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Machine Learning Techniques for Distinguishing Hand Gestures from Forearm Muscle Activity

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Abstract: This research aimed to explore the feasibility of using forearm electromyography (EMG) data for identifying different hand gestures. The study involved 10 participants (7 males and 3 females) who performed eight different hand gestures while their flexor digitorum superficialis (FDS) and extensor digitorum communis (EDC) muscles were recorded. The recorded data was split into 80% for training and 20% for testing. The study compared the effectiveness of Deep Neural Network and Random Forest algorithms based on five different levels of moving window sizes (200, 400, 600, 800, and 1000 milliseconds). A wavelet approach was used to reconstruct the data and remove noise that does not represent the EMG signals accurately. Eighteen features were then extracted from the time and frequency domains of the analysis to characterize the complex signals. The study found that larger moving window sizes had higher accuracy rates than small moving window sizes due to the larger temporal resolution it provides. The Deep Neural Network showed a higher performance with a 1000-millisecond stream, achieving an accuracy rate of 97.13%, while the Random Forest algorithm achieved the highest accuracy rate of 96.65% with the same stream duration. In conclusion, the study found that a Deep Neural Network based on a 1000-millisecond stream was the most accurate, with an accuracy rate of 97.13%, while a Random Forest based on a 200-millisecond stream was the most efficient, with an accuracy rate of 84.77%. Future research could expand the sample size, include more hand gestures, and use different feature extraction methods and modeling algorithms to further improve the accuracy and efficiency of the system.

Keywords: Machine Learning, Electromyography, Extended Reality

1. Introduction

Immersive experiences have been revolutionized by Extended Reality (XR) technologies, including Virtual Reality (VR), Mixed Reality (MR), and Augmented Reality (AR). These technologies, with embedded displays, have gained significant popularity across industries, particularly in healthcare and entertainment. However, along with their transformative impact, XR advancements also pose challenges.

One challenge lies in the discomfort caused by current computer-vision-based hand tracking systems used in XR applications. Users may experience issues like gorilla arm syndrome and rotator cuff injuries. Studies have shown that musculoskeletal pain and injury risks, particularly in the neck and shoulder areas, can result from the use of XR applications. To mitigate such injuries, experts recommend positioning the target site slightly below eye height by 15° (Penumudi et al., 2020). Unfortunately, adherence to this guideline is often challenging due to the limited range of these systems.

Another significant challenge is accurately categorizing hand movements within computer vision-based XR applications. These systems rely on high frame rates to capture precise hand motions, with each frame subsequently processed for gesture classification. The high-dimensional nature of the captured frames, coupled with increased pixel count, requires extensive processing for accurate gesture recognition (Qvarfordt et al., 2018). Consequently, XR environments often suffer from unstable virtual realities (Miller, 2022). Moreover, computer vision systems struggle to perceive body motions accurately due to factors like complex backgrounds, variable lighting conditions, and low-resolution cameras, leading to less reliable categorization outcomes.

To address these challenges, electromyography (EMG) sensors have emerged as a promising alternative to computer vision-based hand tracking systems. EMG sensors monitor the electrical activity in muscle cells, offering more effective

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gesture classification with lower computational requirements. Unlike computer vision systems, EMG sensors can divide data into short clips, extracting minimal features for classification purposes. Additionally, EMG sensors are not influenced by hand position or lighting conditions since they primarily focus on recording muscular activity. Despite being primarily used in medical equipment, the development of affordable and high-quality EMG sensors has sparked renewed interest in their application within XR environments.

The objective of this research is to identify feature extraction methods and machine learning models that offer high performance and analyze algorithm accuracies in relation to spontaneous reactions. This analysis will provide insights into real-world scenarios. To enhance accuracy, this EMG study incorporates features from multidomain analysis. Various machine learning models and their computational expenses at different signal lengths are explored to determine the most effective approach. The hypothesis posits that even with minimal features and simple machine learning models, XR-based environments can achieve high levels of accuracy and quick response.

2. Method

2.1 Participants

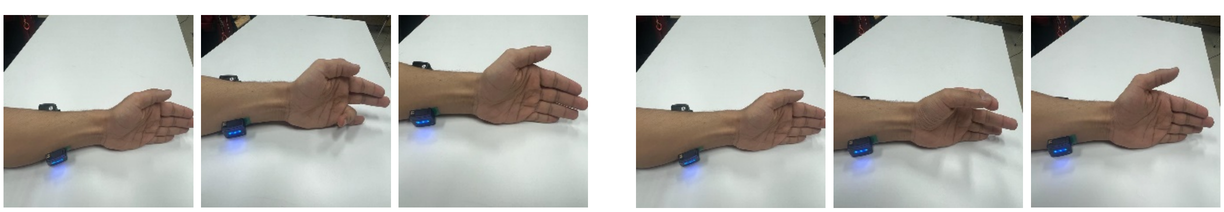
Ten adult students (7 male and 3 female) volunteered to be recorded using EMG sensors during various hand gesture actions. Their height feet, weight in kilograms, and age in years have the following means and standard deviations: 5.546±0.288, 66.6±14.4, and 23.8±1.33. Before beginning the data gathering process, each of these individuals agreed to sign a written consent form from the Institutional Review Board (IRB).

2.2 Experimental Protocol

To capture precise muscle activity during hand gestures in extended reality (XR) environments, we employed two Delsys Trigno electromyography (EMG) sensors provided by Delsys Inc. in Boston, MA. These sensors were strategically positioned on the flexor digitorum superficialis (FDS) and extensor digitorum communis (EDC) muscles, known to be actively involved in hand movements. During the data collection phase, participants were instructed to perform eight hand gestures commonly used in XR applications. These gestures were carefully selected to encompass a wide range of movements and actions typically performed in XR scenarios. Figure 1 provides a visual representation and clear overview of the specific gestures recorded.

While wearing the EMG sensors, participants executed each hand gesture, and the sensors recorded the corresponding muscle activity. The EMG sensors captured muscle activity in microvolts and operated at a sampling rate of 1000 Hz, ensuring detailed and accurate measurements of muscle activity during the execution of the hand gestures. By capturing muscle activity at a high resolution and frequency, the EMG sensors provided valuable data on the intensity and timing of muscle contractions during each hand gesture. This data serves as a crucial foundation for analyzing and understanding the muscle activation patterns associated with XR hand gestures.

The combination of the strategically placed Delsys Trigno EMG sensors on the FDS and EDC muscles, along with the carefully chosen set of eight hand gestures, establishes a robust setup for capturing muscle activity during XR interactions. The acquired data will significantly contribute to our comprehension of the physiological aspects of hand movements in XR environments and aid in the development of more accurate and efficient gesture recognition systems.



Ring Finger Movement　　Index Finger Pinch

Figure 1

2.3 Signal Preprocessing

EMG signals, while useful for detecting electrical activity in specific body parts, often suffer from unwanted signals such as heartbeats, electronic sensor noise, and signal instabilities. To address these challenges, many research papers employ frequency-selective methods like bandpass filters and resampling. However, these methods often result in a significant loss of original signal data when attempting to remove noise (Mamun et al., 2013). An alternative approach recommended for denoising EMG signals is the use of wavelet denoising techniques, which leverage both the time and frequency domains simultaneously. Unlike frequency-selective methods based on the Fourier Transform, wavelet denoising methods retain more signal data by incorporating information from both domains.

Previous studies have demonstrated the effectiveness of the Daubechies order 6 wavelet with four layers of decomposition for denoising EMG data (Sobahi, 2011). This wavelet exhibits spiky patterns that closely match EMG patterns, enabling better preservation of signals during the denoising process. In conjunction with this wavelet, a soft Bayes Shrink threshold is commonly employed. Although typically used for image denoising, the soft Bayes Shrink threshold can also be applied to one-dimensional signals like EMGs.

During each level of wavelet denoising, the EMG signal is divided into two subbands: approximation coefficient and detail coefficient. The approximation coefficient is then recursively divided into the same two subbands in subsequent wavelet decompositions. Each subband is assigned a specific threshold based on a Generalized Gaussian Distribution (GGD). By applying these thresholds to the wavelet coefficients, the denoised estimate is obtained through the inverse wavelet transform (Baldazzi et al., 2020).

To improve the accuracy of training, the denoised EMG data is segmented into clips of a predetermined size, with a 90% overlap between adjacent windows. The use of overlapping windows helps to retain common signal characteristics across larger temporal resolution ranges, thereby enhancing the algorithm's memory retention (Gevins et al., 1999).

By employing wavelet denoising techniques with the Daubechies order 6 wavelet, utilizing a soft Bayes Shrink threshold, and segmenting the denoised data into overlapping windows, the EMG noise can be effectively reduced while preserving important signal information. These denoised and segmented signals provide a cleaner and more accurate foundation for subsequent analysis, such as feature extraction and machine learning algorithms, leading to improved performance in tasks like gesture recognition within XR environments.

2.4 Time Domain Features

In gesture classification, time domain features are often preferred due to their computational simplicity and ability to capture transient responses of bio-signals. For this study, a set of features listed were utilized for feature extraction, providing valuable information for analyzing and classifying the recorded EMG signals.

(1) The Integrated Absolute of Second Derivative: This mathematical approach calculates the rate of change of a signal, enabling the detection of properties such as signal concavity, inflection points, and changes in curvature. It is particularly useful for identifying features that are less affected by signal noise (Azhiri et al., 2021).
(2) The Integrated Absolute of Third Derivative: This method calculates the rate of change of a signal's rate of change to capture the rapid changes in curvatures (Azhiri et al., 2021).
(3) The Integrated Exponential of Absolute Values: This mathematical technique amplifies larger data values while suppressing smaller ones, aiding in the detection of critical elements in a signal that might be challenging to identify using other techniques. It is frequently used in applications requiring the detection of subtle yet significant changes in signals, such as medical or scientific research (Azhiri et al., 2021).
(4) The Integrated EMG function: This function enhances positive samples while suppressing negative sections of a signal, making it valuable for evaluating muscle activation in electromyography (EMG) studies. It can be applied in rehabilitation or sports training to identify and measure the intensity of muscular contractions (Azhiri et al., 2021).
(5) The Mean Absolute Values: This technique calculates the average absolute amplitude of a signal, providing information about the overall amplitude and allowing for the determination of trends or variations over time. It is widely used in data analysis and signal processing applications (Abbaspour et al., 2020).
(6) The Root Mean Square: By calculating the total energy of a signal, this method provides fundamental information about its power or intensity. It is essential in applications where quantifying signal strength is crucial, such as audio or vibration analysis (Abbaspour et al., 2020).
(7) The Variance: This statistical tool measures the amount of change in a signal over time, offering insights into the signal's stability or variability. It is frequently utilized in machine learning and data analysis applications to detect patterns or trends in signals (Burns et al., 2007).

(8) The Zero Crosses: This method determines the frequency of a signal by counting the instances when it crosses the y-axis, revealing periodicity or oscillations. It is commonly used in audio and communication applications (Azhiri et al., 2021).
(9) The Waveform Length: This mathematical method calculates the total length of a signal, facilitating the detection of changes or abnormalities and providing information about the level of activity. It is frequently employed in signal processing and data analysis applications (Azhiri et al., 2021).

2.5 Frequency Domain Features

Signal analysis relies on frequency domain features, which transform time domain signals into power spectral density (PSD) across various frequencies, providing important frequency content information. While the Fast Fourier transform (FFT) is commonly used for frequency domain analysis, it has limitations such as high variance and the assumption of stationary signals, which may not be suitable for rapidly changing EMG signals in XR applications. Alternatively, the Multitaper Periodogram and Welch Periodogram methods can be employed.

The Multitaper Periodogram utilizes multiple Slepian tapers to independently estimate spectral content at different positions in the EMG data. Each tapered time series undergoes FFT to convert them into the frequency domain, and the resulting tapers are averaged to create a Multitaper Periodogram. While this method reduces variance and maintains high frequency resolution, it is computationally intensive (Prerau et al., 2017).

In contrast, the Welch Periodogram divides an EMG signal into smaller windows of data, applies FFT to each window, and averages the resulting spectra to obtain the final result (Rahi et al., 2014). This approach reduces variance by averaging spectra from different windows, providing a smoother estimate of the power spectral density. However, it sacrifices frequency resolution compared to the Multitaper method.

For this study, the Welch Periodogram was chosen over the Multitaper method due to its computational efficiency, which is crucial for XR applications. While both methods offer similar performance, the Multitaper method incurs higher computational costs, making it less suitable for the study's objectives. Empirical evidence suggests that the Welch Periodogram performs well in most cases, except for particularly noisy signals where precision may decrease compared to the Multitaper Periodogram. However, proper sensor connections and appropriate data normalization techniques can help mitigate this issue.

To ensure adequate frequency resolution, the window size for computing the Welch Periodogram was set to 90% of the EMG signal clip, striking a balance between capturing sufficient temporal information within each window and maintaining reasonable frequency resolution. Furthermore, an 80% overlap between adjacent signal clips was implemented to retain common signal characteristics across larger temporal resolution ranges, preserving important temporal dynamics and contributing to the algorithm's memory retention.

The Welch Periodogram was then applied to the EMG signals, extracting various frequency domain features. These features offer valuable insights into the power distribution across different frequencies, enabling the characterization of unique spectral properties associated with specific hand gestures in XR applications. By incorporating these frequency domain features with the previously mentioned time domain features, the gesture classification algorithm can achieve a more comprehensive and robust analysis of the EMG signals.

The extracted features include:

(1) Average Frequency: A standard metric in signal processing, it provides information on the frequency makeup of the signal by considering the power at each frequency bin. It enables the identification of main frequency bands within the signal (Phinyomark et al., 2012).
(2) Median Frequency: This metric represents the frequency at which half of the signal's strength is below and half is above. It helps identify variations in the frequency distribution of the signal and provides details about the signal's center frequency (Phinyomark et al., 2012).
(3) Peak Frequency: It refers to the frequency at which the signal exhibits the highest power. Tracking variations in frequency content over time and determining the dominant frequency in a signal are possible applications of this feature (Phinyomark et al., 2012).
(4) Spectral Entropy: This metric measures the complexity of a signal by assessing how evenly the signal's energy is distributed across its frequency spectrum. It can detect changes in signal complexity, particularly in the presence of noise or other disturbances (Tian et al., 2017).
(5) Total Power: It represents the sum of power at each frequency bin, reflecting the overall energy of the signal. This feature provides insights into the signal's overall strength and allows for comparisons between transmissions with different frequency contents (Phinyomark et al., 2012).

(6) Mean Power Frequency: This feature indicates the mean power expressed throughout the periodogram (Gerdle & Fugl-Meyer, 1992).
(7) Signal to Noise Ratio (SNR): This metric compares the strength of the signal to the assumed noise range. In this study, the lowest 10% of the maximum power was assumed to be noise. SNR is commonly used to evaluate signal quality and can detect the presence of noise or interference (Raez et al., 2006).
(8) Spectral Edge Frequency: It refers to the frequency below which a certain percentage of the signal's power is confined. In this study, a 95% confidence interval was chosen to emphasize this information. The spectral edge frequency detects changes in frequency content and provides insights into the distribution of energy across the frequency spectrum (Jildenstål et al., 2022).
(9) Frequency Ratio: This measure contrasts the power in the frequency ranges of 20–250 Hz and 250–1000 Hz. It allows for the detection of variations in frequency content over time and provides details about the relative strength of different frequency bands in the signal (Wang et al., 2015).

2.6 Machine Learning Models

The dataset used in this study was divided into 80% for training and 20% for testing the machine learning models. However, before incorporating the extracted features into the machine learning algorithms, a preprocessing step was applied to the data using the Standard Scalar method. This method helps normalize the data and prevent any skewed effects that could lead to imbalanced classification results in the machine learning algorithms.

Two different algorithms, namely Random Forest and Deep Neural Network, were evaluated for their performance. Random Forest is a unique ensemble method that creates multiple decision trees from subsets of observations in the dataset. These trees are then aggregated to determine the majority vote for the final classification result. To optimize the Random Forest algorithm and avoid underfitting or overfitting, a hyperparameter optimization technique called GridSearchCV was employed. By performing a grid search and cross-validation with 5 folds, the optimal number of trees for the algorithm was determined, leading to the highest possible accuracy.

The Deep Neural Network (DNN) is a powerful model composed of interconnected nodes arranged in layers that transmit signals and learn from the data. In this project, the DNN architecture consisted of an input layer with 60 nodes, three hidden layers with 1000 nodes each, and an output layer with 8 nodes corresponding to the different classes. The ReLU activation function was used in the input and hidden layers, while the sigmoid activation function was applied in the output layer to produce the algorithm's final output. During the training phase of the DNN, a batch size of 64 was used, which improves the algorithm's generalization and reduces computational expenses.

To assess the performance of the machine learning models, several evaluation metrics were utilized, including the F1 score, precision, recall, and accuracy. The F1 score, precision, and recall help identify any biases in the algorithm's predictions by considering the distribution of classification labels. Even though the dataset had balanced class proportions in both the training and testing sets, these evaluation metrics aid in pinpointing specific errors made by the algorithm using True Positives, False Positives, and False Negatives. Additionally, the overall accuracy of the model on the test dataset was calculated by dividing the number of correctly classified samples by the total number of samples.

3. Results

3.1 Wavelet Denoising

Upon implementing the wavelet denoising technique, the noisy segments of data underwent a transformation, whereby the unwanted noise components were significantly reduced. Simultaneously, the vital characteristics and patterns indicative of the hand motion were successfully preserved. This denoising process allowed for enhanced clarity and accuracy in analyzing the EMG signals, ultimately facilitating more reliable interpretation and classification of hand motions.

3.2 Algorithm Accuracies

Following the denoising process, the study proceeded to evaluate the performance of two distinct machine learning models on the testing dataset, as mentioned earlier. A comprehensive analysis of various metrics was conducted to assess the effectiveness of each algorithm. Notably, the study focused on testing accuracy, precision, recall, and F1 score as key performance indicators.

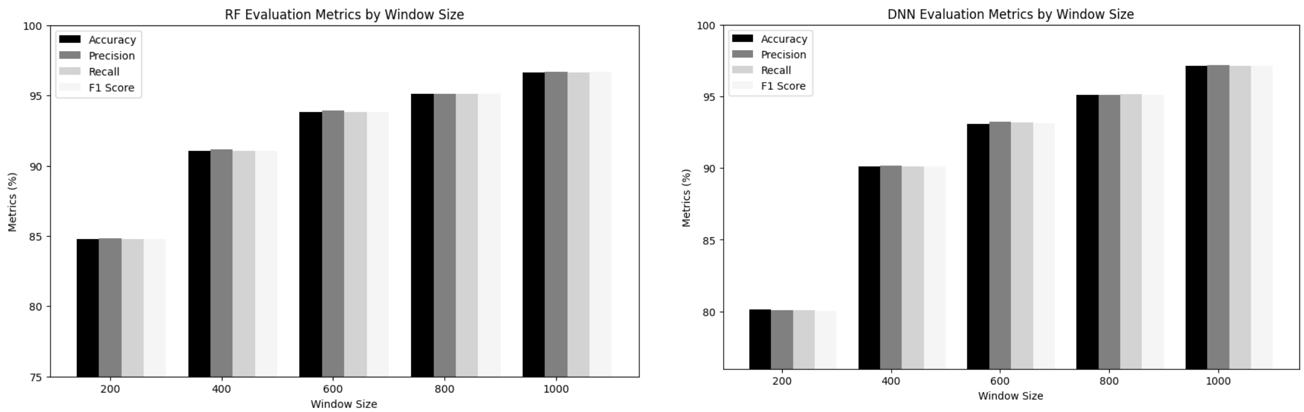


Figure 2

The results of the evaluation, as presented in Figure 2, reveal consistent classification accuracy across different window sizes and techniques. A notable tradeoff exists between window size and accuracy, with longer window clips generally yielding higher algorithm accuracy but lower accuracy with shorter window lengths. It was observed that the Random Forest algorithm performed better when analyzing shorter EMG clips, whereas the Deep Neural Network approach exhibited superior performance when analyzing longer EMG clips. It is important to note that the choice of algorithm in XR (Extended Reality) applications may vary depending on the priorities of the specific use case. Certain applications may prioritize classification accuracy over efficiency. In such cases, a Deep Neural Network algorithm might be preferred, especially for 1000-millisecond streams where classification results are delayed from a larger signal window but returned with higher accuracy. However, scenarios where speed is prioritized over accuracy may benefit from employing a Random Forest algorithm, particularly for 200-millisecond streams, despite the potential decrease in accuracy.

This study's findings provide valuable insights into the suitability of different algorithms for processing and classifying EMG data segments. By considering the tradeoff between accuracy and computational efficiency, researchers and practitioners can make informed decisions when selecting the most appropriate algorithm for their specific XR application. Additionally, the presented metrics and visualizations offer a comprehensive overview of the performance of each algorithm, facilitating a deeper understanding of their strengths and limitations in the context of EMG signal classification.

4. Discussion

4.1 Overview

The main objective of this study was to evaluate various classification methods for eight different hand movements commonly used in XR applications. Two EMG sensors were strategically placed on different muscles, and the analysis focused on the relationship between signal length duration and algorithm accuracy. The aim was to enhance the classification accuracy without considering computational efficiency or speed measurements. The study also explored different feature extraction techniques across multiple domains of analysis, various window lengths, and machine learning algorithms to identify the most effective methods.

One important finding of this study was the significance of wavelet denoising, which is often overlooked in existing literature. By removing noise while retaining signal characteristics, wavelet denoising plays a crucial role in achieving accurate classification results. It was discovered that feature extraction and machine learning model classifications were remarkably fast, without any notable impact on feedback time. These findings suggest that the proposed pipeline can achieve accurate and rapid analysis of EMG data, making it a promising tool for a wide range of real-time applications.

Upon extracting the features, the study observed that algorithm accuracy varied depending on the length of the input signal. The shorter the signal length, the lower the algorithm accuracy tended to be. This relationship between signal length and accuracy has been noted in several other studies (Azhiri et al., 2021). For example, researchers from the University of Texas found accuracies in the 80% range between 250 and 500 milliseconds, which gradually increased and reached a plateau of around 97%. They raised concerns about the execution delay of EMG machine learning systems and chose an algorithm with a 95.5% accuracy rate on an 800-millisecond signal length. They prioritized accuracy over signal efficiency in their selection process.

This phenomenon of algorithm accuracy in relation to signal length presents an opportunity for XR applications. Based on this study, two options can be considered: utilizing the Random Forest algorithm with a 200-millisecond signal length, which emphasizes efficiency and achieves an accuracy rate of 84.77% or employing the Deep Neural network algorithm with a 1000-millisecond signal length, which achieves a higher accuracy rate of approximately 97.13%.

4.2 Future Work

The integration of computer vision in Extended Reality (XR) applications presents numerous advantages, including the elimination of external devices or sensors. In contrast, the electromyography (EMG) approach employed in this study relies on bulky and costly sensors, necessitates meticulous calibration for precise muscular placement, and must account for variations in muscle size and limb proportions. Consequently, data collection using EMG technology may yield divergent results among individuals with varying muscular strengths and arm sizes, a concern absent in computer vision algorithms.

To address this limitation, the study endeavored to assemble a comprehensive and diverse dataset encompassing individuals with a range of muscular profiles. The goal was to develop a generalized machine learning algorithm capable of accommodating a broader population. Such an approach has the potential to foster inclusivity and equality in the utilization of XR technology, particularly in domains such as assistive technologies for individuals with disabilities or injuries.

Despite its limitations, it is essential to acknowledge the potential advantages offered by the EMG approach. Notably, it enables more precise and accurate measurements in specific applications, such as fine motor control and the detection of subtle changes in muscle activity. Consequently, when selecting the appropriate technology, careful consideration of the specific requirements of a given application becomes imperative. In the future, enhancements in EMG technology could involve the reduction of sensor size and cost, streamlining calibration processes, and the development of advanced algorithms that account for individual disparities in muscular profiles. These advancements would contribute to the broader adoption and refinement of EMG-based approaches in XR applications.

5. Conclusions

In conclusion, this study has successfully developed an optimized classification approach that effectively balances the accuracy and efficiency requirements of EMG-based classification for XR applications. Through the implementation of noise reduction techniques and robust feature extraction methods, the study achieved remarkable results. The utilization of a Deep Neural Network with a 1000-millisecond stream yielded the highest accuracy rate of 97.13%, while employing a Random Forest algorithm with a 200-millisecond stream achieved optimal efficiency, attaining an accuracy rate of 84.77%.

An important aspect highlighted by the study is the minimal computational resources required for this classification approach, rendering it highly suitable for integration into XR applications. This characteristic holds significant promise for the future development and implementation of XR technologies. By striking a balance between accuracy and efficiency, this research breakthrough has the potential to revolutionize the XR application landscape.

The findings of this study not only contribute to advancing the field of EMG-based classification but also offer practical implications for the development and deployment of XR applications. The optimized approach presented herein lays a strong foundation for more refined and effective XR technologies. It paves the way for improved user experiences, particularly in fields such as prosthetics, physical therapy, and sports training, where precise real-time measurements are crucial.

In essence, this study represents a significant milestone, demonstrating the potential to reshape the XR landscape by leveraging the advancements achieved in EMG-based classification. The findings provide valuable insights into the optimization of accuracy and efficiency tradeoffs, thereby opening new avenues for innovation and fostering the integration of XR applications into various domains.

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