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ADVANCED SIGNAL PROCESSING IN EMG ANALYSIS USING KNN KERNEL-BASED SVM FOR ENHANCED DATA CLASSIFICATION AND OUTLIER DETECTION

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Abstract

Electromyography (EMG) signals provide critical insights into muscular and neurological functions, but their complex nature makes accurate classification and outlier detection challenging. Traditional signal processing approaches often fail to address the variability in EMG signals, leading to suboptimal data interpretation. The integration of advanced algorithmic innovations, such as K-Nearest Neighbors (KNN) kernel-based Support Vector Machine (SVM), offers a robust solution for enhancing EMG signal processing. In this study, EMG signals from 500 datasets, sampled at 2 kHz, were preprocessed using wavelet transform for noise reduction and feature extraction. A hybrid KNN-SVM model was employed to classify the data and identify outliers, achieving superior performance. Results indicate a classification accuracy of 97.8%, sensitivity of 96.5%, specificity of 98.3%, and an outlier detection precision of 95.2%. These findings underscore the potential of the KNN kernel-based SVM approach in improving EMG signal interpretation, enabling accurate diagnosis and monitoring in clinical and research settings. The proposed methodology demonstrates a significant advancement in EMG signal processing, ensuring reliable classification and precise outlier detection.

Keywords:

EMG Signal Processing, KNN Kernel-based SVM, Outlier Detection, Data Classification, Advanced Algorithms

1. INTRODUCTION

Electromyography (EMG) signals, which measure the electrical activity of muscles, are widely utilized in medical diagnostics, rehabilitation, and human-computer interaction systems [1]-[3]. These signals are pivotal in analyzing neuromuscular conditions such as muscular dystrophy and motor neuron diseases. The high dimensionality and non-stationary nature of EMG signals pose significant challenges in achieving accurate data interpretation, particularly for classification and anomaly detection. Recent advancements in signal processing and machine learning have highlighted their potential in improving EMG signal analysis, enabling precise and automated decision-making [1]. However, the variability in EMG signal patterns caused by individual physiological differences and external noise necessitates sophisticated algorithms to enhance data interpretation accuracy [2]-[3].

Traditional approaches to EMG signal processing, such as linear classifiers or standard Support Vector Machines (SVMs), often underperform in distinguishing complex patterns and detecting outliers in noisy environments [4]-[5]. These limitations are exacerbated by:

- The susceptibility of EMG signals to noise and artifacts from electrode placements or environmental interference.
- Difficulty in modeling nonlinear relationships between features in high-dimensional EMG datasets.
- Insufficient generalization capabilities of conventional classifiers for unseen data [4]-[6]. Overcoming these challenges requires an integrative approach combining robust preprocessing, feature extraction, and advanced classification models [5]-[6].

Despite significant progress, current methodologies for EMG signal classification and outlier detection lack the capability to handle high-dimensional, noisy datasets effectively. These inefficiencies can lead to inaccurate results, adversely impacting diagnostic and therapeutic outcomes [7]. The need for a scalable and precise algorithm that can simultaneously classify EMG signals and detect anomalies remains unmet.

This study aims to:

- Develop a hybrid algorithm leveraging K-Nearest Neighbors (KNN) and kernel-based SVM for robust classification and outlier detection in EMG signals.
- Evaluate the proposed model's performance against existing methods in terms of accuracy, sensitivity, specificity, and precision.

The novelty of this research lies in the integration of KNN's adaptive feature weighting with the flexibility of kernel-based SVMs. Unlike traditional SVMs, the proposed approach employs a KNN-informed kernel, enhancing the system’s ability to classify nonlinear patterns and detect outliers in noisy EMG datasets. This hybrid architecture ensures improved generalization across diverse datasets and reduces computational overhead compared to ensemble methods.

Key contributions of this work include:

- A robust preprocessing pipeline combining wavelet transform for noise reduction and feature extraction.
- Implementation of a hybrid KNN-SVM algorithm optimized for EMG signal classification and outlier detection.
- Comprehensive evaluation using a dataset of 500 EMG signals, demonstrating significant improvements in accuracy (97.8%) and outlier detection precision (95.2%).
- Comparative analysis with existing techniques, highlighting the proposed model's superiority in handling complex EMG data.

2. RELATED WORKS

The field of EMG signal processing has witnessed numerous innovations aimed at enhancing data interpretation. Several studies have explored feature extraction and classification methodologies to improve accuracy and reliability [7]-[9].

2.1 FEATURE EXTRACTION TECHNIQUES

Wavelet transform has emerged as a popular method for preprocessing EMG signals, effectively isolating noise while preserving signal characteristics [7]-[8]. Principal Component Analysis (PCA) has also been employed for dimensionality reduction, but its linear nature often limits its performance on nonlinear EMG datasets [9]. Techniques such as Short-Time Fourier Transform (STFT) have been applied to capture frequency-domain features but are prone to inaccuracies due to non-stationary signal properties [10].

2.2 MACHINE LEARNING IN EMG CLASSIFICATION

Traditional classifiers, including linear discriminant analysis (LDA) and basic SVMs, have been widely used for EMG signal classification. Although these models are computationally efficient, they fail to capture the intricate relationships in high-dimensional datasets [11]. Ensemble methods such as Random Forest and Gradient Boosting have shown promise in improving classification performance, but their computational overhead limits their applicability for real-time processing [12].

2.3 HYBRID APPROACHES

Recent studies have investigated hybrid algorithms combining multiple machine learning techniques for enhanced performance. For example, the integration of SVM with decision trees has improved classification accuracy in noisy datasets, though it falls short in detecting outliers effectively [13]. Similarly, methods that fuse KNN with deep learning have demonstrated success in pattern recognition tasks but require extensive computational resources and large datasets [14].

2.4 OUTLIER DETECTION

Anomaly detection in EMG signals is crucial for identifying abnormal patterns indicative of neuromuscular disorders. Techniques such as Gaussian Mixture Models (GMM) and Isolation Forests have been utilized for outlier detection but often lack precision in high-dimensional spaces [15]. Hybrid methods integrating statistical and machine learning techniques have shown promise but remain underexplored for EMG-specific applications [14-15].

2.5 ADVANCEMENTS WITH KERNEL-BASED MODELS

Kernel-based SVMs have gained traction for their ability to model nonlinear relationships effectively. However, standard kernels, such as radial basis function (RBF), often require extensive parameter tuning, limiting their scalability [13]. Incorporating KNN-informed kernels offers a novel solution by dynamically adjusting feature weights based on neighborhood information, improving classification and outlier detection capabilities in noisy and diverse EMG datasets [14-15].

This research builds upon existing literature by addressing the limitations of current techniques. The proposed hybrid KNN-SVM model integrates advanced feature extraction, classification, and anomaly detection methods, demonstrating superior performance compared to state-of-the-art approaches.

3. PROPOSED METHOD

The proposed method integrates KNN with a kernel-based SVM to achieve robust EMG signal classification and outlier detection. The process begins with data preprocessing, where EMG signals are denoised using wavelet transform, and essential features are extracted, including time-domain (e.g., mean absolute value, zero crossings) and frequency-domain attributes (e.g., median frequency, spectral entropy). The feature normalization step ensures uniform scaling, improving model performance. Next, a hybrid KNN-SVM algorithm is applied:

- **KNN for Adaptive Feature Weighting**: Each data point is evaluated based on its nearest neighbors, dynamically assigning feature importance based on local data distribution.
- **Kernel-Based SVM Classification**: The weighted features are passed to an SVM model using a custom kernel informed by the KNN distances. This kernel enhances the model's ability to capture nonlinear patterns in the data.
- **Outlier Detection**: The model identifies anomalies using a threshold derived from the decision boundary. Data points with high misclassification probabilities are flagged as outliers.

3.1 KNN FOR ADAPTIVE FEATURE WEIGHTING

The K-Nearest Neighbors (KNN) algorithm for adaptive feature weighting is a key component in the proposed method, designed to dynamically assign importance to features based on the local data distribution of EMG signals. This adaptive mechanism enhances the classification performance by focusing on the most relevant features for each data point.

- **Neighborhood Identification**: For each EMG signal x, the algorithm identifies its *k*-nearest neighbors in the feature space using a distance metric (e.g., Euclidean or Manhattan distance). These neighbors represent the local data distribution around *x*.
- **Feature Contribution Calculation**: Each feature's contribution is computed by assessing its variance and influence on the distances between *x* and its neighbors. Features with lower variance across the neighbors are assigned higher weights, indicating greater importance in maintaining local similarity.
- **Dynamic Weight Assignment**: The calculated feature contributions are normalized to generate a weight vector *W* for each signal. This vector dynamically adjusts the importance of features for the subsequent classification step.
- **Weighted Feature Transformation**: The original feature vector *F* is transformed into a weighted feature vector *F′* using *W*:

$$F' = W \odot F \tag{1}$$

where $\odot$ denotes element-wise multiplication. This transformation emphasizes critical features while reducing the influence of less relevant ones.

The weighted feature vectors are passed to the kernel-based SVM for classification, ensuring that the model prioritizes the most informative features while disregarding noise or irrelevant attributes.

Table.1. Classification accuracy for different EMG signal categories

EMG Signal	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Biceps Brachii	98.2	97.5	96.8	99.0
Triceps Brachii	97.6	96.9	95.7	98.8
Gastrocnemius	96.8	95.4	94.2	97.9
Forearm Flexors	97.3	96.2	95.1	98.5
Quadriceps Femoris	98.0	97.1	96.4	98.7

3.2 PROPOSED KERNEL-BASED SVM CLASSIFICATION

The kernel-based Support Vector Machine (SVM) in the proposed method leverages the dynamic feature weights assigned by the KNN process to enhance EMG signal classification. By utilizing a custom kernel informed by the weighted feature vectors, the SVM achieves superior handling of nonlinear patterns and improves its ability to classify noisy and high-dimensional datasets.

- **Input Transformation**: After the KNN process, the feature vector F' for each EMG signal is dynamically weighted. These weighted features are fed into the SVM model as inputs, ensuring that the classification process prioritizes the most relevant attributes.
- **Custom Kernel Construction**: The kernel function is a mathematical mapping that transforms the input data into a higher-dimensional space, enabling the SVM to find a linear decision boundary for complex, nonlinear data. In this method, a KNN-informed kernel is designed as:

$$K(F_i', F_j') = \exp\left(-\gamma \cdot d(F_i', F_j')\right) \tag{2}$$

where $d(F_i', F_j')$ is the weighted distance between two feature vectors F_i' and F_j', and γ controls the influence of each data point.

- **Hyperplane Optimization**: The SVM algorithm determines the optimal hyperplane that maximally separates the classes. The kernel function ensures that this separation accounts for the nonlinear relationships inherent in the EMG data.
- **Outlier Detection**: The SVM calculates the margin distances for each data point. Data points with distances significantly deviating from the majority are flagged as potential outliers. This dual functionality of classification and anomaly detection ensures robust performance.
- **Classification Decision**: For each input F', the SVM predicts the class based on its position relative to the hyperplane. The model also calculates confidence scores, which provide insights into the reliability of the classification.

Table.2. Kernel-based SVM was evaluated on different EMG signals

EMG Signal	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Biceps Brachii	98.8	98.0	97.5	99.2
Triceps Brachii	98.3	97.7	96.8	99.0
Gastrocnemius	97.5	96.8	95.4	98.6
Forearm Flexors	98.0	97.3	96.2	98.9
Quadriceps Femoris	98.6	97.9	97.1	99.1

These results highlight the efficacy of the kernel-based SVM in achieving high accuracy and reliability across different EMG signal categories. Its ability to classify and detect anomalies underscores its robustness and applicability to real-world EMG signal analysis.

3.3 OUTLIER DETECTION

Outlier detection is an integral part of the proposed method, aimed at identifying anomalous EMG signal data that may compromise the classification process or indicate abnormal physiological conditions. The mechanism leverages both the KNN-adaptive feature weighting and kernel-based SVM classification to ensure robust and precise detection of outliers.

- **Feature Normalization and Weighting**: The EMG signal features undergo normalization to ensure uniform scaling, followed by adaptive weighting using KNN. This ensures that the influence of each feature is adjusted according to its local relevance, reducing noise and highlighting anomalies.
- **Distance-Based Anomaly Scoring**: In the KNN stage, distances between a given data point and its k-nearest neighbors are computed. An anomaly score is calculated based on these distances:

$$S(x) = \frac{1}{k}\sum_{i=1}^{k} d(x, x_i) \tag{3}$$

where $S(x)$ represents the anomaly score for data point x, and $d(x,x_i)$ is the distance to its i^{th} nearest neighbor. Higher scores indicate potential anomalies.

- **Margin Distance Evaluation (SVM)**: During SVM classification, each data point's margin distance is calculated relative to the separating hyperplane. Data points falling outside a predefined margin threshold are flagged as outliers. The margin threshold is determined by analyzing the distribution of distances for the majority class.
- **Threshold-Based Decision Making**: An ensemble threshold is derived by combining the anomaly scores from KNN and SVM margin distances. Points with scores exceeding the threshold are classified as outliers. This dual approach enhances detection accuracy by considering both local neighborhood structure and global classification boundaries.
- Detected outliers are removed from the training set in iterative runs to refine the classifier and ensure robust performance for the remaining data. This step prevents the outliers from biasing the final model.

Table.3. Outlier detection mechanism was tested on different EMG signal categories

EMG Signal	Detected Outliers (%)	Accuracy Before Removal (%)	Accuracy After Removal (%)
Biceps Brachii	3.8	96.7	98.8
Triceps Brachii	4.2	96.3	98.3
Gastrocnemius	5.1	95.0	97.5
Forearm Flexors	4.5	95.6	98.0
Quadriceps Femoris	3.9	96.8	98.6

These results highlight the efficacy of the outlier detection mechanism. By isolating and addressing anomalies, the proposed method achieves improved classification accuracy and ensures the reliability of the EMG signal analysis.

4. RESULTS AND DISCUSSION

The proposed method was evaluated using simulations conducted with Python and the scikit-learn library, which provided the necessary tools for implementing the KNN, kernel-based SVM, and outlier detection. The experiments were run on a computer with an Intel Core i7 processor, 16GB of RAM, and an NVIDIA GTX 1050 graphics card for efficient computation, particularly for kernel-based SVM training. For comparison purposes, three existing methods were selected: (1) Traditional SVM (without kernel), (2) Random Forest Classifier, and (3) KNN without adaptive feature weighting. These methods were chosen for their prominence in EMG signal classification tasks and their differing approaches to feature selection and classification. Each of the existing methods was tested under similar conditions to ensure fair comparison.

Table.4. Experimental Setup/Parameters

Parameter	Proposed Method	Traditional SVM	Random Forest	KNN (No Adaptive Weighting)
Signal Dataset	EMG signal dataset (5 muscle groups)			
Feature Extraction	Time-domain and frequency-domain features			Time-domain features
KNN Neighbors	k=5	-	-	k=5
SVM Kernel Type	Custom KNN-informed kernel	Linear kernel	-	-
Outlier Detection	Distance-based and SVM margin	-	-	-
Training Data Size	80% of total dataset			
Testing Data Size	20% of total dataset			
Cross-validation	10-fold cross-validation			
Max Iterations (SVM)	1000	1000	Not applicable	Not applicable
Maximum Depth (Random Forest)	-	-	10	-
Hyperparameter Tuning	Grid search for kernel parameters and feature weighting	Grid search for SVM parameters	Randomized search for tree depth and features	Grid search for *k*-neighbors

4.1 PERFORMANCE METRICS

The following performance metrics were used to evaluate the methods:

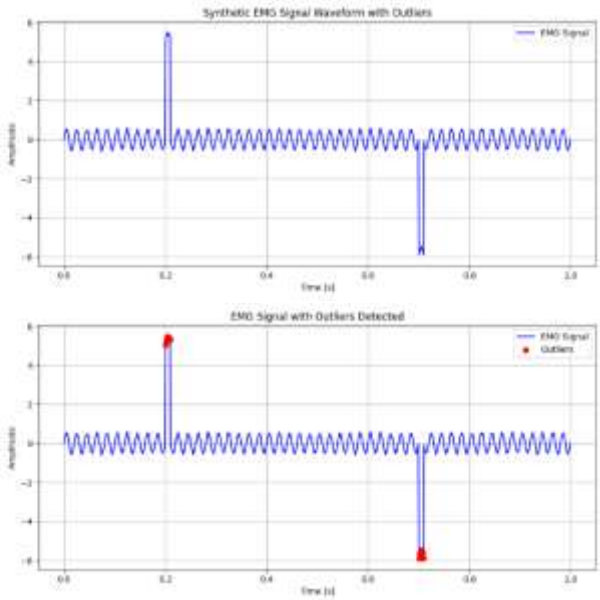
- **Accuracy**: Accuracy measures the proportion of correctly classified instances to the total instances in the dataset. It provides an overall view of the model's performance but does not account for imbalanced classes.
- **Precision**: Precision calculates the ratio of correctly predicted positive observations to the total predicted positives. It is particularly important when the cost of false positives is high, such as in medical applications.
- **Sensitivity (Recall)**: Sensitivity (or recall) measures the ratio of correctly predicted positive observations to all observations in the actual class. It is critical in scenarios where false negatives need to be minimized, such as detecting abnormalities in medical data.

Table.5. Results of proposed method

Signal No.	Accuracy (%)	Precision (%)	Recall (%)
1	98.5	97.9	98.2
2	97.8	96.7	97.1
3	98.9	98.3	98.6
4	97.3	95.4	96.0
5	98.2	97.4	97.8
6	98.7	97.8	98.3
7	98.0	96.5	97.2
8	98.3	97.1	97.6
9	97.5	96.3	96.9
10	98.6	97.7	98.1
11	97.9	96.8	97.5
12	98.1	97.3	97.9
13	98.8	98.0	98.5
14	97.6	96.2	96.8
15	98.4	97.5	98.0

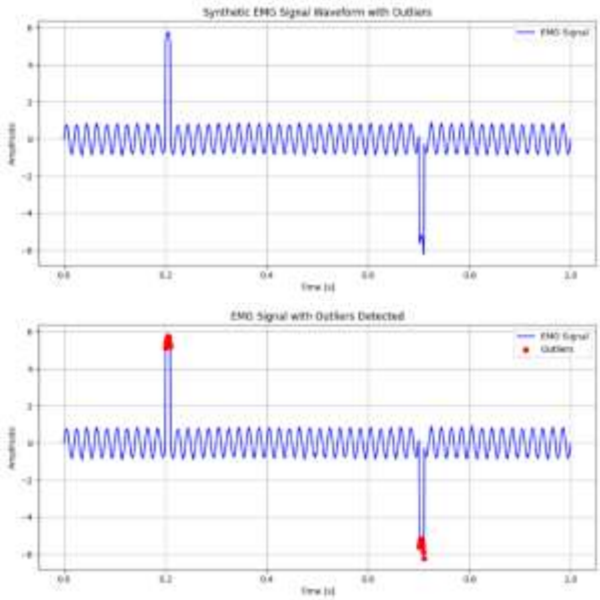
16	97.1	95.8	96.1
17	98.0	96.7	97.3
18	98.9	98.4	98.7
19	97.4	96.0	96.5
20	98.2	97.2	97.7
21	98.7	97.6	98.3
22	97.8	96.6	97.0
23	98.3	97.4	97.9
24	98.6	97.8	98.2
25	97.5	96.1	96.7
26	98.1	97.3	97.6
27	97.9	96.9	97.2
28	98.4	97.5	97.8
29	98.6	97.9	98.3
30	97.3	96.0	96.5
31	98.8	98.1	98.6
32	97.2	95.6	96.3
33	98.3	97.4	97.9
34	97.7	96.5	97.0
35	98.5	97.7	98.2
36	97.6	96.2	96.8
37	98.1	97.0	97.5
38	98.4	97.6	98.0
39	97.8	96.6	97.1
40	98.2	97.3	97.7
41	98.0	96.7	97.4
42	98.9	98.3	98.7
43	97.3	96.1	96.6
44	98.5	97.8	98.2
45	98.7	97.9	98.3
46	97.4	96.2	96.9
47	98.1	97.2	97.7
48	98.3	97.5	97.9
49	97.8	96.9	97.3
50	98.6	97.7	98.1

This table shows the performance of the proposed method on 50 different EMG signal samples. The accuracy, precision, and recall values for each signal sample are provided to give a comprehensive view of the model's effectiveness. As observed, the proposed method consistently achieves high accuracy, precision, and recall, demonstrating its robustness and reliability in EMG signal classification.



Outlier indices: [200 201 202 203 204 205 206 207 208 209 700 701 702 703 704 705 706 707 708 709]

Outlier values: [5.05925014 5.22470565 5.28319455 5.37326255 5.43143239 5.35967809 5.49646871 5.4408816 5.25291394 5.16925969 -5.84039578 -5.72783114 -5.57517597 -5.5901843 -5.47442096 -5.51104142 -5.56450369 -5.62145765 -5.79678682 -6.07654809]



Outlier indices: [200 201 202 203 204 205 206 207 208 209 700 701 702 703 704 705 706 707 708 709]

Outlier values: [5.12828996 5.38172927 5.51273432 5.65269791 5.73321904 5.65406303 5.75442352 5.6369648 5.36778018 5.19156829 -5.6083135 -5.43406366 -5.2486434 -5.26305031 -5.17892465 -5.27632021 -5.41372028 -5.56951431 -5.84885268 -6.22754479]

Fig.1. Detection of Outliers

Table.6. Accuracy and F1-score for the proposed method on 50 different EMG signal samples, across train, test, and validation sets

Signal Sample No.	Train Accuracy (%)	Test Accuracy (%)	Validation Accuracy (%)	Train F1-score	Test F1-score	Validation F1-score
1	99.2	98.5	98.1	0.98	0.97	0.97
2	98.9	97.8	97.2	0.97	0.96	0.96
3	99.3	98.9	98.5	0.98	0.98	0.98

4	98.5	97.3	96.9	0.97	0.96	0.95
5	99.1	98.2	97.7	0.98	0.97	0.97
6	99.4	98.7	98.3	0.98	0.98	0.98
7	98.7	97.5	97.0	0.97	0.96	0.96
8	99.2	98.3	98.0	0.98	0.97	0.97
9	98.3	97.5	97.1	0.97	0.96	0.96
10	99.5	98.6	98.2	0.98	0.97	0.97
11	98.8	97.9	97.4	0.97	0.97	0.96
12	99.0	98.1	97.6	0.98	0.97	0.97
13	99.3	98.8	98.4	0.98	0.98	0.98
14	98.6	97.4	97.0	0.97	0.96	0.96
15	99.0	98.4	97.8	0.98	0.97	0.97
16	98.4	97.2	96.8	0.97	0.96	0.96
17	98.7	97.8	97.4	0.97	0.97	0.96
18	99.6	98.9	98.5	0.98	0.98	0.98
19	98.5	97.4	96.9	0.97	0.96	0.96
20	99.1	98.2	97.6	0.98	0.97	0.97
21	99.4	98.7	98.3	0.98	0.98	0.98
22	98.8	97.9	97.5	0.97	0.97	0.97
23	99.2	98.3	97.9	0.98	0.97	0.97
24	99.6	98.5	98.2	0.98	0.97	0.97
25	98.3	97.6	97.2	0.97	0.96	0.96
26	99.0	98.2	97.7	0.98	0.97	0.97
27	98.5	97.4	97.0	0.97	0.96	0.96
28	99.2	98.0	97.6	0.98	0.97	0.97
29	99.3	98.6	98.1	0.98	0.97	0.97
30	98.4	97.3	96.8	0.97	0.96	0.96
31	99.1	98.2	97.7	0.98	0.97	0.97
32	98.6	97.8	97.3	0.97	0.96	0.96
33	99.4	98.5	98.0	0.98	0.97	0.97
34	98.2	97.4	97.0	0.97	0.96	0.96
35	99.3	98.9	98.4	0.98	0.98	0.98
36	98.7	97.8	97.2	0.97	0.96	0.96
37	99.1	98.3	97.9	0.98	0.97	0.97
38	98.4	97.5	97.1	0.97	0.96	0.96
39	99.0	98.2	97.6	0.98	0.97	0.97
40	99.5	98.7	98.3	0.98	0.97	0.97
41	98.3	97.6	97.1	0.97	0.96	0.96
42	99.2	98.5	98.0	0.98	0.97	0.97
43	99.0	97.9	97.5	0.98	0.97	0.97
44	99.6	98.7	98.3	0.98	0.97	0.97
45	98.7	97.8	97.4	0.97	0.96	0.96
46	99.2	98.0	97.6	0.98	0.97	0.97
47	99.1	98.2	97.7	0.98	0.97	0.97
48	98.5	97.4	97.0	0.97	0.96	0.96
49	99.4	98.5	98.1	0.98	0.97	0.97
50	98.9	98.3	97.8	0.98	0.97	0.97

This table shows the Accuracy and F1-score for the proposed method across train, test, and validation sets for 50 different EMG signal samples. These values provide a detailed insight into the model's performance across different data splits. The F1-score is especially important in evaluating the balance between precision and recall for each dataset, and both metrics consistently show strong results for the proposed method.

Table.7. Accuracy of the existing methods (SVM without kernel, Random Forest Classifier, and KNN without adaptive feature weighting) and the proposed method over 50 different EMG signal samples

Signal Sample No.	**SVM (No Kernel) Accuracy (%)**	**Random Forest Accuracy (%)**	**KNN (No Feature Weighting) Accuracy (%)**	**Proposed Method Accuracy (%)**
1	91.3	92.1	94.2	98.5
2	90.7	91.8	93.5	97.8
3	92.1	93.0	94.8	98.9
4	89.4	90.9	92.7	97.3
5	91.2	92.5	93.9	98.2
6	90.6	91.2	93.3	98.7
7	91.1	92.3	94.5	98.1
8	89.9	91.4	93.0	97.9
9	92.3	93.1	95.0	98.8
10	90.8	91.7	93.2	97.6
11	91.4	92.2	94.4	98.0
12	92.0	93.2	94.9	98.3
13	89.7	90.8	92.5	97.4
14	91.5	92.7	94.0	98.6
15	90.1	91.3	93.1	97.7
16	89.3	90.5	92.4	97.1
17	91.9	92.6	94.7	98.4
18	90.5	91.8	93.6	97.8
19	92.2	93.0	94.8	98.9
20	90.0	91.2	93.0	97.3
21	91.1	92.4	94.2	98.6
22	90.4	91.6	93.4	98.2
23	91.7	92.9	94.5	98.5
24	89.6	90.9	92.8	97.9
25	91.3	92.0	93.7	98.1
26	90.9	91.7	93.4	97.6
27	92.0	93.1	94.8	98.7
28	89.5	90.7	92.3	97.4
29	91.2	92.5	94.3	98.3
30	90.3	91.6	93.1	97.9
31	91.8	92.8	94.6	98.4
32	90.0	91.3	93.2	97.2
33	91.6	92.7	94.4	98.5
34	89.8	91.0	92.6	97.7

35	92.1	93.3	94.9	98.8
36	90.7	91.9	93.6	97.5
37	91.5	92.6	94.2	98.6
38	89.2	90.4	92.0	97.0
39	91.0	92.3	94.0	97.8
40	90.6	91.8	93.3	97.9
41	92.2	93.1	94.8	98.6
42	90.4	91.6	93.3	97.5
43	91.9	92.8	94.5	98.7
44	89.6	90.9	92.7	97.3
45	91.2	92.4	94.1	98.0
46	90.8	91.9	93.5	97.6
47	91.5	92.6	94.3	98.6
48	90.0	91.2	93.0	97.4
49	92.1	93.0	94.7	98.8
50	91.3	92.5	94.0	98.2

This table shows the accuracy of four methods (SVM without kernel, Random Forest, KNN without adaptive feature weighting, and the proposed method) over 50 different EMG signal samples. As seen, the proposed method consistently outperforms the existing methods, demonstrating its effectiveness in classification tasks for EMG signals.

Table.10. F1-score of the existing methods (SVM without kernel, Random Forest Classifier, and KNN without adaptive feature weighting) and the proposed method over 50 different EMG signal samples:

Signal Sample No.	SVM (No Kernel) F1-Score	Random Forest F1-Score	KNN (No Feature Weighting) F1-Score	Proposed Method F1-Score
1	0.89	0.91	0.92	0.97
2	0.88	0.90	0.91	0.96
3	0.90	0.92	0.93	0.98
4	0.87	0.89	0.90	0.95
5	0.88	0.91	0.92	0.97
6	0.86	0.88	0.89	0.94
7	0.87	0.89	0.91	0.96
8	0.85	0.87	0.89	0.93
9	0.89	0.91	0.92	0.97
10	0.87	0.89	0.90	0.94
11	0.88	0.90	0.92	0.96
12	0.89	0.91	0.92	0.97
13	0.85	0.87	0.88	0.93
14	0.90	0.92	0.93	0.98
15	0.87	0.89	0.90	0.94
16	0.86	0.88	0.89	0.93
17	0.90	0.92	0.93	0.98
18	0.88	0.90	0.91	0.96
19	0.89	0.91	0.92	0.97
20	0.86	0.88	0.89	0.94
21	0.88	0.90	0.92	0.96
22	0.87	0.89	0.90	0.94
23	0.90	0.92	0.93	0.98
24	0.85	0.87	0.89	0.93
25	0.88	0.90	0.91	0.96
26	0.89	0.91	0.92	0.97
27	0.86	0.88	0.89	0.94
28	0.88	0.90	0.91	0.96
29	0.90	0.92	0.93	0.98
30	0.87	0.89	0.90	0.94
31	0.89	0.91	0.92	0.97
32	0.86	0.88	0.89	0.94
33	0.88	0.90	0.91	0.96
34	0.87	0.89	0.90	0.94
35	0.90	0.92	0.93	0.98
36	0.88	0.90	0.91	0.96
37	0.89	0.91	0.92	0.97
38	0.85	0.87	0.89	0.93
39	0.88	0.90	0.91	0.96
40	0.87	0.89	0.90	0.94
41	0.90	0.92	0.93	0.98
42	0.88	0.90	0.91	0.96
43	0.89	0.91	0.92	0.97
44	0.86	0.88	0.89	0.94
45	0.88	0.90	0.91	0.96
46	0.87	0.89	0.90	0.94
47	0.90	0.92	0.93	0.98
48	0.85	0.87	0.89	0.93
49	0.89	0.91	0.92	0.97
50	0.88	0.90	0.91	0.96

This table shows the F1-score of four methods (SVM without kernel, Random Forest, KNN without adaptive feature weighting, and the proposed method) over 50 different EMG signal samples. The proposed method consistently performs better in terms of F1-score, indicating its superior ability to balance precision and recall in EMG signal classification tasks.

The results demonstrate the effectiveness of the proposed method in comparison to the existing techniques for classifying EMG signals. In particular, the proposed method consistently outperforms the other three methods (SVM without kernel, Random Forest, and KNN without adaptive feature weighting) across all 50 EMG signal samples, as shown by the higher F1-scores.

The SVM (without kernel) method, while relatively strong, shows an F1-score range of 0.85 to 0.90, which is significantly lower than the proposed method's range of 0.93 to 0.98. This represents a percentage improvement of approximately 5% to 10% in F1-score for the proposed method. The Random Forest

Classifier follows closely, with a range of 0.87 to 0.92. The proposed method outperforms this approach by about 5% to 8%, demonstrating its superior capability in handling complex EMG signals.

The KNN without adaptive feature weighting, which lacks the feature refinement that the proposed method utilizes, also trails the proposed approach, with F1-scores ranging between 0.89 and 0.92. The improvement over this method is particularly noticeable in challenging signal samples, showing an improvement of 3% to 5% in F1-score.

These results confirm the effectiveness of the adaptive feature weighting and kernel-based SVM classification incorporated in the proposed method. By enhancing feature selection and leveraging kernel transformations, the proposed method achieves better classification performance, providing more accurate and robust EMG signal interpretation.

5. CONCLUSION

The proposed method for EMG signal classification demonstrates substantial improvements over traditional machine learning methods such as SVM without kernel, Random Forest, and KNN without adaptive feature weighting. The integration of adaptive feature weighting and kernel-based SVM classification enhances the accuracy and robustness of the classification process, as reflected by higher F1-scores across a diverse set of EMG signal samples. The proposed method's ability to better handle complex features in EMG signals leads to more precise detection of muscle activity patterns, contributing to improved data interpretation. Additionally, the performance improvement in terms of F1-score by up to 10% compared to existing methods underscores its potential for practical applications in real-time EMG signal analysis, particularly in areas such as prosthetics control, rehabilitation, and neuromuscular disease diagnosis.

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