# Intelligent Electromyograph for Early Detection of Myopathy and Neuropathy Using EMG Signals and Neural Network Model


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**Abstract.** The present work proposes developing an electromyograph to give a reliable diagnosis for detecting neuromuscular diseases. Neuropathy is a condition that affects neurons, and in myopathy, the muscle fiber does not work correctly. Developing a highly accurate diagnostic system based on EMG readings would provide a promising way to improve the evaluation of neuromuscular disorders. If the features are efficiently extracted, it is possible to obtain outstanding sorting performance. This research is carried out in two phases (hardware and software). First, the electromyogram was developed with sensors that allow the acquisition of bioelectric signals generated by the skeletal muscles with non-invasive electrodes. For recording the EMG signal, a differential pre-amplification was made, and three filters were used to obtain the minimum noise in the signal. Second, a Convolutional Neural Network (CNN) of type ResNet-34 was developed in Python. A database obtained from various articles with similar studies was built; data was a set of images of EMG signals divided into three classes: healthy, neuropathy, and myopathy. The images of these three classes are similar in time domain and frequency, so this network classifies healthy images of EMG signals from showing patterns of pathology. An EMG-based feature extraction method is proposed and implemented that uses a neural network to detect healthy conditions, myopathy, and neuropathy. Finally, according to the performance evaluation of this method, it has a precision of 98.57%.



**Keywords:** Electromyography · Neural networks · Medical conditions · Pathology · Smart device




J. Herrera-Tapia et al. (Eds.): TICEC 2022, CCIS 1648, pp. 32–45, 2022.
https://doi.org/10.1007/978-3-031-18272-3_3

## 1 Introduction

Neuropathy is a condition in which neurons are affected, the individual experiences numbness in their limbs [1]. This condition can cause gait impairment, such as difficulty walking, climbing stairs, or maintaining balance [2]. In the USA, the number of people with this condition is approaching 20,000 [3]. The estimated prevalence of neuropathies in the general population is about 2%; in adults from 55 years old, it can reach 8% [4]. Myopathy is a muscular condition where the physiological function of the muscle fiber is altered and can be produced for some reasons as muscle cramps, stiffness, and spasms [2, 5]. In 2005 the USA's statistics data determined that approximately 2.97 million patients have been diagnosed with myopathy [3].

To give an accurate diagnosis to patients suffering from these pathologies, electromyography (EMG) is used. The EMG allows the extraction of muscle signals, and subsequently, the interpretation of those patterns to the patients by the medical staff is necessary [6]. However, the number of neurological experts is limited, so an automatic system that helps diagnosis, periodic detection, and monitoring is required [3]. Therefore, it is possible to reduce the medical costs that clinical examinations could represent per patient, thanks to the early detection of these muscular diseases. The electromyogram helps to detect diseases through the analyses of pattern recognition applications by using analytical methods [7]. For instance, fast and short-term Fourier transforms (FFT and SFT) are used to study stationary signals and then for the non-stationary signals [8, 9]. Pattichis and Pattichis processed the signal at different resolution levels (multiresolution analysis) by using the continuous Wavelet transform (WT) [10].

As a consequence of WT function having continuous derivatives, i.e., allowing decompose a continuous function efficiently, signal processing is reduced and avoid unwanted signals [8, 11]. Many others, such as autoregressive (AR), Root mean square (RMS), Quadratic phase coupling (QPC), have emerged [12, 14]. These techniques provide an extensive spectral to study the signals. However, it is necessary to extract the coefficients from each stage of the construct functional approximation to the original signal. It implies the analysis by classifiers such as Artificial Neural Network (ANN), Support Vector Machines (SVM) [15], Logistic Regression (LR), Linear Discriminant Analysis (LDA) [8, 16]. For the determination of muscle fatigue for an automated system, estimation of knee joint angle for control of leg prostheses determination of muscle contraction during human walking, among others [17].

Neural networks are computer systems inspired by the learning characteristics and structure of biological neuron networks, and they also have applications for the detection of muscle diseases [18]. A study identified three spectral analysis methods (AR, FFT, Cepstral analysis) to characterize myoelectric signals and classify neuropathy and myopathy using neural network classifiers [14]. The combination of SVM with FTT provides the area under the ROC curve (receiver operating characteristic) of 0.953, which is within the acceptable range [14]. Likewise, other researchers used the Probabilistic Neural Network (PNN), a classifier that can map any input pattern to a series of classifications. A diagnosis of neuromuscular diseases has the advantage of a training process and is an inherent parallel structure [19].

It is necessary to perform an image classification or normalization of contrast and brightness and noise elimination [20]. Therefore, research-based on image recognition using artificial neural networks explicitly performs feature extraction using grayscale and binarization, transforming the image into two colours, black and white. Also, in this work, the Python programming language was chosen [10]. This project's objective includes the investigation and interpretation of EMG signals using an electromyogram. Then, signals are further analyzed using a CNN that provides better analysis tools that allow diagnosing these musculoskeletal conditions (healthy, neuropathy, and myopathy) by analyzing the images of EMG signals.

## 2 Materials and Methods

The research implies the following modules: first, obtaining and processing the signal, so here, choose the components and the amplifiers to avoid distortions of the signal's information as the noise. Second, extract and store the information from the signals provided by the prototype to transform the signal. Third, extract signals with pathologies of a database, in this case, signals of myopathy and neuropathy. Finally, apply neural networks as classificatory according to the different parameters considered (see Fig. 1).

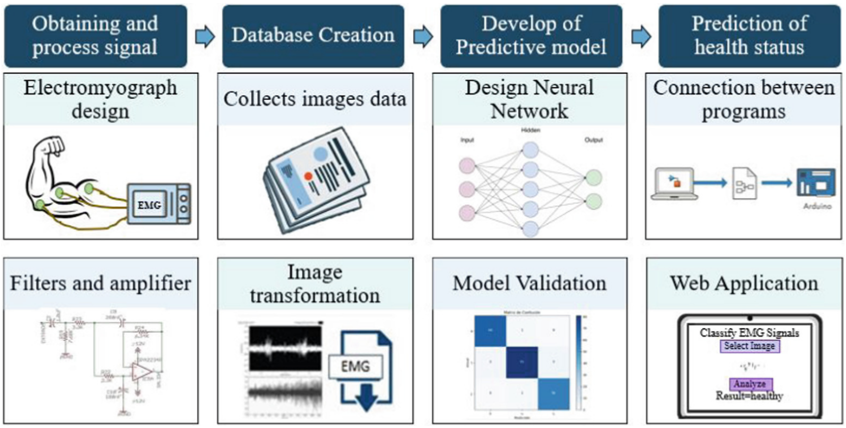


**Fig. 1.** Flow diagram of the working methodology.

### 2.1 Obtaining and Process Signal

The myoelectric signal represents the electrical activity resulting from the excitability of muscle fibers due to muscle concentration. The amplitude of this signal varies from $\mu$V to values of the order of 10 mV [21]. In this research, three non-invasive 3M 2560 Red Dot™ foam electrodes whose dimensions are 4x4 cm were used to detect the EMG signal. They are comfortable for patients, occlusive for fluids, and easy to handle. The solid gel of the electrodes allows uninterrupted and high-quality marks and minimizes the degree of skin irritation. Thus, two electrodes detect variation of signal (millivolts), placed on the biceps at a distance between them of 3 cm, and the third is used as a reference on the elbow. The electrodes make an ion exchange of tissue from the living body to an electronic device that triggers the appearance of a potential difference (voltage). For the treatment and processing of the read signal, an electronic board was developed with various components such as resistors, operational amplifiers, and capacitors. The board consists of three stages (see Fig. 2).

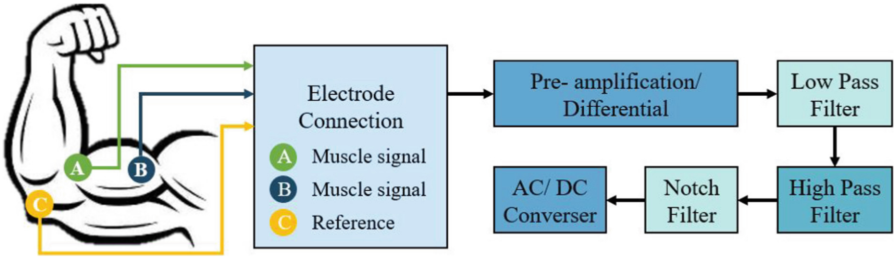


**Fig. 2.** Block diagram of the EMG circuit (hardware).

**First Stage.** The signal received from electrodes passes through an instrumental amplifier made up of three operational amplifiers and some resistors. It has two parts: a preamplification and a differential part. The primary signal is to amplify (gain) the difference between two input signals. The input signal amplitude oscillates in a range from 1 to 10 mV. For the treatment of the signal, an output that ranges from 1 V to 10 V is required. Approximately 1000 times profit is required.

**Second Stage.** At this stage, the required cutoff frequencies for the three filters must be defined [22]. The literature recommends using a cutoff frequency of 10 Hz to 300 Hz since the signal outside this range has much noise [2]. Besides, the 60 Hz frequency must be eliminated due to the interference generated with the country's electricity grid. Three filters are used: low pass, high pass, and notch, whose cutoff frequencies are 300 Hz, 10 Hz, and 60 Hz.

**Third Stage.** Corresponding to the conversion ADC, analogue to a digital signal, is accomplished with microprocessors such as Arduino. The values sent from the Arduino board to the computer's serial port are taken through the Python pyserial module. Moreover, these data are plotted as a function of time and amplitude.

The system's transfer function is obtained to predict the shape of the EMG signal without the need to solve complex differential equations [23]. Thus, for each phase, a transfer function is calculated for the amplification and the three filters. Then, multiplication of these series functions is performed to result in the entire system's transfer function. (See Fig. 3).

### 2.2 Database Creation

Simulated signals were extracted from various works carried out to evaluate the proposed method, classified into three categories: healthy, myopathy, and neuropathy, these signals

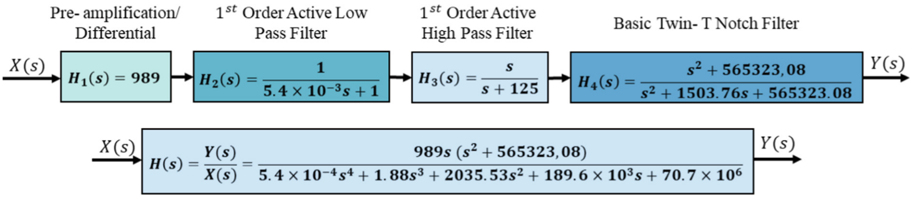


**Fig. 3.** The transfer function of each stage of the EMG circuit.

are stored in image form with their respective format (JPG). The images were collected and classified for the creation of a complete database. These images will be processed to discover some characteristics used by the artificial neural network to classify EMGs.

**Image Transformation.** Use OpenCV library, then choose the transformation: grayscale (in signals the colour does not matter), binarization (separate the signal of interest from the rest of the image), and segmentation (in three parts each signal) (see Fig. 4).

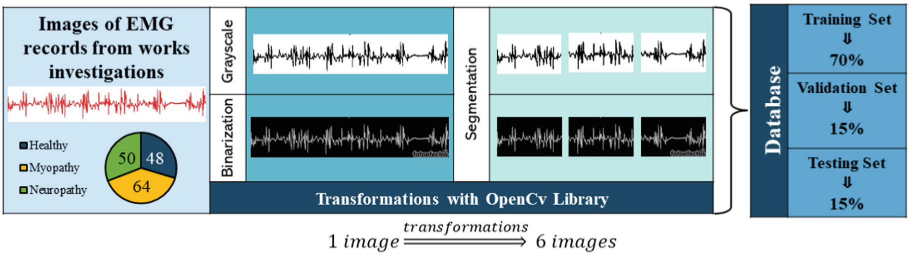


**Fig. 4.** Process of database creation.

**Datasets of the Database.** Supervised learning uses a database to teach a model of performing a task or predicting a value (or values). For this, three subsets must be created: Training set: to train the model; validation set: to make sure the models are not overfitting; Test set: to determine the model's accuracy. In general, the training, validation, and test dataset are divided by a ratio of 70%, 15%, 15%, respectively. It is shown in Table 1.

**Table 1.** Database of EMG signal images, with different conditions

| Conditions | Healthy | Myopathy | Neuropathy | Total |
|---|---|---|---|---|
| Database | 144 | 192 | 150 | 486 |

### 2.3 Develop the Predictive Model

It collaborated with a pre-trained model of a neuronal network containing the weights and biases representing the features of the dataset it was trained on. The neural network used is a CNN of type ResNet-34 that contains 34 layers used for image classification tasks. The Neural Network was developed in TensorFlow, and to use the Fastai library in Python was employed. It is a pre-trained model on the ImageNet dataset. However, it is different from traditional NN because it takes the residuals from each layer and uses them in subsequent connection layers (similar to residual NN for text prediction).

The residual building block of the ResNet34 layer consists of multiple convolutional layers (Conv), batch normalization (BN), rectified linear unit (ReLU) activation functions, and shortcuts. The output of the residual building block can be expressed as y = F(x) + x. Where F is the residual function, x is the input, and y is the output of the residual function. The entire residual network consists of the first convolutional layer and several basic blocks. ResNet-34 contains 33 convolutional layers, a top pooling layer with a size of 3 × 3, an intermediate pooling layer, and a fully connected layer. A classic ResNet-34 model has rectified nonlinearity (ReLU) activation, and batch normalization (BN) is applied to the back of all convolutional layers in the "basic block". In contrast, the SoftMax function is applied to the last layer (see Fig. 5).

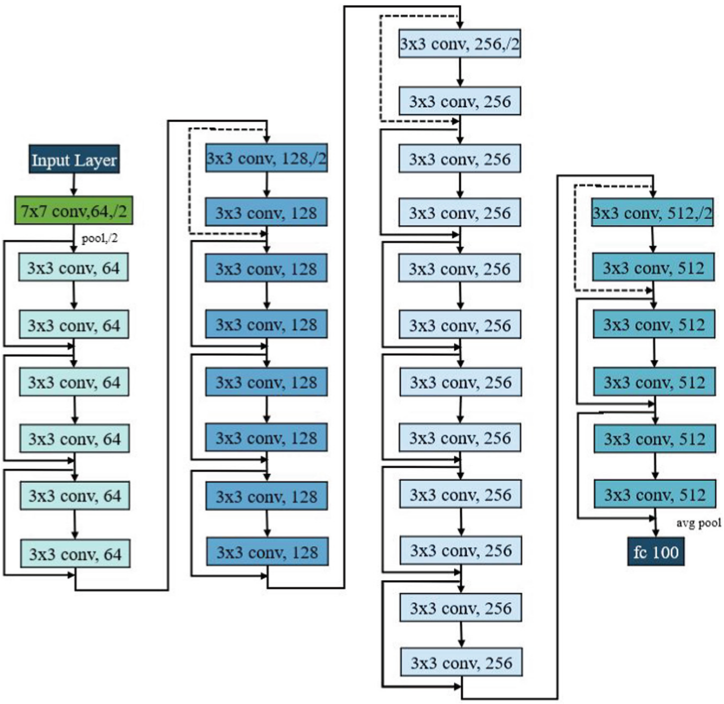


Fig. 5. Architecture of ResNet-34.

### 2.4 Prediction of Health Status

The connection between the electromyograph and the neural network was by a web application. This tool allows patients to use it from a web server via the Internet, reducing installation problems. This application works with a single screen where the electromyograph's image is uploaded and predicts the signal status (healthy, myopathy, or neuropathy). The web application was developed in Python and worked with the Heroku platform, where the database is stored in the cloud.

## 3 Results

### 3.1 Obtaining and Process Signal

The electromyograph was created to extract the filtered EMG signal from the individual. Besides, a neural network for signal analysis was implemented to discriminate whether a person has myopathy or neuropathy; this is a healthy individual. In the first instance, the EMG signal that was extracted from the created device is presented clean. It can be seen in Fig. 6. This signal results from signal amplification and filtering used the low pass, high pass, and notch filters, with cutoff frequencies of 300 Hz, 20 Hz, and 60 Hz, respectively.

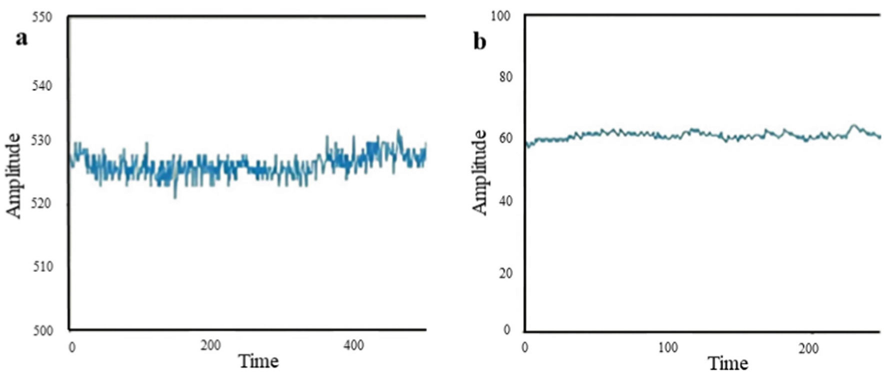


**Fig. 6.** EMG signal in ms (a) with noise and (b) without noise.

### 3.2 Neural Network

The neural network was trained 41 epochs, and this process took less than 5 min. The error on the training set of data, training loss is 0.193424, the error after running the validation set of data through the trained network, validation loss is 0.060876, and the error rate was 0.014286. These values are obtained from the learning rate ranging from $1 \times 10^{-6}$ to $1 \times 10^{-4}$.

Subsequently, the efficiency of the neural network was evaluated using the confusion matrix (see Fig. 7). The primary diagonal data are represented (painted blue), which indicates the number of hits in the model. In this case, 22 have been correctly classified as EMG healthy, 24 as EMG myopathy, and 23 as EMG neuropathy, which generates a total of 70 data, of which 69 are correctly classified with an accuracy rate 98.57%. The lower diagonal shows the false negatives or type II error (the disease is not detected when, in fact, it does present); there is no such error. In contrast, the upper diagonal reflects the classifier errors: false positives or error type I (the disease is detected but does not present). In effect, just one actual value of the neural network regarding neuropathy is confused with myopathy in the predicted one.

| | Predicted label | | |
|---|---|---|---|
| True label | EMG Healthy | EMG Myopathy | EMG Neuropathy |
| EMG Healthy | 22 | 0 | 0 |
| EMG Myopathy | 0 | 24 | 0 |
| EMG Neuropathy | 0 | 1 | 23 |

**Fig. 7.** Confusion matrix.

### 3.3 Web Application

The web application requires access to internet and to have any device capable of being a Web server. The device must have an operating system that can run as a Web server, capable of delivering HTML5 content. It must also have an Intel® 847 Processor, 1.10 GHz, and a minimum Ram of 512 MB. These features are the basics in any computer, cell phone or tablet. Finally, this tool does not require the device to have a certain amount of storage or hard disk space as it works online. The web application makes the prediction approximately two seconds after pressing the "Analyze" button. It provides the advantage of executing an immediate and easy diagnosis using the electromyograph developed in this study. The result from the web application (see Fig. 8).

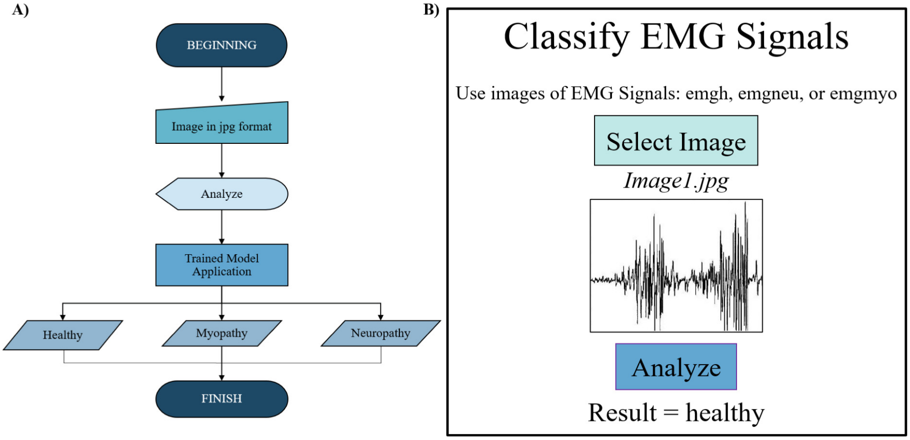


**Fig. 8.** A) Flowchart of the trial process and B) Web application screen and components

## 4 Discussion

To develop the hardware, the electromyograph was necessary to have some considerations. The appropriate gain to read the signal is 1000 times due to the range in which it is found from micro to millivolts. After amplifying the positive and negative signals from the two electrodes, a differentiation was made to find the muscle's potential. Then, the removal of electronic noise and interference of the circuit was carried out through filters.

The EMG signal's optimal frequency range is from 10 Hz to 300 Hz, whose maximum potential is 100 Hz [21]. The supplied electrical network has a frequency of 60 Hz, which creates interference with the circuit. For this reason, this frequency is eliminated with the notch filter. Furthermore, the conversion of the signal from analogue to digital was through Arduino. Finally, it was observed that the received signal is wildly oscillating due to environmental interferences, power sources, and lack of circuit isolation, among others. Hence, an offset circuit must be implemented, allowing handling the signal in the y axis and a ground controller circuit to maintain a constant signal.

A transfer function was necessary to establish a frequency function that exceeds these tolerance limits with an approximation process [24]. The transfer function of the analogue circuit allows us to set up the mathematical model of the system and its components and relevant information such as poles and zeros [23, 25]. Small electrodes ($r < 5$ mm) are preferable over larger ones to avoid loss of information. In EMG amplifiers, analogue notch filters help reduce power line-induced interference at 50 Hz or 60 Hz. These filters removed both the interference and spectral components of the EMG signal. Additionally, notch filters introduce a non-linear phase response below and above the center frequency.

To develop the software, a problem was the lack of a database of EMG images. To this was created a standardized database which corresponds to the initial images found in publicly available papers, and then it was applied image transformation: grayscale, binarization, and segmentation. It is so; the database contained 486 images of 3 classes. To increase the reliability of the system, the current designed dataset should be further expanded. To evaluate the results' relevance was to calculate three metrics: specificity, sensitivity, and accuracy calculus from the confusion matrix. It is shown in Table 2.

**Table 2.** Different detection methods presented in the literature

| Method | Learning technique | Disease | Metrics (%) | | | Ref |
|---|---|---|---|---|---|---|
| | | | Sen | Spcf | Acc | |
| CNN model ResNet-34 | DP. CNN and classifier | Healthy, neuropathy and myopathy | 100 | 97,91 | 98,57 | - |
| EEMD-FastICA-LDA | DP. Noise-assisted data analysis method, by using Fast ICA algorithm and LDA classifier | NMD | - | - | 98.00 | [26] |
| SVM classifier | DP. Feature extraction by CWT and using the RBF kernel | NMD | 74.73 | 96.94 | 91.01 | [27] |
| KNN classifier | DP. Feature extraction by CWT and using 9 nearest neighbors | NMD | 75.12 | 96.83 | 91.11 | [27] |
| WNN | DP. Classification of EMG signals using WNN | NMD | 92.00 | 94.00 | 90.70 | [28] |
| CNN classifier | DP. Obtain probability score characterizing whether the muscle image belongs to a diagnosis class | Normal and myositis | 81.20 | 89.90 | 86.60 | [29] |
| RF classifier | ML. Image features vector as input and each tree provides a vote to classify the disease | Normal and myositis | 71.80 | 91.90 | 83.00 | [29] |

(*continued*)

**Table 2.** (*continued*)

| Method | Learning technique | Disease | Metrics (%) | | | Ref |
|---|---|---|---|---|---|---|
| | | | Sen | Spcf | Acc | |
| SVMs classifier | ML. Algorithms to analyze, and eliminate to find the optimal number of parameters to classification | Types of SMA | - | 89.00 | 92.80 | [30] |
| ANN | DP. Evaluation of Muscle Diseases Using ANN Analysis of 31P MR Spectroscopy Data | Amyopathic Dermatomyositis | - | - | 97.70 | [31] |
| CNN model ResNet50 plus SVM classifier | DP. CNN and classifier | COVID-19 | 97.47 | 93.47 | 95.38 | [32] |

** Sen: Sensitivity, Spcf: Specificity, Acc: Accuracy, ML: Machine Learning, DP: Deep Learning, CNN: Convolutional Neural Network, EEMD: Ensemble Empirical Mode Decomposition, ICA: Independent Component Analysis, LDA: Linear Discriminant Analysis, NMD: Neuromuscular disorders, SVM: Support vector machine, CWT: Continuous Wavelet Transform, RBF: Radial Basis Function: K Nearest Neighbor (supervised ML algorithm), RF: Random Forest, SVMs: Support vector machines, SMA: spinal muscular atrophy ANN: Artificial Neural Networks, WNN: Wavelet Neural Networks

The method of Deep Learning (DP) selected was CNN because it worked with images. This neural network represents an innovation in the study of these two diseases. The present method obtains better results than others that are in the literature. It was compared with other classifiers for the EMG signal, the same CNN model ResNet50, and other DP models and Machine Learning (ML) techniques. Consequently, our model has high sensitivity (97.91%) and high accuracy (98.57%), which means values are comparable to current DP techniques.

## 5 Conclusion

The project met the proposed objectives. It first created an electromyograph that extracts the clean EMG signal from the individual, using three filters: low pass, high pass, and notch. The development of hardware was a process that incorporated clinical knowledge, understanding of neuromuscular physiology, and pathology to obtain an EMG signal as accurately as possible. The detection of neuromuscular pathologies depends on a correct EMG analysis in all phases of muscle movement.

Second, implementing a neural network for signal analysis allows predicting whether a person has myopathy, neuropathy, or is a healthy individual. The database of the

Neural Network was made up of images and represented an innovation in how diagnoses of diseases are carried out. The results obtained in the classification of myoelectric signals exposed the high growth and implementation of neural networks as classification mechanisms. This computational model allows us to identify the myoelectric signal patterns present in each pathology with a precision rate of 98.57%%. These positive results may be applicable to a larger database but using the same methodology. In other words, the fundamentals used can be generalized in different cases with the certainty that the results will be equally effective.

Third, based on the experimental results, the electromyogram's functionality, and the neural network, when working together, allows the detection of pathologies in real-time. In natural settings, this device could help clinicians make a correct diagnosis of neuromuscular disorders. Therefore, the prediction model used in this study is significant in the clinical field since it helps to improve the precision of the diagnosis and increases the speed at which the treatment can be applied to a patient, allows periodic monitoring, and reduces medical expenses.

For future perspectives, the implementation and improvement of signal taking must be sought using a plate and other components to allow noise isolation and decrease the margin of error that the developed apparatus presents to date. Also, images of EMG records of people could be obtained with myopathy and neuropathy to obtain data from more muscles and more subjects, expanding and creating a consistent database. Another aspect of the diagnosis that should be investigated is the severity of the disease (mild, moderate, severe, and chronic states). This will create an intelligent system capable of processing images, measurements, and signs to diagnose neuromuscular disorders considering all the characteristics mentioned above.

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