International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 56, No. 4, August, 2023, pp. 641-649
Journal homepage: http://iieta.org/journals/jesa

# Myoelectric Prosthesis Using Sensor Fusion Between Electromyography and Pulse Oximetry Signals

Karen Torres[1], Jhon Espinoza[1], Víctor Asanza[2*], Leandro L. Lorente-Leyva[2,3], Diego H. Peluffo-Ordóñez[2,4,5]

[1] Mechanical and Production Science Engineering Department, Escuela Superior Politecnica del Litoral, Guayaquil 090211, Ecuador
[2] SDAS Research Group, Ben Guerir 43150, Morocco
[3] Faculty of Law, Administrative and Social Sciences, Universidad UTE, Quito 170147, Ecuador
[4] College of Computing, Mohammed VI Polytechnic University, Ben Guerir 43150, Morocco
[5] Faculty of Engineering, Corporación Universitaria Autónoma de Nariño, Pasto 520001, Colombia

Corresponding Author Email: victor.asanza@sdas-group.com

https://doi.org/10.18280/jesa.560413

**Received:** 24 May 2023
**Revised:** 22 August 2023
**Accepted:** 28 August 2023
**Available online:** 31 August 2023

***Keywords:***
*myoelectric prosthesis, electromyography, bioelectric signal, sensor fusion, artificial intelligence, neural network*

**ABSTRACT**

Approximately 215,156 people in Ecuador grapple with physical disabilities, of whom nearly half fall within the 30 to 49% disability range, and a considerable number lack limbs. Moreover, there's been a surge in amputation cases, a trend linked to the increasing diabetes prevalence estimated at around 537 million cases by 2021 as per the International Diabetes Federation (IDF). While prosthetic solutions exist, they might incur high costs or offer constrained movement, even when more affordable. Thus, an alternative is proposed: a myoelectric upper limb prosthesis. This prosthesis would be maneuvered through electromyography and pulse oximetry signals, leveraging artificial intelligence methods. Employing a multi-layer neural network model, a structure comprising an input layer, four hidden layers, and an output layer, yields an impressive 93% prediction accuracy for user movement intentions. For AI model training, data from EMG and PPG sensors were recorded and scrutinized, leading to the condensation of classes from four to three. The model was embedded within an ESP32 C3 DevKit-M1 development board, and open-source blueprints facilitated the prosthesis's creation, complemented by supplementary components for electronics integration. The model attains a 93% precision in predicting classes, while the prosthesis's endurance spans approximately three hours and costs $295, equipped to handle diverse lightweight objects.

## 1. INTRODUCTION

The most common means of communication in any situation is through hands, and their dexterity enables us to perform many activities. Therefore, losing a hand entails numerous disadvantages that significantly interfere with daily living. However, despite various studies indicating the feasibility of a prosthetic hand, over 45% of people with amputations do not possess one [1], and additionally, around 40% feel resistant to the idea [2]. According to the International Diabetes Federation (IDF), approximately 537 million people were affected by diabetes in 2021. It is projected that this number will increase to 783 million by 2045. Consequently, an increase in the amputation rate is also anticipated. Diabetes can result in significant complications like peripheral vascular disease. This, in turn, may lead to unhealed wounds and the necessity of amputations to prevent severe infections. Prosthetics play a vital role in the lives of people who have undergone amputations due to diabetes, enabling them to recover lost mobility and independence [3-6].

The demand for prosthetics in the market is influenced by various factors, including the increase in healthcare spending in developing countries, the growing importance of public-private partnerships in several regions, and the rise in the prevalence of joint-related diseases due to population aging. Technological advancements, including artificial intelligence and machine learning, have been crucial in the growth of the prosthetics market. Chronic diseases such as cancer and diabetes, major causes of amputations, also contribute to the high demand for prosthetics. The combination of population aging, technological advancements, the promotion of an active lifestyle, and interdisciplinary collaboration is generating a consistent increase in the adoption of prosthetics, which are essential for improving the quality of life for individuals with amputations [7]. An important factor regarding prosthetics is their cost, as prices range from around 30,000 to 80,000 dollars [8]. Computer-aided design, additive manufacturing, and open-source resources play an essential role, with 3D printing being a potential option for cost reduction, as well as allowing control over factors such as weight and customization [9-11].

The construction of a piece, by adding material deposition layer by layer, demonstrates the ability of printing to adapt to disabilities in various types of patients who lack upper limbs, without the need for additional expensive tools or their production. Some authors describe that of the 33 possible grip postures in a human hand, a prosthetic hand can only perform three of them [12].

Regardless of whether a patient was born without a limb or lost it due to amputation, their daily life will be extremely challenging. The robotic prosthetic devices available today are capable of providing users with improved functionality. However, the available methods for prosthetic control limit their use to simple actions, which is the main reason for amputees rejecting technological prosthetics.

The emergence of various myography techniques has created a promising approach to address these control issues [13]. Active prostheses in the market are extremely expensive, while passive prostheses are often available at a lower cost. However, passive prostheses have even more restrictions in their movements. Therefore, the possibility of implementing an economically accessible active prosthesis is presented, which at the same time allows the recovery of a large part of the motor skills provided by the original limb, emulating its functionality.

## 2. LITERATURE REVIEW

Resulting from numerous investigations, anthropomorphic myoelectric hands have been developed. These hands exhibit the capacity to execute diverse grip patterns, adjust grip precision, and enable finger mobility [14]. The operational mechanism of these prostheses involves capturing patterns within a system through electromyography (EMG) signals employing various channels for sensors like pressure sensors, inertial measurement units (IMUs), Hall effect sensors, and others. In his thesis, Garibho outlines the implementation of a multimodal approach that integrates Force Myography (FMG), surface electromyography (sEMG), and IMU sensors, yielding more dependable and consistent outcomes by merging these modalities [15].

In their research, Jung et al. [16] gauge signals from muscles including the brachioradialis, biceps brachii, deltoid, and pectoralis major. They employ a dry PDMS (polydimethylsiloxane) electrode for EMG measurement, demonstrating that the peak RMS (root mean square) voltage values attained surpass those achieved with a wet Ag-AgCl commercial electrode.

Niu et al. [17] undertake a comparison of the merits and demerits of distinct types of dry electrodes. Notably, electrodes made of metallic material for conduction highlight their flexibility and ability to conform to the contours of the skin.

Basumatary and Hazarika [18] present a review of different studies where they demonstrate the data fusion technologies used in them, which are shown in Table 1.

**Table 1.** Applied sensor fusion technologies

| **Camera Sensor + Distance Sensor + EMG Sensor** |
|---|
| Inertial Measurement Unit (IMU) + EMG sensor |
| EMG + Accelerometer |
| Stereo vision + Augmented reality + EMG interface |
| Computer vision + Inertial sensor |
| IMU + Force sensor + Myoelectric sensor |
| EEG + ENG |

On the other hand, the use of electroencephalography (EEG) techniques is preferred mainly for prosthetic control due to their non-invasive nature, while electrocorticography (ECOG) and targeted muscle reinnervation (TMR) are invasive techniques [19]. EEG can be a viable option for directly controlling prosthetics using brain signals. However, these signals present several challenges [20], such as limited reliability, low precision, poor user adaptability, slow data transfer speed, and complex acquisition setup [21]. Surface electromyography (sEMG) is a non-invasive technique for measuring muscle electrical activity. Surface EMG can be applied to estimate intention, force, limb angle, and muscle contraction level of the subject [22].

### 2.1 Data fusion

An embedded system is an information processing system integrated into a product. It is applied in various fields such as transportation (automotive, aerospace, railway, and maritime), manufacturing (IoT and Industry 4.0), robotics, healthcare (measurement and control of vital signs), agriculture (control of variables and animal detection), and telecommunications, among others [23].

Data fusion involves the amalgamation of measurements sourced from diverse sensors. This enables a more intricate and robust understanding of the controlled process or activity. Consequently, the susceptibility of this system to disturbances that may impact both the system itself and sensor measurements is reduced [24]. A series of investigations has led to the development of anthropomorphic myoelectric hands. These hands exhibit the capability to execute a range of grip patterns, adjust grip precision, and facilitate finger mobility [25]. The functionality of these prostheses entails the analysis of patterns within a system utilizing EMG signals. Various channels are employed for instruments such as pressure sensors, inertial measurement units, Hall effect sensors, among others.

### 2.2 Artificial intelligence

Artificial intelligence is a branch of computer science. When implemented in a prosthetic device, it provides the opportunity for more adaptive control, allowing the system to operate according to the desires of the person with limb loss [26]. The technique applied to the EMG signal focuses on pattern recognition. The output signals store data about possible movements for the residual limb [27]. The patterns are classified based on their characteristics to recognize different EMG patterns. A command is then sent through a controller to execute the movement [28].

The analyzed works explore different approaches in the field of prosthetics, including anthropomorphic myoelectric hands, dry electrodes for EMG signals, data fusion, and AI integration. These prosthetic hands offer versatile grips and precise control. Dry electrodes provide a signal of higher quality than wet ones. Data fusion enhances understanding and robustness against disturbances, while AI and pattern recognition allow adaptable control. However, weaknesses were identified: dry electrodes may degrade signal quality over time, and sensor accuracy is crucial for data fusion. Errors in AI pattern recognition can result in involuntary movements.

Considering this, the study proposes an alternative myoelectric upper limb prosthesis to address challenges in individuals with disabilities, especially in Ecuador. This prosthesis is controlled using EMG and pulse oximetry signals, employing AI methods.

## 3. METHODOLOGY

The methodology followed in this research includes the following steps: environment setting, experiment design, implementation of data logging system, data organization, preprocessing of EOG bioelectrical signals, and bioelectric signal classification for hand movement detection.

### 3.1 Environment preparation

In the context of this experiment, the subject is seated in a chair with an upright backrest, ensuring that their heels are firmly placed on the floor to maintain a stable posture. Next, the patient is presented with a screen displaying an interface detailing the actions they must carry out. Specific details of the experimental conditions are illustrated in Figure 1.

**Figure 1.** Volunteer position diagram

Through this visual interface, the patient receives clear instructions about the types of actions and movements they need to perform. These instructions are conveyed in real-time through strategically placed physical sensors that accurately capture the movements and actions executed by the patient.

Collecting real-time data required the active cooperation of the patient. Following the ethical principles of the Helsinki Declaration, the experiment was conducted with a focus on informed consent and research integrity. Throughout the process, the patient's well-being was ensured, making sure they were comfortable and in a safe environment.

The tests focused on recording signals from the patient's stump, obtaining valuable information for the advancement of the research. At the conclusion of the tests, the patient's well-being was prioritized, implementing the procedure in the most suitable and effective manner. As a result of these efforts, solid and meaningful conclusions were obtained, contributing to the advancement of the work.

### 3.2 Sensor location

The optimal area to place the sensors and detect movements performed on the flexor muscles was determined. During the measurements, it was found that the patient should be relaxed and in a comfortable position. As dry electrodes are used, no gel is required. However, it is preferable that the area is clean and free from any irritating substances.

Figure 2 shows the location of EMG1 sensor on the carpal flexor muscle, EMG2 on the brachioradialis muscle, and on the superficial palmar branch for the PPG signal. The EMG signals do not depend on a voltage reference, only on the muscle direction. However, for the PPG signal, the location with the strongest pulse in the radial artery was selected.

### 3.3 Experimental design

The actions performed by the subject are as follows (Figure 3):

**Open hand (Rest):** The subject opens the hand when instructed on the screen. This action is performed after the other actions.

**Move to anterior side:** The subject moves the hand towards the anterior side of the arm.

**Move to back side:** The subject moves the hand towards the posterior side of the arm.

**Close hand:** The subject clenches the hand into a fist.

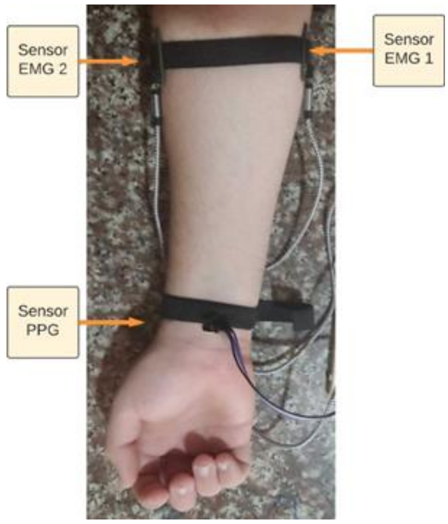



**Figure 2.** Sensors placement

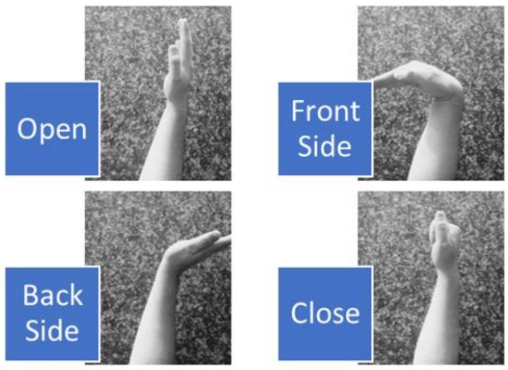



**Figure 3.** Presentation of visual stimuli used for data recording

### 3.4 Implementation of the data registration system

When using the sensors, it is necessary to consider the interferences that affect them. For this reason, it is important to highlight the filtering and amplification stages that were carried out. Of the two types of sensors, the EMG sensor (SEN0240) presents a higher amount of interference. The following stages were performed in the signal collection process. The components and types of signals in this embedded system are shown in Figure 4.

Filtering stage: Three filters are applied in the following order: notch filter, low-pass filter, and high-pass filter. The filters were designed considering second and fourth-order transfer functions.

These filters were carefully chosen to address specific issues that can affect the accuracy and interpretation of the recorded signals. For instance, the need to eliminate noise. The notch filters tackle electric grid interference, the low-pass filters remove unwanted high-frequency noise, and the high-pass filters filter out low-frequency components that are not relevant. The combination of these filters in the filtering stage helps enhance the quality of the recorded signals, ensuring that the captured data is as clean and relevant as possible for scientific analysis and interpretation.

Amplification stage: The filtered signal is amplified by squaring its value.

These stages are implemented through software using the ESP32-C3 Dev Module microcontroller, configured at a sampling frequency of 100 Hz.

In addition, a Python script was used, which presented the movements to be performed and collected data to be stored in a CSV file for each task performed.

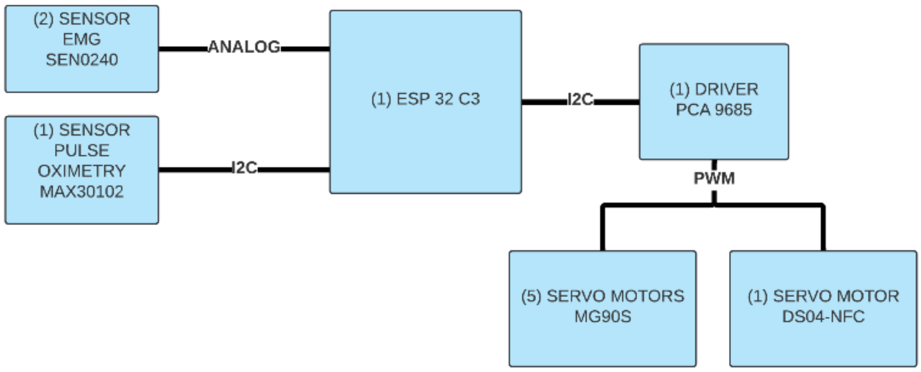



**Figure 4.** Embedded system components and signal types

### 3.5 Data organization

For each task, 100 CSV files were recorded, resulting in a total of 400 files for one subject. Based on the obtained sampling frequency, each file contains 500 data points. Each data point consists of four values: EMG1, EMG2, IR, and RED.

The first two values correspond to each EMG sensor, while the third and fourth values correspond to the readings of the infrared and red LEDs of the Pulse Oximetry sensor. The dataset [29] can be found at the following link: http://ieee-dataport.org/11092.

### 3.6 Bioelectric signal preprocessing

Using a Jupyter notebook with Python, each file was collected, and the data was filtered using the moving average method. Furthermore, the columns were normalized using the min-max method.

### 3.7 Feature extraction and selection

Signal characteristics were computed for each sensor utilizing the Root Mean Square (RMS) technique with a sliding window of 100 ms. The study's emphasis was on extracting time-related attributes due to their reduced processing demands, leading to quicker computations and consequently, faster classification. The RMS method, a signal processing approach, was employed to characterize a signal's amplitude or overall magnitude. This involves finding the square root of the mean of the squared signal values within a designated time interval. In the study's context, which involves analyzing signals generated by sensors, RMS offers insights into the signal's intensity or energy within that particular time frame.

### 3.8 Classification of bioelectrical signals for movement detection

An artificial intelligence (AI) model using neural networks was established to classify the signals from the sensors for executing the desired movements. A multi-layer neural network model was employed, consisting of an input layer, four hidden layers, and an output layer. The model was trained using the Adam optimizer, which was chosen after evaluating its performance against other optimizers, for a duration of 200 epochs. Ultimately, the model that exhibited the lowest validation error was selected. This model is trained using the data previously collected in the experiment.

## 4. RESULTS

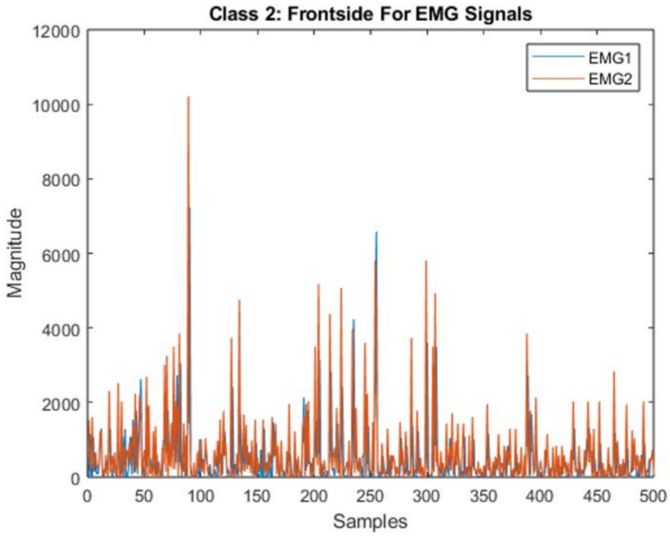
### 4.1 Signals extracted by the system

Different behavior patterns were obtained for each task in the signals. As shown in Figure 5, line 1 represents the signal from the first EMG sensor, line 2 represents the signal from the second EMG sensor. In Figure 6, line 1 represents the signal from the infrared LED, and line 2 represents the signal from the red LED. The range of the signals is observed in their magnitude of digital values.

These signals, after being normalized, modify their range between 0 and 1.

### 4.2 AI model building

The AI model was built using the TensorFlow library. The model consists of an input layer, four hidden layers, and an output layer. For the input layer, a vector of 20 elements is used as input. The first hidden layer comprises 100 perceptrons, with 30% of them being deactivated using the Dropout function. Subsequently, the ReLU activation function is applied. For the second hidden layer, the number of perceptrons is reduced to 80, and the same functions as the previous layer are applied. In the third hidden layer, the number of perceptrons is further reduced to 60, with the Dropout rate lowered to 20%. The ReLU function is also applied here. As for the fourth hidden layer, the perceptrons are decreased to 20, with the Dropout rate reduced to 10%, and the ReLU function is applied. The output layer is composed of 3 perceptrons, and the Softmax function is applied to obtain the predicted probabilities. The model architecture is shown in Figure 7.



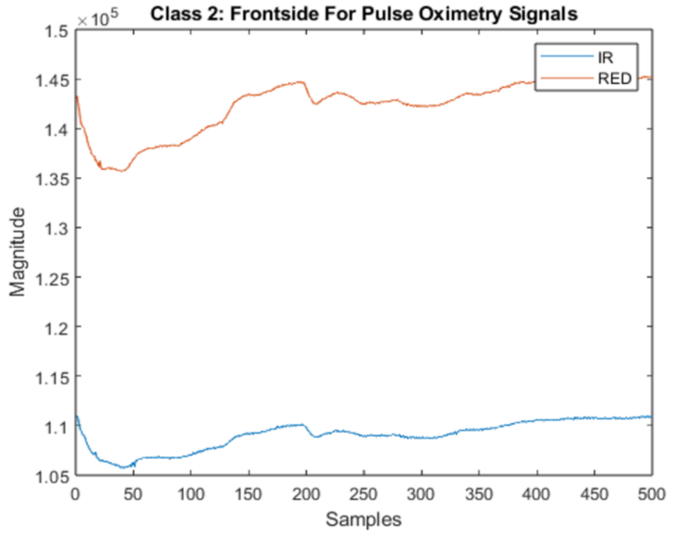




**Figure 5.** EMG Signals recording during experiment

**Figure 6.** Pulse oximetry signals recording during experiment

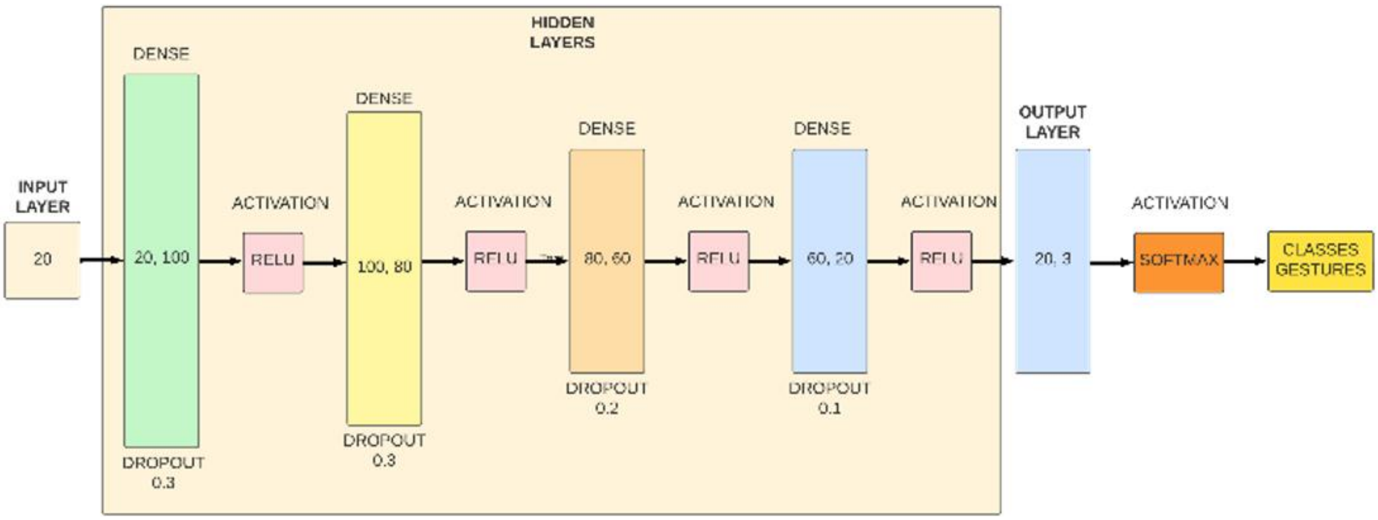
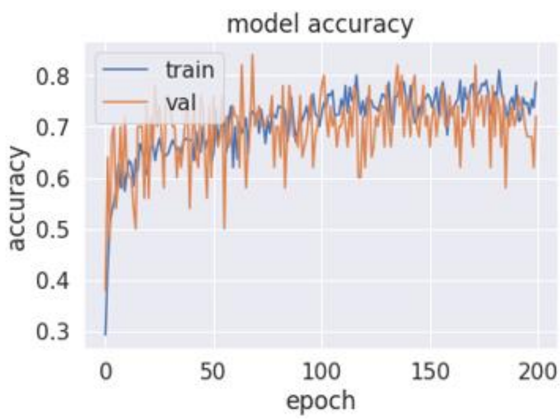



**Figure 7.** Neural network model



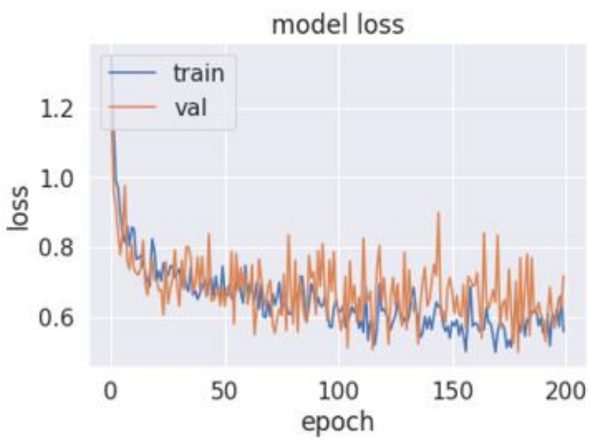




**Figure 8.** Model accuracy

**Figure 9.** Model loss

### 4.3 Bioelectric signal classification

With the neural network model in place, training is carried out using the data collected during the experiment. Accuracy metrics were considered as they provide a direct way to measure model performance, and error was taken into account as it allows for evaluating model convergence and avoiding both overfitting and underfitting. Other metrics were not considered in this case as these were sufficient to assess the model's performance, indicating its ability to learn from the data and generalize to new data. The performance is shown in Figure 8, displaying the accuracy, and Figure 9, depicting the decrease in training and validation error.

Additionally, considering the features, the confusion matrix is shown, which evaluates the classification of each task using a specific dataset focused on testing. This is presented in Figure 10. The misclassified outcomes are represented on the off diagonals of the confusion matrix. False positive at the left and false negative at right of the diagonal.

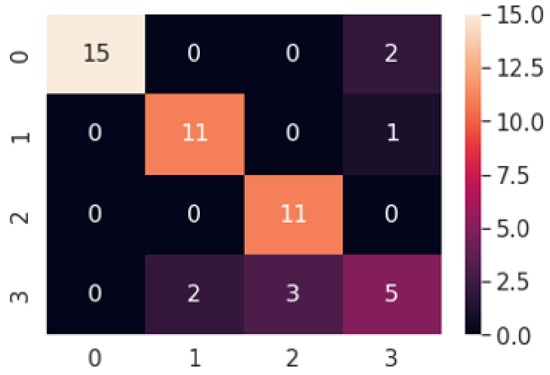



**Figure 10.** Confusion matrix for the NN model

For this matrix, the percentages of correct and incorrect predictions are obtained, as shown in Table 2.

To decrease the wrong predictions, task 3, which had similar behavior to the other classes, was eliminated, obtaining the accuracy shown in Figure 11, the error in Figure 12 and the confusion matrix in Figure 13.

For the matrix in Figure 13, the percentages of correct and incorrect predictions are obtained, as shown in Table 3.

Once the model was obtained, it was implemented in the embedded system, in this case using an ESP32-C3 microcontroller. The prosthesis was tested with different types of grips using various objects, as shown in Table 4. The spherical grip is shown in Figure 14.

For the respective objects, the results are shown in Table 5.

**Table 2.** Percentages of correct and incorrect predictions for four classes

| Task | Correct [%] | Incorrect [%] |
|---|---|---|
| 0 | 100 | 0 |
| 1 | 86 | 14 |
| 2 | 64 | 36 |
| 3 | 88 | 12 |

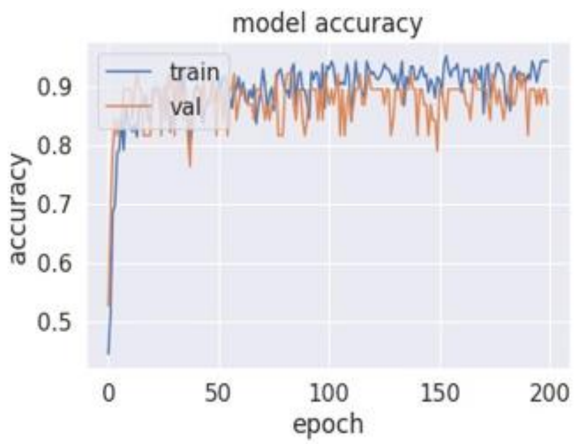



**Figure 11.** Model accuracy for 3 classes

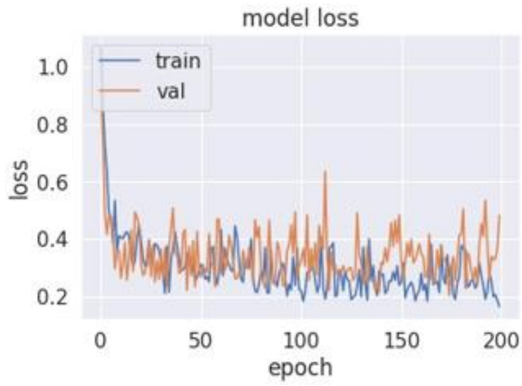



**Figure 12.** Model loss for 3 classes

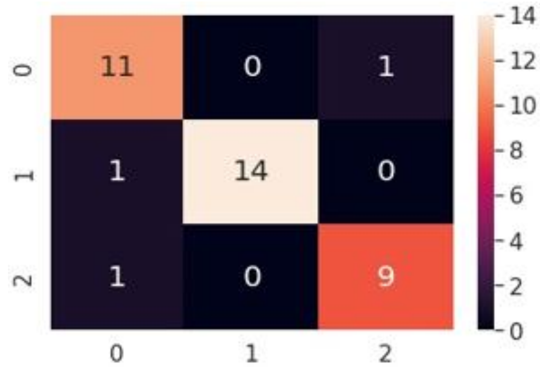



**Figure 13.** Confusion matrix for the NN model for 3 classes

**Table 3.** Percentages of correct and incorrect predictions for three classes

| Task | Correct [%] | Incorrect [%] |
|---|---|---|
| 0 | 100 | 0 |
| 1 | 96 | 4 |
| 2 | 94 | 6 |

**Table 4.** Types of grips used on objects

| Object | Size | Type of Grip |
|---|---|---|
| Card | 8 × 6 × 0.3 cm³ | Lateral Grip Tip Grip |
| Paper folded twice | 8.5 × 7 × 0.3 cm³ | Lateral Grip Tip Grip |
| Empty Bottle | radius 3 cm | Cylindrical Grip |
| Full Bottle | radius 3 cm<br>625 cc | Cylindrical Grip |
| Alcohol | radius 2.5 cm | Cylindrical Grip |
| Flute | length 30 cm<br>radius 1 cm | Hook Grip |
| Ball | radius 3 cm | Spherical Grip |

**Figure 14.** Spherical grip with ball

**Table 5.** Grip test results

| Type of Grip | Successful Result | Comment |
|---|---|---|
| Lateral Grip | No | It cannot be held because the index finger is not stable on the sides. |
| Tip Grip | Yes | This is possible due to the pressing capability of the index finger against the thumb. |
| Lateral Grip | Yes | Because it has a larger surface area and thickness, it allows for better grip. |
| Tip Grip | Yes | |
| Cylindrical Grip | Yes | |
| Cylindrical Grip | No | It cannot be lifted, there is not a complete grasp of the bottle. |
| Cylindrical Grip | Yes | |
| Hook Grip | Yes | |
| Spherical Grip | Yes | This is possible because the grip is carried out with each of the fingers of the prosthesis. |

## 5. DISCUSSION

In order to select the most appropriate model for the prosthesis, a series of tests were conducted using various tools and configurations. The values obtained in both Matlab and a model developed by our team were compared. The model developed in this study incorporates an artificial neural network, employing multiple layers within a sequential framework. Before arriving at the final results, diverse models were experimented with. While the proposed model encompassed training involving a total of four classes, yielding an accuracy of 79%, it exhibited mispredictions when attempting to execute the hand-closing action.

Upon scrutinizing the acquired signals for each task, it becomes evident that the values for task 3, "Close," exhibit a similar pattern to those of tasks 1 and 2, "Front" and "Back," respectively. By narrowing down the classification to only three classes, our model demonstrated an improvement. This enhancement is depicted in Figure 11, which showcases the model's efficiency, reaching a peak of 93%. Conversely, Figure 12 illustrates the error loss. It is noteworthy that both graphs demonstrate suitable behavior, as there is no evidence of overtraining or overfitting, given the congruent trends in the training and validation values.

Through these graphical representations, the efficacy of the proposed model is validated. This validation is the result of numerous iterations and tests involving the fusion of sensor measurements. These tests aimed to discern the most accurate signals related to movements, contributing to the prediction of these movements.

The confusion matrix made it possible to identify the predictions made by the model. The correct predictions were quite high, as the true positives and true negatives were classified quite well, while the erroneous predictions were made in relatively low proportions.

For real-time testing, different types of grips were defined and programmed to be executed by the prosthesis. These movements were used to achieve better grasping for various types of objects, including side grip, tip grip, cylindrical grip, and hook grip. In this Table 5, it can be observed that due to the design of the prosthesis itself, such as the dimensions of the fingers and the torque of the servo motors, there are difficulties in performing lateral grips for cards and for bottles filled with water. However, it allows for successfully achieving grips on lightweight objects.

## 6. CONCLUSIONS

The application and testing of different gripping patterns provided the user with more convenience in their daily life for grasping objects of different shapes and sizes, compared to other prostheses that only offer a single type of grip. The design of the prosthesis allowed for hand closing and opening, as well as the ability to perform other types of movements due to having a greater number of degrees of freedom, which contributes to better object grasping.

The biggest challenge in the project is data collection, as in the case of the MAX30102 sensor, it was necessary to find a suitable location where different movements could be easily detected. This involved conducting the data collection experiment multiple times until obtaining a suitable dataset.

A database of 400 records of signals from the 3 sensors was created, with each sensor storing 500 data points. However, only 300 records were used for training the AI model due to the reduction of one class. This achieved a prediction accuracy of 93% for the user's movement intentions, specifically opening, moving front, and moving back. This accuracy is within the range when compared to other models consulted in the literature review, which are around 90%, even approaching 97%. However, these models utilize a combination of sensors of different types from those used in this work.

The AI model was embedded in the ESP32 C3 Dev Kit M1 microcontroller, which receives and processes the readings from the sensors. Real-time prediction was performed based on these data, and the corresponding action was then executed.

The utility of the MAX30102 sensor for identifying human movements was confirmed, providing an alternative option to the common use of EMG sensors. This represents one of the early instances of applying this practice.

The MAX30102 sensor can influence new applications as it expands the range of movements that can be detected and controlled with a myoelectric prosthesis. By incorporating additional information about blood flow and tissue oxygenation, it can reflect the user's level of effort or fatigue.

As future work, it is proposed to reduce the temporal windows of data recording from the current 5-second value to 1 second in order to assess how this affects the precision and error of the neural network model. Additionally, this will allow for a reduction in the execution time of the prosthesis. Another aspect to explore is analyzing the energy consumption by implementing the proposed changes to the model, observing how it varies when performing different movements with the prosthesis.

## 7. RECOMMENDATIONS

Perform additional validations with a person who has the disability, as individuals with hand amputations are the target group for prosthetic design.

Expand the number and types of sensors to encompass new characteristics and a greater number of classes to broaden the range of predictions. In this case, it's important to consider that this could entail a cost increase, as it involves not only adding more sensors but also changing the prosthesis design. Additionally, the compatibility of the sensors with the microcontroller used would need to be analyzed, which would require experimentation for each of these scenarios. Despite these factors, it could be beneficial depending on the application and user. Additionally, it is possible to reduce measurement errors by having a larger number of data sources.

Redesign a portion of the mechanical design to support a greater load, as it is currently limited by being subject to arm rotation. Implement a coupling system to attach the prosthesis to the user's arm, facilitating its use.

During data collection, slightly vary the position of the sensors to have more data variety, as it cannot be guaranteed that the sensors will always be placed in the same position.

Improving aesthetics to make it more pleasing is crucial, as a more natural and discreet prosthesis contributes to social and work integration. Furthermore, it enhances confidence and motivation in daily life while reducing the user's burden without compromising functionality. This reduction in weight aids in diminishing fatigue, pain, and injuries that may arise from prolonged use. This is achieved by employing lighter and more resilient materials, including the utilization of 3D printing techniques to customize designs according to user preferences.

## REFERENCES


[1] Ziegler-Graham, K., MacKenzie, E.J., Ephraim, P.L., Travison, T.G., Brookmeyer, R. (2008). Estimating the prevalence of limb loss in the United States: 2005 to 2050. Archives of Physical Medicine and Rehabilitation, 89(3): 422-429. https://doi.org/10.1016/j.apmr.2007.11.005

[2] Adams, B.D., Grosland, N.M., Murphy, D.M., McCullough, M. (2003). Impact of impaired wrist motion on hand and upper-extremity performance. The Journal of Hand Surgery, 28(6): 898-903. https://doi.org/10.1016/S0363-5023(03)00424-6

[3] Raichle, K.A., Hanley, M.A., Molton I., Kadel, N.J., Campbell, K., Phelps, E., Ehde, D., Smith, D.G. (2008). Prosthesis use in persons with lower-and upper-limb amputation. Journal of Rehabilitation Research and Development, 45(7): 961. https://doi.org/10.1682/jrrd.2007.09.0151

[4] Phillips, B., Zingalis, G., Ritter, S., Mehta, K. (2015, October). A review of current upper-limb prostheses for resource constrained settings. In 2015 IEEE Global Humanitarian Technology Conference (GHTC), Seattle, WA, USA, pp. 52-58. https://doi.org/10.1109/GHTC.2015.7343954

[5] Desveaux, L., Goldstein, R.S., Mathur, S., Hassan, A., Devlin, M., Pauley, T., Brooks, D. (2016). Physical activity in adults with diabetes following prosthetic rehabilitation. Canadian Journal of Diabetes, 40(4): 336-341.https://doi.org/10.1016/j.jcjd.2016.02.003

[6] Davidson, J. (2002). A survey of the satisfaction of upper limb amputees with their prostheses, their lifestyles, and their abilities. Journal of Hand Therapy, 15(1): 62-70. https://doi.org/10.1053/hanthe.2002.v15.01562

[7] Wood, L. (2022). Global prosthetic arm market report 2022: Growing use of technology, artificial intelligence, and machine learning presents. Technical Report, Businesswire.

[8] Mühlbauer, P., Löhnert, L., Siegle, C., Stewart, K.W., Pott, P.P. (2020). Demonstrator of a low-cost hand prosthesis. IFAC-PapersOnLine, 53(2): 15998-16003. https://doi.org/10.1016/j.ifacol.2020.12.398

[9] Cabibihan, J.J., Alkhatib, F., Mudassir, M., Lambert, L. A., Al-Kwifi, O.S., Diab, K., Mahdi, E. (2021). Suitability of the openly accessible 3D printed prosthetic hands for war-wounded children. Frontiers in Robotics and AI, 7: 594196. https://doi.org/10.3389/frobt.2020.594196

[10] Asanza, V., Peláez, E., Loayza, F., Lorente-Leyva, L.L., Peluffo-Ordóñez, D.H. (2022). Identification of lower-limb motor tasks via brain-computer interfaces: A topical overview. Sensors, 22(5): 2028. https://doi.org/10.3390/s22052028

[11] Avilés-Mendoza, K., Gaibor-León, N.G., Asanza, V., Lorente-Leyva, L.L., Peluffo-Ordóñez, D.H. (2023). A 3D printed, bionic hand powered by EMG signals and controlled by an online neural network. Biomimetics, 8(2): 255. https://doi.org/10.3390/biomimetics8020255

[12] Feix, T., Romero, J., Ek, C.H., Schmiedmayer, H.B., Kragic, D. (2012). A metric for comparing the anthropomorphic motion capability of artificial hands. IEEE Transactions on Robotics, 29(1): 82-93. https://doi.org/10.1109/TRO.2012.2217675

[13] Bajaj, N.M., Spiers, A.J., Dollar, A.M. (2019). State of the art in artificial wrists: A review of prosthetic and robotic wrist design. IEEE Transactions on Robotics, 35(1): 261-277. https://doi.org/10.1109/TRO.2018.2865890

[14] Birglen, L., Laliberté, T., Gosselin, C.M. (2008). Underactuated robotic hands, 40. Springer Berlin Heidelberg.

[15] Gharibo, J.S. (2021). Data and sensor fusion using FMG, sEMG and IMU sensors for upper limb prosthesis control. Doctoral dissertation, The University of Western Ontario, Canada.

[16] Jung, J.M., Cha, D.Y., Kim, D.S., Yang, H.J., Choi, K.S., Choi, J.M., Chang, S.P. (2014). Development of PDMS-based flexible dry type SEMG electrodes by micromachining technologies. Applied Physics A, 116: 1395-1401. https://doi.org/10.1007/s00339-014-8244-3

[17] Niu, X., Gao, X., Liu, Y., Liu, H. (2021). Surface bioelectric dry electrodes: A review. Measurement, 183: 109774. https://doi.org/10.1016/j.measurement.2021.109774

[18] Basumatary, H., Hazarika, S.M. (2020). State of the art in bionic hands. IEEE Transactions on Human-Machine Systems, 50(2): 116-130. https://doi.org/10.1109/THMS.2020.2970740

[19] Cordella, F., Ciancio, A.L., Sacchetti, R., Davalli, A., Cutti, A.G., Guglielmelli, E., Zollo, L. (2016). Literature review on needs of upper limb prosthesis users. Frontiers in Neuroscience, 10: 209. https://doi.org/10.3389/fnins.2016.00209

[20] Prakash, A., Sahi, A.K., Sharma, N., Sharma, S. (2020). Force myography controlled multifunctional hand prosthesis for upper-limb amputees. Biomedical Signal Processing and Control, 62: 102122. https://doi.org/10.1016/j.bspc.2020.102122

[21] Fifer, M.S., Acharya, S., Benz, H.L., Mollazadeh, M., Crone, N.E., Thakor, N.V. (2012). Toward

electrocorticographic control of a dexterous upper limb prosthesis: Building brain-machine interfaces. IEEE Pulse, 3(1): 38-42. https://doi.org/10.1109/MPUL.2011.2175636

[22] Cheesborough, J.E., Smith, L.H., Kuiken, T.A., Dumanian, G.A. (2015). Targeted muscle reinnervation and advanced prosthetic arms. Seminars in Plastic Surgery, 29(1): 62-72. https://doi.org/10.1055/s-0035-1544166

[23] Marwedel, P. (2021). Embedded system design: Embedded systems foundations of cyber-physical systems, and the Internet of Things. Springer Nature.

[24] Appriou, A. (2014). Uncertainty theories and multisensor data fusion. John Wiley & Sons.

[25] Novak, D., Riener, R. (2015). A survey of sensor fusion methods in wearable robotics. Robotics and Autonomous Systems, 73: 155-170. https://doi.org/10.1016/j.robot.2014.08.012

[26] Nayak, S., Das, R.K. (2020). Application of artificial intelligence (AI) in prosthetic and orthotic rehabilitation. In Service Robotics. IntechOpen.

[27] Stinus, H. (2000). Biomechanics and evaluation of the microprocessor-controlled c-leg exoprosthesis knee joint. Zeitschrift fur Orthopadie und ihre Grenzgebiete, 138(3): 278-282. https://doi.org/10.1055/s-2000-10149

[28] Li, G., Schultz, A.E., Kuiken, T.A. (2010). Quantifying pattern recognition - Based myoelectric control of multifunctional transradial prostheses. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18(2): 185-192. https://doi.org/10.1109/TNSRE.2009.2039619

[29] Espinoza Tutiven, J.E., Torres Medina, K.T., Asanza Armijos, V.M. (2012). Diseño e implementación de una prótesis mioeléctrica controlada por fusión de sensores en un sistema embebido. Tesis de Grado, Escuela Superior Politecnica del Litoral.