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RESEARCH ARTICLE

Patient-Specific Movement Regime: Investigating the Potential of Upper-Extremity Motions for Intelligent Myoelectric Prosthetic Control

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Local Ethics Committee of the National University of Sciences and Technology, Islamabad, Pakistan, under Approval ref # BMES/REC/22/030, and performed in line with the Declaration of Helsinki.

ABSTRACT Amputation can have varying impacts on amputees depending on the extent of residual muscles left. Commercial prosthetics prioritize functional movements, neglecting patient-specific gestures related to the amputation type. Therefore, examining user-specific non-functional movements is pivotal. Rather than training on innumerable motions, prioritizing efficiently identifiable movements enhances prosthetic user-specificity. We examined 16 distinct wrist and finger motions using five classifiers (Wide Neural Networks, Ensemble Bagged Trees, Cubic SVM, Fine KNN, Logistic Regression Kernel). One-Way Anova testing ($p<0.05$) revealed significant classifier differences, with Wilcoxon signed-rank tests ($p<0.05$) distinguishing finger and wrist gestures. Ensemble Bagged Trees excelled ($p<0.05$) for finger (98.2% ± 0.81) and wrist (99% ± 0.73) movements; Fine KNN and Cubic SVM scored up to 96.3% ± 0.81 and 95.9% ± 1.43, respectively. Notably, Abduction of thumb and flexion of others consistently showed high accuracies for finger gestures. Wrist Radial Deviation (Clockwise) and Wrist Extension emerged as top wrist movements. Our study addresses the oversight of non-functional movements in myoelectric control. Our innovative approach focuses on selecting optimal finger and wrist movements for accurate gesture recognition, a departure from prior research neglecting these critical movements. By pinpointing these movements' significance and performance, we provide a solution to enhance personalized prosthetic development. Our findings mark a pioneering step in leveraging accurate finger and wrist gestures to craft more effective and personalized myoelectric control systems. These insights bridge the gap in existing research and pave the way for improved prosthetic device design.

INDEX TERMS Amputation, classification, EMG, gesture recognition, KNN, logistic regression Kernel, movements, myoelectric control, neural networks, SVM, trees.

I. INTRODUCTION

Surface electromyography (sEMG) is a non-invasive method of capturing muscle activity that reveals the strength of the underlying muscle's contraction. EMG signals have long been utilized to operate prosthetic devices for amputees of

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the upper limb, and they have progressively benefited from pattern recognition (PR) methods [1]. Throughout the course of human history, accidents, conflicts, and birth abnormalities have all taken place. Amputation and disability have thus been experienced in many forms throughout history. Expectations for upper limb prosthesis control have always been high because of the bar set by non-disabled dexterity. According to the World Health Organization (WHO), about 1.3 billion people live with a physical impairment. This equates to 16% of the world's population which points to one out of every six people [2]. This covers, among other things, ailments including amputations, spinal cord injuries, cerebral palsy, and mobility limitations brought on by problems in joints. Due to a significant increase in population of the upper limb amputees globally, one of the most active research areas in biomedical engineering and robotics is the development of an appropriate mobility restoration device for hand deficiencies.

Amputation can have varying impacts on individuals, necessitating customized prosthetic devices that consider both functional motions and the specific activities affected by the type of amputation. In the context of classifying hand gestures for prosthetic devices, it is crucial to select distinguishable movements and appropriate classifiers. Focusing on movements that can be efficiently and accurately identified would be preferable over training the model on a wide range of different movements.

Prosthetic device manufacturing industries primarily focus on developing devices that cater to functional movements, often overlooking the importance of non-functional movements. However, it is essential to investigate the performance and significance of these non-functional user-specific movements in order to enhance the functionality and user experience of prosthetic devices. By encompassing both functional and non-functional movements, we can not only enhance the overall utility and performance of prosthetic devices, but also enable users to experience a broader range of motion and elevated functionality.

Wrist and finger movements are crucial components of many hand gestures, such as pointing, waving, and making a fist. Accurately recognizing these movements can improve the accuracy and versatility of hand gesture recognition systems. This will lead to greater usability and a better quality of life for individuals with amputations. State-of-the-art prosthetic hand technologies use a combination of wrist and finger movements. This type of control enables the hand to provide users with the ability to perform a wide range of activities of daily living. The Be-bionic hand enables 14 different grips and hand positions, allowing users to perform daily tasks such as eating, carrying bags, and opening doors [3]. i-limb quantum allows users to perform grasping motions, point, rotate the wrist, and control individual finger movements [4]. Similarly, Hero Arm, a myoelectric prosthetic arm, can perform a range of movements. These movements include a pinch grip, power grip, rotate the wrist and perform flexion and extension of the elbow joint, allowing users to reach and lift objects at different heights [5]. The Michelangelo Hand and Vincent Prosthetic perform a range of grasping motions, such as a pinch grip, power grip, precision grip, and adaptive grip, and can also control individual finger movements, and thumb and wrist rotation [6], [7]. All these movements performed by prosthetics are functional in nature lacking the implementation of user-specific efficient movements at first. Therefore, in this study, we selected a total of 16 distinct wrist and finger motions to evaluate their impact and effectiveness. We employed five different classification algorithms to assess the accuracy and reliability of classifying these movements.

Several studies have contributed significantly to the field of gesture recognition (wrist and finger gestures) for myoelectric control systems. Botros et al. compared wrist and forearm signals during 17 distinct single-finger, multi-finger, and wrist gestures. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classifiers achieved an average accuracy of 92.1% for single-finger, 91.2% for multi-finger, and 94.7% for typical wrist motions [1].

Xu Zhang et al. achieved high accuracy (96.1% $\pm$ 4.3%) in identifying limb movement intentions using high-density surface EMG and classifiers like LDA, SVM, and Gaussian Mixture Model (GMM) [8]. Pan et al. continuously estimated finger joint angles under various static wrist motions, achieving notable results [9].

Jiang et al. explored real-time hand and surface recognition using sEMG and IMU (Inertial Measurement Unit) sensing, achieving classification scores of 92.6% and 88.8% for different gestures [10]. Lee et al. demonstrated impressive accuracies of 94.0%, 87.6%, and 53.9% using ANN (Artificial Neural Networks), SVM, and logistic regression kernel classifiers for specific finger gestures [11]. Additionally, Karnam et al. showcased Fine KNN's (K-nearest Neighbors) performance on the Ninapro DB1 dataset, achieving accuracies of 88.8% and 87.6% [12]. Kaczmarek et al. investigated hand gestures using SVM and KNN, achieving high accuracies ranging from 87% to 90% [13]. Asif et al. identified consistent accuracies (ranging from 71.2% to 83.7%) for specific hand motions, indicating their potential for robust myoelectric control systems [14].

Our study contributes by comprehensively analyzing hand gesture recognition utilizing classical machine learning algorithms, aligning with previous findings. By exploring these aspects in depth, we aim to enhance the understanding and development of intelligent myoelectric control systems, identifying the best-performing hand motions.

The existing literature provides valuable insights into the classification of certain movements. However, a comprehensive comparative analysis of non-functional movements, which are equally important, is lacking in previous research. Furthermore, the reviewed literature reveals a lack of in-depth exploration and understanding of these movements in the context of employing various classification techniques. Therefore, this research aims to address this limitation by applying a range of classification techniques

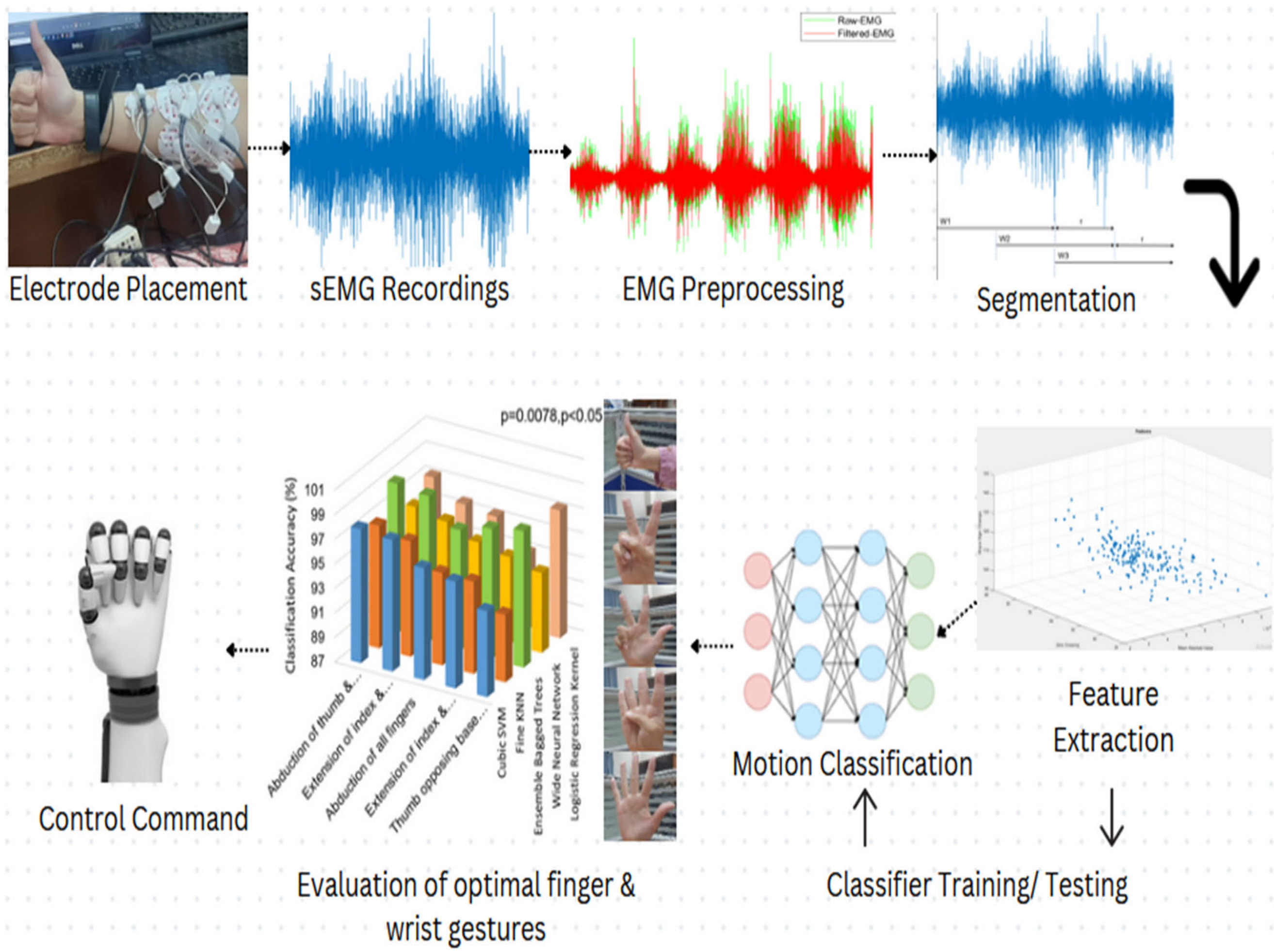


FIGURE 1. A simple Block Diagram that outlines the fundamental flow of this research. The research flow involves collecting surface EMG data, segmenting, and processing it, then utilizing five algorithms to evaluate 16 wrist and finger motions. Optimal movements, determined by classification accuracy, are recommended for advanced prosthetic control.

to accurately classify and differentiate the identified wrist and finger movements. By focusing on these previously underexplored movements, we seek to contribute to the existing body of knowledge and provide a more comprehensive understanding of their characteristics and potential applications.

Our research, therefore, involves prioritizing efficiently and accurately identifiable movements rather than training classifiers on a wide range of motions, which will, in turn, enhance the functionality and user experience of prosthetic hands. For this purpose, we used data of 10 healthy subjects obtained from a publicly available database i.e. NINAPRO. This was followed by self-data collection for 10 intact subjects using a commercial myoelectric amplifier (EMG USB2+, OT Bioelettronica, Italy). We employed five different classifiers, namely cubic support vector machine (SVM), fine k-nearest neighbors (KNN), ensemble bagged trees (EBT), wide neural network (NN), and logistic regression kernel (LRK).

The aforementioned machine learning algorithms were carefully chosen based on a thorough analysis of various aspects. Ensemble Bagged Trees were selected to improve predictive accuracy by combining multiple decision trees, which suits the complexity of our dataset. Support Vector Machines were chosen for their capability in handling complex classification tasks involving diverse data channels. Additionally, Deep Neural Networks were utilized for their proficiency in capturing intricate movement patterns.

Moreover, k-Nearest Neighbors and Logistic Regression Kernels were included for their simplicity, robustness, and applicability in supervised learning, offering a comprehensive exploration of both linear and non-linear aspects. These selections were guided by their complexity and adaptability, making them well-suited for potential real-time application in rehabilitation contexts.

The basic pipeline employed for the proposed study is shown in Fig. 1. The diagram outlines the fundamental flow of this research, beginning with data collection, followed by

TABLE 1. List of abbreviations.

Sr No.	Original Term	Abbreviation
1.	Surface electromyography	sEMG
2.	Electromyography	EMG
3.	Pattern Recognition	PR
4.	Linear Discriminant Analysis	LDA
5.	Support Vector Machine	SVM
6.	K-nearest Neighbors	KNN
7.	Ensemble Bagged Trees	EBT
8.	Logistic Regression Kernel	LRK
9.	Time-Domain	TD
10.	Mean Classification Accuracy	MCA

pre-processing, segmentation, feature extraction, and classification. In total, 16 distinct wrist and finger motions are assessed using five state-of-the-art algorithms. The evaluation identifies the optimal finger and wrist movements based on classification accuracy as the performance metric. Subsequently, the best performing movements are suggested for advanced prosthetic control based on the findings of this study.

The remaining portion of the paper is structured as follows: Section-II describes the methodology and protocol followed to conduct the study, Section-III and Section-IV sums up the resultant findings and their inferences, and Section-V consists conclusion resulting from the study and recommendations for future work. Below given is a list of abbreviations in Table 1 that are used frequently throughout the article.

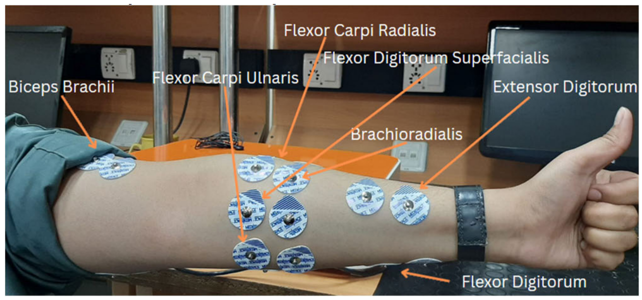
II. METHODOLOGY

The strategies used to accomplish the objective of the research are described in this section. At first, the surface EMG data was preprocessed using Butterworth band-stop and band-pass filters, and then, features were extracted from the segmented and preprocessed data. The classification performance of wrist and finger motions was then examined using five different classifiers, including the cubic support vector machine (SVM), fine k-nearest neighbors (KNN), ensemble bagged trees, logistic regression kernel and wide neural network. Three common evaluation metrics, namely classification accuracy, F1 score, and sensitivity were used to assess each classifier's performance and one-way Anova testing was performed to find out if there existed a significant difference between the classification performance of wrist and finger movements. An analysis of the findings was done at the end of the study.

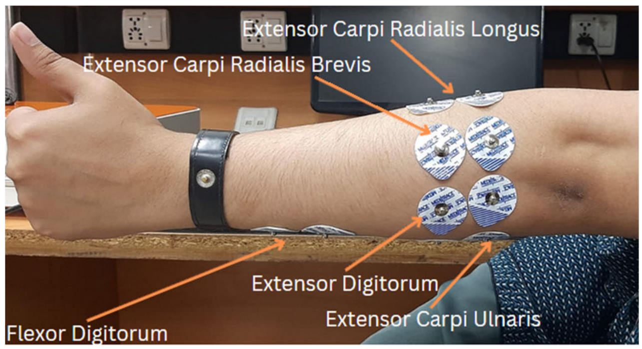
In order to achieve generalization, original features were taken into account throughout training and testing. No feature reduction or selection was carried out. MATLAB software was used for the entire data analysis in this study.

A. DATA COLLECTION

In this research, we conducted a comprehensive study combining the utilization of a publicly available Ninapro dataset



(a). Electrode Placement on the Anterior (Medial) Inner Side of Forearm



(b). Electrode Placement on the Posterior (Outer) Side of Forearm

FIGURE 2. Experimental set-up illustration.

and subsequent self-data collection efforts. The data from both datasets consisted surface EMG signals.

Initially, an extensive EMG dataset was obtained for this study which was downloaded from publicly available database NINAPRO DB2 (http://ninaweb.hevs.ch/data2) [15]. The Ninapro dataset DB2 comprises data from 40 healthy subjects recorded using the Delsys Trigno Wireless EMG system, the sampling frequency of which is 2 kHz. EMG data of 8 basic wrist movements and 8 basic finger movements for 10 healthy subjects was used for this study. The wrist movements include wrist supination (axis: middle finger) (WS:MF), wrist pronation (axis: middle finger) (WP:MF), wrist supination (axis: little finger) (WS:LF), wrist pronation (axis: little finger) (WP:LF), wrist flexion (WF), wrist extension (WE), wrist radial deviation (WRD) and wrist ulnar deviation (WUD). While the finger movements include thumbs up (TU); extension of index and middle, flexion of the others (EIM); flexion of the ring and little finger, the extension of others (FRL); thumb opposing base of little

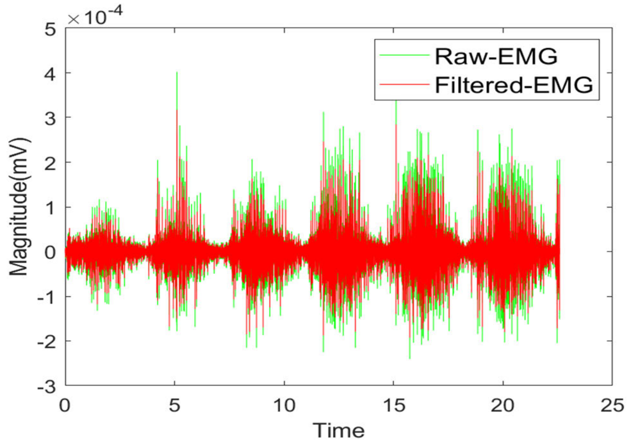


FIGURE 3. Raw and filtered EMG signal ("Wrist Supination Axis: Middle Finger").

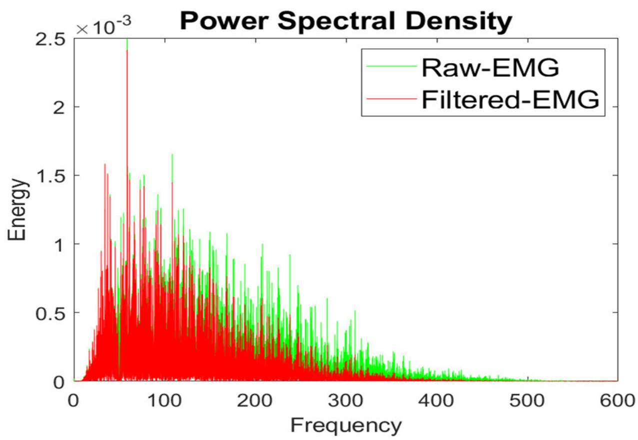


FIGURE 4. Power spectral density of raw and filtered EMG signal ("Wrist Supination Axis: Middle Finger").

finger (TBLF); abduction of all fingers (AAF); fingers flexed together in fist (FFF); pointing index (PI) and adduction of extended fingers (AEF).

1) PARTICIPANTS

In addition, the study protocol was repeated on self-collected data to ensure the robustness and accuracy of our findings. For this purpose, 10 healthy subjects were recruited to perform the 16 wrist and finger movements. The signed consent of each subject was acquired before the experimental procedure. The possibility of withdrawing out of the study at any point throughout the experiment session was made clear to participants. The experiment protocol was in accordance with the Declaration of Helsinki and approved by local ethics committee of the National University of Sciences and Technology, Islamabad, Pakistan, with approval number ref # BMES/REC/22/030 granted for data recording.

2) EXPERIMENTAL PROTOCOL

The subjects were positioned upright and at ease on a height-adjustable chair, with both of their upper limbs at rest. Eight bipolar differential electrodes were evenly spaced around the

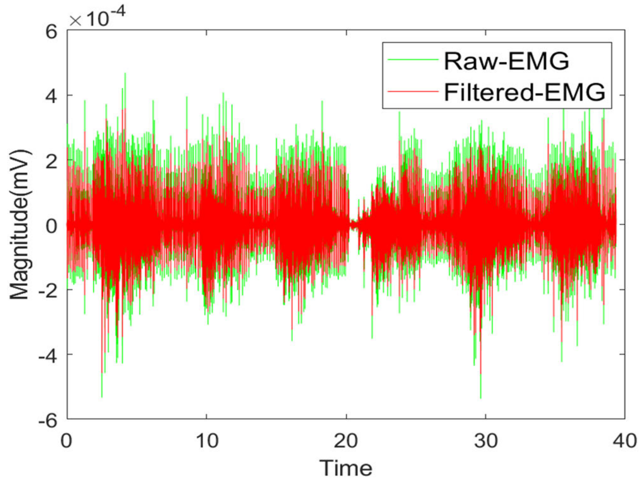


FIGURE 5. Raw and filtered EMG signal ("Abduction of Thumb & Flexion of Others").

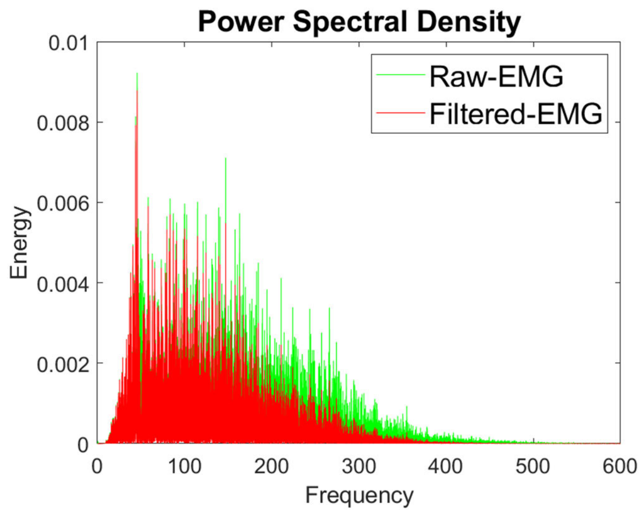


FIGURE 6. Power spectral density of raw and filtered EMG signal ("Abduction of Thumb & Flexion of Others").

forearm in proximity to the radio humeral joint as shown in Fig. 2, with two electrodes placed on the main activity spots of the flexor digitorum and the extensor digitorum muscles and one electrode on the main activity spot of the biceps. Fig. 2(a) illustrates detailed electrode placement on the Anterior (Inner) side, while Fig. 2(b) demonstrates placement on the Posterior (Outer) side of the forearm. In order to combine a dense sampling method with an exact anatomical placement strategy, the stated sites have been selected. To assist the subject in performing the required motions, a laptop screen was placed in front of them which displayed visual instructions in a video. The sEMG signals were obtained using a commercial amplifier (EMG USB2+, OT Bioelettronica, Italy). The device's bandpass settings were at 10-500 Hz, and the sampling rate was 2048 Hz. The gain was set at 1000. These settings enabled us to generate eleven bipolar channels from the data, with each channel created by taking the differential voltage between a pair of surface EMG electrodes.

TABLE 2. Non-functional movements (Wrist & Finger).

Movements	Wrist	Finger
Movement-1	Wrist supination (axis: middle finger) (WS:MF)	Thumbs up (TU) / Abduction of thumb and flexion of others
Movement-2	Wrist pronation (axis: middle finger) (WP:MF),	Extension of index and middle, flexion of the others (EIM)
Movement-3	Wrist supination (axis: little finger) (WS:LF)	Flexion of the ring and little finger, the extension of others (FRL)
Movement-4	Wrist pronation (axis: little finger) (WP:LF),	Thumb opposing base of little finger (TBLF)
Movement-5	Wrist flexion (WF),	Abduction of all fingers (AAF)
Movement-6	Wrist extension (WE),	Fingers flexed together in fist (FFF)
Movement-7	Wrist radial deviation (WRD),	Pointing index (PI)
Movement-8	Wrist ulnar deviation (WUD)	Adduction of extended fingers (AEF)

The participants performed 16 wrist and finger movements as stated above. In each experimental session, each movement was repeated four times with relaxation gaps in between to avoid muscle fatigue. Each repetition period lasted 5 seconds with a 3 seconds relaxation period between the two consecutive gesture repetitions making each experimental session lasting for a time period of 544 seconds.

Table 2 includes the entire list of wrist and finger gestures employed in this research and their abbreviated and full forms to provide ease in understanding.

B. PRE-PROCESSING

EMG signals are intrinsically noisy, therefore significant signal processing is needed to remove motion distortions and power line noise in order to obtain a meaningful command control signal. The signal was filtered using first-order Butterworth Band-pass Filter of 10-500 Hz and a Butterworth Band-stop Filter of 50 Hz in order to eliminate unwanted signal constituents such as motion artifacts and power line noise from the recorded EMG data (Figs. 3 & 5).

C. SEGMENTATION

Raw data is segmented into windows in order to calculate features over a range of points. In real-world applications, segment length is crucial because too-short segments can lead to significant variation within individual features and too-long segments might impair real-time operation [11].

After pre-processing, the EMG signals were segmented by means of overlapping segmentation with a window size of 250 ms and an overlapping size of 50% (Fig. 7). The sliding movable window had a length of 250 ms and was extended in 125 ms increments (50% overlap).

It has been suggested in most researches that the best length for windowing is between 100 and 300 milliseconds as it contains the most information in the signal [16]. Also, it has been reported that longer window lengths produce the minimum/ least classification error. Despite longer controller delay and response time, the prosthesis performance increases. The new segment slides over the present segment in overlapping segmentation, and the time delay between two successive segments is less than the length of the segment but greater than the processing time.

D. FEATURE EXTRACTION

Feature Extraction includes converting raw data into a related structure or numerical features by reducing noise and emphasizing vital information from the original data set. It involves the reduction of the initial raw data set to a set of groups that are easier to manage for classification.

The gesture recognition system's response time must be fast enough for users to perceive real-time recognition. The primary advantage of utilizing Time Domain features in gesture classification is that the more straightforward implementation of TD features can help to minimize the total reaction time since this latency also accounts for the time needed to extract features. As a result, TD features have undergone extensive testing for EMG-based hand gesture identification [17], [18], [19], [20], [21], [22].

Time Domain features [23] are typically extracted from pre-processed EMG data without any sort of modification and have a minimal computational cost as well as are simple to implement. In this research, a total of 18 TD features were extracted for all the time windows. Time Domain Features were extracted from the segmented EMG data and the resultant feature vectors were then fed into various classifiers to train and classify motor intent. The features that were employed to determine signal attributes included Mean Absolute Value, Root Mean Square, Waveform Length, Cardinality, Zero Crossing, Slope Sign Change, Willison Amplitude, Standard Deviation, Variance, Skewness, Kurtosis, Integrated EMG, Simple Square Integral, Average Energy, Interquartile Range, Mean Absolute Deviation, Temporal Moment and Variance of EMG.

E. CLASSIFICATION

A classifier is trained offline by making the user execute repeats of numerous motion classes that would be further included in the myoelectric prosthesis. The trained classifier decides which movement class the user is using considering a series of EMG features in the real-time application. The time it takes for the classifier to make a judgment is the time addition of an overlapping window. Once a movement is identified, a command is given to the prosthetic controller so that the movement can be completed. To enable continuous control over the prosthesis, the classification is performed again at overlapping intervals.

Following feature extraction, the feature vectors representing 8 wrist motions and 8 finger motions were fed into classifiers: Cubic Support Vector Machine (SVM) [18], [23], [24], [25], Fine K-Nearest Neighbors (KNN) [23], [26], Ensemble Bagged Trees [27], [28] Wide Neural Network [18], [23], [29], and Logistic Regression Kernel [18],

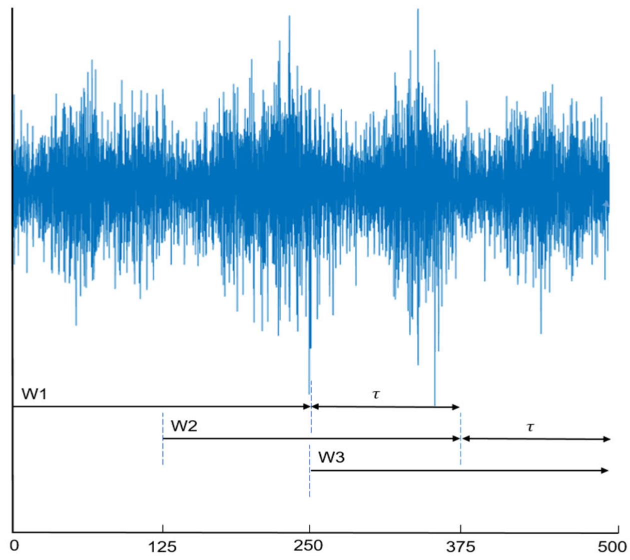


FIGURE 7. Overlapping segmentation. Three moving windows are denoted by W1, W2, and W3, each with a length of 250 ms, and the time interval between two successive windows is 125 ms, which is represented by τ.

[30]. Firstly, these classifiers were trained using the repetitions of the wrist and finger motion classes. Then, test data from the same datasets was fed into the classifiers in order to make decisions regarding the type of wrist and finger movement.

The entire dataset for each finger and wrist movement was divided into 80% training and 20% testing data. The classifiers were validated with K-fold Cross-validation [31] keeping number of folds equal to 5.

F. PERFORMANCE EVALUATION

The utilized classification algorithms were assessed using the standard performance evaluation metric i.e. mean classification accuracy (MCA) [32]. Besides, F1 score and sensitivity were also estimated for each dataset and classifier.

i ***Classification Accuracy***: It measures the proportion of correctly classified instances to the total number of instances. The mathematical expression of Accuracy in percentage is as follows:

$$Accuracy\,(\%) = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FN} + \mathrm{FP} + \mathrm{TN}} \times 100 \tag{1}$$

ii ***F1 score:*** The F1 score [33] is a single performance metric that combines both precision and recall. It balances a model's precision (ability to correctly identify true positives) and recall (ability to find all positive instances) into one value

$$F1 = 2 \times (\text{precision} \times \text{recall})/(\text{precision} + \text{recall}) \tag{2}$$

iii ***Sensitivity:*** Sensitivity, also known as True Positive Rate or Recall [29], [34], measures the model's ability to correctly identify positive instances. It's important for cases where missing a positive instance has serious consequences. It represents the proportion of true positive predictions (correctly identified positive cases) relative to all actual positive cases.

$$\text{Sensitivity} = \text{True Positives}/(\text{True Positives} + \text{False Negatives}) \tag{3}$$

where precision = TP / (TP + FP), recall = TP / (TP + FN), TP = true positive, FP = false positive, TN = True Negative, FN = false negative.

TABLE 3. Classification performance comparison (Wrist vs Finger); ninapro data.

	Wrist		Finger	
Accuracy	Training	Validation	Training	Validation
Cubic SVM	94.5%	95.4%	95.9%	96.5%
Fine KNN	93.6%	94.6%	94.7%	95.2%
Ensemble Bagged Trees	98.4%	99.0%	98.2%	98.2%
Wide Neural Network	91.7%	93.5%	94.1%	94.6%
Logistic Regression Kernel	94.7%	95.0%	94.5%	95.0%

TABLE 4. Classification performance comparison (Wrist vs Finger); self-collected data.

	Wrist		Finger	
Accuracy	Training	Validation	Training	Validation
Cubic SVM	94.6%	95.8%	95.1%	95.9%
Fine KNN	95.1%	96.3%	94.9%	95.2%
Ensemble Bagged Trees	92.8%	94.1%	93.0%	93.5%
Wide Neural Network	93.6%	94.1%	94.7%	95.7%
Logistic Regression Kernel	59.4%	62.1 %	70.8%	72.3%

III. RESULTS

As previously discussed, prioritizing efficiently and accurately identifiable movements is the key to enhancing the functionality and user experience of prosthetic hands. Therefore, evaluating and analyzing 16 distinct wrist and finger motions using 5 different classifiers yielded the following findings.

Table 3 shows the obtained classification training and validation accuracies for wrist and finger movements using the

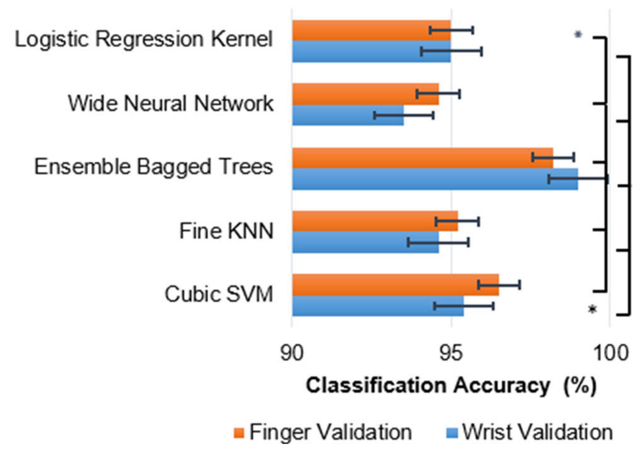


FIGURE 8. Validation performance comparison (Wrist vs Finger) for all classifiers (LRK, WNN, EBT, KNN, SVM). No significant difference between wrist and finger movements (0.33) was found. Significant difference ($p<0.05$) between the classifiers is represented by '*'.

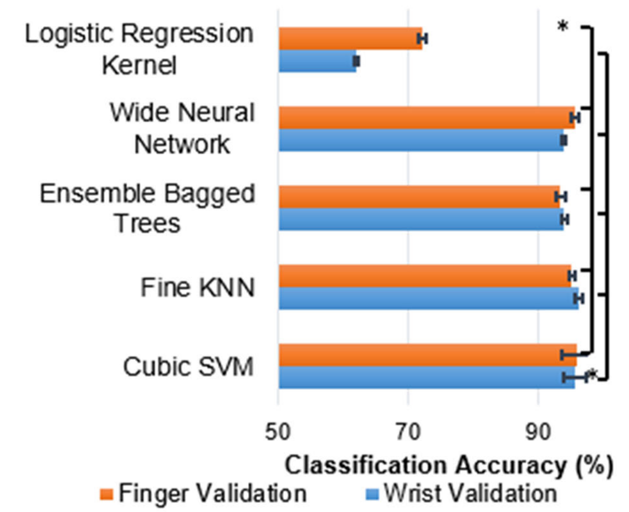


FIGURE 9. Validation performance comparison (Wrist vs Finger) for all classifiers (LRK, WNN, EBT, KNN, SVM) using self-collected data. No significant difference between wrist and finger movements (0.38) was found. Significant difference ($p<0.05$) between the classifiers is represented by '*'.

Ninapro DB2 dataset while Table 4 displays the accuracies obtained using self-collected surface EMG data.

The classifiers employed were Cubic SVM, Fine KNN, Ensemble Bagged Trees, Wide Neural Networks and Logistic Regression Kernel.

Figs. 8 and 9 show the mean accuracy and standard errors of the different classification methods evaluated with each dataset of wrist and finger movements using Ninapro DB2 and self-collected surface EMG data.

A paired t-test, performed between the accuracies of wrist and finger movements, displayed no significant difference between the two using both Ninapro and self-collected datasets (0.33; 0.38) as evident in Figs. 8 and 9.

TABLE 5. Standard error for all datasets.

STANDAR-D ERROR	SELF-COLLECT-ED FINGER	SELF-COLLECT-ED WRIST	NINAPR-O FINGER	NINAPRO WRIST
Logistic Regression Kernel	2.1708	1.7925	0.99702	0.93692
Wide Neural Network	0.44548	0.53387	0.52326	0.72125
Ensemble Bagged Trees	0.76368	0.55154	0.28638	0.25809
Fine K-Nearest Neighbors	0.62579	0.28638	0.53387	0.61872
Cubic Support Vector Machines	0.50558	0.27577	0.61872	0.57983

The best accuracies for both wrist and finger movements were obtained with a novel algorithm Ensemble Bagged Trees using the Ninapro dataset. While cubic SVM and KNN outperform all others, considering the self-collected dataset.

Based on the results depicted in Figure 9, the Cubic SVM and Fine KNN models consistently demonstrate high accuracy for both wrist and finger movements. The Ensemble Bagged Trees and Wide Neural Network models also perform well, but with slightly lower accuracies compared to the SVM and KNN models. However, it's worth noting that the Logistic Regression Kernel model shows significantly lower accuracies compared to the other models.

A. STATISTICAL ANALYSIS

A paired t-test was performed between the accuracies of wrist and finger movements which displayed no significant difference between the two (0.33; 0.38). The Wilicoxon signed-rank test performed between the individual wrist and finger gestures depicted a significant difference between the individual finger and wrist gestures ($p<0.05$). One-way Anova testing between the classifiers ($p<0.05$) revealed a significant difference which is depicted in Fig 8 and 9.

Table 5 displays the standard error [35] for all classifiers with each dataset i.e. self-collected (wrist & finger) and Ninapro (wrist & finger).

It is evident from the results of both datasets that the highest accuracy with each classifier was obtained with Movement-1 i.e. "Abduction of thumb and flexion of others" as shown in Tables 6 and 7. It is evident from the results that the highest accuracy with each classifier was obtained with Movement-7 i.e. "Wrist Radial Deviation (Clockwise)".

From the results obtained with self-collected wrist data, it was inferred that the Fine KNN model generally achieves the highest accuracies for most of the movements. Movement-2 i.e. "Wrist Extension" consistently shows higher accuracies across all classification models.

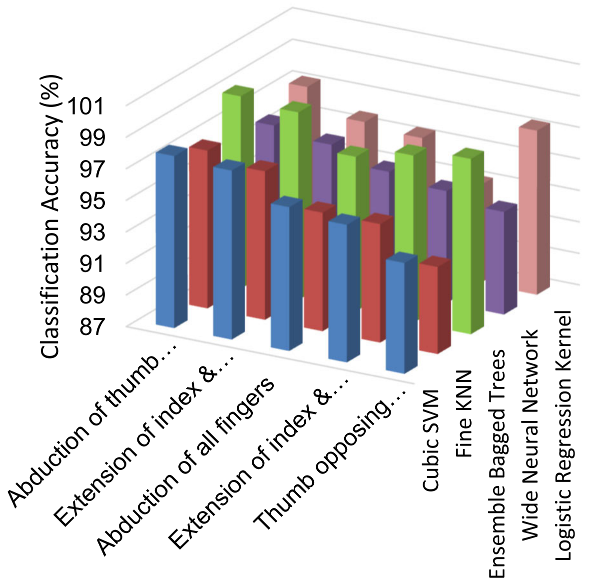


FIGURE 10. Finger movements classification accuracies (%) with Ninapro Dataset. Significant difference (p<0.05) between the individual finger gestures was found.

TABLE 6. Best finger movements with respect to accuracy (Ninapro).

Nina-pro dataset Finger Gestures	Cubic SVM	Fine KNN	Ensemble Bagged Trees	Wide Neural Network	Logistic Regression Kernel
Abduction of thumb & flexion of others	97.9%	97.0%	99.2%	96.1%	97.3%
Extension of index & flexion of others	97.7%	96.4%	98.9%	95.6%	95.8%
Abduction of all fingers	96.1%	94.5%	96.8%	94.6%	95.5%
Extension of index & middle fingers	95.7%	94.5%	97.6%	94.1%	93.2%
Thumb opposing base of little finger	94.0%	92.5%	98.1%	93.5%	97.4%

The results provided in Table 9 offer a summary of the best performing wrist movements obtained from self-collected EMG data. Notably, Wrist Movement-2 i.e. "Wrist Extension" consistently achieves the highest accuracy across all models, indicating that this gestures holds unique and easily distinguishable patterns. Further, Movement 1, 4, 6 and 8 i.e. "Wrist flexion", "Wrist Ulnar Deviation", "Wrist Pronation Axis: middle finger" and "Wrist Pronation Axis: little finger", respectively show competitively good accuracies.

When considering wrist movements using the Ninapro dataset, the highest accuracy was achieved by Ensemble

TABLE 7. Best finger movements with respect to accuracy using self-collected data.

Real-Time Finger Gestures	Cubic SVM	Fine KNN	Ensemble Bagged Trees	Wide Neural Network	Logistic Regression Kernel
Abduction of thumb & flexion of others	96.3%	96.3%	96.2%	95.9%	76.4%
Extension of index & flexion of others	95.6%	96.3%	94.7%	94.4%	76.7%
Flexion of all fingers	96.1%	96.6%	93.9%	96.0%	74.5%
Thumb opposing base of little finger	96.3%	96.3%	94.7%	95.6%	63.1%
Extension of index, middle finger and thumb	94.1%	93.6%	91.6%	94.2%	73.9%

Bagged Trees with a training accuracy of 98.4% and a validation accuracy of 99% as shown in Fig. 8. The second-best performance was seen with Cubic SVM, which achieved a training accuracy of 94.5% and a validation accuracy of 95.4%. The other classifiers, including Fine KNN, Wide Neural Network, and Logistic Regression Kernel, also demonstrated relatively high accuracies ranging from 91.7% to 94.7% in training and from 93.5% to 95.0% in validation for wrist movements.

When analyzing finger movements using the Ninapro Dataset, Ensemble Bagged Trees, once again achieved the highest accuracy among all classifiers, with a training and validation accuracy of 98.2%. Cubic SVM and Fine KNN exhibited slightly lower accuracies but remained robust, with accuracies ranging from 94.7% to 95.9% in training and from 95.2% to 96.5% in validation. Wide Neural Network and Logistic Regression Kernel also showed competitive results, with accuracy ranging from 94.1% to 94.5% in training and 94.6% to 95.0% in validation for finger movements.

Table 6 illustrates the best finger movements across the classifiers. Notably, Movement-1 i.e. "Abduction of thumb and flexion of others" consistently obtained the highest accuracy across all classifiers, indicating its strong discriminative features and ease of classification. Movements 7, 5, 2 and 4 i.e. "Extension of index and flexion of others", "Abduction of all fingers", "Extension of index & middle fingers" and "Thumb opposing base of little finger", respectively consistently achieved higher accuracies in most classifiers, suggesting their robustness in terms of classification.

We observed in Table 7 that Finger Movement-1 i.e. "Abduction of thumb and flexion of others" leads the table with the highest classification accuracy. Then comes Finger Movement-7 i.e. "Extension of index & flexion of others" at the second place. Movement 6, 4 and 3 i.e "Flexion

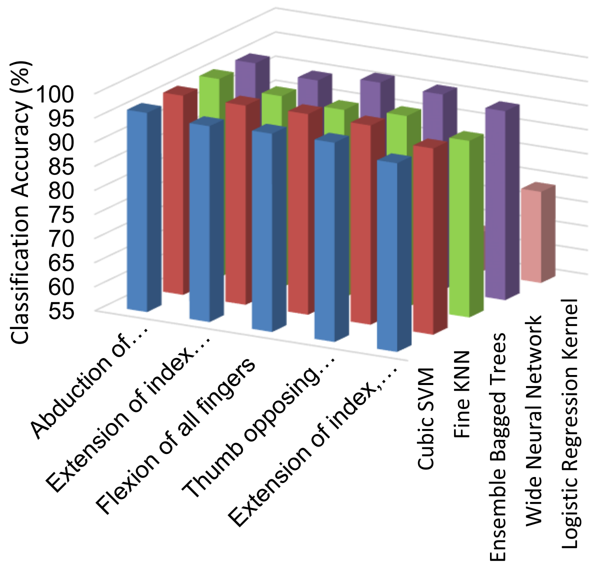


FIGURE 11. **Finger movements classification accuracies using self-collected data. Significant difference between the individual finger gestures (p<0.05) was found.**

of all fingers'', ''Thumb opposing base of little finger'' and ''Extension of index, middle & thumb'' respectively, also show competitive performance accuracies with most classifiers.

The results of the best wrist gestures w.r.t accuracy is shown in Table 8. Among the classifiers, Ensemble Bagged Trees consistently demonstrated the highest accuracies for most wrist movements, ranging from 97.0% to 99.3%. Logistic Regression Kernel and Cubic SVM also showed competitive performance, achieving accuracies ranging from 95.0% to 95.4%. Fine KNN and Wide Neural Network exhibited relatively lower but good accuracies.

Table 8 illustrates the best wrist movements obtained using the Ninapro dataset w.r.t their accuracies across the classifiers. Wrist Movement-7 i.e. ''Wrist Radial Deviation (Clockwise)'' consistently achieved the highest accuracies across all classifiers, indicating potential ease in accurately distinguishing this movement. On the other hand, Wrist Movement-2 i.e. ''Wrist Supination (Axis: middle finger)'' consistently grabbed the second position, indicating its better discriminative features and ease of classification. Other than these, wrist gestures 1, 3 and 8 i.e. ''Wrist Pronation Axis: little Finger'', ''Wrist Pronation Axis: middle finger'' and ''Wrist Ulnar Deviation (Anti-clockwise)'' respectively, exhibited considerably good performances.

A summary of the performance of different models in classifying wrist movements obtained from self-collected EMG dataset is discussed as follows. Fine KNN consistently achieves high rankings across multiple wrist movements. Cubic SVM also demonstrates competitive performance. Ensemble Bagged Trees and Wide Neural Network show mixed results, performing well in certain wrist movements but having lower rankings in others. Logistic Regression Kernel consistently obtains lower rankings, suggesting its limitations in accurately classifying wrist movements in this analysis.

TABLE 8. **Best wrist movements with respect to accuracy (Ninapro).**

Nina-pro dataset Wrist Gestures	Cubic SVM	Fine KNN	Ensemble Bagged Trees	Wide Neural Network	Logistic Regression Kernel
Wrist Radial Deviation (Clockwise)	96.3%	95.8%	99.3%	94.9%	96.9%
Wrist Supination Axis: middle finger	96.2%	96.2%	98.9%	93.2%	95.5%
Wrist Pronation Axis : little Finger	94.3%	94.8%	98.9%	93.7%	95.7%
Wrist Pronation Axis: middle finger	95.4%	92.2%	98.1%	90.9%	94.3%
Wrist Ulnar Deviation (Anti-clockwise)	94.5%	92.1%	98.7%	89.6%	95.7%

From Table 9, notably, Wrist Movement-2 i.e. ''Wrist Extension'' consistently achieves the highest accuracy across all models, indicating that this gesture holds unique and easily distinguishable patterns. Further, Gestures 1, 4, 6 and 8 i.e. ''Wrist flexion'', ''Wrist Ulnar Deviation'', ''Wrist Pronation Axis: middle finger'' and ''Wrist Pronation Axis: little finger'', respectively show notable performances. ''Wrist supination (axis: middle finger)'' can also prove to be a good movement with certain classifiers.

Figs. 10, 11, 12 and 13 display the best five movements obtained using Ninapro and self-collected datasets. Figs. 10 and 11 show the best five finger movements for both datasets while Figs. 12 and 13 show the best five wrist movements with each dataset. Figs. 10 and 11 relate to the Tables 6 and 7 while Figs. 12 and 13 relate to the Tables 8 and 9.

The comprehensive classification performance of the top-performing gestures, coupled with the most effective classifiers, is precisely presented through a series of distinct confusion matrices, as illustrated below in Figs. 14, 15, 16, 17, and 18.

B. SUBJECT-WISE ANALYSIS

Below are the results of the subject-specific analysis, detailing the top-performing wrist and finger gestures for each classifier. The consistent findings across datasets confirm the authenticity and reliability of our overall analysis. Two-way ANOVA unveiled a statistically significant difference ($p<0.05$) between wrist and finger movements as well as between classifiers within each dataset. The detailed findings as stated as follows.

TABLE 9. Best wrist movements with respect to accuracy using self-collected data.

Real-Time Wrist Gestures	Cubic SVM	Fine KNN	Ensemble Bagged Trees	Wide Neural Network	Logistic Regression Kernel
Wrist Extension	95.0%	96.4%	93.4%	95.6%	65.0%
Wrist Pronation Axis: little finger	95.7%	96.0%	94.9%	94.7%	59.1%
Wrist Flexion	95.0%	95.5%	94.6%	94.4%	57.6%
Wrist Pronation Axis: middle finger	95.1%	94.4%	92.8%	91.5%	67.1%
Wrist Ulnar Deviation	93.8%	95.0%	92.7%	95.0%	56.8%

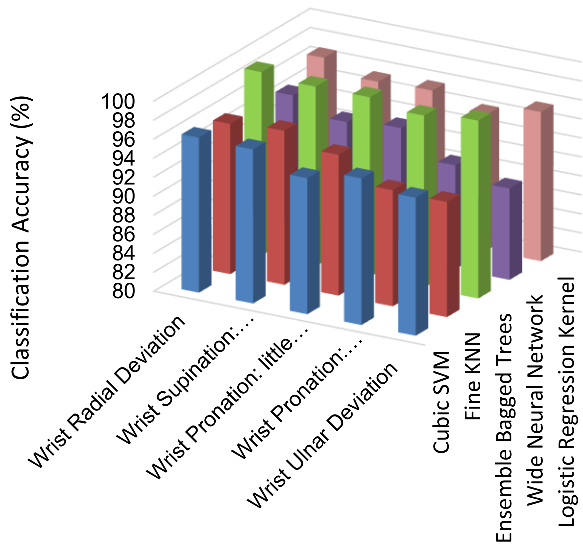


FIGURE 12. Wrist movements classification accuracies (%) with Ninapro Dataset. Significant difference (p<0.05) between the individual gestures was found.

1) NINAPRO AND SELF-COLLECTED (WRIST)

Our subject-specific analysis on the Ninapro Dataset reveals notable efficiency in certain wrist movements across multiple subjects. The 'Wrist Radial Deviation (Clockwise)' movement stands out, with consistent perfect accuracies across all classifiers for a subset of subjects. Additionally, the 'Wrist Supination Axis: Middle Finger' movement demonstrates impressive performance, achieving high accuracies across multiple classifiers. Moreover, the 'Wrist Pronation Axis: Little Finger' movement exhibits remarkable results. In the self-collected dataset, distinctive subject-wise performances emerge for various wrist movements. For instance, 'Wrist Movement M6 - Wrist Extension' showcases consistent excellence, while 'Wrist Movement M4 - Wrist Pronation Axis: Little Finger' excels, particularly with specific

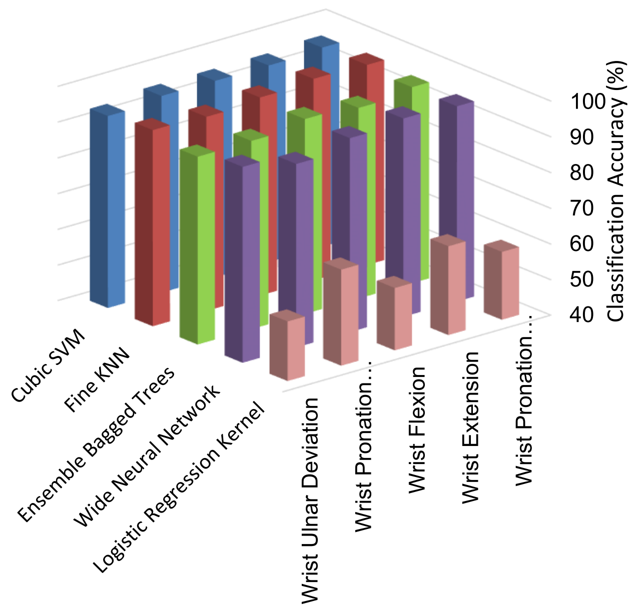


FIGURE 13. Wrist movements classification accuracies using self-collected data. Significant difference (p<0.05) between the individual wrist gestures was found.

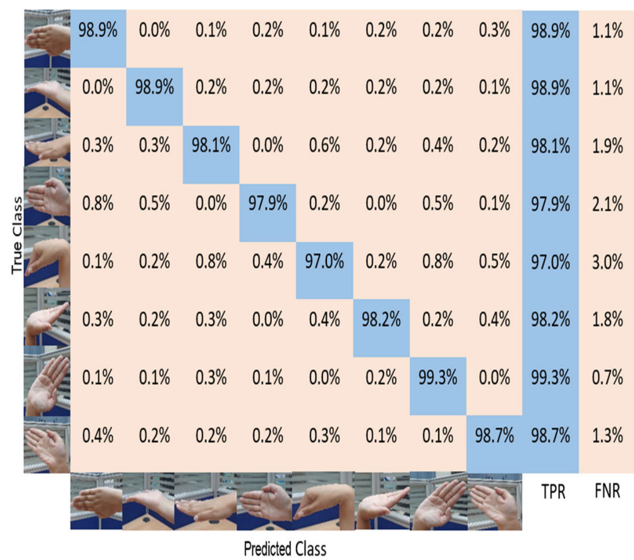


FIGURE 14. Wrist gesture recognition with ensemble bagged trees (Nina-pro dataset).

classifiers. Similarly, 'Wrist Movement M5 - Wrist Flexion' stands out with high accuracies across most classifiers. These results underscore the importance of considering both specific movements and individual subjects in gesture classification research.

2) NINAPRO AND SELF-COLLECTED (FINGER)

Our analysis of Ninapro Finger movements reveals subject-specific proficiency in various gestures across different classifiers. 'Ninapro Finger Movement M1 - Abduction of

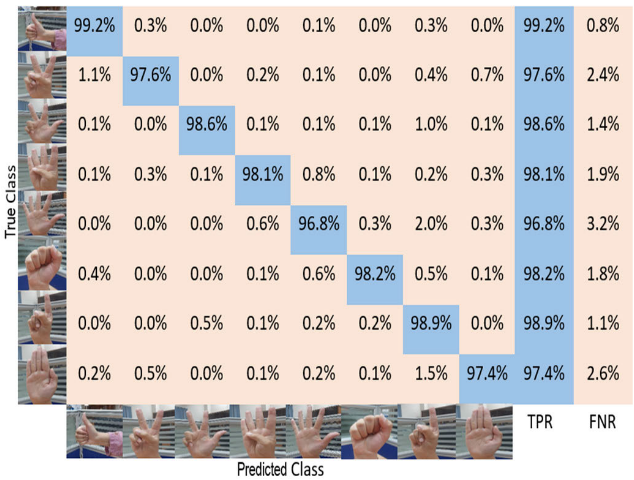


FIGURE 15. **Finger gesture recognition with ensemble bagged trees (Nina-pro dataset).**

FIGURE 17. **Finger gesture recognition with SVM (Self-collected dataset).**

FIGURE 16. **Wrist gesture recognition with KNN (Self-collected dataset).**

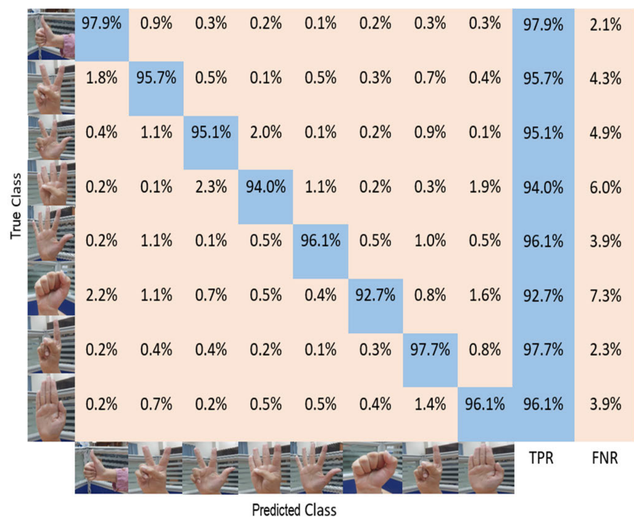


FIGURE 18. **Finger gesture recognition with SVM (Nina-pro dataset).**

Thumb & Flexion of Others' and 'Ninapro Finger Movement M7 - Extension of Index & Flexion of Others' demonstrate exceptional and superior performance, respectively, with notable accuracies across specific classifiers. Additionally, 'Ninapro Finger Movement M5 - Abduction of All Fingers' exhibits impressive results, emphasizing subject-specific variations in performance and the effectiveness of individualized approaches to gesture recognition. In the self-collected Finger movements, subjects exhibit varying performance levels across different gestures and classifiers. 'Self-collected Finger Movement M1 - Abduction of Thumb & Flexion of Others' and 'Self-collected Finger Movement M7 - Extension of Index & Flexion of Others' show notable and substantial accuracy, respectively, with proficiency across specific classifiers. Similarly, 'Self-collected Finger Movement M6 - Flexion of All Fingers' displays a range of performance among subjects, highlighting subject-specific variations and the importance of tailored approaches in gesture recognition.

C. PERFORMANCE EVALUATION—–F1-SCORE AND SENSITIVITY

Table 10 displays F1 scores for each movement with each dataset for the classifier Fine KNN. Table 11 presents the F1 scores corresponding to each movement within every dataset, focusing on the Cubic SVM classifier's performance. In Table 12, the F1 scores are detailed for the same movements and datasets, but this time, we delve into the outcomes of the Ensemble Bagged Trees classifier. The performance of the Wide Neural Networks classifier for each movement in various datasets is depicted in Table 13, displaying their respective F1 scores. Lastly, Table 14 provides a comprehensive overview of F1 scores for each movement across different datasets, emphasizing the Logistic Regression Kernel classifier's performance.

Fig. 19 depicts F1 scores for each movement with each dataset for the classifier Fine KNN. It can be seen that Finger Movement-1 "Abduction of Thumb & Flexion of others"

TABLE 10. F1 scores of all datasets with fine KNN.

F1 Score (Fine KNN)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	0.9456	0.9648	0.971	0.9736
M2	0.9691	0.9486	0.9643	0.9559
M3	0.9362	0.9477	0.9487	0.9533
M4	0.9244	0.9444	0.9587	0.9512
M5	0.9402	0.9604	0.9554	0.9333
M6	0.9378	0.9566	0.9455	0.9632
M7	0.975	0.9657	0.9546	0.9619
M8	0.9257	0.9536	0.9619	0.9479

TABLE 11. F1 scores of all datasets with cubic SVM.

F1 Score (Cubic SVM)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	0.941	0.943	0.9648	0.9592
M2	0.9455	0.9141	0.9491	0.9492
M3	0.9162	0.9289	0.9251	0.9451
M4	0.9048	0.9214	0.9368	0.9556
M5	0.9329	0.9416	0.9272	0.9225
M6	0.9054	0.915	0.9226	0.9608
M7	0.9481	0.957	0.9148	0.9464
M8	0.9125	0.9292	0.9429	0.9493

outperforms all other movements with multiple datasets in terms of F1 score too as seen when estimating the classification accuracies. Similarly, Wrist Movement-7 i.e. "Wrist Radial Deviation" claims the top position in the table following the similar trend as of classification accuracies. Other best performing movements include M1 i.e. "Wrist Supination (Axis: Middle Finger), M2 i.e. "Wrist Pronation (Axis: Middle Finger)" and M7 i.e. "Pointing Index".

Fig. 20 shows the performance of Cubic SVM over each movement for each Ninapro and Self-collected Dataset in terms of F1 score. It can be observed that Finger Movement-1 "Abduction of Thumb & Flexion of others" once again outperformed all others. The table shows that Finger Movement M6 i.e. "Fingers flexed together in fist" grabs the second position when considering finger movements with self-collected data. Besides M1 & M6, Finger Movement M7 i.e. "Pointing Index" and M4 i.e. "Thumb opposing Base of Little Finger" also show notable F1 scores with Cubic SVM. Wrist Movement M1 i.e. "Wrist Supination (Axis: Middle Finger)" leads the table when analyzing movements with Cubic SVM. Similarly, Wrist Movement M2 i.e. "Wrist Pronation (Axis: Middle Finger)" can also be considered a good movement.

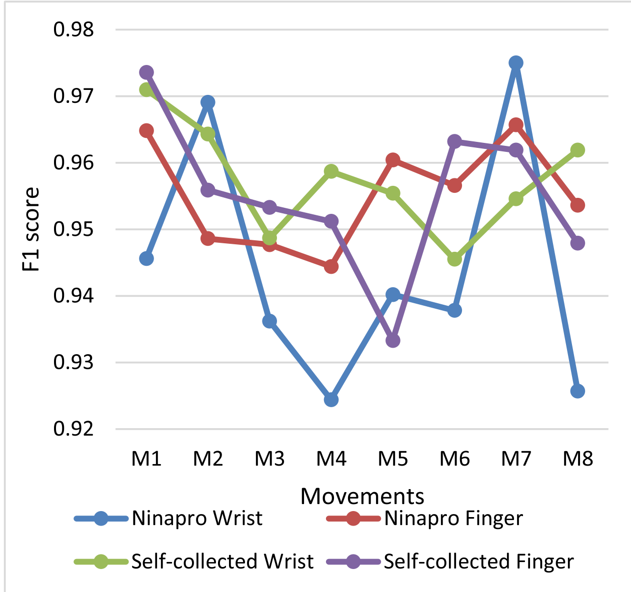


FIGURE 19. F1-scores for all datasets with Fine KNN.

TABLE 12. F1 scores of all datasets with ensemble bagged trees.

F1 Score (Ensemble Bagged Trees)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	0.9896	0.9898	0.9594	0.9489
M2	0.9905	0.9836	0.9437	0.9316
M3	0.9881	0.9873	0.9379	0.9217
M4	0.9889	0.9876	0.9516	0.9475
M5	0.9814	0.9788	0.9322	0.9177
M6	0.9862	0.9872	0.9152	0.9583
M7	0.986	0.9748	0.9198	0.9341
M8	0.9906	0.9814	0.935	0.9394

Fig. 21 represents the performance of Ensemble Bagged trees over each movement with all the datasets. It shows that Ninapro Datasets i.e Wrist and Finger give exceptional F1 scores if we observe the line plot of all the movements. We observe that M2 i.e. "Wrist Pronation (Axis: Middle Finger)" once again attains exceptionally high F1 score with Ensemble Bagged Trees. Besides, Wrist Movements M4 i.e. "Wrist pronation (axis: little finger)", M8 "Wrist Ulnar Deviation" and M1 "Wrist Supination (Axis: Middle Finger)" exhibit significant F1 scores. In the context of Finger Movements, it is noteworthy that M1 i.e. "Abduction of Thumb and Flexion of others" and M3 i.e. "Flexion of the ring and little finger, the extension of others" displayed

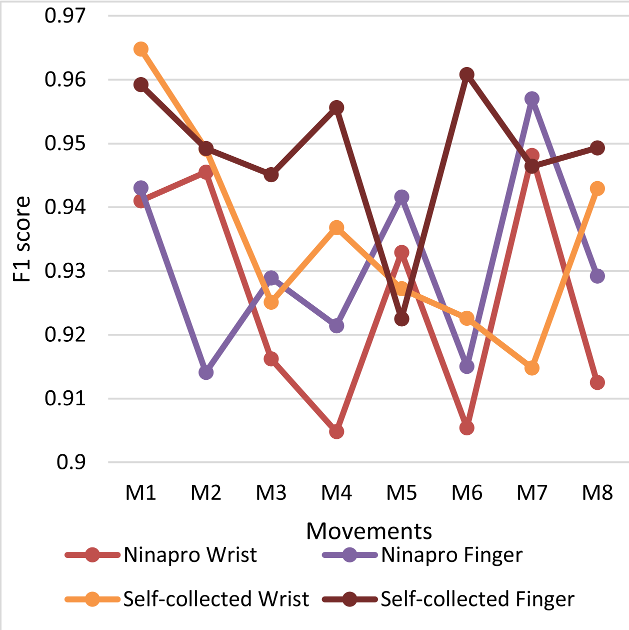


FIGURE 20. F1-scores for all datasets with Cubic SVM.

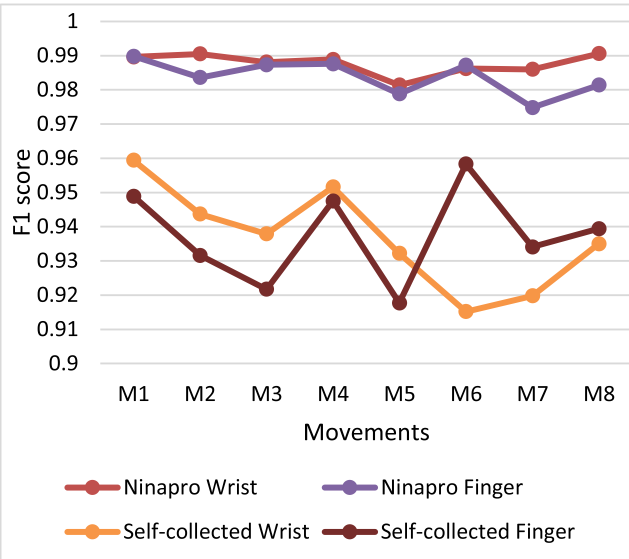


FIGURE 21. F1-scores for all datasets with ensemble bagged trees.

TABLE 13. F1 scores of all datasets with wide neural networks.

F1 score (Wide Neural Networks)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	0.9418	0.9679	0.961	0.961
M2	0.9479	0.951	0.9577	0.9499
M3	0.9205	0.952	0.9326	0.951
M4	0.9202	0.941	0.9571	0.9636
M5	0.9253	0.9506	0.9308	0.9295
M6	0.9271	0.9274	0.9314	0.9588
M7	0.9566	0.9663	0.9356	0.951
M8	0.9224	0.9423	0.944	0.9474

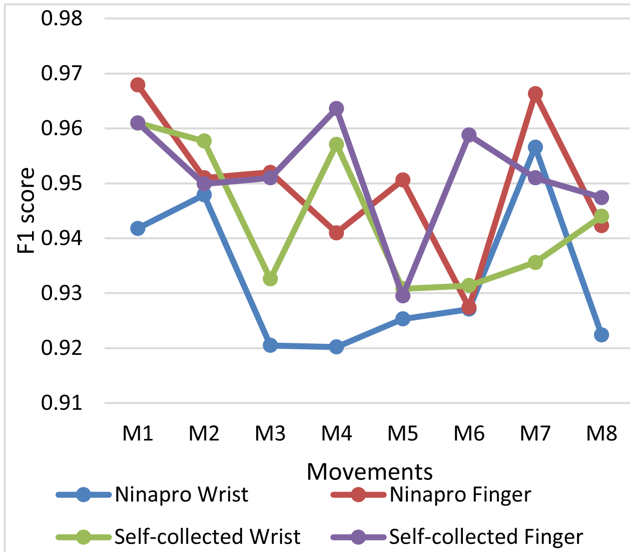


FIGURE 22. F1-scores for all datasets with wide neural networks.

the most outstanding performances with Ensemble Bagged Trees.

Fig. 22 demonstrates the efficiency of Neural Networks in the context of evaluating best movements/gestures. When examining finger movements, M1 i.e. "Abduction of Thumb and Flexion of others" and M7 i.e. "Pointing Index" exhibit the highest F1 scores with Wide Neural Networks, while in the context of wrist motions, M1 i.e. "Wrist supination (axis: middle finger)" and M2 i.e. "Wrist pronation (axis: middle finger)" emerge as the top performers.

Fig. 23 demonstrates the performance of Logistic Regression Kernel with respect to each movement and dataset. For finger movements, M4 i.e. "Thumb opposing Base of Little Finger" and M5 i.e. "Abduction of all Fingers" exhibit the highest F1 scores, whereas for wrist movements, M7 i.e. "Wrist Radial Deviation" and M8 i.e. "Wrist Ulnar Deviation" achieve the top F1 scores.

Table 15 showcases sensitivity scores for each movement within all 4 datasets, focusing on the Fine KNN classifier. Table 16 provides a similar breakdown for the Cubic SVM classifier. Table 17 shows sensitivity scores for Ensemble Bagged Trees, while Table 18 and Table 19 present sensitivity data for the Wide Neural Networks and Logistic Regression Kernel classifiers, respectively.

Fig. 24 and Fig. 25 show sensitivity scores of all the wrist and finger gestures with Fine KNN and Cubic SVM. The sensitivity data depicted in Fig. 36 and Fig. 37 reaffirm the

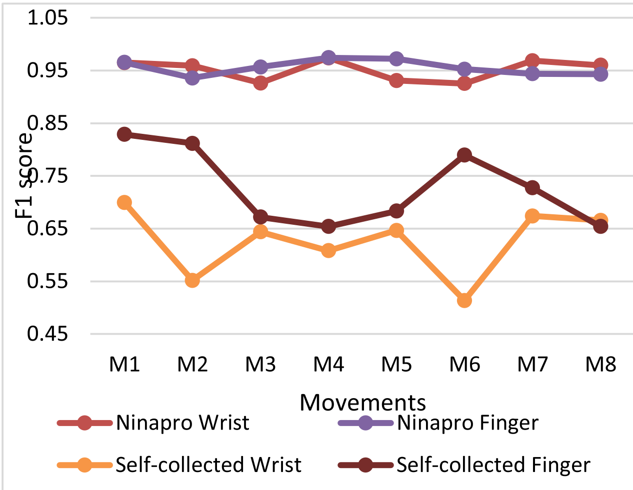


FIGURE 23. F1-scores for all datasets with logistic regression kernel.

TABLE 14. F1 scores of all datasets with logistic regression kernel.

F1 Score (Logistic Regression Kernel)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	0.9652	0.9655	0.6994	0.8288
M2	0.959	0.9359	0.5517	0.8119
M3	0.9263	0.9568	0.644	0.6718
M4	0.9741	0.9743	0.6081	0.6539
M5	0.9312	0.9724	0.6465	0.6833
M6	0.9253	0.9527	0.5135	0.7893
M7	0.9687	0.9439	0.6741	0.7274
M8	0.9601	0.9431	0.6656	0.6539

TABLE 15. Sensitivity for all datasets with fine KNN.

Sensitivity (Fine KNN)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	94.8	97.65	95.91	96.65
M2	96.81	94.92	96.46	95.79
M3	93.24	94.64	95.37	95.18
M4	93.53	93.7	95.55	95.67
M5	93.34	95.18	95.24	93.48
M6	93.69	95.07	95.79	96.65
M7	97.23	97.1	95.43	96.22
M8	92.64	95.09	96.22	94.39

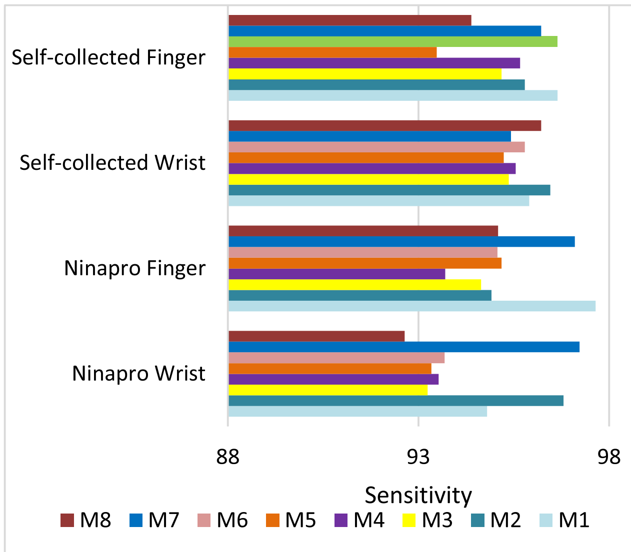


FIGURE 24. Sensitivity for all datasets with Fine KNN.

outcomes derived from performance evaluation metrics previously such as F1 score and classification accuracy. This evidence highlights that for wrist and finger movements, M1 i.e. "Abduction of Thumb & Flexion of others" and M7 i.e. "Wrist Radial Deviation" emerge as the top-performing choices respectively.

Fig. 26 shows the performance evaluation of the classifier Ensemble Bagged Trees by means of the evaluation metric sensitivity. The bar chart visualization of sensitivity scores in Fig. 26 underscores that among finger gestures, M1 i.e. "Abduction of Thumb & Flexion of others" and M7 i.e. "Pointing Index" exhibit the highest sensitivity, whereas in wrist movements, M1 i.e. "Wrist supination (axis: middle finger)" and M7 i.e. "Wrist Radial Deviation" deliver the most robust results.

Fig. 27 and Fig. 28 provide graphical illustrations of sensitivity achieved with Wide Neural Networks and Logistic Regression Kernel. The results in these figures confirm the effectiveness of wrist movements, particularly M7 i.e. "Wrist Radial Deviation", M4 i.e. "Wrist pronation (axis: little finger)", M2 i.e. "Wrist pronation (axis: middle finger)", and M1 i.e "Wrist Supination (Axis: Middle Finger)". In finger movements, M7 i.e. "Pointing Index", M4 i.e. "Thumb opposing Base of Little Finger", and M1 i.e. "Abduction of Thumb & Flexion of others" also exhibit superior performance.

The F1 scores and sensitivity data obtained in this study were subjected to normality tests, such as the Kolmogorov-Smirnov Test [36], [37], to assess the distribution of the data. The results of these tests revealed that the data did not follow a normal distribution and, therefore, did not meet the assumptions required for one-way analysis of variance (ANOVA). To address this, a non-parametric test, namely the Kruskal-Wallis test, was employed as an extension of ANOVA suitable

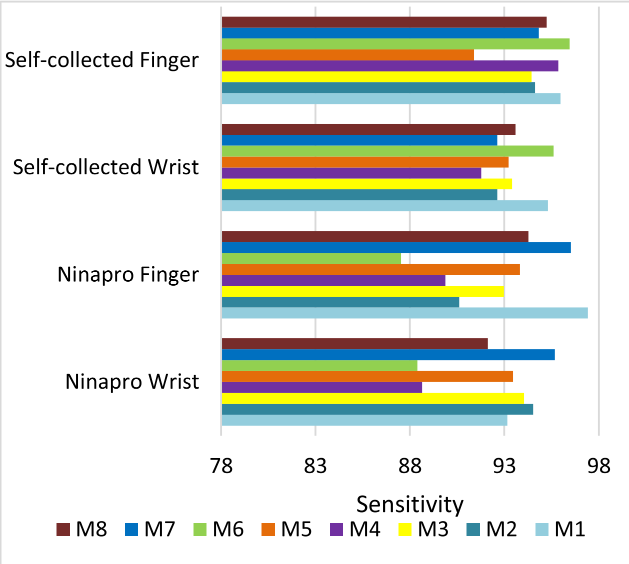


FIGURE 25. Sensitivity for all datasets with Cubic SVM.

TABLE 16. Sensitivity for all datasets with cubic SVM.

Sensitivity (Cubic SVM)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	93.16	97.42	95.3	95.98
M2	94.53	90.61	92.62	94.63
M3	94.04	92.98	93.41	94.45
M4	88.65	89.88	91.77	95.85
M5	93.46	93.83	93.23	91.4
M6	88.4	87.53	95.61	96.46
M7	95.68	96.53	92.62	94.82
M8	92.13	94.28	93.6	95.24

for non-normally distributed data. The Kruskal-Wallis test was used to evaluate whether statistically significant differences existed between the various groups (movements) based on rank order. The outcomes of the Kruskal-Wallis test [38] indicated a significant difference between movements ($p < 0.05$) for both F1 scores and sensitivity within each dataset, i.e. Ninapro and self-collected.

IV. DISCUSSION

The purpose of this research is to prioritize efficiently and accurately identifiable movements over a wide range of motions in order to enhance the functionality and user-specificity of prosthetic hands, focusing both wrist and finger movements. The study evaluates different machine learning models' performance in distinguishing between gestures to improve user-specificity.

TABLE 17. Sensitivity for all datasets with ensemble bagged trees.

Sensitivity (Ensemble Bagged Trees)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	99.45	99.33	95.12	96.28
M2	99.29	97.72	93.96	92.99
M3	98.84	98.52	93.54	92.62
M4	98.36	98.52	94.09	95.12
M5	97.52	97.56	92.62	90.43
M6	98.15	98.07	94.15	95.24
M7	99.23	99.08	91.65	94.63
M8	99.04	97.5	94.27	92.62

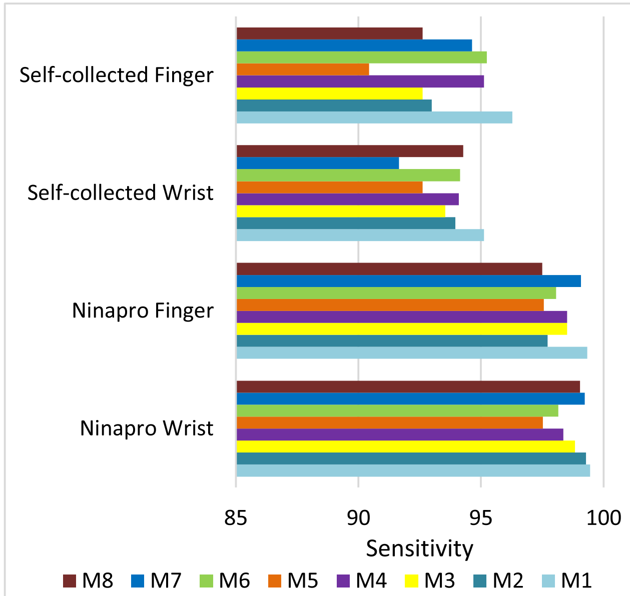


FIGURE 26. Sensitivity for all datasets with ensemble bagged trees.

While existing literature addresses certain movements, this research provides a unique perspective by conducting a comprehensive analysis of both functional and non-functional movements. It fills the gap in prior research by exploring the interplay between various movements and classifiers, offering insights into their symbiotic relationship. This holistic approach uncovers individual classifier strengths and weaknesses while revealing nuanced performances across different movements, a novel perspective not explored in previous studies.

Our study distinguishes itself with a holistic approach, moving beyond the individual-focused analyses common in previous research. By exploring both overall and subject-specific perspectives, we uncover universal patterns in upper-extremity movements, providing a robust

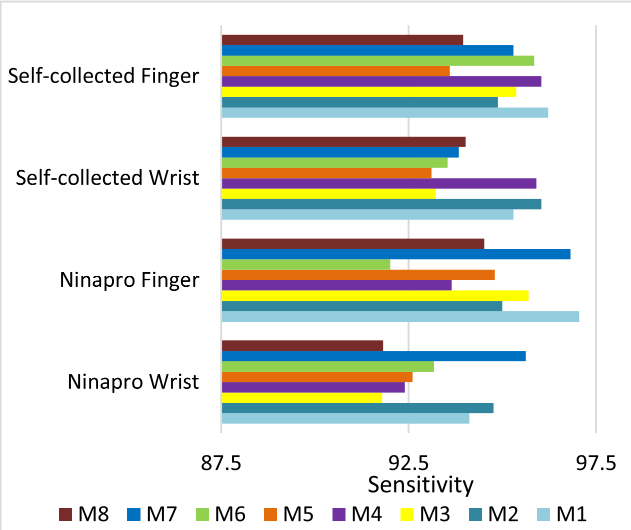


FIGURE 27. Sensitivity for all datasets with wide neural networks.

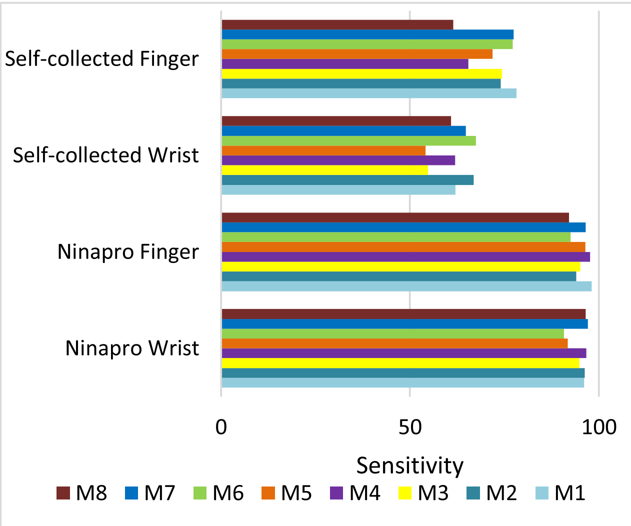


FIGURE 28. Sensitivity for all datasets with logistic regression kernel.

TABLE 18. Sensitivity for all datasets with wide neural networks.

Sensitivity (Wide Neural Networks)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	94.12	97.05	95.3	96.22
M2	94.77	095	96.04	94.88
M3	91.8	95.7	93.23	95.37
M4	92.4	93.65	95.91	96.04
M5	92.61	94.8	93.11	93.6
M6	93.18	92.01	93.54	95.85
M7	95.63	96.82	93.84	95.3
M8	91.82	94.52	94.02	93.96

TABLE 19. Sensitivity for all datasets with logistic regression kernel.

Sensitivity (Logistic Regression Kernel)	Ninapro Wrist	Ninapro Finger	Self-collected Wrist	Self-collected Finger
M1	96.08	98.15	62.07	78.23
M2	96.24	94.03	66.89	74.09
M3	94.85	95.1	54.82	74.39
M4	96.71	97.66	62.01	65.49
M5	91.82	96.43	54.15	71.89
M6	90.82	92.52	67.5	77.2
M7	97.12	96.5	64.82	77.44
M8	96.5	92.11	60.91	61.46

understanding of how specific motions reliably identify and meet the needs of the majority of amputees. Notably, our findings from per-subject analyses align with global perspectives, reinforcing the efficiency of movements identified through our comprehensive approach. Our research, in short, redefines the exploration of upper-extremity movements and classifiers, contributing valuable insights to enhance prosthetic designs and assistive technologies for a diverse range of amputees.

In the realm of hand and wrist gesture recognition, the studies [1], [9], [11], [12], [13], and [14] have provided valuable insights into the landscape of classification accuracy for a diverse range of gestures. These works have shown that various classifiers, such as LDA, SVM, ANN, KNN, and more, were able to achieve impressive classification accuracies for different hand and wrist gestures, with reported scores often exceeding the 90% threshold. Particularly, wrist movements seemed to garner significant attention, with [1] and [9] reporting accuracy rates of 94.7% and 96.1%, respectively, using LDA and SVM classifiers.

However, with the introduction of the proposed methods in this study, there is a clear and compelling case for advancements in the field. For wrist gestures, the results consistently outperformed the earlier findings, with Cubic SVM and Fine KNN achieving remarkable training and testing accuracies of 94.5% and 95.4%, and 93.6% and 94.6%, respectively. Ensemble Bagged Trees emerged as a powerful classifier, with an astounding 98.4% training accuracy and a flawless 99.0% in testing accuracy, underscoring its potential as a robust choice for wrist gestures. The Wide Neural Network offered competitive results with training accuracy at 91.7% and testing accuracy at 93.5%, while the Logistic Regression Kernel displayed consistent high performance, boasting a training accuracy of 94.7% and a testing accuracy of 95.0%. The superiority of the proposed methods also extended to finger gestures, where Cubic SVM and Fine KNN achieved training and testing accuracies of 95.9% and 96.5%, and 94.7% and 95.2%, respectively. Ensemble Bagged Trees showcased its exceptional performance with a training accuracy of 98.2% and a testing accuracy of 98.2%. The Wide Neural Network remained competitive, with training accuracy at 94.1% and testing accuracy at 94.6%, while the Logistic Regression Kernel consistently delivered high accuracy, recording a training accuracy of 94.5% and a testing accuracy of 95.0%. While the previous studies have undoubtedly laid a strong foundation, the shortcomings primarily lie in the need for more robust and accurate classifiers, a gap that this research aims to address with the introduction of the proposed methods.

The detailed assessment of various machine learning models and presets, yielded some notable insights. The Wide Neural Network consistently outperformed others in prediction speed, making it an ideal choice for real-time applications. Conversely, Cubic SVM had the longest training times, whereas Fine KNN was the fastest to train but had lower prediction speed. Ensemble Bagged Trees showed strong prediction speeds but with longer training times, illustrating a trade-off between complexity and efficiency. Logistic Regression Kernel, although slow to train, emphasized interpretability.

Previous studies regarding hand gesture recognition lacked a thorough comparative analysis of different hand gestures involving wrists and fingers. This study enables us to practically consider the relatively lower accuracies for certain wrist and finger movements when designing control strategies for prosthetic devices or other rehabilitative applications. In the future, the challenges associated with certain gestures should be addressed and importance of considering the above mentioned movements as a more reliable option in hand gesture recognition systems must be underscored. Future research can focus on investigating the specific features and patterns within the best performing movements that contribute to their superior classification performance. Also, further investigations could explore the underlying factors contributing to the varying accuracies of different movements, such as the complexity of muscle activation patterns or the level of difficulty in distinguishing between certain movements. Such insights can inform the development of more robust and accurate hand gesture recognition systems for applications like prosthetic control or human-computer interaction.

The paper sets up a good foundation for further research into what makes certain movements better classifiers than others and how can prosthetic devices' performance benefit from such focused model training. It assesses multiple classifiers, identifying the most effective ones for this application. The findings provide valuable insights into the selection of optimal movements for efficient hand gesture recognition and can contribute to advancements in the design and development of more effective and personalized prosthetic devices.

Additionally, while our study primarily focuses on evaluating the potential of the best performing wrist and finger movements, there exists potential for further enhancement through the utilization of compressed data methodologies coupled with sparse techniques. Incorporating these advanced data processing approaches in future investigations could significantly optimize the efficiency of movement classification in intelligent myoelectric recognition systems for prosthetic control. By leveraging compressed data techniques and sparse methodologies, future research can aim to reduce data redundancy and enhance computational efficiency, ultimately refining the precision and responsiveness of prosthetic devices to user-specific movements. Exploring these avenues stands as a promising direction for improving the robustness and real-time applicability of hand gesture recognition systems in assistive technologies.

V. CONCLUSION

In conclusion, our study underscores the vital importance of a patient-specific prosthetic scheme that considers functional and non-functional motions, prioritizing efficiently identifiable movements over a broad spectrum. Through employing state-of-the-art classifiers for intelligent hand gesture myoelectric recognition, our findings distinctly highlight the superior performance of specific movements over others. Notably, Ensemble Bagged Trees demonstrated exceptional accuracy (98.2% $\pm$ 0.81) for finger and wrist (99% $\pm$ 0.73) movements (One-Way Anova Test), while Wrist Radial Deviation (Clockwise) and Wrist Extension emerged as optimal wrist motions (Wilicoxon signed-rank test). Additionally, Fine KNN and Cubic SVM achieved substantial accuracies of up to 96.3% $\pm$ 0.81 and 95.9% $\pm$ 1.43, respectively. Whereas, Abduction of thumb and flexion of others consistently exhibited high accuracies for finger gestures. Future research avenues could explore integrating compressed data methodologies and sparse techniques to further enhance intelligent hand gesture myoelectric recognition systems. These advancements promise significant improvements in the functionality and user experience of personalized prosthetic devices, contributing to the continuous evolution of prosthetic technology for individuals with upper-extremity amputations.

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