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# EMG CLASSIFICATION FOR THE PROSTHETIC HAND USING NEURAL NETWORK

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**Abstract**

*Electromyography (EMG) is procedure by which we measure the electrical activity of the muscles responsible for contraction and relaxation and can be used to track the abnormalities of mobility. Lately pattern recognition through EMG has been widely used with the traditional machine learning and deep learning methodologies to control the upper limb prostheses. The primary of this paper is the classification of hand gestures by obtaining EMG signals obtained from MYO bracelet channeled with 8 medical grade electrodes that provide signal information during muscle contraction. To categorize the hand movements i.e., radial and ulnar deviation, extension and flexion of wrist, hand at rest, supervised model of Artificial neural network is trained with the help of window function. A neural network is used to generate the model, which has input, middle, and output layers. A dataset of 4.2 million was constructed with the help of electrodes from where signals ae extracted seven features from each of the eight electrodes. After feature extraction the ANN model is trained with traditional back propagation technique to identify the given classes. This strategy resulted in a success rate of 90% when classifying EMG signals that are collected from the upper arm muscles. The saved model is then transferred to the GUI-based model of NN, which is easy to understand and one can predict the outcomes. The research concluded that artificial neural network can be used in EMG pattern recognition and can be used in various aspects such as human-computer interaction and rehabilitation training.*

## INTRODUCTION

### Background

Biosignals or Bioelectrical signals are widely researched and used extensively to carry out many researches for decades. Moreover, in the rapidly evolving society, to utilize these human body signals in the domain of information technology is perpet6ually progressing as the healthcare continues to innovate. Among these bioelectrical signals, Electromyography (EMG) is the one that is the purpose of this study. Electromyography (EMG) is the procedure that helps to assess the health conditions of muscles when they contract and relax with the help of nerve cells called motor neurons. An EMG converts the contracted and relaxed signals into graphs for diagnostic purposes. This electromyography can be utilized in different applications that incorporate distinguishing brain-related illnesses, control prosthetic gadgets and robotic machines, and so on. This electrical activity of the muscle opens many doors to study the detection of hand pattern recognition. The signals can be extracted by using surface or needle electrodes.

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Surface electromyography (SEMG) is the reliable source in signal control to develop a prosthetic myoelectric hand (Abu et al., 2019). Previously it was very stressful to use prosthesis as it required immense mental and physical practice to adjust with the simple EMG signal-based devices. In new techniques, specialized EMG sensors like MYO bracelets are used with a neural network technique for gesture classification. In these types of cases, artificial neural networks (ANN) play a major role to execute hand gesture, recognition models.

For the assistance of amputees in their daily lives, myoelectric interfaces based on electromyograms (EMG) have been created recently. Myoelectric interfaces have developed into a valuable technology, especially because of how simple and non-intrusive they are to use for aiding daily activities by communicating with external equipment (Castellini, Fiorilla, & Sandini, 2009; Hargrove, Losier, Lock, Englehart, & Hudgins, 2007). Myoelectric interfaces comprise prosthetic limbs (arm/hand), and tele operable robotic devices (Fukuda, Tsuji, Kaneko, & Otsuka, 2003; Shenoy, Miller, Crawford, & Rao, 2008). The EMG signals are produced by the way the user executes their movements. After that, relevant features are extracted and categorized using advanced machine learning and pattern recognition algorithms. Too far, multiple optimum classifiers and time and frequency domains-based features have been thoroughly researched to enhance the act of the categorization of movement determined, by variable degrees of success (Phinyomark et al., 2013). The movement of the human upper extremities when grabbing something is complicated, for which several trials and studies have been conducted (Fligge, Urbanek, & Van der Smagt, 2013). Particularly, the degrees of freedom (DOFs) of the hand makes it challenging to provide distinct control of all fingers (Batzianoulis et al., 2017). The human hand contains 29 muscles and 21 degrees of freedom ("Human Hand Function - Lynette A. Jones, Susan J. Lederman - Google Books," n.d.). This indicates that humans are capable of efficiently controlling the numerous degrees of freedom (DOFs) in their hands through the central nervous system-controlled variables. Through the employment of postural synergies connected to several hand postures when gripping items, this multidimensional reduction, or significant decrease of DOFs, may be achieved (Santello, Flanders, & Soechting, 1998). In this context, various studies investigated a mapping amongst hand postures and upper-limb EMG signals as a way to regulate a significant portion of the hand's movement (Dalley, Varol, & Goldfarb, 2012; Ouyang, Zhu, Ju, & Liu, 2014; Young, Smith, Rouse, & Hargrove, 2012). These experiments examined the possibility of gripping after the hand had already assumed its ultimate position. In this instance, object size can simultaneously impact transit time and peak speed, and rotation of humorous straight connected to orientation of object(Marotta, Medendorp, & Crawford, 2003). Recently, (Brochier, Spinks, Umilta, & Lemon, 2004) verified that monkeys' upper arm and shoulder muscles carry important information to distinguish between different grip styles and object placements. The intrinsic muscles and long flexor muscles in this study appear active during the phase associated with the force generation only, while all muscles of the upper and lower limb were active during different phases and demonstrated a substantial support between the actions carried out during reach-to-grasp. The recording of activity at distal muscles, for example the wrist muscles, may not be necessary for the categorization of various grasping tasks. Classification algorithms for the healthy participants used in most of the amputees associated with transradial region since they have the EMG data from the flexor carpi radialis and extensor carpi radialis.

In fact, several researches have been done to categorize upper limb motions in trans radial patients by the activation patterns of the muscles around the wrist (Batzianoulis et al., 2017). There are, however, instances of trans radial amputees who lack the muscles below the elbow or struggle to control the muscles as a result of impairments in muscular strength and control that might occur as a result of injuries at very early ages. The classification of elbow, wrist and finger motions utilizing upper limb muscles like biceps and triceps has only recently been studied in these circumstances (Batzianoulis et al., 2017; Gaudet, Raison, & Achiche, 2018; Young et al., 2012) demonstrated the potential for identifying wrist flexion/extension and hand open/close utilizing EMG signals originated on

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biceps and triceps. Moreover, (Jarrasse et al., 2017) demonstrated that just EMG data retrieved at the upper arm may be used to classify the individual phantom finger motions, as well as the wrist and elbow. Furthermore, (Gaudet et al., 2018) demonstrated the potential to distinguish between the upper limb phantom motions (elbow flexion/extension, forearm pronation/supination, etc.) and a no-movement, just utilizing the EMG from location on the amputation stump. Simple upper limb motions, i.e. flexion or extension, were categorized to explore the potential in the aforementioned investigations (Jarrasse et al., 2017; Young et al., 2012). However, more research is needed to examine the feasibility of sophisticated upper-limb motions, such as reaching and grasping, in order to operate the prosthetic hand. (Jitaree & Phukpattaranont, 2019) have categorized various degrees of pinch grip force for EMG signals in healthy people. (Al-Timemy, Khushaba, Bugmann, & Escudero, 2016) used the EMG data from the trans-radial amputees to classify three broadly categorized degrees of grip forces. The patient's residual limb muscles above the elbow were not yet measured in these researches, which mostly examined EMG data from the forearm.

In this research work, a back-propagation algorithm for the artificial neural network was created when contrasted in connection and coordination with their precision in distinguishing the EMG signals. Human muscle activity's classification is viewed as an arising area for analysis and research for the human-machine connection, which can assist those incapacitated individuals with cooperating with this present reality with no inabilities, with advanced mechanics application (Yamanoi, Ogiri, & Kato, 2020). The EMG signal is used to measure the electrical movement of muscular systems, which includes the muscle activity of a human. EMG signals concoct more data identified with the actual work. This Project proposes a deep learning-based approach to classify human muscle activities and to help the disabled using ANN.

## Materials and Methods

### Dataset

The dataset to build this model is extracted from the Kaggle website. The recording of the signal is done on the MYO Thalamic bracelet worn on a forearm. 11 columns show the attributes while there are 4237907 rows which are showing the number of instances. This downloaded EMG dataset is created using 36 individuals that are performing each gesture individually. Each gesture in the dataset was performed for 3 seconds with a respite of 3 seconds between each gesture. The recorded dataset was partitioned into 7 sub-datasets, shown in Table 1, each dedicated to individual gestures. This dataset is used as an ideal input for the neural model for training and testing which is later used for the prediction. The result of these predicted outcomes is displayed on the created GUI.

**Table 1. Dataset of Hand Gestures**

| S.no | Time | channel 1 | Channel 2 | Channel 3 | Channel 4 | Channel 5 | Channel 6 | Channel 7 | Channel 8 | Class | Label |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1.00E- 05 | -2.00E- 05 | -1.0E- 05 | -3.00E- 05 | 0 | -1.0E- 05 | 0 | -1.0E- 05 | 0 | 0 |
| 2 | 5 | 1.00E- 05 | -2.00E- 05 | -1.0E- 05 | -3.00E- 05 | 0 | -1.0E- 05 | 0 | -1.0E- 05 | 0 | 0 |
| 3 | 9 | -1.0E- 05 | 1.00E- 05 | 2.00E- 05 | 0 | 1.00E-05 | -2.00E- 05 | -1.0E- 05 | 1.0E- 05 | 0 | 0 |
| 4 | 13 | -1.0E- 05 | 1.00E- 05 | 2.00E- 05 | 0 | 1.00E-05 | -2.00E- 05 | -1.0E- 05 | 1.0E- 05 | 0 | 0 |

### The Structure of ANN and EMG Signal Classification

In this work, a deep learning-based ANN algorithm is used with back-propagation, a supervised learning method, used for multilayer feed-forward networks in ANN. The BP algorithm continuously updates the weights in the layers and minimizes the error which is a very important step during ANN model training. The use of the learning rule is to compensate the weights between the layer and ANN. The NADAM optimizer is used that is the combination of NAG and ADAM. NADAM optimizer enhances the

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accuracy of the model by summarizing the exponential decay. In this project, the architecture of ANN consists of 7 layers; 1 input layer, 5 hidden layers with a RelU, an activation function for hidden layers, and an output layer with a Softmax, an activation function for the output layer. The first input layer consists of nodes while all the other layers consist of neurons. The BP network's architecture has 8 nodes in the input layer, so as there are 1024, 512, 128, 64, 32 neurons respectively in 5 hidden layers and the outcome layer comprises 8 neurons. The normalized features have been shown in **Table 2**. The algorithm defines to adjust the weight for each layer, starting from the last layer that is the output layer, and to the hidden layer. The importance of B.P is that it furnishes a systematic method to find the error of many hidden layers of the ANN architecture internally. The algorithm was also concluding to avoid over-fitting during training. The early stopping function is also used with the patience of 2. The weights of each layer are saved after each epoch. When the results of recreation are not acceptable, ANN re-trained once more with previously saved weights or parameters. The reason to retrain the model is to increase the accuracy level and reduce the loss.

**Table 2. Feature Normalization**

| | channel 1 | Channel 2 | channel 3 | channel 4 | channel 5 | channel 6 | channel 7 | channel 8 |
|---|---|---|---|---|---|---|---|---|
| count | 4.2e06 | 4.23e06 | 4.23e06 | 4.2e06 | 4.2e+06 | 4.2e06 | 4.2e06 | 4.2e06 |
| mean | -7.9e-06 | -9.4e-06 | -9.5e-06 | -9.6e-06 | -1.5e-05 | -1.08e-05 | -9.3e-06 | -9.6e-06 |
| std | 1.6e-04 | 1.9e-04 | 1.2e-04 | 2.2e-04 | 2.7e04 | 2.1e-04 | 1.5e-04 | 1.7e-04 |

## Results and Discussions

### Recognition Accuracy

After training, we get an accuracy of 90.0% as shown in Figure 1. The confusion matrix is shown in Figure 2. There are seven gestures for classification. The accuracy of individual gestures shown in Table 2. The primary signal that is hand exceptionally still has a 94% accuracy level. The 2nd motion that is hand grasped in a holding hand has 90% accuracy. The 3rd motion that is wrist flexion has 91% precision. The 4th motion that is the wrist extension has 92% accuracy. The 5th motion is a radial deviation that has 89% accuracy and the 6th motion that is ulnar deviation has 90% accuracy. Lastly, the 7th motion that is expanded palm has 85% accuracy. The best accuracy of the motion is the hand at rest.

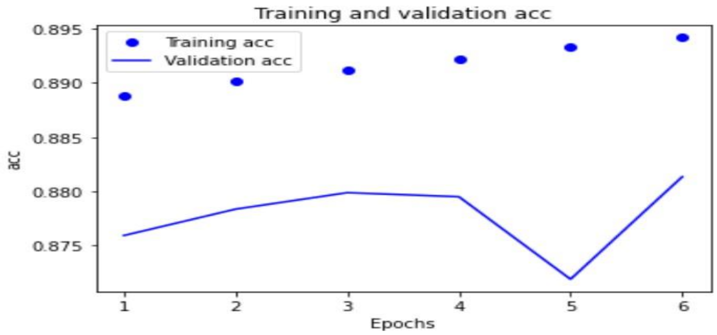


**Figure 1. Accuracy Graph**

**Table 3. Accuracy of Individual Gesture**

| Gesture | Accuracy |
|---|---|
| Hand at rest | 94% |
| Hand clenched in a fist | 90% |
| Wrist flexion | 91% |
| Wrist extension | 92% |
| Radial deviations | 89% |

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| | |
|---|---|
| Ulnar deviations | 90% |
| Extended Palm | 85% |

**Graphical User Interface (GUI)**

The testing is a very important part of the software-based project that should be easy to be used. Testing has been divided into a graphical interface (GUI) based testing, logical testing, etc. So, in this project, for the gesture classification, Python language-based Graphical User Interface (GUI) is designed which can be shifted to real-time prediction. In this interface, 8 channel data have to be entered and after putting the channel data and clicking the Gesture button, the GUI will display the generated predicted gesture as shown in Figure 4. The confusion matrix of the project as shown in Figure 3.

```
[[49572    92   154   273   183    60     3]
 [   69 46296   791   404   340   572    40]
 [  185   502 47733   140   260   686    34]
 [   88   421   146 48073   880   405    34]
 [  259   622   441  2371 46650   197    31]
 [   96   741  1576   949   264 46965   144]
 [    6    34    63    49    27   100  2529]]
```

**Figure 3 Confusion Matrix**

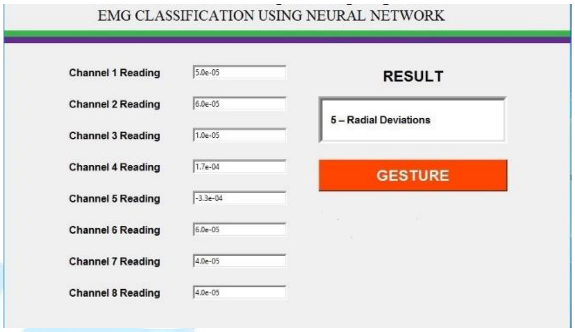


**Figure 4 Graphical User Interface**

The research work aimed at classifying hand gestures for the movement of prosthetic devices using EMG signals and deep learning techniques. In this paper, an Artificial Neural Network (ANN) was trained to recognize seven distinct hand motions, including at rest, fist, wrist flexion, extension, radial and ulnar deviation, and the extension of the palm. The trained model achieved an accuracy of 90.0%. It was observed that the accuracy of individual gestures varied, with the highest accuracy being achieved for the hand at rest (94%) and the lowest accuracy being achieved for the expanded palm (85%). These results offer esteemed insights into the classifier's performance and highlight the importance of more significant EMG signals to improve gesture classification efficiency. The testing of the software-based project was conducted through a Graphical User Interface (GUI) based on the Python programming language. Electromyography (EMG) has drawn a lot of attention lately because of how it can be used to operate powered upper-limb prosthetics. These methods utilize the EMG signal produced by muscular contraction and collected by skin-mounted sensors to transmit control signals (Jafarzadeh, Hussey, & Tadesse, 2019). According to the quantity of mean absolute value of signals, the early myoelectric hands controlled by EMG signals could only be in "on" or "off" states (Roche, Rehbaum, Farina, Oskar, & Aszmann, 2014). If the mean absolute value of the EMG signal exceeds a given threshold value, the output is "on" and a straightforward activation takes place; otherwise, the output is "off" and no activation takes place. The GUI was designed for real-time prediction of hand gestures and allows for easy input and output of data. The confusion matrix was presented in Figure 3, which provides a visual representation of the accuracy of the classifier and highlights which hand motions may require further improvement. The use of a GUI in the testing process and the user-centered design of the project demonstrates the importance of considering user experience in software-based projects. A well-designed interface and testing process can greatly enhance the accessibility and functionality of the system for its users. This research highlights the potential of deep learning techniques and ANNs in classifying hand gestures for the movement of prosthetic devices. The results demonstrate the effectiveness of the trained model in achieving high accuracy levels and provide valuable insights into the performance of the classifier. Further studies can aim to improve the accuracy of the classifier by incorporating more significant EMG signals. This method results in prosthetic hands

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doing just a small subset of the movements that a human hand would normally carry out.

Surface electrodes linked to the subject's arm are used to detect EMG signals, which are used to operate the prosthesis. It is considered that the extracted EMG signals represent the subject's desired muscle motions. There are several kinds of prosthetic hands and/or arms that can be controlled by EMG. However, before these devices can be used in practice, two major issues must be resolved, namely EMG pattern analysis/classification and the precision with which the person can provide the EMG signals. The majority of arm and hand motions are produced by the coordinated action of multiple muscles. Therefore, crosstalk from adjacent muscles may be detected in the EMG data from a surface electrode on one muscle. This obviously makes it more difficult to separate and categorize EMG signals that are obtained from muscles. Using learning processes such the linear separation function and Perceptron LS to assess and categorize the EMG signals from multi-channel. These learning algorithms still struggle with classification capability and convergence performance, though. To put it another way, they occasionally fail to converge when there are too many EMG patterns to learn, and they perform poorly when trying to categorize EMG patterns. EMG pattern analysis and subject ability categorization now face a new issue. In order for subjects to consistently produce the EMG, they must train their muscles. signals required to operate the prosthetic device. Additionally, since each person essentially has their own muscle control ability, such training frequently necessitates exhausting physical and mental exertion. Due to its excellent capacity to learn, adapt, and separate non-linearly, neural networks have received interest in the field of analysis and classification. Particularly when used as a supervised learning method, back-propagation networks provide a potent and practical way to handle ambiguous input.

## Conclusion

The research work is accomplished for the grouping of EMG signals for 7 hand motions. Hand gesture classification signals are used for the movement of prosthetic devices. In this research, deep learning techniques are used for the classification of hand gestures among which, ANN is chosen. The trained model can characterize 7 distinctive hand motions: at rest, fist, flexion and extension of the wrist, deviation of radial and ulnar muscles, and the extension of palm. The accuracy we get from the trained ANN model is 90.0%. The classification of gesture efficiency can be improved if the EMG signals are more significant. However, the EMG signals may vary from person to person and from period to period. The GUI which is created is very user-friendly that shows the precisely predicted gesture at the output when data is inserted in the 8 channels. This research highlights the potential of deep learning techniques and ANNs in classifying hand gestures for the movement of prosthetic devices. The results demonstrate the effectiveness of the trained model in achieving high accuracy levels of the classifier. Further studies can aim to improve the accuracy of the classifier by incorporating more significant EMG signals.

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## Conflict of interest

No conflicts of interest are disclosed by the writers, who also attest that this work is original and devoid of plagiarism from other sources, including print and electronic media. All of the sources of the information are appropriately acknowledged and credited here.

## Ethical information

It is declared that this article does not contain any studies with human participants or animals performed by any of the authors.

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## Author contribution

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