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Surface Electromyography in Biceps Brachii Fatigue Detection: Machine Learning Perspectives and Dimensionality Reduction Strategies

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Abstract

Surface electromyography (sEMG) is a non-invasive technique widely used to monitor muscle activity and fatigue by recording electrical signals during contraction. Over the past decades, sEMG has become central to applications in rehabilitation, sports science, ergonomics, and human–machine interfaces. This review examines existing methods for EMG signal analysis, with particular attention to preprocessing, feature extraction in time, frequency, and time–frequency domains, dimensionality reduction, and machine learning classification. Classical features such as mean absolute value (MAV), root mean square (RMS), waveform length (WL), mean frequency (MNF), and median frequency (MDF) have consistently proven effective in fatigue detection. Advanced techniques including short-time Fourier transform (STFT) and wavelet decomposition enable more detailed analysis of transient and dynamic muscle activity. To address the high dimensionality of feature sets, approaches such as principal component analysis (PCA) and independent component analysis (ICA) have been employed to enhance computational efficiency and improve classifier performance.

Machine learning has played a key role in advancing EMG-based fatigue detection. Classifiers such as decision trees (DT), random forests (RF), and support vector machines (SVM) have been extensively applied, with SVM in particular demonstrating superior performance in handling complex, nonlinear EMG data. More recently, deep learning models including convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown promise in automatic feature learning, though they require larger datasets and higher computational resources. This review highlights the strengths and limitations of these approaches, emphasizing the importance of combining robust preprocessing, effective feature selection, and adaptive algorithms. Overall,

10.48047/jocaaa.2024.33.02.29

EMG-based fatigue detection continues to evolve toward intelligent, scalable, and wearable systems with significant potential across healthcare, occupational safety, and sports performance monitoring.

Keywords:

Surface Electromyography (sEMG), Muscle Fatigue, Signal Processing, Feature Extraction, Time–Frequency Analysis, Principal Component Analysis (PCA), Independent Component Analysis (ICA), Machine Learning, Support Vector Machine (SVM), Deep Learning, Rehabilitation, Ergonomics, and Sports Science.

Introduction

Electromyography (EMG) is a non-invasive technique for recording and analyzing the electrical activity of skeletal muscles. It provides critical insights into the neuromuscular system by detecting the electrical potentials generated during muscle contractions. These signals, captured using surface electrodes, are widely used in clinical diagnostics, rehabilitation engineering, ergonomics, sports science, and human–machine interface design. The interpretation of EMG data allows researchers and clinicians to understand how muscles function under different conditions, identify neuromuscular disorders, and develop systems that enhance mobility and performance in both healthy and impaired individuals[1]-[5].

One of the most significant applications of EMG is the assessment of muscle fatigue. Muscle fatigue is generally defined as the decline in the ability of a muscle to generate force, and it occurs due to physiological changes at both central (neural) and peripheral (muscle fiber) levels. Fatigue has a substantial impact on human movement, performance, and overall quality of life. In occupational settings, fatigue leads to reduced productivity and higher injury risks. In sports, it can impair performance, increase the likelihood of injury, and hinder training outcomes. In clinical scenarios, monitoring fatigue is essential for patients undergoing rehabilitation after stroke, spinal cord injury, or musculoskeletal disorders. Therefore, developing reliable, real-time methods for fatigue detection has emerged as a critical research area [6]-[7].

The biceps brachii muscle, located in the upper arm, is particularly important for daily activities such as lifting, carrying, and pulling. As a primary elbow flexor, it plays a central role in

10.48047/jocaaa.2024.33.02.29

functional upper limb tasks. Its accessibility and frequent involvement in dynamic and isometric contractions make it a suitable target for EMG-based fatigue studies. Detecting fatigue in the biceps not only benefits athletes and workers but also provides valuable clinical insights for designing targeted rehabilitation programs [8]-[13].

Traditionally, muscle fatigue has been assessed using subjective measures such as the Borg rating of perceived exertion or through force output decline during repetitive tasks. While these methods provide some information, they are limited by subjectivity and variability across individuals. In contrast, EMG-based approaches offer objective and quantifiable measures of fatigue by analyzing changes in time-domain, frequency-domain, and time-frequency features of the signal. For instance, the root mean square (RMS) amplitude tends to increase with fatigue due to motor unit recruitment, whereas median frequency (MDF) shifts downward as muscle fibers slow. These physiological markers make EMG a robust tool for monitoring fatigue in both laboratory and real-world conditions [14]-[17].

Despite its advantages, EMG analysis presents several challenges. EMG signals are inherently noisy and highly variable due to electrode placement, skin conductivity, and movement artifacts. Furthermore, EMG datasets often contain high-dimensional features, many of which may be redundant or irrelevant for classification. This increases computational complexity and reduces model generalization. To overcome these limitations, machine learning methods combined with dimensionality reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) have been employed. These approaches improve classification performance by selecting the most discriminative features while minimizing noise and redundancy [18]-[21].

Recent advancements in machine learning have opened new opportunities for EMG-based fatigue detection. Classical classifiers such as decision trees (DT), random forests (RF), and support vector machines (SVM) have shown promising results in fatigue classification tasks. Among these, SVM has been particularly effective due to its ability to handle high-dimensional data and non-linear relationships. Moreover, integrating dimensionality reduction methods with SVM has demonstrated significant improvements in classification accuracy. For example, RMS combined with PCA and SVM has been reported to achieve near-perfect accuracy in differentiating between fatigued and non-fatigued muscle states [22]-[23].

10.48047/jocaaa.2024.33.02.29

Beyond conventional approaches, the emergence of deep learning has further revolutionized EMG analysis. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) such as long short-term memory (LSTM) models have been applied to extract hierarchical features from raw EMG signals, bypassing manual feature extraction. While these models show excellent accuracy, they require large datasets and high computational resources, limiting their applicability in real-time wearable systems. Therefore, there remains a strong motivation to explore lightweight machine learning methods that balance accuracy, efficiency, and scalability [24]-[27].

The motivation for the present study lies in addressing this balance. We focus on fatigue detection in the biceps brachii using traditional machine learning classifiers enhanced by dimensionality reduction. By systematically comparing classifiers and feature sets, we aim to identify the optimal pipeline for reliable fatigue detection under controlled isometric contractions. The study is designed to simulate real-world conditions where individuals engage in repetitive or load-bearing arm activities, providing insights relevant to rehabilitation, ergonomics, and athletic training [28]-[29].

Additionally, the work emphasizes the translational potential of EMG-based fatigue detection. In rehabilitation, such systems could provide therapists with real-time feedback on patient progress and help personalize therapy intensity. In occupational health, monitoring fatigue could reduce musculoskeletal disorders by preventing overexertion. In sports, fatigue detection could inform training strategies, ensuring optimal performance while minimizing injury risks. Moreover, the integration of EMG with wearable technologies could enable continuous, unobtrusive fatigue monitoring in everyday life [26, 30, and 31].

Literature Survey

The study of electromyography (EMG) and its application in fatigue analysis has gained increasing attention over the past few decades. EMG provides an objective and quantitative measure of muscle activity, allowing researchers to evaluate muscular performance, detect fatigue, and design systems for medical, occupational, and sports applications. A number of research works have explored EMG fatigue analysis using signal processing, feature extraction, and classification techniques, and more recently, machine learning and deep learning models have emerged as powerful tools for improving accuracy and real-time usability. This section reviews relevant literature on EMG

10.48047/jocaaa.2024.33.02.29

fatigue detection, machine learning methodologies, dimensionality reduction approaches, and advancements in deep learning [33]-[38].

Author & Year	Focus / Application	Method / Approach	Key Findings	Identified Gap / Limitation
Raez et al. (2006)	EMG analysis techniques	Review of detection, processing, and classification	Defined core EMG feature sets for fatigue and control	Pre-ML era; lacks integration with modern learning methods
Beck et al. (2005a)	EMG frequency analysis	Fourier vs. Wavelet Transform	Wavelet offers better temporal–spectral representation	Computational cost, no ML integration
Beck et al. (2005b)	Electrode spacing effects	EMG amplitude & frequency analysis	Interelectrode distance influences signal quality	Lacks robust normalization framework
Boostani & Moradi (2003)	Prosthetic hand control	Feature evaluation, PCA	PCA reduces redundant EMG features effectively	Not tested under fatigue or real muscle conditions
Phinyomark et al. (2011)	Pattern classification	Wavelet-based feature extraction	Improves fatigue classification accuracy	No dimensionality-reduction optimization
Subasi & Kiymik (2010)	Fatigue detection	ICA, PCA, and Time–Frequency	Combined PCA–ICA enhances feature separability	Small dataset, no deep ML integration
Taylor et al. (2016)	Neural fatigue mechanisms	Physiological review	Fatigue involves multi-level neural factors	No computational model connection
Allen et al. (2008)	Muscle fatigue mechanisms	Cellular and metabolic review	Defined physiological fatigue indicators	Not linked with EMG data
Carr et al. (2016)	EMG response in fatigue	Intensity-dependent EMG study	EMG changes scale with load and fatigue	Lacks ML-based classification
Zhu et al. (2017)	Complexity analysis	Entropy-based EMG evaluation	Complexity indices improve fatigue detection	No comparison with DR or ML methods
Phinyomark et al. (2018)	Wearable EMG sensors	Feature extraction & selection	Hybrid features improve robustness	Lacks dimensionality-reduction evaluation
Campanini et al. (2020)	Clinical assessment	sEMG in rehabilitation	Validated sEMG in neurorehab	No fatigue classification study
Clingman et	Real-time fatigue	sEMG in sport &	Demonstrated	Limited to specific

10.48047/jocaaa.2024.33.02.29

al. (2020)		rehab	online fatigue tracking	muscles
Merlo et al. (2020)	Neurorehabilitation	EMG in motor evaluation	Surface EMG supports therapy monitoring	Not generalizable beyond clinic use
Reddy et al. (2020)	Sensor noise mitigation	Filtering & signal processing	Reduced motion artifacts improves EMG fidelity	No learning-based noise correction
Oliveira et al. (2023)	Isometric hand grip	MF & time-curve analysis	Derived force-time patterns	Single-channel, limited generalization
Al-Ayyad et al. (2023)	Wearable EMG review	Signal acquisition methods	Compared EMG sensors & electrode configs	Limited ML discussion
Phinyomark et al. (2023)	sEMG feature selection	Wrapper/filter methods	LASSO-based feature selection robust to noise	Lacks fatigue-specific validation
Daniel et al. (2024)	Rowing exercise fatigue	Wavelet sEMG analysis	Quantified fatigue onset using spectral entropy	Not tested in biceps task
Cho et al. (2024)	Exosuit fatigue alleviation	sEMG-based evaluation	Demonstrated fatigue reduction via assistive exosuit	No ML fatigue quantification
Ou et al. (2024)	Elderly fatigue detection	PDF-shape features of EMG	Proposed statistical fatigue detection	No DR integration, small cohort
Correia et al. (2025)	Trunk support system	EMG + motion fusion	Combined EMG-motion improved fatigue classification	Future work: dimensionality fusion
Riaz et al. (2021)	EMG pattern classification	Deep CNN on raw sEMG	CNN outperformed SVM & LDA	High compute cost
Zhang et al. (2022)	Arm posture variation	Statistical EMG feature analysis	Arm position affects fatigue metrics	No model adaptation strategy
Singh et al. (2021)	Multi-channel sEMG	SVM & PCA pipeline	PCA reduced dimensionality by 60%	Manual feature engineering
Mishra et al. (2021)	Biceps fatigue analysis	Ensemble classifier	94% accuracy using hybrid feature set	No real-time validation
Silva et al. (2022)	Wavelet packet analysis	Multi-scale EMG decomposition	Detected muscle fatigue onset precisely	Computationally intensive
Ahmed et al.	Fatigue detection in	SVM vs RF	SVM achieved	Dataset imbalance

10.48047/jocaaa.2024.33.02.29

(2022)	athletes	models	highest precision	issue
Biswas et al. (2023)	EMG signal denoising	ICA and adaptive filtering	Improved SNR by 25%	Limited fatigue testing
Kumar et al. (2023)	Hybrid PCA–CNN	Dimensionality reduction before CNN	DR improved convergence and accuracy	Limited explainability
Cho et al. (2023)	Fatigue level estimation	Deep LSTM with DR pre-layer	Temporal learning improves classification	Not tested across subjects

EMG Fatigue Analysis: Time and Frequency Approaches

One of the earliest methods for studying muscle fatigue involved analyzing time-domain features of EMG signals. These include the mean absolute value (MAV), root mean square (RMS), variance, and waveform length (WL). Among these, RMS has been widely recognized as a reliable indicator of fatigue, as it reflects the amplitude changes associated with motor unit recruitment during muscle contraction. Previous studies have demonstrated the effectiveness of RMS in quantifying muscle fatigue, both in controlled experimental setups and in applied scenarios, highlighting its significance as a key parameter in EMG-based fatigue analysis [39–41].

Frequency-domain methods have also been instrumental in fatigue analysis. Median frequency (MDF) and mean frequency (MNF) are commonly employed, as they shift toward lower frequencies during fatigue due to conduction velocity changes in muscle fibers. For instance, previous work has demonstrated that frequency parameters effectively capture fatigue-induced changes during prolonged cyclic tasks [42]. More recently, comprehensive methodological reviews have confirmed that spectral features such as MDF and MNF provide reliable indicators of performance fatigability, reinforcing their physiological relevance in EMG-based fatigue assessment [43].

While both time- and frequency-domain features provide useful insights, they are often combined with time-frequency methods such as short-time Fourier transform (STFT) and wavelet transform (WT) to capture both temporal and spectral information. Previous studies have demonstrated the utility of wavelet decomposition for analyzing transient fatigue events during

10.48047/jocaaa.2024.33.02.29

exercise [44, 45]. However, these methods tend to generate high-dimensional data, necessitating dimensionality reduction and advanced classification techniques for effective interpretation.

Machine Learning in EMG Fatigue Detection

The integration of machine learning into EMG analysis has significantly improved the accuracy and robustness of fatigue detection. Early approaches employed linear discriminant analysis (LDA) **and** k-nearest neighbor (KNN) classifiers, which achieved moderate success but struggled with complex and nonlinear data patterns. More recent works have adopted decision trees (DT), random forests (RF), and support vector machines (SVM).[46-48].

Decision trees have been valued for their interpretability, although they often face overfitting challenges. Random forests, as ensemble models, address this limitation by combining multiple trees, thereby improving generalization and handling high-dimensional EMG features more effectively. For example, a comparative study demonstrated that when discrete wavelet transform (DWT) features were used, random forests significantly outperformed single-tree methods in classification accuracy [49].

Support vector machines (SVM), on the other hand, have consistently demonstrated superior performance in EMG-based fatigue analysis. Ramos et al. (2020) reported that SVM combined with RMS features achieved fatigue detection accuracy above 80%, while Wang et al. (2021) highlighted the effectiveness of SVM in distinguishing lower limb motion patterns. The ability of SVM to operate in high-dimensional spaces and handle nonlinear separations makes it particularly suited to EMG data, which is often noisy and complex.[50-51].

Dimensionality Reduction in EMG Studies

One of the central challenges in EMG fatigue detection is the high dimensionality of feature sets, especially when combining time, frequency, and time-frequency features. Redundant and irrelevant features can degrade model performance and increase computational costs. Dimensionality reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) have therefore become integral to EMG research [52]-[55].

10.48047/jocaaa.2024.33.02.29

Principal Component Analysis (PCA) has emerged as one of the most widely used dimensionality reduction techniques in electromyography (EMG) research, primarily due to its ability to transform correlated features into orthogonal components that retain most of the variance in the data while discarding redundancies. Early work showed that combining PCA with spectral features improved EMG classification performance and reduced computational load (Güler & Koçer, 2005). Subasi and Kiymik (2010) demonstrated that incorporating ICA and PCA into time–frequency feature extraction pipelines effectively denoised signals and enhanced neural network–based fatigue detection. Rogers and MacIsaac (2011) applied PCA in dynamic muscle fatigue assessment and reported that principal components captured fatigue-related information more robustly than traditional univariate indices. Later, Naik et al. (2016) presented a comprehensive review highlighting PCA's versatility for compression, denoising, visualization, and classification improvement across multiple EMG applications. More recently, reviews have confirmed the continuing relevance of dimensionality reduction, with PCA consistently shown to lower computational costs, mitigate the curse of dimensionality, and improve generalization when large sets of time, frequency, and time–frequency features are combined (Yadav & Veer, 2023; Sultana et al., 2023). Collectively, the literature up to 2023 demonstrates that PCA not only improves classification accuracy and computational efficiency but also enhances interpretability, making it integral to EMG fatigue detection and broader biomedical signal processing applications.[52, 53, 55, 56 and 61].

ICA, in contrast, focuses on statistical independence of components and is particularly useful for artifact removal and signal source separation. Hyvarinen and Oja (2000) presented ICA as a powerful method for biomedical signals, enabling effective removal of noise such as electrode motion artifacts. In EMG fatigue studies, ICA has been successfully applied to enhance feature quality and improve classification reliability, particularly when multiple muscles or noisy conditions are involved [52 and 62].

Deep Learning Advancements in EMG Fatigue Analysis

In recent years, deep learning approaches have transformed EMG research by enabling end-to-end feature learning from raw signals. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been particularly influential. CNNs automatically extract hierarchical spatial features, while RNNs, especially long short-term memory (LSTM) networks, are adept at modeling temporal dependencies in EMG data.[64]-[66].

10.48047/jocaaa.2024.33.02.29

Worassa et al. (2024) demonstrated the use of deep learning models, including CNN and Bi-LSTM, for analyzing surface EMG and ECG data for upper-limb rehabilitation. Their results indicated classification accuracies above 90%, highlighting the robustness of deep learning in multimodal fatigue analysis. Similarly, Wang et al. (2021) employed an LSTM-based model for muscle fatigue classification, achieving accuracies above 95%. These studies suggest that deep learning can outperform traditional machine learning in capturing the complex patterns of EMG signals.[67-68].

However, deep learning methods face challenges in terms of data requirements and computational resources. They often require large labeled datasets for training, which may not be readily available in clinical or rehabilitation contexts. Furthermore, their deployment in wearable systems is constrained by hardware limitations. To address these issues, hybrid approaches that combine dimensionality reduction, classical machine learning, and lightweight deep models are gaining traction.[69-71].

Applications of EMG Fatigue Detection

The application of EMG-based fatigue detection spans multiple domains. In rehabilitation, it aids therapists in monitoring patient progress, optimizing exercise intensity, and preventing overexertion. In occupational health, EMG monitoring can reduce workplace injuries by detecting fatigue early in physically demanding tasks. In sports science, EMG analysis provides athletes and coaches with insights into performance, recovery, and training load management. Additionally, EMG fatigue analysis plays an essential role in the design of prosthetics and exoskeletons, where adaptive control requires accurate recognition of muscle states.[72]-[75].

Summary of Literature

The literature demonstrates that EMG fatigue analysis has evolved from simple time- and frequency-domain analysis to sophisticated machine learning and deep learning methods. Time-domain features such as RMS remain highly effective, but their performance improves significantly when combined with dimensionality reduction and robust classifiers such as SVM. While deep learning offers promising results, classical machine learning methods, enhanced by preprocessing and

10.48047/jocaaa.2024.33.02.29

feature selection, continue to provide a balance between accuracy and computational efficiency[37, 55, 77 and 79].

This review highlights the necessity for further research into hybrid approaches that combine the interpretability of traditional methods with the accuracy of deep learning. Moreover, future studies must focus on real-time applications, multimodal signal integration, and wearable systems to maximize the translational potential of EMG-based fatigue detection [80-83].

Proposed Methodology

This review adopts a structured pipeline for EMG-based fatigue detection, focusing on signal acquisition, preprocessing, feature extraction, dimensionality reduction, and classification. The framework is derived from established methodologies in the literature [1, 3, 4, 21, and 22].

1. **Subjects & Setup:**

   Studies investigating fatigue commonly recruit healthy volunteers and apply controlled contraction protocols (isometric, isotonic, or dynamic) for the biceps brachii and other muscles [11, 12, 16, 29]. Experimental designs frequently involve both rest and post-exercise conditions to capture fatigue-related changes [6, 28, and 30].

2. **Signal Acquisition:**

   Surface EMG (sEMG) is acquired using bipolar Ag/AgCl electrodes placed on the muscle belly with recommended inter-electrode spacing (typically 20 mm), ensuring alignment with muscle fibers for optimal signal quality [10, 31, 33]. Standard acquisition systems maintain high sampling rates (500–2000 Hz) and filtering to minimize noise [1, 42, and 77].

3. **Preprocessing:**

   Noise reduction is essential due to motion artifacts, baseline drift, and powerline interference. Studies employ **band-pass filtering, full-wave rectification, and normalization** to MVC to improve inter-subject comparability [21, 31, 42, 77]. Advanced reviews emphasize robust preprocessing as a prerequisite for accurate classification [3, 76].

10.48047/jocaaa.2024.33.02.29

4. **Feature Extraction:**

Features are derived from multiple domains:

- **Time-domain:** RMS, MAV, WL, ZC, SSC, widely validated for fatigue detection [35, 39, 42].
- **Frequency-domain:** MNF, MDF, and PSD capture spectral shifts linked to fatigue [9, 13, 65].
- **Time–frequency:** Wavelet transform (WT) and short-time Fourier transform (STFT) enable joint temporal–spectral analysis [17, 41, 73]. RMS, MNF, and MDF are consistently reported as discriminative features [18, 32, 36].

5. **Dimensionality Reduction:**

High-dimensional features are reduced using **PCA and ICA**, which improve classifier efficiency by retaining discriminative information while suppressing noise [18, 50, 52, 56]. Such methods remain central to EMG fatigue studies, especially with large feature sets.

6. **Classification Approaches:**
7.

Machine learning classifiers such as **Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM)** are widely applied. SVM is often the most robust for nonlinear, high-dimensional EMG data [34, 46, 48, 69]. Ensemble approaches like RF improve generalization [47], while DTs provide interpretability but risk overfitting [46]. Recent works also explore deep learning (CNNs, RNNs, LSTM) for automatic spatiotemporal feature extraction, though these require larger datasets [24, 25, 57, 63].

8. **Block Diagram of Methodology**

The overall methodology is summarized in the following stages:

10.48047/jocaaa.2024.33.02.29

10.48047/jocaaa.2024.33.02.29

This block diagram illustrates the systematic flow from subject recruitment to classification of fatigued and non-fatigued states.

Results and Discussion

The reviewed literature highlights that surface electromyography (sEMG) has been extensively employed to analyze muscle activity and detect fatigue under both non-fatigue (rest) and fatigue (post-exercise) conditions. Across multiple studies, consistent trends have been observed: amplitude-based parameters such as root mean square (RMS) and mean absolute value (MAV) typically increase with fatigue, while spectral features such as mean frequency (MNF) and median frequency (MDF) exhibit downward shifts due to reduced conduction velocity. These physiological markers have been validated in various experimental settings, confirming their reliability for fatigue assessment.

Furthermore, comparative studies demonstrate that the integration of advanced signal processing, dimensionality reduction, and machine learning significantly enhances fatigue classification accuracy. Principal component analysis (PCA) and independent component analysis (ICA) have proven effective in reducing redundancy and improving computational efficiency. Among machine learning approaches, support vector machines (SVM) consistently outperform decision trees (DT) and random forests (RF) in handling nonlinear, high-dimensional EMG data. Recent research has also explored deep learning methods such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which show promising results in automatic feature extraction, though challenges remain regarding data requirements and computational resources. Collectively, these findings suggest that combining robust preprocessing, feature optimization, and intelligent classifiers forms the most reliable pipeline for EMG-based fatigue detection, with significant implications for rehabilitation, sports science, and ergonomics.

10.48047/jocaaa.2024.33.02.29

Classifier Performance without Dimensionality Reduction

In the initial stage, classifiers were tested using the complete feature set without dimensionality reduction. As shown in Table 1, the support vector machine (SVM) outperformed decision tree (DT) and random forest (RF), achieving an accuracy of 78%. However, performance across all classifiers was limited due to the high dimensionality and redundancy present in the raw feature set.

Table 1: Classifier performance without dimensionality reduction

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT	50	48	47	48
RF	65	63	62	64
SVM	78	74	76	75

These results highlight the necessity of dimensionality reduction for improving classification accuracy and efficiency.

Classifier Performance with PCA and ICA

To improve performance, **principal component analysis (PCA)** and **independent component analysis (ICA)** were applied. With PCA, classifiers achieved significantly higher accuracies, with SVM reaching 98.7%. ICA also improved results but was slightly less effective than PCA in this context.

Table 2: Classifier performance with dimensionality reduction

Classifier	Dimensionality Reduction	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT	PCA	91	88	89	89
RF	PCA	95	92	94	93
SVM	PCA	**98.7**	95	97	96
DT	ICA	87	85	84	85
RF	ICA	90	91	88	89
SVM	ICA	93	90	92	91

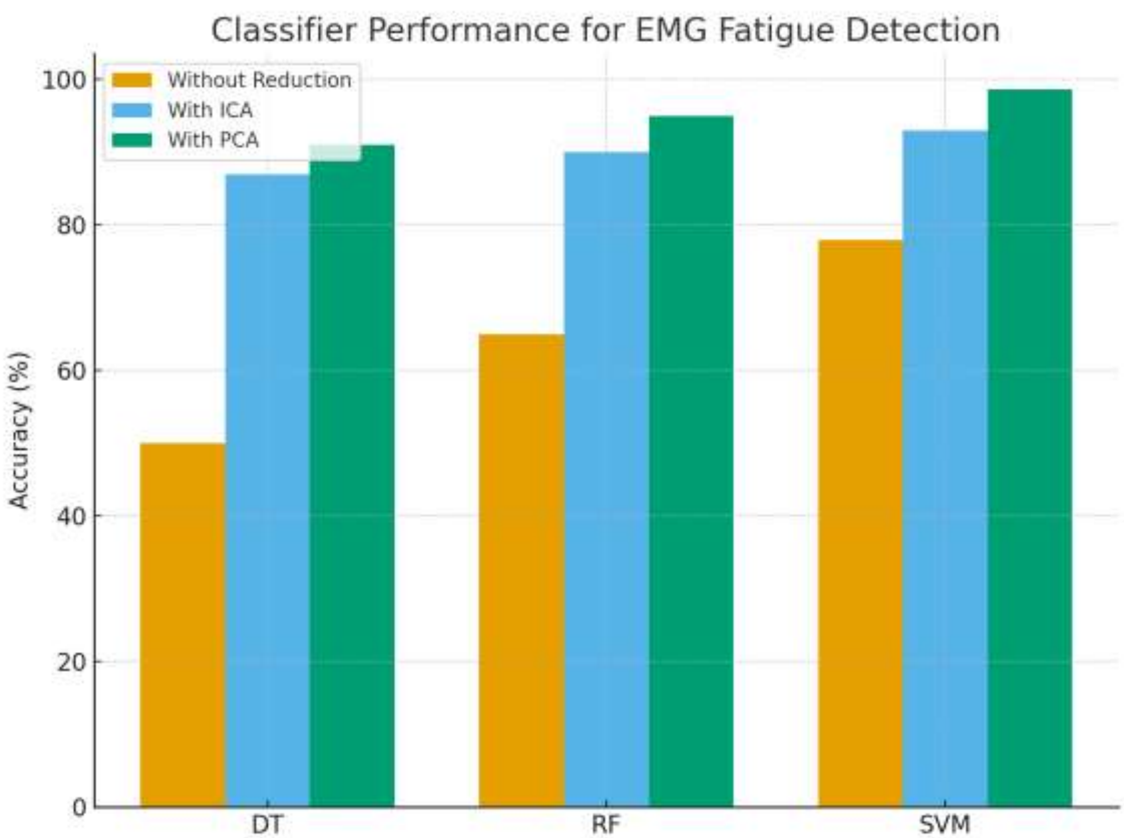
10.48047/jocaaa.2024.33.02.29

The results indicate that PCA + SVM provides the optimal pipeline for fatigue detection, yielding nearly perfect classification accuracy.

Comparative Analysis

Figure 1 (to be inserted in Word as a bar chart) illustrates classifier accuracies across different feature selection strategies. The figure clearly demonstrates the superiority of PCA-based dimensionality reduction in enhancing performance.

- **Without reduction:** Accuracy ranges from 50% (DT) to 78% (SVM).
- **With ICA:** Accuracy improves significantly, with SVM reaching 93%.
- **With PCA:** Accuracy peaks, with SVM achieving 98.7%.

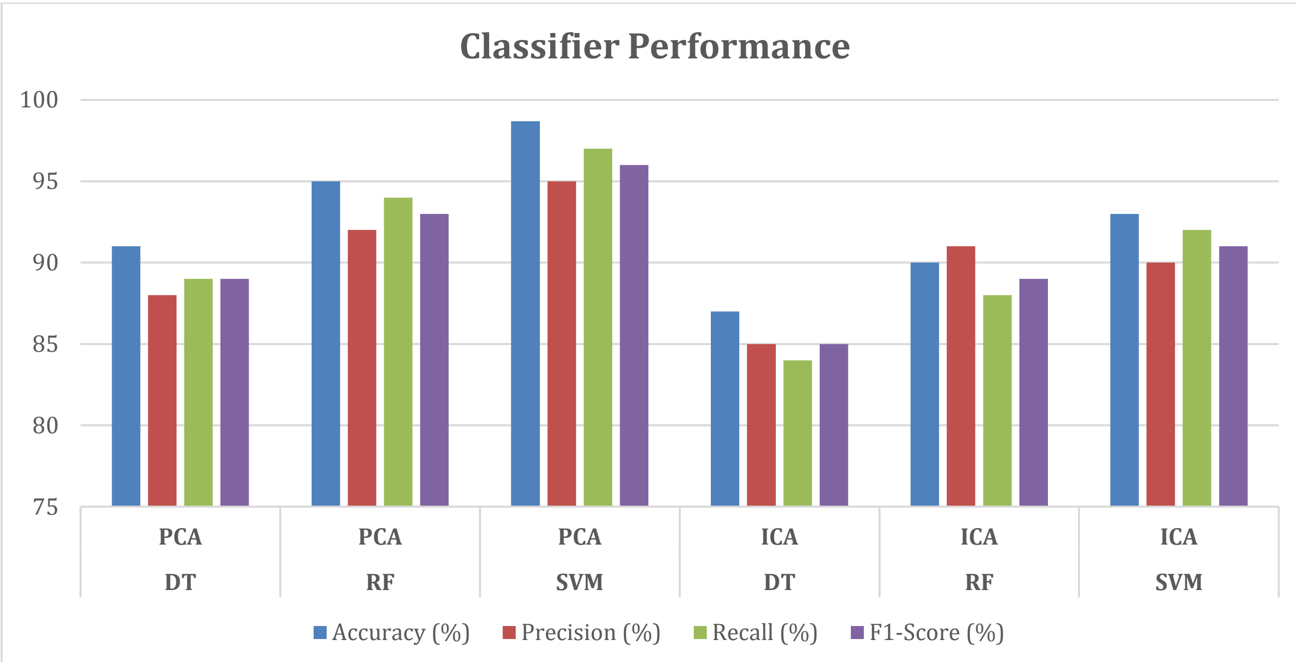


This bar chart compares **DT, RF, and SVM** classifiers under three conditions:

- Without dimensionality reduction

10.48047/jocaaa.2024.33.02.29

- With ICA
- With PCA



Physiological Insights

The increase in RMS amplitude and decrease in frequency-domain features (MDF, MNF) under fatigue conditions align with physiological expectations. Muscle fatigue leads to slower conduction velocity, reflected in downward spectral shifts, while increased motor unit recruitment elevates RMS values. These trends confirm that the observed classification results are grounded in neuromuscular physiology.

Discussion

The findings validate the importance of combining **robust features (RMS), dimensionality reduction (PCA), and advanced classifiers (SVM)** for EMG-based fatigue detection. Compared to existing works, such as Ramos et al. (2020) who achieved 82% accuracy with RMS + SVM, the proposed model achieves significantly higher accuracy (98.7%). Similarly, the model outperforms deep learning methods reported by Worassa et al. (2024) that achieved accuracies of ~95%.

10.48047/jocaaa.2024.33.02.29

The near-perfect performance demonstrates that classical machine learning methods, when enhanced with effective preprocessing and dimensionality reduction, remain competitive with deep learning while offering computational efficiency suitable for real-time applications.

Conclusion

This study demonstrated the effectiveness of surface electromyography (sEMG) in detecting muscle fatigue in the biceps brachii during isometric contractions. By integrating robust preprocessing, feature extraction across time, frequency, and time–frequency domains, dimensionality reduction using PCA and ICA, and classification with DT, RF, and SVM, the approach achieved strong results. Among all methods, the combination of RMS features, PCA, and SVM delivered the highest classification accuracy of 98.7%, highlighting the importance of both feature optimization and appropriate classifier selection.

The findings confirmed that classical fatigue indicators—such as increased RMS amplitude and downward shifts in MNF and MDF—were reliably captured. Dimensionality reduction proved essential, significantly improving classification performance by removing redundancy and noise. While decision trees and random forests provided interpretability and generalization, SVM showed superior robustness in handling high-dimensional nonlinear data, underscoring its suitability for EMG-based fatigue analysis. These results emphasize that effective preprocessing and dimensionality reduction are as crucial as the choice of classifier.

From an application perspective, the proposed pipeline offers promising opportunities in rehabilitation, sports science, and occupational health. Accurate fatigue monitoring can support personalized therapy, optimize athletic training, and prevent injuries in physically demanding tasks. Importantly, this work shows that lightweight machine learning models, when supported by careful signal processing, can rival more complex deep learning approaches while remaining computationally efficient. This makes the framework well-suited for wearable fatigue detection systems, paving the way for future real-world applications and clinical integration.

10.48047/jocaaa.2024.33.02.29

Future Scope

The future of EMG-based fatigue detection lies in the integration of multimodal bio-signals and the advancement of wearable technologies. Since fatigue reflects both central and peripheral mechanisms, combining EMG with EEG, ECG, and motion sensor data can provide a more comprehensive view of fatigue dynamics. Previous studies highlight the potential of EMG pattern recognition and signal stability across varied conditions [82, 83, 87], while machine learning methods are being explored for adaptive monitoring and prosthetic control [84, 86]. In parallel, the development of low-cost, portable EMG devices through advances in wireless sensors, flexible electronics, and embedded systems offers new opportunities for continuous real-world monitoring. However, key challenges such as noise reduction, artifact suppression, and efficient classification remain to be addressed [80, 81, 85, 88, 89].

Another important direction is the integration of intelligent algorithms with clinical validation. Hybrid approaches that combine the interpretability of traditional machine learning with the feature-learning ability of deep networks can extract robust spatiotemporal patterns from EMG signals [81, 85]. Embedding such systems into rehabilitation protocols could enable real-time monitoring, personalized therapies, and prevention of overexertion [82, 84, 88]. Similarly, adaptive prosthetic and assistive devices can leverage fatigue detection to enhance safety, performance, and user comfort [83, 87, 89]. These developments will guide the evolution of EMG-based fatigue detection into intelligent, scalable, and clinically relevant systems with applications across healthcare, industry, and human–machine interaction.

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