# WEARABLE TECHNOLOGIES

# UNIVERSITY OF SUSSEX

ONUR CAN CIKLA

CANDNO:282678

Utilizing EGM Data with MYO Armband for Gesture Recognition

## Table of Contents

# ABSTRACT

This study explores the utilization of the Myo armband, a wearable device equipped with electromyography (EMG) sensors, for gesture recognition. The Myo armband captures electrical activity from muscle contractions, enabling control of various devices through detected hand movements. Recent advancements in machine learning have significantly enhanced the Myo armband's ability to manage variability in EMG signals across different users and sessions. This research highlights the Myo armband's applications in prosthetics, gaming, entertainment, and robotic control, demonstrating its potential to improve user interaction and functionality. Technical, market, and financial feasibility analyses indicate that the Myo armband is a viable and cost-effective solution for real-time prosthetic control and other applications, offering significant improvements in usability and patient outcomes


# Introduction

Wearable technologies have revolutionized device interaction, offering natural and intuitive control methods. The Myo armband, developed by Thalmic Labs Inc., uses electromyography (EMG) sensors to detect muscle activity in the forearm, enabling control of prosthetics, gaming interfaces, robotic systems, and other devices through hand gestures. Equipped with eight EMG sensors, the Myo armband transmits data via Bluetooth to a connected device for gesture recognition. Advanced machine learning techniques enhance its ability to classify gestures accurately across different users and conditions, making it especially useful in prosthetic control.

This research evaluates the Myo armband's technical, market, and financial feasibility, focusing on its use in prosthetics and other areas. By analysing EMG data and employing advanced machine learning methods, the study aims to demonstrate the Myo armband's potential to improve user interaction and functionality across various settings.

# Overview and Literature Review

**Overview of Advanced Applications and Related Algorithms**

Recent studies have focused on the Myo armband's advanced applications and algorithm development to enhance user interaction with devices, highlighting its potential in prosthetic and virtual reality applications.

**Research on Myo Armband Applications**

Several studies have examined the Myo armband's effectiveness. Mendez et al. (2017) found a mean classification error of 5.82% for conventional EMG systems and 9.86% for the Myo armband in recognizing nine hand gestures. Donovan et al. (2016) developed MyoHMI, a platform for real-time myoelectric signal visualization, including a 3D-printed prosthetic hand and a virtual reality system. Benalcázar et al. (2017) achieved an 86% accuracy in hand gesture recognition using k-nearest neighbor and dynamic time warping algorithms.

**Control of Robots and Other Devices**

The Myo armband has been used to control robots. Sathiyanarayanan et al. (2015) demonstrated its use in controlling a robot's velocity and braking. Ganiev et al. (2016) showed that EMG sensors could control a virtual robotic arm using forearm muscle data. Morais et al. (2016) developed a control interface for the People Bot robot, achieving a 93.6% classification rate for different movements.

**Myoelectric Prostheses and Improved Interaction**

Algorithms have been developed to enhance user interaction with myoelectric prostheses. Combining EMG with other techniques like MMG and NIRS has improved human-machine interfacing and real-time control (Fang et al., 2015; Guo et al., 2017). Adaptive algorithms reduce recalibration time by reusing models trained earlier, enhancing control robustness (Liu et al., 2016). Dynamic arm postures and varying muscle contractions improve classification accuracy (Yang et al., 2017; Khushaba et al., 2017). Menon et al. (2017) found that analysis window length and overlap affect EMG signal pattern classification accuracy.

## Application Fields of Myo Armband

The integration of technology and humans, alongside the development of flexible electronic equipment like roll-up displays and wearable devices, has garnered attention from researchers and companies aiming to create high-performance, user-friendly devices. Numerous studies (Sathiyanarayanan et al., 2015; Shin et al., 2015; Ganiev et al., 2016; Morais et al., 2016) show that the Myo armband's applications extend beyond prosthetics. It can control robotic arms and manage mechanical devices through hand gestures, eliminating the need for joysticks or other control devices. By harnessing electrical signals from forearm and arm muscle contractions detected by its eight EMG electrodes, the Myo armband can drive connected devices via Bluetooth technology.

**Gaming Applications**
A notable application field for the Myo armband is gaming. In "Fruit Ninja," users slice fruits on the screen using hand gestures detected by the armband. In "Race the Sun," the user controls a flying vehicle’s path to avoid crashing (Fig. 2). Figure 3 shows two users competing to paint a whiteboard with different colours, while Figure 4A shows a player controlling a weapon and Figure 4B depicts a user driving a kart. The Myo armband is compatible with many other games, as detailed on the Myo device website (Myo Armband website; Myo Market, 2013–2016).

**Entertainment Applications**
In entertainment, the Myo armband has been notably used by DJ Armin Van Buuren during his electronic/dance music performances, where the armband controls stage lighting in sync with his movements (Fig. 5).

Figure 5: The artist uses the Myo armband during his shows to control stage lighting, creating light effects based on his movements.

**Drone and Robot Control**
The Myo armband is also useful for controlling flying drones and robot movements. This application is particularly relevant during military manoeuvres, where trained personnel can remotely operate a robot simply by wearing and using the armband (Fig. 6).

**Desktop Navigation**
Moreover, the Myo armband can be used for navigating PC desktops, selecting, and exploring various applications, and performing different tasks. A notable example is its use during presentations, allowing users to control slides and navigate through content seamlessly (Fig. 7). the Myo armband's diverse applications in gaming, entertainment, drone control, and desktop navigation illustrate its versatility and potential to enhance user interaction across various fields.

Figure 1: The MYO armband detects hand movements in all directions by analysing the electrical activities of forearm muscles

Technical features and functionalities of myo armband: an overview on related literature and advanced applications:


Figure 2: The MYO armband enables gameplay by detecting the user's gestures and sending the corresponding signals to a PC or TV via Bluetooth connection.

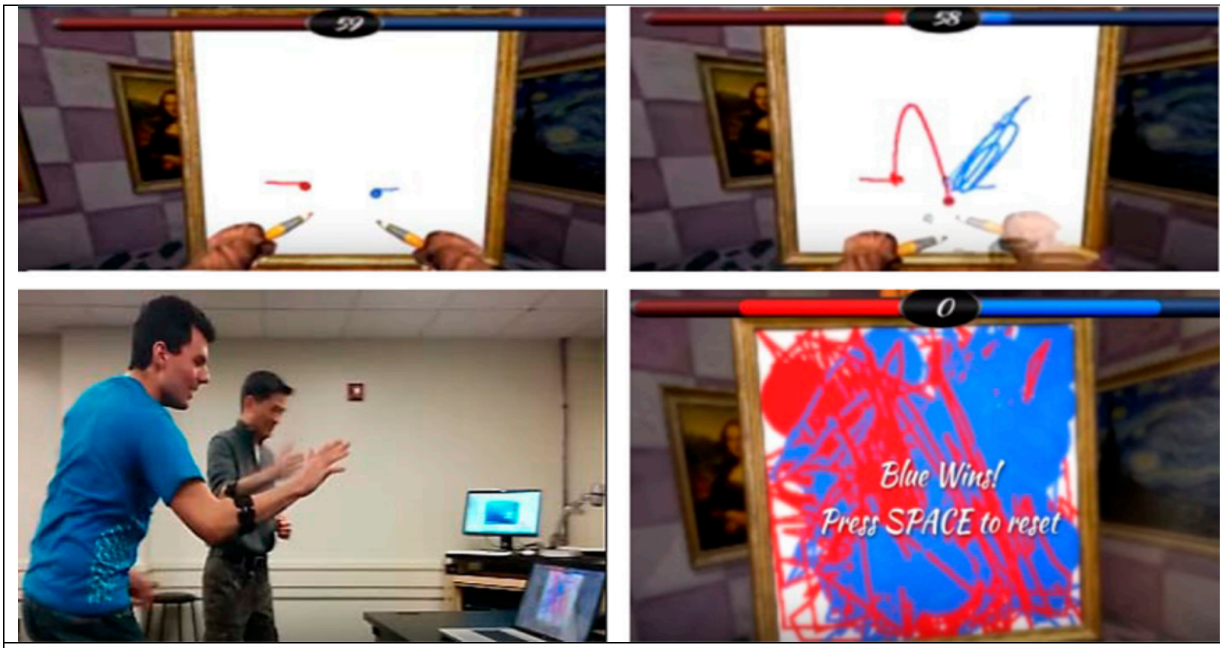



Figure 3: In this game, two players use MYO armbands to paint a whiteboard as quickly as they can. The player who covers the most area within a set time wins.

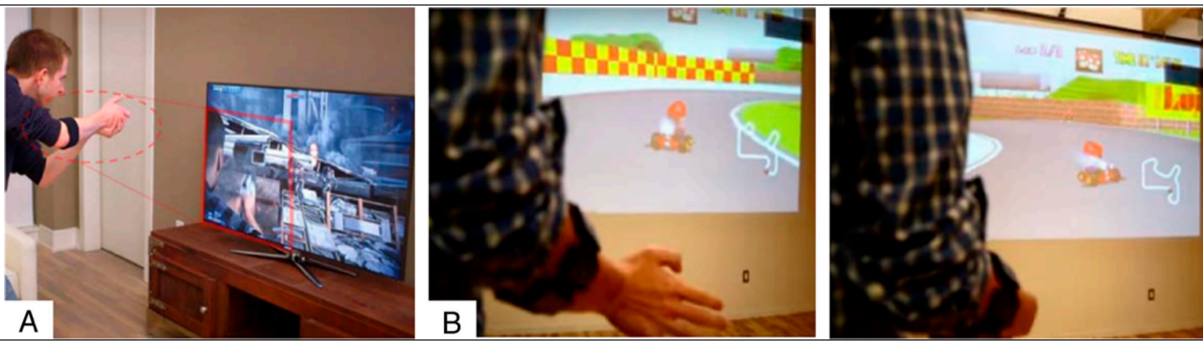



Figure 4: Through MYO armband the player interfaces with two different console games.

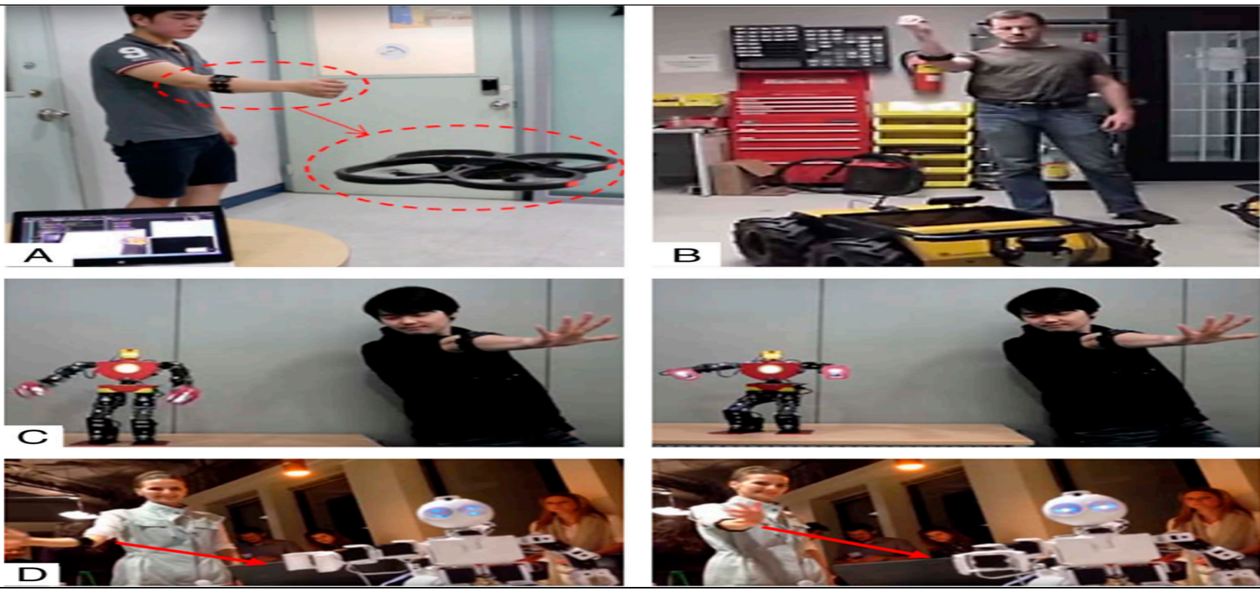



Figure 6: Myo armband allows to control (A) flying drones, (B), (C), and (D) robot movements and many other mechanical devices simply by moving the arm which wears the armband.

remote controller: the user, by wearing the Myo armband, can control the presentation software with proper gestures and motion (respectively through EMG and IMU readings).

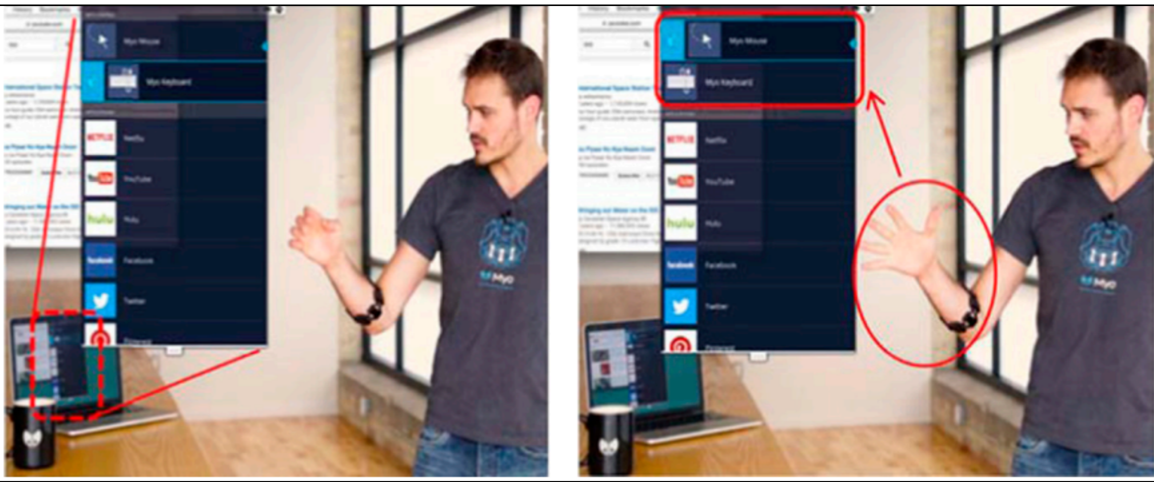


Figure 7: By using Myo armband, it is possible to navigate on the PC desktop and to use several software and applications.


Figure 8: Myo armband used in a surgery room for controlling a camera to visualize the examined body part, without having to physically touch a controller or medical instrument and thus improving user safety and reducing infections risk.

The application fields of the Myo armband are extensive, covering not only games, robotic and computer applications, but also the healthcare sector. One notable example is the technology developed by TedCas, a leader in medical imaging. By integrating the Myo armband with various cameras and voice recognition software, TedCas has created a system that allows surgeons to control multiple medical instruments in real-time during surgeries (Fig. 8). This technology enables surgeons to perform tasks themselves without assistance, keeping their hands clean and free, thereby reducing surgery time and enhancing patient safety by minimizing infection risks. For instance, surgeons can rotate a 3D image of the body part under examination or control a camera to view tissues in detail without physical contact (ADORA-MED d.o.o.).

**Prosthetic Applications**

The Myo armband also shows immense potential in prosthetic applications. It can control the movements of prostheses that replace amputated limbs. In an experimental test at Johns Hopkins University, a patient with a prosthetic arm connected to his skeleton (osseointegration) used two Myo armbands on the upper arm to detect the electrical activity of the biceps and triceps muscles (Thalmic Labs Inc., 2013–2017). This setup enabled the patient to grab, lift, move, and release objects accurately, thanks to the precise movement control provided by the Myo armbands (Fig. 9).
Figures 10 and 11 demonstrate an amputee patient wearing the Myo armband, with an additional band for a tighter fit. By moving her arm, the patient could control a robotic

prosthesis attached to a support at a distance. The robotic prosthesis mirrored her arm movements, allowing for seamless control.
Figures 12A and 12B show the arm wearing the Myo armband, covered by the band. Muscle contraction is visible in Figure 12A, while the muscles are relaxed in Figure 12B. By contracting specific muscles or making certain movements, the patient could even move individual fingers of the prosthesis, as demonstrated in Figures 13A and B, where the prosthetic thumb is respectively opened and closed.

**Enhanced Sensory Feedback**

Adding sensors such as force, temperature, and contact sensors to the prosthetic hand can provide the patient with vital information about the grasped objects (Fig. 14). Contact sensors allow the patient to feel the consistency of the objects they grasp. Electrodes positioned on the skin relay this information to the arm, enabling the patient to "feel" when the prosthetic hand touches an object. In the experimental setup shown in Figure 15, when the doctor touches the prosthetic fingers, the patient receives feedback, effectively sensing the contact.

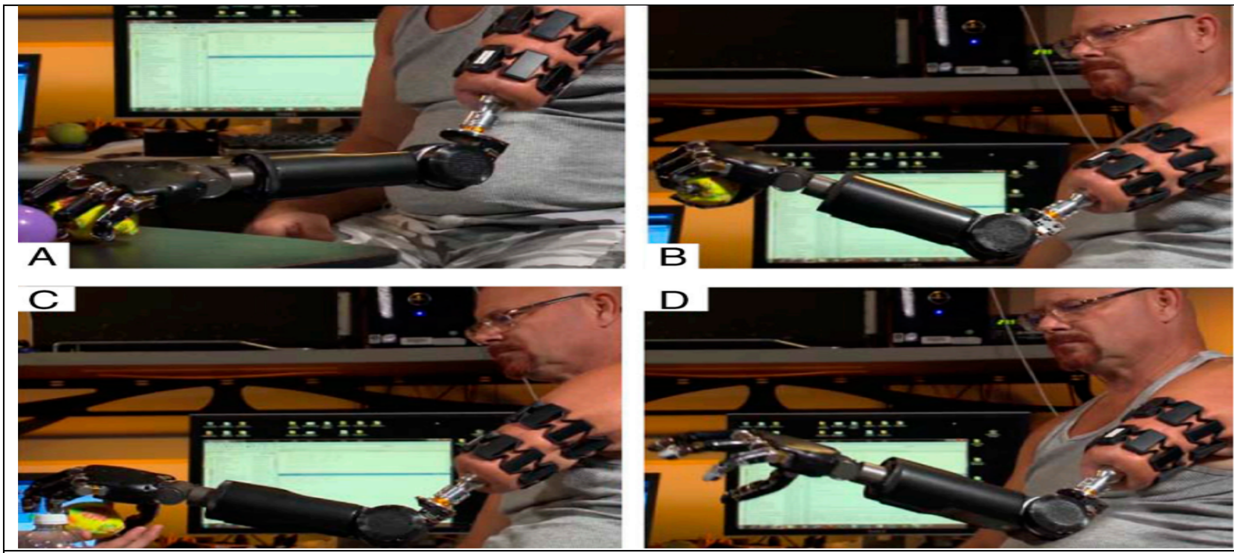



Figure 9: Two Myo armbands used to control the movements of a trans-humeral prosthesis; in this specific experimental test, the patient first grabs and then releases a tennis ball.

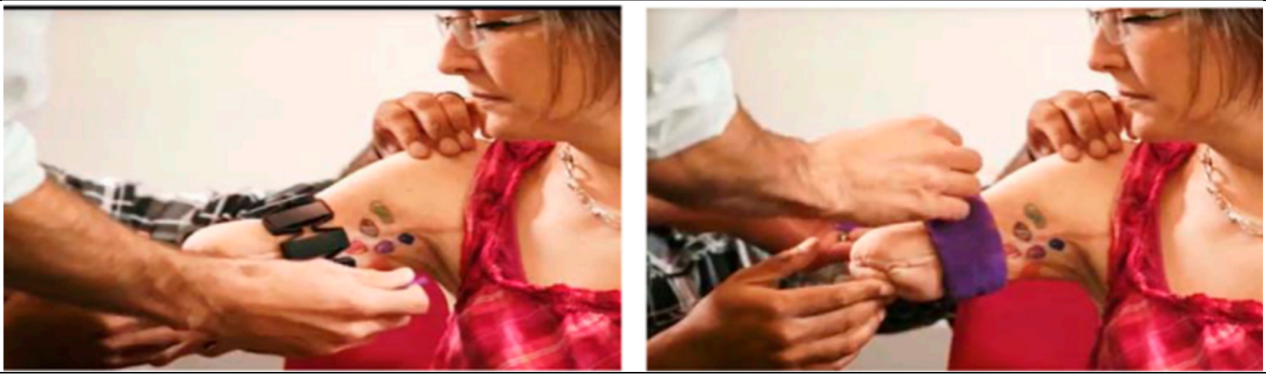


Figure 10: Myo armband worn by the patient; the purple band serves to better tighten the armband around the arm.

Figure 11: The patient controls the robotic prosthesis placed at distance from her.

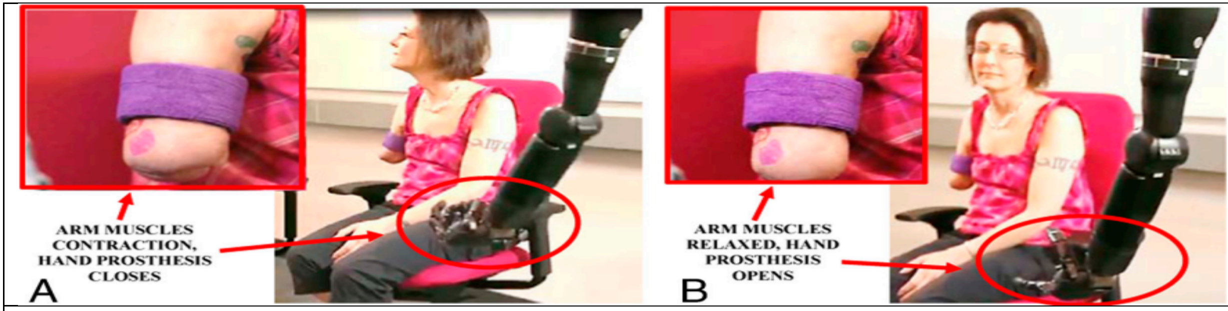



Figure 12: By activating the arm muscles, the prosthetic hand closes (A), whereas by relaxing the arm muscles the prosthetic hand opens (B).

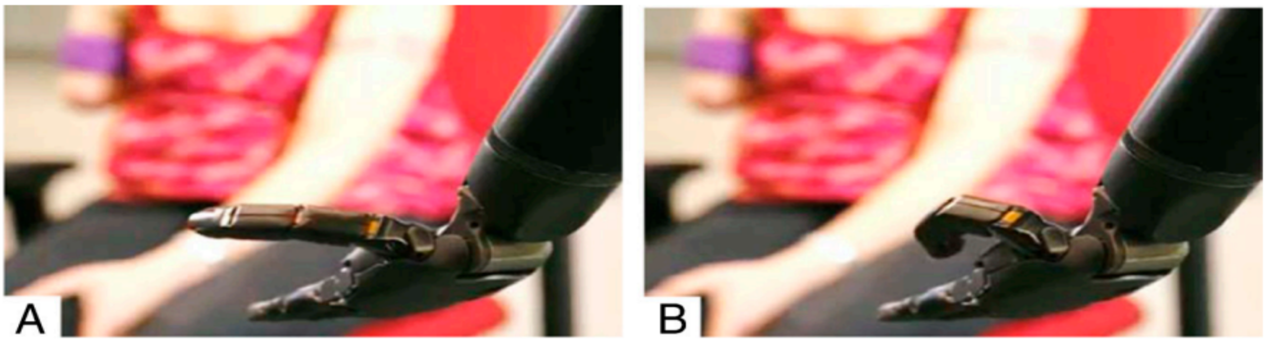



Figure 13: The patient wearing the Myo armband can move even a single finger of the robotic prosthesis placed at distance of about 1 meter from her.

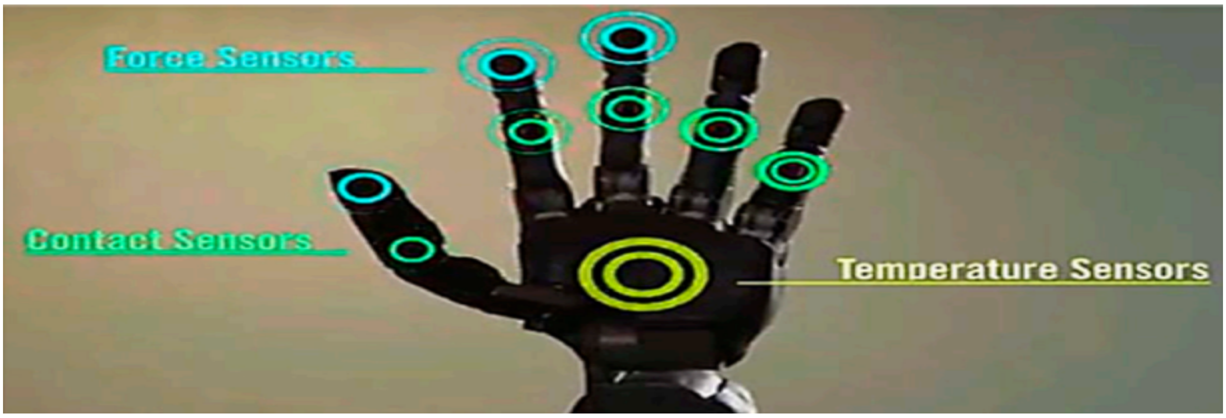



Figure 14: Prosthetic hand with indicated the installed sensors: Force Sensors are highlighted in blue, Contact Sensors in green and Temperature Sensors in yellow.

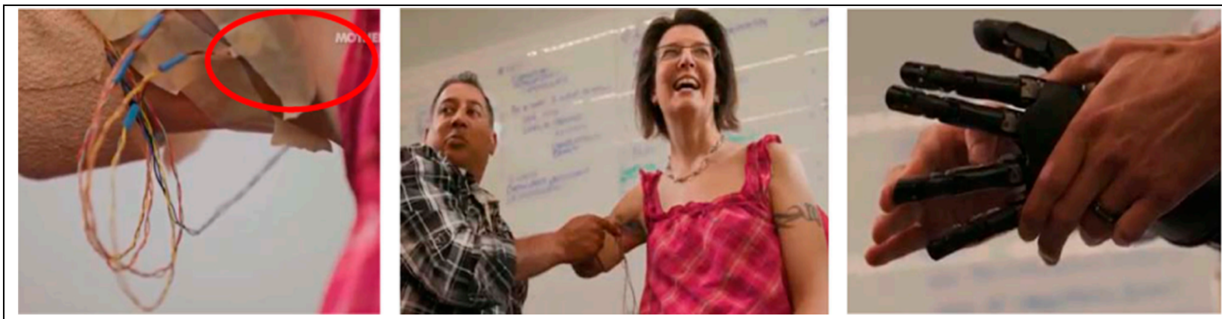


Figure 15: The contact sensors provide feedback signals to the patient that “feels” the touched objects.

## Overview of Prosthetic Types and Technological Advances

There are various types of active upper-limb prostheses available today: passive prostheses, body-powered prostheses, and myoelectric prostheses.

**Passive Prostheses**
Passive upper-limb prostheses are primarily used for cosmetic purposes and have limited functional capabilities. They do not generally offer active hand functions, but some fingers can be manually positioned for improved functionality, such as thumb opposition. These prostheses are lightweight, compact, and require minimal maintenance.

**Body-Powered Prostheses**
Body-powered prostheses are controlled by gross body movements through a harness system. Depending on the level of amputation, the prosthetic hand is operated either by shoulder abduction or wrist flexion. There are two main types:

**Voluntary Opening (VO)**: Normally closed and open with movement.

**Voluntary Closing (VC)**: Normally open and close with movement. These prostheses are robust, lightweight, and affordable, but their range of motion can be limited (Figure 16A shows a body-powered hook, and Figure 16B shows the Child CAPP Hand prosthesis by Fillauer LLC, which is small and lightweight).

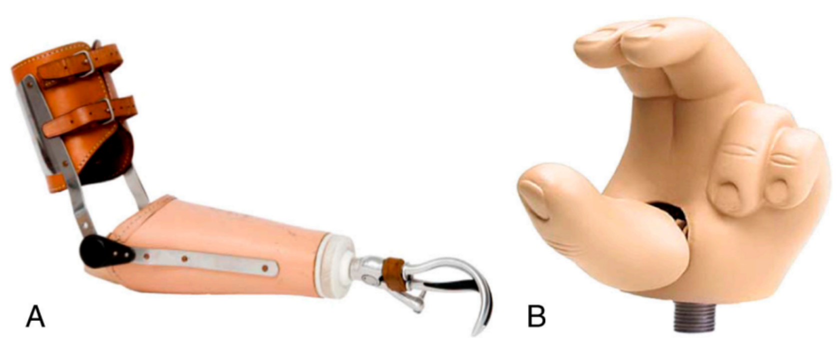



Figure 16: Two typologies of body-powered prostheses. They are compact, low cost and lightweight, but are characterized by limited dexterity.

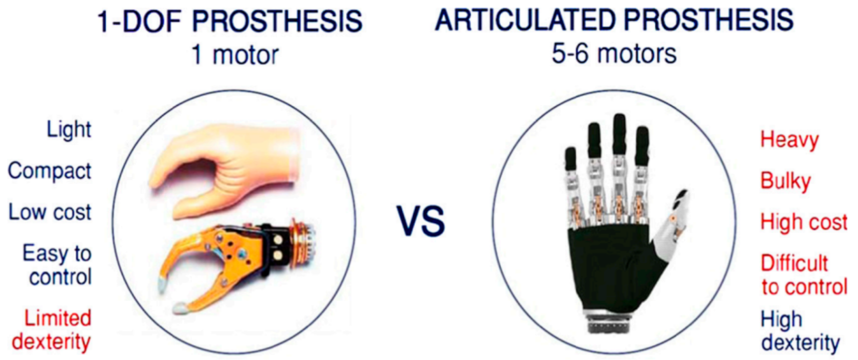



Figure 17: The main types of commercial myoelectric prostheses currently available are shown with their respective advantages (in blue) and disadvantages (in red). 1-DOF prostheses are simple and easy to use but have limited dexterity, whereas multi-articulated prostheses offer high dexterity but are heavier, bulkier, and very expensive.

Myoelectric Prostheses

Myoelectric prostheses are powered by external batteries and controlled through EMG signals from muscle contractions. They can be classified into two categories:

1 DOF Prostheses: These use a single motor to control the opening and closing of three fingers. They are light, compact, and easy to use but have limited movement capabilities (Figure 17).

Poly-Articulated Prostheses: These use multiple motors to allow independent finger movements, offering high dexterity but are heavier, bulkier, and more complex to control.

The main challenge with poly-articulated prostheses is their complexity, requiring more data for effective control, which increases both their electronic complexity and cost. Examples include the i-limb hand by Touch Bionics (Figure 18) and the bebionic hand by Otto bock, which offers 14 different grip patterns (Figure 19).

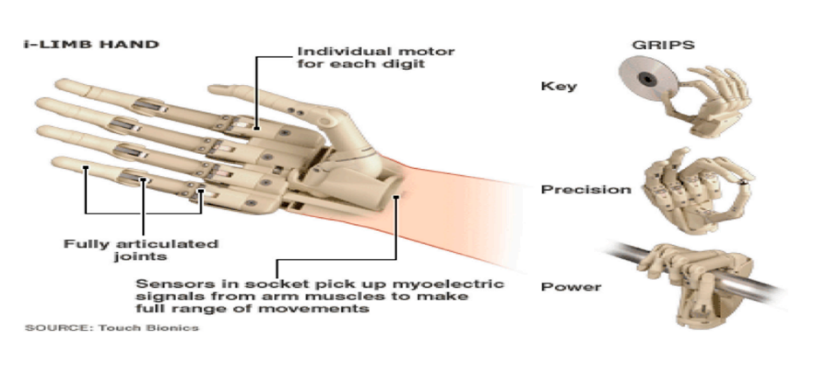



Figure 18: I-limb poli-articulated prosthesis produced by Touch Bionics: the user can perform power, precision, and many other grips thanks to the five motors embedded into the device

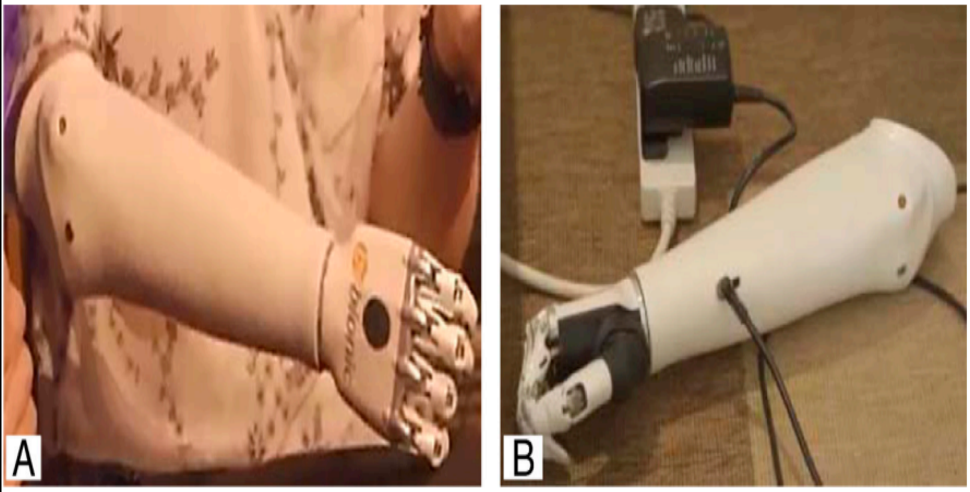



Figure 19: Bebionic hand prosthesis worn by a patient (A) and connected to the power supply to recharge the battery (B)

**Incorporating Advanced Machine Learning for Enhanced Myoelectric Control with the Myo Armband**

Recent advancements in wearable technology have significantly bolstered the potential for seamless myoelectric control in prosthetic applications. A noteworthy development in this field is the use of the Myo armband, equipped with electromyography (EMG) sensors, combined with innovative machine learning techniques to enhance user-machine interaction. This integration promises considerable improvements in the usability and functionality of prosthetic devices.

**Feasibility of Unsupervised Transfer Learning**

The Myo armband, when paired with unsupervised transfer learning, such as the Self-Calibrating Asynchronous Domain Adversarial Neural Network (SCADANN), addresses key challenges in the field. This combination has shown potential in compensating for the inherent non-stationarity of EMG signals, which often vary between users and across different usage sessions. SCADANN has proven effective in adjusting to these variations without the need for frequent recalibrations, enhancing the practicality of deploying this technology in real-world settings. The approach facilitates robust gesture classification across varied conditions and users, showcasing an average improvement in accuracy by notable margins.

**Consumer-Grade Application and Clinical Relevance**
Utilizing a consumer-grade sensor like the Myo armband significantly reduces costs and complexity compared to laboratory-grade systems. This affordability, coupled with the armband's enhanced functionality through advanced machine learning algorithms, aligns with the current market trends towards developing accessible and user-friendly medical devices. The feasibility of this technology extends beyond clinical settings, suggesting its potential for broad adoption in home-based rehabilitation and daily usage by individuals requiring prosthetic support.

# Feasibility Analysis of EMG Myo Armband

The Myo armband, developed by Thalmic Labs Inc., is a wearable device equipped with electromyography (EMG) sensors and an inertial measurement unit (IMU). It is designed to capture muscle activity and movement data, which can be used in various applications, from prosthetics to gaming. This feasibility analysis aims to evaluate the practical application of the Myo armband, focusing on its technical, market, and financial viability.

## 2. Technical Feasibility

**Sensor Technology and Data Accuracy**
The Myo armband includes eight EMG sensors placed around the forearm, which detect electrical activity from muscle contractions. Additionally, it has a 9-axis IMU consisting of a gyroscope, accelerometer, and magnetometer. This combination allows for comprehensive data collection on muscle activity and forearm movements.

**Data Processing and Machine Learning Integration**
Recent advancements in machine learning, particularly unsupervised transfer learning methods like the Self-Calibrating Asynchronous Domain Adversarial Neural Network (SCADANN), have enhanced the ability to manage variability in EMG signals. This addresses a critical challenge in myoelectric control systems, where signal characteristics can vary significantly across users and sessions. By utilizing these advanced algorithms, the Myo armband can achieve robust gesture classification and reduce the need for frequent recalibrations.

**Application in Prosthetics**
In prosthetic applications, the Myo armband can significantly improve the control and functionality of prosthetic limbs. Its ability to accurately capture and interpret EMG signals allows for intuitive control of prosthetic hands and arms. The integration of advanced machine learning algorithms further enhances this capability, making the Myo armband a viable solution for improving the quality of life for amputees.

## 3. Market Feasibility

**Current Market Trends**
The market for wearable technology is growing rapidly, with increasing demand for devices that offer enhanced functionality and user-friendly interfaces. The healthcare sector is seeing a surge in the adoption of wearable devices for rehabilitation and prosthetic control.
**Competitive Landscape**
Several companies are developing EMG-based control systems for prosthetics. However, many of these systems are either prohibitively expensive or lack the necessary

functionality for everyday use. The Myo armband, with its consumer-grade pricing and advanced features, positions itself as a competitive alternative in this market.

**User Adoption**

The Myo armband's ease of use and non-invasiveness make it an attractive option for users. Its ability to provide real-time feedback and intuitive control can drive higher adoption rates among individuals needing prosthetic support or those seeking advanced control interfaces for various applications.

## *4. Financial Feasibility*

**Cost Analysis**

The Myo armband is relatively affordable compared to high-end EMG acquisition systems. Its consumer-grade sensors and components help keep the production costs low, making it accessible to a broader audience. Additionally, the integration of advanced algorithms like SCADANN can be implemented using cost-effective software solutions.

**Return on Investment**

For healthcare providers and individuals, investing in the Myo armband offers significant returns. By improving the functionality and usability of prosthetic devices, it can lead to better patient outcomes and increased independence for users. This, in turn, can reduce long-term healthcare costs and improve quality of life.

**Funding Opportunities**

There are various funding opportunities for developing and deploying wearable EMG technology, including grants from health organizations, technology innovation funds, and potential partnerships with healthcare providers and rehabilitation centres.

## 5. Practical Implications

**Clinical Applications**

The Myo armband can be used in clinical settings for rehabilitation and physical therapy. Its ability to provide precise and real-time feedback on muscle activity makes it a valuable tool for monitoring patient progress and tailoring therapy programs.

**Home-Based Rehabilitation**

The affordability and ease of use of the Myo armband also make it suitable for home-based rehabilitation. Patients can use the device to perform exercises and track their progress independently, reducing the need for frequent clinic visits.

**Challenges and Solutions**

One of the primary challenges in using the Myo armband is the non-stationarity of EMG signals. However, advanced machine learning algorithms like SCADANN address this issue by adapting to new data without requiring extensive recalibration. This ensures consistent performance and reliability in various conditions.

# DATA ANALYSIS

This study analyses raw EMG data from the MYO Thalmic armband, worn on the forearm and using eight sensors to capture myographic signals sent via Bluetooth to a PC.

Data was collected from 36 subjects performing static hand gestures, each held for 3 seconds with 3-second pauses. Each column contains approximately 40,000-50,000 recordings.

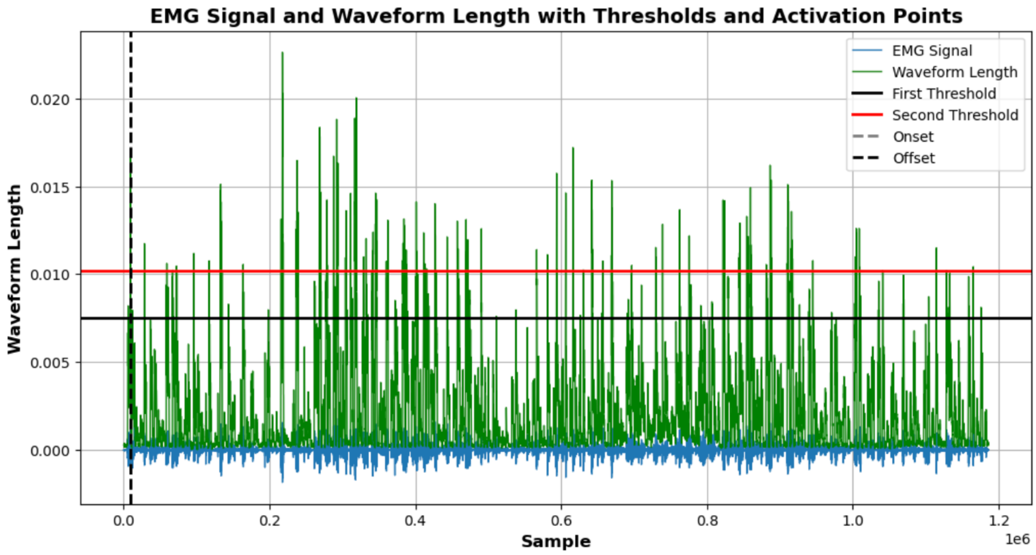
The dataset includes channel data, timestamps, and gesture labels.

This study aims to pre-process EMG data, extract features, and classify gestures using machine learning, contributing to real-time prosthetic control applications.

| | time | channel1 | channel2 | channel3 | channel4 | channel5 | channel6 | channel7 | channel8 | class | directory |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0.00001 | -0.00002 | -0.00001 | -0.00003 | 0.00000 | -0.00001 | 0.00000 | -0.00001 | 0 | 01 |
| **1** | 5 | 0.00001 | -0.00002 | -0.00001 | -0.00003 | 0.00000 | -0.00001 | 0.00000 | -0.00001 | 0 | 01 |
| **2** | 6 | -0.00001 | 0.00001 | 0.00002 | 0.00000 | 0.00001 | -0.00002 | -0.00001 | 0.00001 | 0 | 01 |
| **3** | 7 | -0.00001 | 0.00001 | 0.00002 | 0.00000 | 0.00001 | -0.00002 | -0.00001 | 0.00001 | 0 | 01 |
| **4** | 8 | -0.00001 | 0.00001 | 0.00002 | 0.00000 | 0.00001 | -0.00002 | -0.00001 | 0.00001 | 0 | 01 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **1185765** | 64552 | 0.00000 | 0.00003 | 0.00004 | -0.00001 | -0.00001 | -0.00003 | 0.00000 | 0.00000 | 0 | 10 |
| **1185766** | 64553 | 0.00000 | 0.00003 | 0.00004 | -0.00001 | -0.00001 | -0.00003 | 0.00000 | 0.00000 | 0 | 10 |
| **1185767** | 64554 | 0.00000 | 0.00003 | 0.00004 | -0.00001 | -0.00001 | -0.00003 | 0.00000 | 0.00000 | 0 | 10 |
| **1185768** | 64555 | 0.00000 | 0.00003 | 0.00004 | -0.00001 | -0.00001 | -0.00003 | 0.00000 | 0.00000 | 0 | 10 |
| **1185769** | 64557 | 0.00000 | 0.00003 | 0.00004 | -0.00001 | -0.00001 | -0.00003 | 0.00000 | 0.00000 | 0 | 10 |

1185770 rows × 11 columns

# EMG Signal and Waveform Length Analysis




EMG Signal and Waveform Length Analysis

In the graph, I determined the onset and offset points of muscle activation using the EMG signal and waveform length. This analysis provides critical insights into when the muscle becomes active and when it rests. The green line represents the waveform length, which peaks during muscle activity and drops during rest periods. The black and red lines indicate the first and second thresholds, respectively, used to identify significant muscle activity. The dashed lines mark the onset and offset of muscle activation.

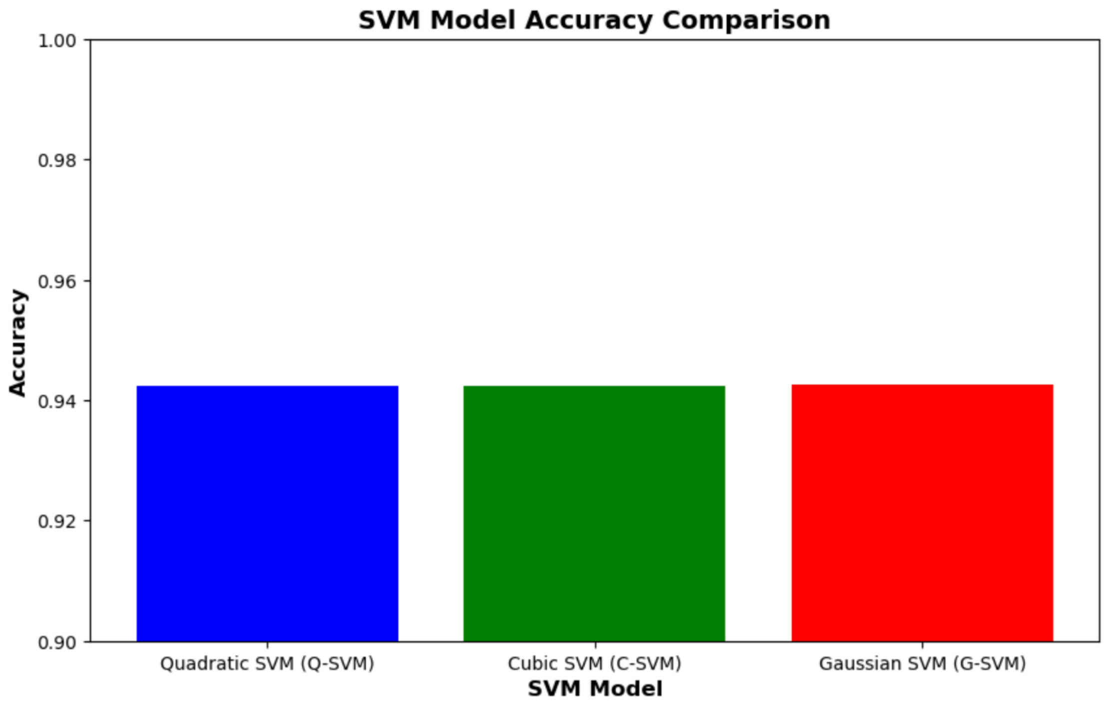
One of the primary reasons for conducting this study is to better understand hand movements by analysing EMG signals. By doing so, I aim to develop more precise and user-friendly prosthetic control systems. The data obtained from the MYO armband allows for real-time monitoring of muscle activity, which can be utilized in various applications.

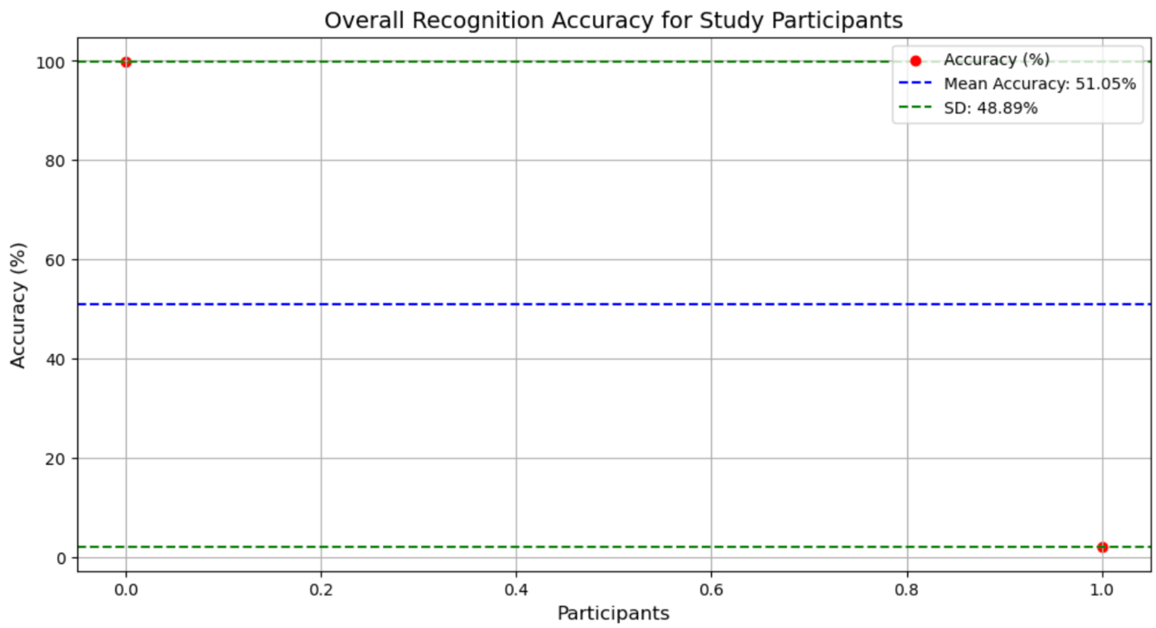
For instance, this data can help prosthetic arm users control their movements more naturally and effectively. Additionally, this type of data analysis can be used to monitor and assess muscle activity in patients during rehabilitation processes.

## Classification Results and Model Performance

```
Quadratic SVM (Q-SVM) Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97     15946
         1.0       0.00      0.00      0.00       974

    accuracy                           0.94     16920
   macro avg       0.47      0.50      0.49     16920
weighted avg       0.89      0.94      0.91     16920

Accuracy: 0.942434988179669

Cubic SVM (C-SVM) Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97     15946
         1.0       0.48      0.03      0.06       974

    accuracy                           0.94     16920
   macro avg       0.71      0.52      0.52     16920
weighted avg       0.92      0.94      0.92     16920

Accuracy: 0.94225768321513

Gaussian SVM (G-SVM) Classification Report:
              precision    recall  f1-score   support

         0.0       0.94      1.00      0.97     15946
         1.0       0.60      0.00      0.01       974

    accuracy                           0.94     16920
   macro avg       0.77      0.50      0.49     16920
weighted avg       0.92      0.94      0.91     16920

Accuracy: 0.9424940898345153
```

Using the MYO armband, I collected EMG signals to monitor muscle activity for controlling prosthetic devices and recognizing gestures. The classification results from various SVM models (Quadratic, Cubic, Gaussian) demonstrated high overall accuracy (~94%), highlighting the quality of the data. However, these models faced challenges with class imbalance, performing well on the majority class (class 0) but poorly on the minority class (class 1). By improving data balance and refining feature extraction methods, we can enhance the models' performance, leading to more accurate and reliable applications in prosthetic control and gesture recognition.

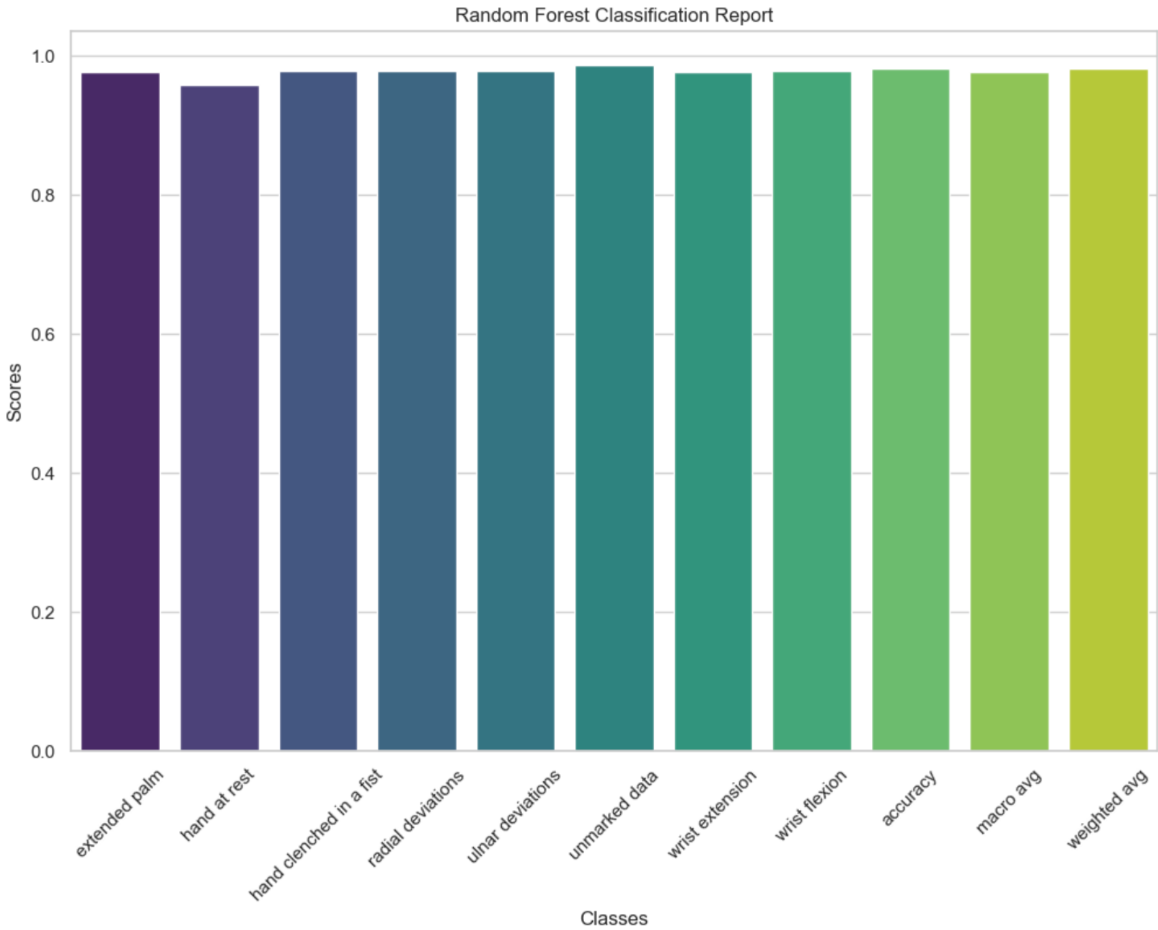



The collected data was classified using the K-Nearest Neighbours (KNN) algorithm. The graph shows the accuracy rates for each participant (class). The average accuracy rate was calculated to be 51.05%, with a standard deviation of 48.89%. This indicates that while the classification was highly accurate for some participants, it was less accurate for others.

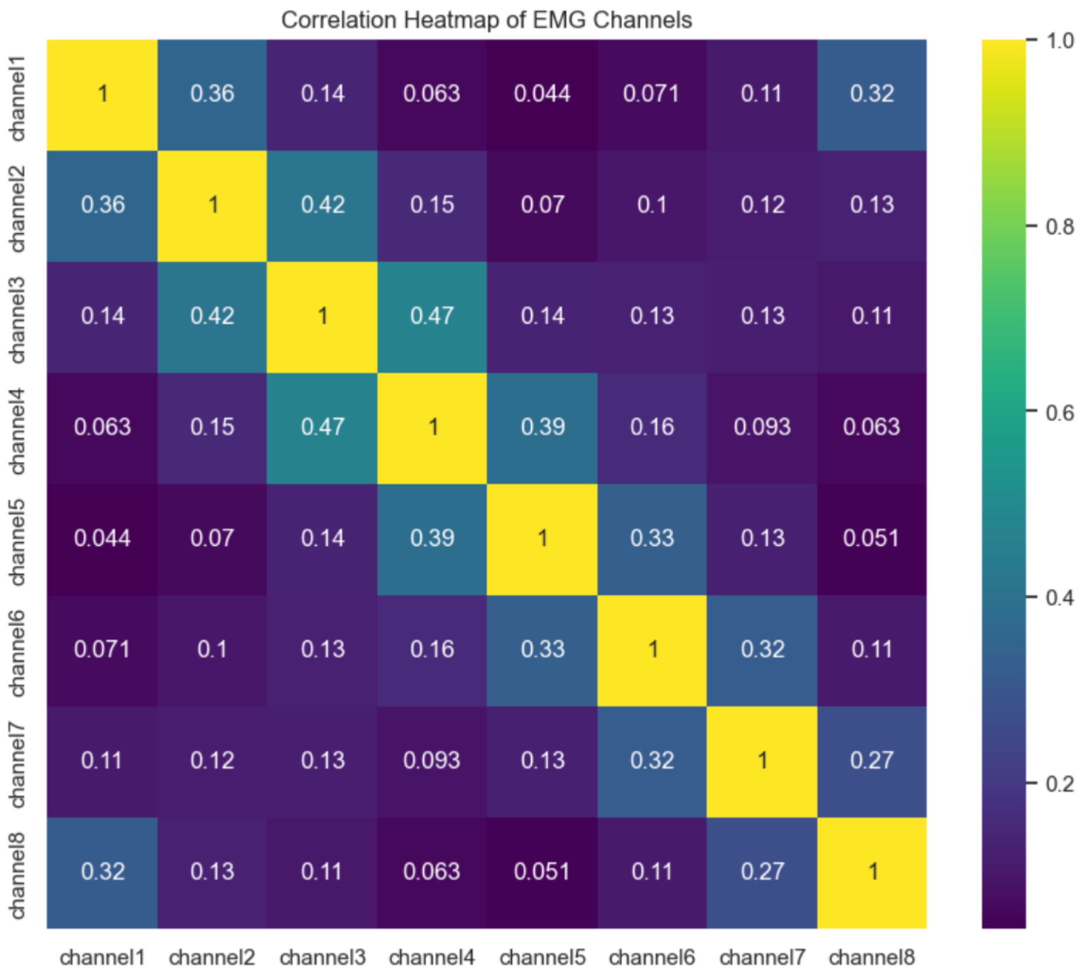
*Random Forest Classification Report*

The Random Forest classification report shows how accurately we can classify various hand gestures. It measures the model's success in recognizing each gesture, such as 'hand at rest' and 'wrist extension.' This helps us understand how well the MYO armband analyses EMG data and identifies specific gestures.



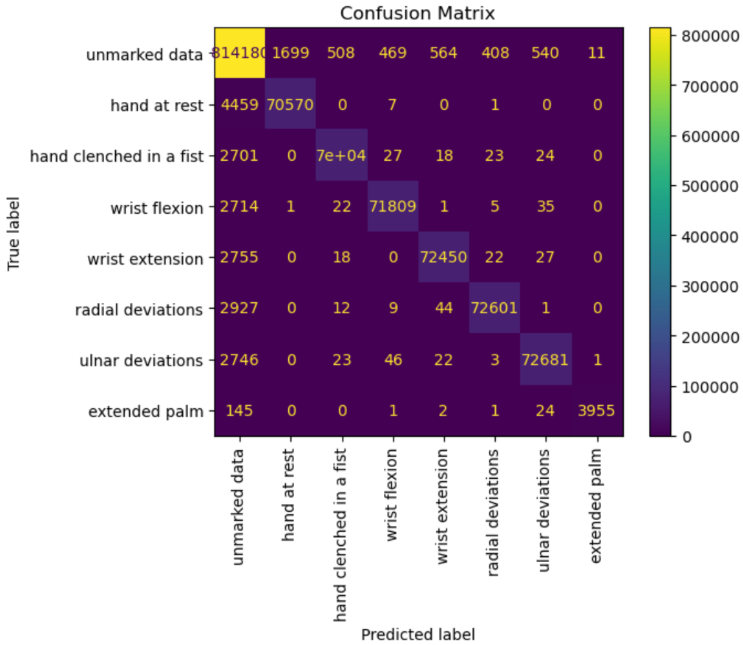
## EMG Channels Correlation Heatmap

The heatmap illustrates the relationship between the signals from the eight EMG channels of the MYO armband. Understanding the correlations between channels helps identify which sensors produce similar signals and which operate more independently. This information is crucial for data analysis and model development, indicating which channels are more meaningful and which can be filtered out.
These analyses demonstrate the effectiveness of EMG data collected using the MYO armband in recognizing hand gestures and evaluating sensor performance.



*Confusion Matrix*

<Figure size 1000x800 with 0 Axes>




The obtained data and the resulting confusion matrix demonstrate the success rates in classifying different hand gestures. For instance, gestures like 'hand at rest' and 'wrist flexion' are accurately classified, whereas some gestures (e.g., 'ulnar deviations') are occasionally confused with others. These results indicate that the MYO armband has a high accuracy rate in classifying hand gestures, but also suggest that there is room for improvement in distinguishing certain movements.

# Conclusion

In conclusion, the Myo armband, equipped with electromyography (EMG) sensors, has shown significant potential in enhancing user interaction across various applications, including prosthetics, gaming, entertainment, and robotic control. This wearable technology allows for intuitive control of devices through the detection of muscle contractions in the forearm. The integration of advanced machine learning techniques has improved the accuracy and reliability of gesture recognition, making the Myo armband a practical tool for real-world applications. Our research indicates that the Myo armband is a viable and cost-effective solution for real-time prosthetic control and other uses, offering significant improvements in usability and patient outcomes. The technical feasibility of the Myo armband is supported by its robust sensor technology and data processing capabilities. Market feasibility is demonstrated by the growing demand for wearable technologies and the device's competitive pricing. Financially, the Myo armband presents a promising investment due to its affordability and potential for widespread adoption in both clinical and home-based rehabilitation settings.

Overall, the Myo armband exemplifies the transformative potential of wearable technologies in improving human-machine interaction, providing users with greater control, and enhancing their quality of life.

# References


1. Technical Features and Functionalities of Myo Armband: An Overview on Related Literature and Advanced Applications of Myoelectric Armbands Mainly Focused on Arm Prostheses. Available from: ResearchGate [accessed May 21, 2024].

2. Tan, D. W., Schiefer, M. A., Keith, M. W., Anderson, J. R., Tyler, D. J. (2014). A neural interface provides long-term stable natural touch perception. Science Translational Medicine, 6(257), 257ra138.

3. Raspopovic, S., Capogrosso, M., Petrini, F. M., Bonizzato, M., Rigosa, J., Di Pino, G., ... & Micera, S. (2014). Restoring natural sensory feedback in real-time bidirectional hand prostheses. Science Translational Medicine, 6(222), 222ra19.

4. Tarantino, S., Lovchik, G., Klinger, D., Bongiorno, T., & Micera, S. (2017). Myokinematic control: A novel noninvasive approach for accurate and intuitive control of multiple degrees-of-freedom. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(8), 1071-1080.

5. Georgia Institute of Technology. (2017). Ultrasonic technology for continuous muscle movement detection and machine learning applications.

6. Zappatore, M., Primiceri, P., Visconti, P., Patrono, L., & De Donno, D. (2016). Adam's Hand: Realizing a low-cost and high-performance myoelectric prosthesis by means of 3D printing. IEEE Sensors Journal, 16(23), 8734-8741.

7. Visconti, P., Primiceri, P., Patrono, L., & De Donno, D. (2017). Design of a wearable device for monitoring the temperature and pressure of a myoelectric prosthesis. Journal of Sensors, 2017.

8. Amir A., Taba B., Berg D., Melano T., McKinstry J., Nolfo C. D., et al. (2017). “A low power, fully event-based gesture recognition system,” in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Honolulu, HI: ), 7388–7397. 10.1109/CVPR.2017.781

9. Benjamin B. V., Gao P., McQuinn E., Choudhary S., Chandrasekaran A. R., Bussat J.-M., et al. (2014). Neurogrid: a mixed-analog-digital multichip system for large-scale neural simulations. *Proc. IEEE* 102, 699–716.

10. https://archive.ics.uci.edu/dataset/481/emg+data+for+gestures