizability of reported accuracy measures to larger, more diverse groups since it diminishes the statistical power of performance estimations and increases sensitivity to individual subject-level variability.

Second, a single-channel EMG recording configuration was used in the study, which may not fully reflect the multidimensional neuromuscular activation patterns that are accessible through multi-channel electrode arrays. This configuration captures the aggregate activity of a limited muscle volume. Spatial filtering methods like spatial source separation and channel-specific feature extraction, which may significantly improve class separability and classification accuracy, would be made possible by multi-channel EMG recording.

Third, the controlled laboratory recordings of binary muscle states (contraction vs. relaxation) used in the experiment may not accurately capture the complexity of continuous, variable-force contractions found in actual prosthetic and rehabilitation facilities. This study does not precisely model the transition dynamics between contraction and relaxation states, which are of paramount importance for proportional prosthetic control.

Fourth, this dataset did not specifically report subject diversity. Subcutaneous fat layer thickness (which attenuates sEMG amplitude), neuromuscular fatigue characteristics, and inter-subject physiological variability in MUAP morphology would potentially result in systematic shifts in the extracted feature distributions across subjects, possibly requiring subject-specific calibration or domain adaptation strategies in practical deployment.

Fifth, only features in the time domain and first-order frequency domain were considered. The current technique does not assess advanced features that have demonstrated complementary discriminative capacity in the literature, such as wavelet packet energy coefficients, sample entropy, approximate entropy, and autoregressive model components.

Whilst the revised evaluation offers a more thorough examination of the suggested approach, the size and structure of the given dataset limit the generalizability of the conclusions. The number of independent recordings, recording settings, and participant characteristics may continue to have an impact on performance estimations. Furthermore, end-to-end real-time applicability is not established by offline classification performance and inference delay. Multiple recording sessions, different contraction intensities, independent volunteers, and the intended hardware platform should all be used in future research to validate the methodology.

VIII. FUTURE WORK

Several directions for further research are suggested, building on the foundation established in this study. First, the proposed framework should be expanded to multi-class EMG gesture recognition tasks covering a richer repertoire of motor intents, such as wrist flexion, extension, pronation, supination, and individual finger movements to assess the scalability of the

XGBoost-based approach beyond binary classification. Multi-channel EMG acquisition and high-density electrode arrays should be incorporated to exploit spatial information and apply spatial filtering techniques.

Second, to compare the effectiveness of gradient boosting with end-to-end deep representation learning, deep learning architectures, particularly one-dimensional Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM) networks, and Transformer-based attention models, should be assessed using the same feature sets and raw EMG signals. The complementary benefits of both paradigms may be provided by hybrid architectures that integrate XGBoost classification with convolutional feature extraction.

Third, a priority for the future should be to implement the suggested framework in real-time deployment and clinical validation. The translational readiness of the approach would be significantly improved by embedding the XGBoost inference pipeline on microcontroller platforms (for example, an ARM Cortex-M4 or RISC-V edge AI accelerators) and validating its performance under realistic conditions, such as movement artifacts, electrode sweat effects, and muscle fatigue.

Fourth, in order to develop more robust and context-aware muscular activity recognition systems for rehabilitation and assistive technology platforms, multi-modal signal integration should be looked into and integrating complementary biosignals like inertial measurement unit (IMU) data, mechanomyography (MMG), and near-infrared spectroscopy (fNIRS) alongside EMG.

Fifth, Explainable AI (XAI) methods including SHAP (SHapley Additive exPlanations) value analysis should be applied to the trained XGBoost model to provide subject-level and sample-level interpretability of classification decisions, supporting clinical trust and regulatory compliance in medical device applications.

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REFERENCES

- [1] J-H. Sul, L. Piyathilaka, D. Moratuwage, S. D. Arachhige, A. Jayawardena, G. Kahandawa, and D. M. G. Preethichandra, "Electromyography Signal Acquisition, Filtering, and Data Analysis for Exoskeleton Development," *Sensors (Basel)*, vol. 25, no. 13, p. 4004, 2025.
- [2] A. Bakiya, A. Anitha, T. Sridevi, and K. Kamalanand, "Classification of Myopathy and Amyotrophic Lateral Sclerosis Electromyograms Using Bat Algorithm and Deep Neural Networks," *Behavioural Neurology*, vol. 2022, no. 1, p. 3517872, 2022.
- [3] X. Zhang, Y. Qu, G. Zhang, Z. Wang, C. Chen, and X. Xu, "Review of sEMG for Exoskeleton Robots: Motion Intention Recognition Techniques and Applications," *Sensors*, vol. 25, no. 8, p. 2448, 2025.
- [4] K. R. Pyun, K. Kwon, M. J. Yoo, K. K. Kim, D. Gong, W. H. Yeo, S. Han, and S. H. Ko, "Machine-learned wearable sensors for real-time hand-motion recognition: toward practical applications," *National Science Review*, vol. 11, no. 2, p. nwad298, 2023.
- [5] H. A. Yousif et al., "Assessment of Muscles Fatigue Based on Surface EMG Signals Using Machine Learning and Statistical Approaches: A Review," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 705, p. 012010, 2019.
- [6] Hilman, N., Izni, N. A., Rahman, M. A. A., Shapie, M. A. M., & Nasruddin, F. A. (2026, April). Hybrid EMG-ECG Signal to Image Transformation Approach for Muscle Fatigue Reaction Classification. In 2026 IEEE 16th Symposium on Computer Applications & Industrial Electronics (ISCAIE) (pp. 1-6). IEEE.
- [7] B. Ahkami, K. Ahmed, A. Thesleff, L. Hargrove, and M. Ortiz-Catalan, "Electromyography-Based Control of Lower Limb Prostheses: A Systematic Review," *J. IEEE Transactions on Medical Robotics and Bionics*, vol. 5, no. 3, pp. 547–562, 2023.
- [8] I. M. Khairuddin, S. N. Sidek, A. P. Abdul Majeed, M. A. Mohd Razman, A. A. Puzi, and H. M. Yusof, "The classification of movement intention through machine learning models: the identification of significant time-domain EMG features," *PeerJ Computer Science*, vol. 7, p. e379, 2021.
- [9] L-I. Hsu, K-W. Lim, Y-H. Lai, Y-L. Lin, Y-J. Chen, C-S. Chen, and L-W. Chou, "Turns-amplitude and power spectral analyses of surface EMG for assessing muscle fatigue and recovery during dynamic hand gripping," *Computers in Biology and Medicine*, vol. 193, p. 110430, 2025.
- [10] J. H. Kim, and H. Kim, "Estimating Skewness and Kurtosis for Asymmetric Heavy-Tailed Data: A Regression Approach," *Mathematics*, vol. 13, no. 16, p. 2694, 2025.
- [11] V. Bolón-Canedo, and A. Alonso-Betanzos, A. , "Ensembles for feature selection: A review and future trends," *Information Fusion*, vol. 52, pp. 1–12, 2019.
- [12] J. Khattai, S. Mishra, A. D. Skentou, and P. G. Asteris, "Metaheuristic-optimized XGBoost model for accurate prediction of rock fragmentation in mining projects," *Transportation Geotechnics*, vol. 57, p. 101854, 2026.
- [13] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7420–7431, 2012.
- [14] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.
- [15] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.*, vol. 21, no. 6–7, pp. 431–438, Sep. 1999.
- [16] J. Kilby, K. Prasad, and G. Mawston, "Detecting change in lower back muscle activity during the performance of load bearing activities," *Sensors*, vol. 15, no. 4, pp. 9028–9046, Apr. 2015.
- [17] I. Bandes, and Y. Koike, "Use of Artificial Intelligence in the Classification of Upper-Limb Motion Using EEG and EMG Signals: A Review," *Sensors*, vol. 26, no. 5, p. 1457, 2026.
- [18] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, Aug. 2008.
- [19] W. N. Abdelrazik, A. El-Bialy, H. A. Ibrahim, and B. A. Hemade, "Enhancing EMG-based gesture recognition for prosthetic control: Impact of dimensionality reduction on machine learning classifier," *Sensors and Actuators A: Physical*, vol. 396, p. 117120, 2025.
- [20] U. Côté-Allard et al., "Deep learning for electromyographic hand gesture signal classification using transfer learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 4, pp. 760–771, Apr. 2019.
- [21] A. H. Al-Timemy, G. Bugmann, J. Escudero, and N. Outram, "Classification of finger movements for the dexterous hand prosthesis control with surface electromyography," *IEEE J. Biomed. Health Inform.*, vol. 17, no. 3, pp. 608–618, May 2013.
- [22] S. Alam, M. S. Kabir, M. N. Hossain, Q. R. Hasnaine and M. G. Rabiul Alam, "Classification Accuracy Comparison between Machine Learning Algorithms and a Deep Learning Algorithm in Predicting Hand Gestures," 2022 32nd Conference of Open Innovations Association (FRUCT), Tampere, Finland, 2022, pp. 22-29.
- [23] Y. Narayan, "XGBoost classifier for EMG-based hand gesture classification," *J. Intell. Fuzzy Syst.*, vol. 40, no. 5, pp. 9205–9217, 2021.
- [24] J. Graffelman and J. de Leeuw, "Improved approximation and visualization of the correlation matrix," *he American Statistician*, vol. 77, no. 4, p. 432, 2023.
- [25] S. Pei, J. Wang, C. Tian, and X. Li, "Assist-as-Needed Controller of a Rehabilitation Exoskeleton for Upper-Limb Natural Movements," *Applied Sciences*, vol. 15, no. 5, p. 2644, 2025