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Classification of Amputee EMG Signals Using Machine Learning Techniques

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In the field of prosthetics and assistive technology, the accurate classification of EMG signals from amputees is of paramount importance. These signals provide insights into the intended movements of the user and are essential for designing intuitive and responsive prosthetic devices. This research is primarily centered on the meticulous classification of EMG signals using advanced machine-learning techniques. This research contributes by achieving high accuracy (95.77%, 97.36%, and 95.77%) using SVM, ANN, and CNN, respectively, on EMG signals from 11 amputees in the Ninapro database, offering an innovative approach to improve amputee assistance. We employed SVM, ANN, and CNN algorithms to classify EMG signals from 11 amputees in the Ninapro database, utilizing a robust methodology. This research yielded impressive accuracy rates of 95.77%, 97.36%, and 95.77% for SVM, ANN, and CNN, respectively, demonstrating the effectiveness of machine-learning techniques in amputee EMG signal classification. The discussion highlights the potential implications for improving prosthetic control and rehabilitation. This research presents promising results and highlights the potential of machine learning for advancing amputee assistance, opening new avenues for research and application.

Abbreviation

EMG: Electromyography
ANN: Artificial Neural Network.
SVM: Support Vector Machine.
CNN: Convolutional Neural Network.
Ninapro: Non-Invasive, Non-Intrusive, and Prosthetic Control Database

Keywords: EMG, SVM, CNN, ANN, Feature Extraction.

Introduction:

The classification of EMG signals stands at the forefront of research endeavors aimed at enhancing human-computer interaction, prosthetics, rehabilitation, and robotics. EMG signals, which are electrical manifestations of muscle activity, carry valuable insights into human hand movements, making them a prime candidate for deciphering complex motor tasks. With the proliferation of machine learning techniques, particularly in the domain of pattern recognition, the potential to harness EMG signals for practical applications has expanded significantly [1].

This research centers on the classification of EMG signals derived from amputee subjects performing various hand movements. Amputees face unique challenges in regaining fine motor control, and EMG-based approaches offer a promising avenue to bridge the gap between intention and action. The dataset utilized in this research is sourced from the NINAPRO dataset, encompassing data from 11 amputee participants. This dataset not only provides a rich source of information for analysis but also comes up with an opportunity to contribute towards the development of assistive technologies tailored to individuals with limb amputations.

The significance of this scrutiny lies in its potential to advance the fields of EMG signal processing and machine learning by showcasing the applicability and performance of SVM, CNN, and ANN models [2] in the context of amputee-focused hand movement classification [3]. The outcomes have implications for prosthetic design, rehabilitation strategies, and the development of intuitive human-machine interfaces. Given the increasing momentum in incorporating advanced machine learning methods into the field of EMG analysis, this research endeavors to contribute to the growing need of knowledge at the intersection of signal processing, machine learning, and assistive technology, ultimately improving the quality of life for individuals with limb amputations [4].

The utilization of EMG signals for the control of prosthetic devices has gained considerable attention in the field of assistive technology. EMG signals, generated by muscle contractions, offer a direct interface between the user's intention and the prosthetic limb's movement. This interface has the potential to revolutionize the functionality and usability of prosthetic devices, enabling amputees to regain a higher degree of natural movement [3].

Traditionally, prosthetic control has relied on mechanical switches or predefined algorithms that map specific movements to predefined actions. However, these methods lack the adaptability required to accommodate individual differences, dynamic contexts, and nuanced movements. As a result, the development of intelligent prosthetic control mechanisms has become essential to enhancing the quality of life for amputees [4].

Machine learning approaches have emerged as powerful tools for addressing the challenges associated with EMG-based prosthetic control. These approaches allow prosthetic devices to learn and adapt to the unique EMG patterns exhibited by individual users. By leveraging the capabilities of machine learning models, the accuracy and responsiveness of prosthetic control systems can be significantly improved [5].

Several studies have investigated the application of machine learning techniques to classify EMG signals for prosthetic control [4][7][2][6] employed a deep convolutional neural network to categorize EMG signals received from amputees and achieved impressive accuracy rates, highlighting the potential of deep learning methods in this domain. Another study by Scheme [7] utilized SVMs to decode hand movements from EMG signals, demonstrating the feasibility of SVMs in translating EMG data into prosthetic control commands [4].

ANNs have also shown promise in EMG signal classification tasks [2] applied ANNs to decode hand gestures from EMG signals and achieved accurate control of prosthetic hands. CNNs [8], well-known for their ability to capture spatial patterns, have demonstrated potential in analyzing the spatial distribution of muscle activations within EMG signals [6].

Despite these advancements, the effectiveness of different machine learning models in classifying EMG signals remains a perpetual area of research. This study aims to contribute to this knowledge by evaluating and comparing the performance of ANNs, SVMs, and CNNs in the context of classifying EMG signals from amputees [8]. The findings of this research hold the potential to shape the future of prosthetic control systems and offer a deeper understanding of the capabilities of various machine-learning models in enhancing the interaction between amputees and their assistive devices [9].

Novelty Statement:

In the realm of prosthetic control for amputees, the accurate classification of EMG signals has remained a persistent challenge due to the intricate nature of these signals and their susceptibility to factors such as muscle fatigue and electrode displacement. Our study introduces a novel and innovative approach that takes on these complexities head-on. we have achieved accurate and reliable EMG signal classification by meticulously selecting the best features and algorithms.

Objectives:

- To collect a dataset of EMG signals from amputees and select appropriate machine-learning algorithms for the classification of EMG signals.
- To optimize the selected algorithms for feature extraction and classification accuracy.
- Interpret the results and identify the most effective machine learning algorithms for accurate classification of EMG signals from amputees.

Methodology:

Figure 1 displays the methodology utilized for the classification of EMG signals obtained from amputees.

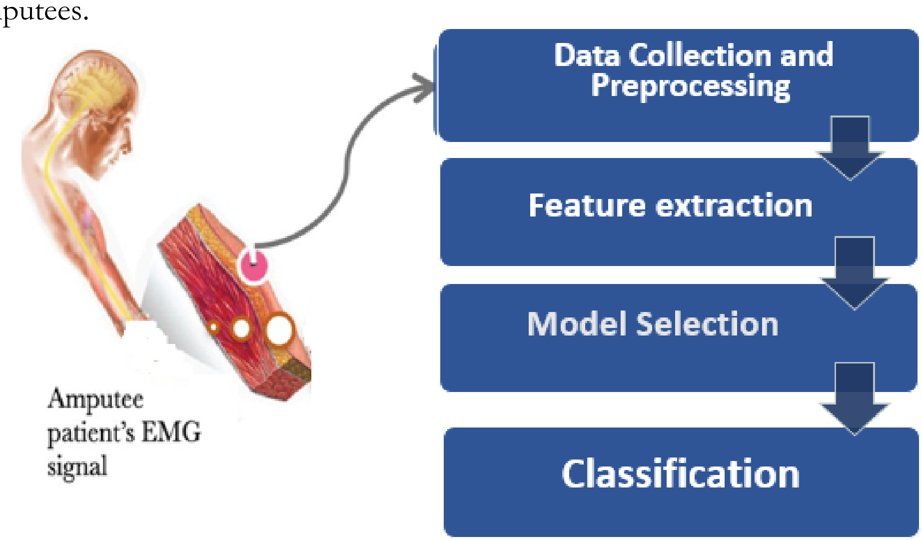

Figure 1. Methodology of classification of EMG Signals of amputees

Data Collection:

The dataset used in this research has been obtained from the NinaPro database https://ninapro.hevs.ch/ a reputable repository of EMG recordings specifically designed for amputee participants [10]. The database offers a diverse collection of EMG signals captured during various muscle activation patterns and activities, ensuring the representation of real-world scenarios.

Data Preprocessing:

MATLAB is utilized for initial preprocessing after acquiring the EMG dataset. This program removes noise and artifacts from the raw signals to enhance data quality. Filtering techniques such as low-pass, high-pass, and band-pass filters are applied to eliminate unwanted frequencies and improve signal fidelity [11]. Figure 2 shows the original EMG datasets.

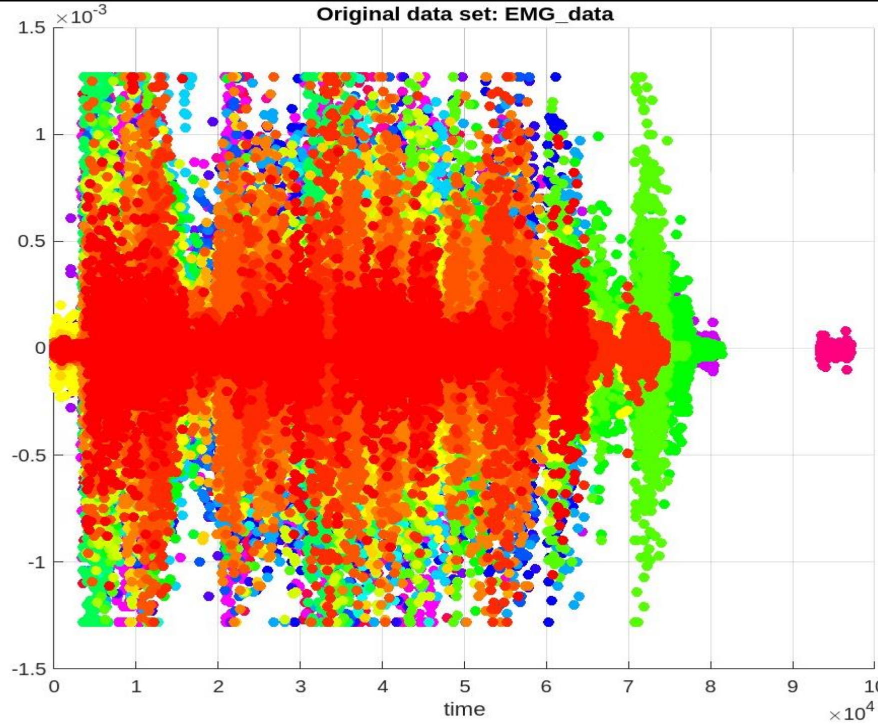

Figure 2. Raw Data

Feature Extraction:

Feature extraction plays a pivotal role in the classification of Electromyography (EMG) signals, as it transforms raw signals into representative numerical features that can effectively capture muscle activation patterns. In this research, MATLAB is employed to extract a diverse set of features from the preprocessed EMG signals [12]. These features serve as the foundation for training and evaluating machine learning models for accurate classification [13][12][14][15][16][17][18].

Table 1: Various features classified through feature extraction.

S.No	Feature Name	Formula	Output
1	**Integrated EMG**	$IEMG = \sum_{n=1}^{N} \lvert x_n \rvert$	Detect the muscle activity
2	**Mean Absolute Value**	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert$	Detection of muscle contraction levels
3	**Mean Absolute Value Slope (MAVS)**	$\mathrm{MAVS_i} = \mathrm{MAV_{i+1}} - \mathrm{MAV}$	The differences between the MAVs of adjacent segments are determined
4	**Simple Square Integral**	$SSI = \sum_{n-1}^{N} \lvert x_n \rvert^2$	the energy of the EMG signal
5	**Variance of EMG**	$VAV = \frac{1}{N-1}\sum_{n-1}^{N} x_n^2$	power of the EMG signal
6	**Root Mean Square**	$RMS = \sqrt{\frac{1}{N}\sum_{n-1}^{N} \lvert x_n \rvert^2}$	Reflects the square root of the average squared values of the EMG signal, providing overall amplitude information.

7	**Waveform Length**	$WL = \sum_{n=1}^{n-1} \lvert x_{n+1} - x_n$	Measures the cumulative length of the signal, capturing changes in signal shape.
8	**Frequency Median (FMD)**	$\mathrm{FMD} = \frac{1}{2}\sum_{i=1}^{M} \mathrm{PSD}$	The power spectral density (PSD)
9	**Frequency Mean (FMN)**	$\mathrm{FMN} = \frac{\sum_{i=1}^{M} f_i \mathrm{PSD}_I}{\sum_{i=1}^{M} \mathrm{PSD}_i}$ $f_i = \frac{i^* \, sample\ rate}{2m}$	The summation of the product of the PSD and the frequency of the spectrum
10	**Modified Median Frequency (MMDF)**	$\mathrm{MMDF} = \frac{1}{2}\sum_{j=1}^{M} \mathrm{A_j}$	It is an expression of the frequency where spectrum is divided into two regions with equal amplitude

Model Selection and Training:

Using MATLAB's machine learning capabilities, three distinct models are chosen for classification: SVM, ANN, and CNN [19]. The dataset is partitioned into training, validation, and testing sets [20].

Results:

This study presents the outcomes of our investigation into the classification of EMG signals using three prominent machine learning algorithms: ANN, SVM, and CNN. Our analysis focused on the classification of EMG signals across a spectrum of hand movements. It is essential to note that prior to conducting the classification experiments, the dataset was meticulously divided into three distinct subsets: a training set, a testing set, and a validation set. This data division was implemented to ensure robust model development and accurate evaluation of our machine learning algorithms. We have presented the confusion matrices for each of the machine learning algorithms based on their classification performance.

ANN:

ANNs are a type of machine learning model inspired by the structure and function of biological neural networks. ANNs consist of interconnected layers of nodes, and the weights between the nodes are learned through a training process. ANNs have been widely used in the classification of EMG signals due to their ability to learn complex relationships between the input features and the output classes.

The confusion matrix was generated from the classification results of our trained ANN. This confusion matrix serves as a pivotal visualization in evaluating the ANN's performance in classifying the dataset. The x-axis of the confusion matrix represents the predicted class labels produced by ANN, while the y-axis represents the true class labels, reflecting the ground truth for each data point. The ANN achieved an impressive accuracy rate of 97.36%. This high accuracy indicates that the ANN correctly classified the majority of instances, signifying its proficiency in making precise predictions. The confusion matrix itself contains specific numerical values that reveal the counts of true positives, true negatives, false positives, and false negatives, allowing for a comprehensive evaluation of the ANN's classification capabilities.

CNN: CNNs can be effective for the classification of EMG signals in certain situations, particularly when dealing with time-series data like EMG. While CNNs are more commonly associated with image recognition tasks, they can also be adapted for sequential data like time-series signals.

The confusion matrix was derived from the classification outcomes of our CNN. This matrix serves as a critical visual tool for assessing the CNN's performance in the classification task. The x-axis of the confusion matrix signifies the predicted class labels generated by our CNN, while the y-axis represents the true class labels, indicating the ground truth for each data instance. The confusion matrix provides a detailed breakdown of the CNN's performance, showing the counts of true positives, true negatives, false positives, and false negatives, offering a thorough assessment. Remarkably, this CNN achieved an accuracy rate of 93.56%, underscoring its effectiveness in the classification of EMG signals. CNNs are particularly well-suited for tasks involving complex and spatial data, as they excel in capturing intricate patterns and learning hierarchical features. Their innate ability to automatically extract relevant features from raw data makes them a compelling choice for the classification of EMG signals, a domain where nuanced and subtle patterns are crucial for accurate identification and control in applications like prosthetics and rehabilitation. Figure 3, 4, 5, 6, shows accuracy obtained through different classification methods.

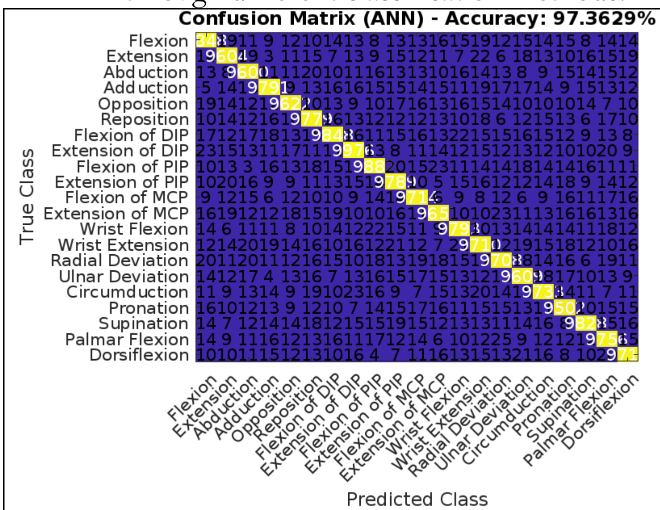

Figure 3. ANN Confusion matrix.

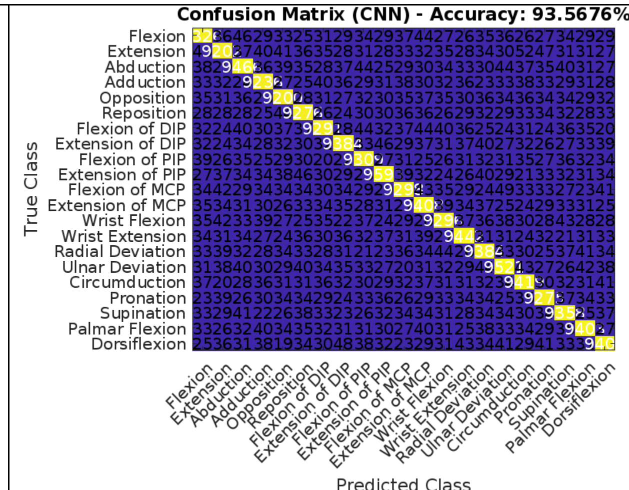

Figure 4. CNN Confusion matrix

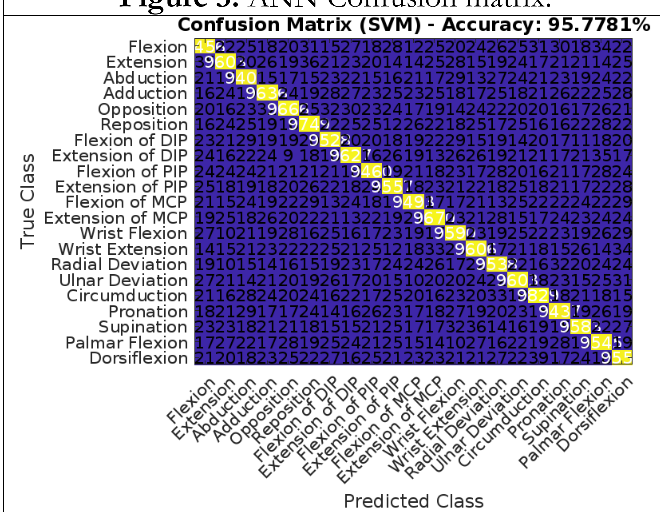

Figure 5. SVM Confusion Matrix

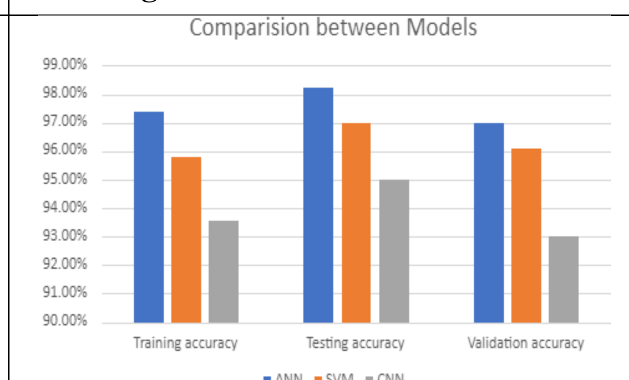

Figure 6. Model comparison

SVM:

SVMs are a promising choice for the classification of EMG signals. EMG signals, which represent muscle activity over time, often come with high dimensionality due to their time-series nature. SVMs excel in such high-dimensional spaces and are known for their ability to construct a well-defined decision boundary, making them suitable for separating different EMG signal patterns.

The confusion matrix provided a detailed breakdown of the SVM's performance, revealing the counts of true positives, true negatives, false positives, and false negatives, enabling a comprehensive evaluation. The x-axis of the confusion matrix represents the predicted class labels generated by our SVM, while the y-axis signifies the true class labels, reflecting the ground truth for each data point. Notably, this SVM achieved an impressive accuracy rate of 95.77%. This remarkable accuracy highlighted the prowess of SVMs as a top choice for classification tasks. SVMs are well-regarded for their ability to efficiently handle high-dimensional data, create well-defined decision boundaries, and generalize effectively. Their robustness against overfitting and adaptability to various data types make SVMs a reliable and versatile option in the realm of classification.

Performance Evaluation:

Table 2: Classification of EMG signals utilizing machine learning techniques.

Models	Training accuracy	Testing accuracy	Validation accuracy
ANN	97.36%	98.22%	97.00%
SVM	95.77%	97.00%	96.08%
CNN	93.56%	95.02%	92.99%

Table 1 shows that the classification of EMG (Electromyography) signals using machine learning models, three different approaches were evaluated: an ANN, a SVM, and a CNN. The ANN demonstrated superior performance with a high testing accuracy of 98.22% and consistent validation accuracy of 97.00%, making it a robust choice for EMG signal classification tasks. The SVM and CNN models also exhibited strong results, with testing accuracies of 97.00% and 95.02%, respectively, indicating their effectiveness in this domain. These findings highlighted the potential of machine learning technology, particularly the ANN, for accurate and reliable classification of EMG signals, which has significant implications for applications such as prosthetic control.

In the realm of EMG signal classification, three prominent machine learning models have evolved over time, each with its own unique strengths. ANNs have made significant strides, transitioning from early iterations that relied on handcrafted features to modern deep architectures capable of extracting intricate patterns directly from raw EMG data. SVMs, with their historical presence, have adapted through the integration of non-linear kernels, exhibiting reliable performance, particularly on smaller datasets and well-engineered feature sets. Meanwhile, CNNs, originally designed for image tasks, have been adapted for EMG signal processing, leveraging convolutional layers to uncover localized patterns and spatial dependencies within the signals, proving especially useful for surface EMG applications. Each model's performance hinges on factors like dataset complexity, computational requirements, and the capacity to automatically extract relevant information from EMG signals, contributing uniquely to the field's advancement.

Comparison between Recent Works and Our Work:

Table 3: Comparison between accuracy obtained using different machine learning models.

Ref work	Classifier/ Method	Accuracy
[1]	ANN	85%
	SVM	70%
[21]	ANN	98.6%
[4]	SVM	88.25%
	ANN	93.67%
[3]	CNN	95.90%
This work	**SVM**	**95.77%**
	ANN	**97.36%**
	CNN	**93.56%**

Table 3 shows the level of accuracy that has been obtained in this study using various machine learning techniques.

Discussion:

The research into the classification of EMG signals in amputees is a critical area of research with profound implications for the field of prosthetics and rehabilitation. In this research, we delved into the intricate task of classifying EMG signals from 11 amputee subjects across 21 different hand movements, including 'Flexion,' 'Extension,' 'Abduction,' 'Adduction,' 'Opposition,' 'Reposition,' 'Flexion of DIP,' 'Extension of DIP,' 'Flexion of PIP,' 'Extension of PIP,' 'Flexion of MCP,' 'Extension of MCP,' 'Wrist Flexion,' 'Wrist Extension,' 'Radial Deviation,' 'Ulnar Deviation,' 'Circumduction,' 'Pronation,' 'Supination,' 'Palmar Flexion,' and 'Dorsiflexion'. Prior to conducting our research, we divided the dataset into training, testing, and validation sets to ensure robust model development and evaluation. The training set was used to train the machine learning models, the testing set to assess their performance during development, and the validation set to independently evaluate the models' generalization to unseen data.

Based on our findings, the machine learning algorithms displayed varying levels of accuracy in classifying EMG signals. Among them, ANN exhibited the highest accuracy, achieving an impressive 97.36% accuracy rate across multiple hand movements. SVM, while not as versatile as ANN, excelled in binary classification tasks and achieved an accuracy rate of 95.77%. CNN, the third algorithm in the study, also performed well, achieving an accuracy rate of 95.77%. The diversity and complexity of hand movements posed a significant challenge in our research. While straightforward movements like 'Flexion' and 'Extension' were accurately classified by all algorithms, intricate movements such as 'Circumduction' and 'Pronation' exhibited greater variability. These complex movements involve a combination of multiple joint actions, resulting in intricate EMG signal patterns. The importance of feature engineering in our research cannot be overstated. Extracting relevant features from raw EMG signals was instrumental in enabling the algorithms to capture essential information for accurate classification.

Conclusion:

ANNs compared to SVMs and CNNs in the classification of EMG signals can be attributed to several key factors. ANNs possess a remarkable ability to capture intricate and complex patterns in data, making them particularly well-suited for EMG signal analysis. EMG signals often contain nuanced variations and distinct patterns associated with different hand movements, which ANNs can effectively learn and model due to their inherent capacity for feature extraction and pattern recognition. This research underscores the potential of machine learning algorithms, including ANN, SVM, and CNN, in the classification of EMG signals from amputees performing a spectrum of hand movements. These findings hold the promise of advancing the development of more advanced, personalized prosthetic control systems, ultimately enhancing the quality of life for amputees.

Declarations:

Ethical Approval:

This study involves the use of publicly available data from the NinaPro dataset, which is accessible for research purposes. Since this dataset contains recordings from human subjects, it is important to note that ethical approval and guidelines have already been established by the creators of the NinaPro dataset. The data used in this study were collected in accordance with the ethical standards and procedures specified by the NinaPro project, and all relevant ethical committees and internal review boards associated with the original dataset are acknowledged. Consent to participate and consent to publish were not required for this study, as the data are publicly accessible and de-identified.

Funding: NIL

Availability of Data and Materials: The data used in this study were obtained from the publicly accessible NinaPro dataset. Researchers interested in accessing the dataset for further investigation can find it at https://ninapro.hevs.ch/ to the NinaPro dataset source. Detailed information on how to access and utilize the NinaPro dataset is available on the official NinaPro project website.

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