Classification of Surface Electromyography Recordings from Healthy and Peripheral Neuropathy Subjects

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Abstract. Peripheral Neuropathy are lesions of the peripheral nervous system, they could be caused by a wide variety of problems being the most common worldwide, diabetes mellitus. The most common methods of detection are a clinical diagnosis and an electromyography with invasive electrodes. Both of them represent a risk to the patient because they can cause lesions or infections, for these reasons, the objective of this work is to propose a non-invasive method, based on surface electromyography and that, supported by statistical analysis, may suggest the presence of Peripheral Neuropathies. Based on the literature, two muscles (flexor *digits brevis* and abductor *digiti minimi*) responsible for the mobility of the cortexes were identified as suitable for the study. Once the information was acquired, it was conditioned though digital filters, rectification and smoothing of the signal and later processed to extract the characteristics (in time and in frequency domain) of the signal which were the input to different classifiers in order to determine their performance in differentiating subjects with neuropathy from healthy subjects. The results indicate that it is possible to differentiate both groups with a percentage greater than 83% with at least 5 of the classification algorithms tested in this work: Weighted KNN (84%), RUSBoosted Trees (83.3%), Quadratic SVM (83.3%), Cubic KNN (83.3%) y Medium Gaussian SVM (83.3%). However, it is necessary to increase the sample size to corroborate the good performance of this methodology.

Keywords: Peripheral Neuropathies, Diabetes Mellitus, Electromyography, Decision Trees.

1 Introduction

Peripheral Neuropathy (PN) is a condition affecting the peripheral nervous system, primarily impacting the lower limbs, causing numbness in the affected area, tingling, sharp pain, hypersensitivity, burning sensations, muscle atrophy, and/or muscle weakness [1]. The causes of PN range from physical injuries, autoimmune diseases, tumors, and toxin exposure to metabolic disorders and hereditary factors. One of the most common causes is Diabetes Mellitus (DM), which, in Mexico alone, affected 12.8 million adults in 2019, with projections estimating 22.3 million cases by 2045 [1,2]. It is estimated that between 2.8 and 5.9 million Mexicans suffer from the disease but remain undiagnosed.

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By 2030, the number of people with diabetes is expected to reach between 9.7 and 20.6 million, and by 2045, this number could rise to 26.8 million [2].

To provide context, it is important to examine the statistics surrounding this issue: approximately 70% of older adults experience some form of increased or decreased sensitivity in their feet, and in Mexico, 60% of adults with type 2 DM develop some form of PN as they live longer with the disease [3]. PN is characterized by infection, ulceration, and/or destruction of deep tissues, which progresses rapidly and increases the fragility of arteries in the extremities. When this condition affects the lower limb, specifically the foot, even minor trauma can lead to ulcers or infections [4,5].

The diagnosis of neuropathy-related infections is primarily clinical, based on the presence of suppuration or at least two inflammatory signs (erythema, induration, pain, tenderness, and/or warmth). According to a study published in 2016 by the Mexican Institute of Social Security (IMSS), approximately 100,000 Mexicans undergo some form of amputation annually due to this condition [6].

1.1 Classification of Peripheral Neuropathies

PN is classified based on three criteria: pathological findings, etiology, or clinical syndrome. A neurological examination typically reveals sensory loss, lower motor neuron weakness, atrophy, reduced tone, and decreased reflexes, depending on the affected nerves. Electromyography (EMG) and nerve conduction studies can be useful as extensions of the neurological exam.

Peripheral neuropathies are categorized as follows: Polyneuropathies: Distal, symmetrical abnormalities (often subacute, slow-progressing) affecting sensation, strength, or both. These are generally secondary to metabolic, toxic, or hereditary disorders. **Focal neuropathy:** Dysfunction affecting a single nerve (e.g., carpal tunnel syndrome), typically due to compression or focal nerve stretching. **Multiple mononeuritis:** Several individual nerves are affected asymmetrically, either simultaneously or progressively. This is usually secondary to inflammatory disorders and requires analysis for vasculitis [7,8].

Symptoms and Diagnosis. PN symptoms vary depending on the patient, affected area, and severity. A complete neurological examination is conducted to determine the cause, severity, and type of nerve damage. The medical evaluation considers social habits, work environment, family history, and disease risk factors. More specialized tests can clarify cardiovascular diseases, connective tissue disorders, and/or tumors. Additionally, genetic tests are available for certain hereditary neuropathies [1,4].

Physical examinations (strength tests, fasciculation/cramp assessments, and sensory evaluation) can reveal systemic disorders, nerve damage, and/or motor or sensory fiber impairments. Blood tests help detect diabetes, vitamin deficiencies, metabolic disorders, and abnormal immune system activity. A cerebrospinal fluid (CSF) test can reveal abnormal antibodies associated with certain immune-mediated neuropathies [1,4].

Additional Diagnostic Tests for PN. Nerve conduction velocity tests: Measure the degree of damage in large nerve fibers and determine whether PN is caused by myelin sheath degeneration or axonal damage. **Electromyography (EMG)**: Involves inserting a thin needle into the muscle to record electrical activity at rest and during contraction. It detects abnormal electrical activity in motor neuropathies and helps determine whether the disorder originates from the muscle or nerve. **Magnetic resonance imaging (MRI)**: Displays muscle size and condition, facilitating the detection of fatty tissue replacement, hernias, or tumors that could be causing PN. **Nerve biopsy**: A small nerve tissue sample is removed and examined. Although this test provides valuable information about nerve damage, it is an invasive procedure with potential neuropathic side effects. **Skin biopsy**: A small skin sample is extracted to examine the nerve fiber endings. This test determines damage in the smallest muscle fibers and is less invasive than a nerve biopsy, with fewer side effects [1].

Need for Non-Invasive Diagnostic Methods. Given the aforementioned challenges, it is crucial to develop or improve existing diagnostic mechanisms for PN by offering non-invasive, low-cost alternatives for patients. The diagnostic method must align with the current needs of individuals at risk of PN, enabling early detection.

Currently, the most medically accepted EMG recording method uses needle electrodes, as recommended by the National Institute of Neurological Disorders and Stroke (NINDS) and Mayo Clinic [1,4]. However, trauma can trigger PN [1,5], making invasive EMG electrodes a disadvantageous option.

Development of Low-Cost, Non-Invasive EMG Detection. This need has led to the development of non-invasive, low-cost EMG detection methods to identify tissue degradation and decreased foot sensitivity in diabetic individuals at different disease stages.

Yousaf et al. [9] studied the feasibility of using non-invasive EMG as a tool for detecting neuromuscular disorders, focusing on EMG signal acquisition and processing. Ullah et al. [10] conducted a study on detecting abnormal muscle contractions using non-invasive EMG, evaluating several lower limb muscles during walking—although they did not include foot muscles—demonstrating the applicability of their method.

This study explores the use of myoelectric signals through surface electrodes. The measurement area for these signals is the pretibial region of the patient. Measurements are taken immediately after repetitive toe flexion movements in three groups: Control subjects (healthy individuals), Subjects at risk of PN, and Subjects diagnosed with neuropathy. Since diabetes is the leading cause of PN, efforts should be focused on developing a low-cost, accessible detection method to improve the quality of life of affected individuals.

2 Materials and Methods

For this study, only the recordings obtained through a myoelectric signal amplifier built by the authors of this work were used.

2.1 Materials

INA 128 Amplifier. Myoelectric signals have an approximate amplitude of 250 µV when the muscles contract; they are so small that any noise or interference can lead to misinterpretation. An instrumentation amplifier has the necessary characteristics to detect these small signals, amplify them, and reject part of the noise [9]. For this stage, an INA 128 amplifier was used, an integrated circuit with a low offset that commonly rejects noise in both electrodes using an external resistor (RG), providing a gain defined by the equation [11]:

$$G = 1 + \frac{50k\Omega}{RG} \tag{1}$$

Analog Filters. Analog filters are responsible for defining the parameters for the signal's cutoff frequencies. For our design, we will use two of them [12].

Low-pass filter: It is calculated using the following equation.

$$\omega_L = \frac{1}{R_F G} \tag{2}$$

High-pass filter: It is calculated using the following equation.

$$\omega_H = \frac{1}{2\pi RC} \tag{3}$$

Based on equations (1), (2), and (3), an EMG circuit was designed (Fig. 1), featuring a low-pass filter at 568 Hz with a gain of 27 and a high-pass filter at 23 Hz with a gain of 11.

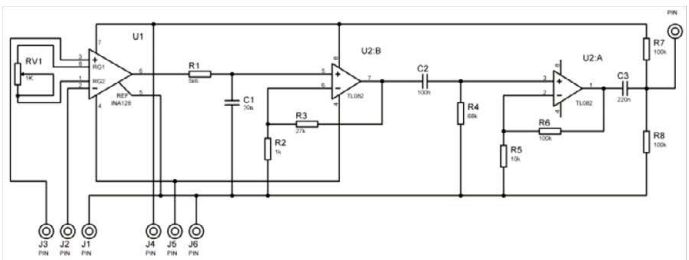

Fig. 1. EMG Signal Amplifier Circuit.

With the circuit schematic, the design of the printed circuit board (PCB) was carried out.

ARDUINO UNO Acquisition Board. An ARDUINO UNO board was used to digitize the EMG signal, which was acquired at a sampling rate of 1000 samples/s on analog pin 2 and connected to the USB port of a laptop. The signal data captured by the ARDUINO was set to a DC value of 2.5V since the board does not detect negative voltages. The data was then processed in MATLAB® to obtain its value in millivolts after subtracting the 2.5V offset to account for the negative values of the signal.

Acquisition Circuit Construction. The construction of the EMG signal amplifier circuit consisted of six main steps, as illustrated in Fig. 2:

1. Printing the PCB on coated paper
2. Ironing the PCB onto a bakelite board
3. Immersing it in ferric chloride to remove excess copper
4. Drilling the bakelite board
5. Placing and soldering components
6. Placing the circuit inside a case with input and output connections

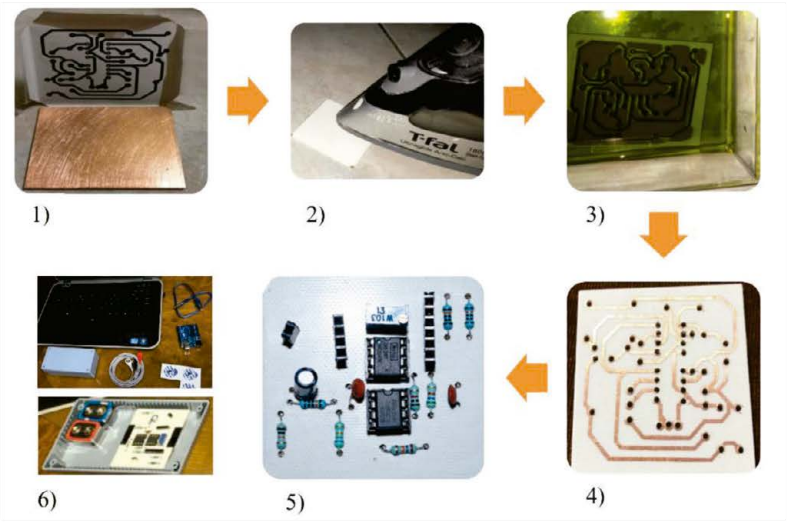

Fig. 2. EMG Circuit Fabrication.

Electromyography. EMG is responsible for detecting the electrical signals generated by muscle contraction. These signals are produced by the exchange of ions across the membranes of muscle fibers. The signal can be influenced by both muscle physiology and nervous system control [13].

The electrical signal resulting from muscle activation anywhere in the body is known as the motor unit action potential (MUAP) [1], which typically has an amplitude ranging from 0 to 250 μV, with a frequency content concentrated between 20 and 500 Hz [14].

To record these signals, invasive (needle) or non-invasive (surface or cutaneous) electrodes can be used. In this study, we focus on the latter, which use an electrolytic gel as a conductor between the skin and the metallic part of the electrode. When placed correctly, these electrodes reduce the risk of displacement during sudden movements. They are commonly used for physiological studies, human-machine interface applications, and superficial neurophysiological studies [13].

The main risk for patients when using EMG is electrical in nature, which occurs when the system lacks proper isolation [13].

Studied Muscles. The selection of muscles for this study was based on the fact that **Peripheral Neuropathy (PN) begins in the toes** [13]. Therefore, two muscles were chosen:

Flexor digitorum brevis: Originates in the **calcaneus process** and intermuscular septa, dividing into four tendons that insert into the base of the phalanges of the toes (excluding the big toe). This muscle is located on the **plantar surface of the foot** [15, 16], as illustrated in Fig. 3.

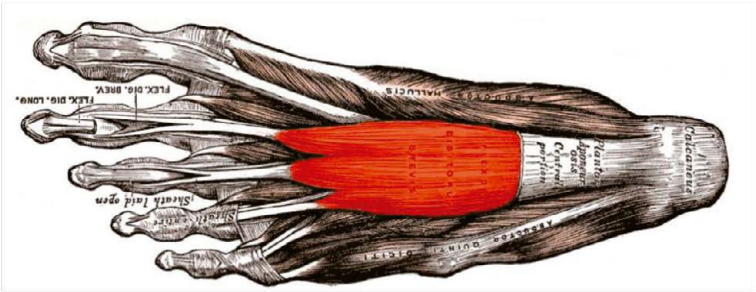

Fig. 3.Illustrative image of the flexor digitorum brevis muscle. Image retrieved from H. Gray, *Anatomy of the Human Body*. London, England, 2000 [17].

Abductor hallucis: It originates from the medial process of the calcaneus and inserts on the medial side of the big toe, at the base of the proximal phalanx of the hallux, located on the proximal dorsum of the foot [15, 16], as shown in Fig. 4.

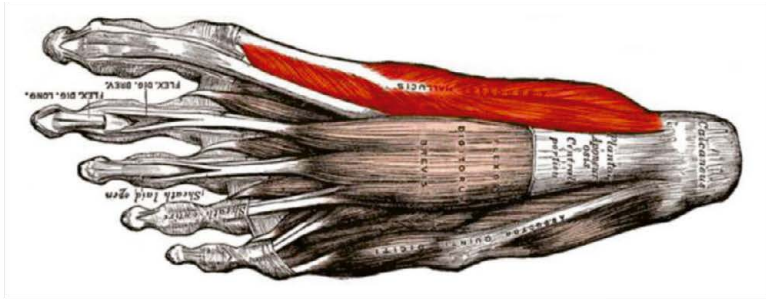

Fig. 4. Illustrative image of the Abductor Hallucis muscle. Image retrieved from H. Gray, *Anatomy of the Human Body. London, England, 2000 [17].*

2.2 Methods

Selection of Study Subjects. A study was conducted among healthy subjects (controls), subjects at risk of developing neuropathy, and a subject with a diagnosed neuropathy, using a surface electrode EMG recording. The subjects were grouped as shown in Table 1:

Table 1. Sample Characteristics.

Groups	Subject	Description
Healthy Group (Control): considering the criteria of being individuals over 18 years old with no pathological history indicating any risk of developing neuropathy.	Healthy Subject 1 (HS1)	22-year-old woman with no previous pregnancies and no significant pathological history.
	Healthy Subject 2 (HN2)	52-year-old man with no significant pathological history.
	Healthy Subject 3 (HN3)	19-year-old man with no significant pathological history.
At **Risk Group for Neuropathy**: considering the criteria of being individuals over 18 years old who are at risk of developing neuropathy.	Subject at Risk 1 (SR1)	52-year-old woman with 4 previous pregnancies and vascular problems.
	Subject at Risk 2 (SR2)	78-year-old man with diabetes for 4 years, ex-smoker, with a history of alcoholism and strokes in 1999.
	Subject at Risk 3 (SR3)	80-year-old woman with no previous pregnancies and vascular problems.
	Subject at Risk 4 (SR4)	53-year-old woman with 3 previous pregnancies and diabetes for 2 years.
Neuropathy Group: considering the criteria of being individuals with a diagnosed neuropathy.	Neuropatic Subject (NPS)	52-year-old man with diabetes for 33 years, renal problems, and diabetic neuropathy for 5 years.

It should be mentioned that all subjects signed an informed consent form in which the purpose and procedure of the study were explained, and that there were no associated risks with the study. They were also informed about the study duration, confidentiality, data storage, and participants' rights. Due to the nature of the research, the number of subjects is limited, with a total of 8, and samples were taken from both the right foot (RF) and left foot (LF).

Electromyographic Study. To carry out the EMG recording, the guidelines from the SERMEF Rehabilitation and Physical Medicine Manual were followed, which states that for diagnostic recordings, repetitive movements of finger flexion and relaxation must be performed [18].

Electromyographic Signal Conditioning. Once all the recordings were obtained, rectification was applied to the EMG signal, followed by smoothing to select a threshold that would allow us to extract the segments of interest from the signal (activity parts), creating windows for each repetition of muscle activity (illustrative graphs are shown in Figure 5).

Each window had a feature vector extracted for later classification using different classification algorithms. The windows were obtained through a semi-automatic process in which data segments before and after segments with zero values (see Figure 5. d) were selected. These zero-value segments were previously obtained using a thresholding technique applied to the rectified and smoothed EMG signal. The threshold was chosen as a percentage of the maximum peak value recorded during the entire recording duration, which varied depending on the subject.

Feature Extraction. Twelve features were extracted from the conditioned signal, forming a feature vector [19, 20]:

1. Mean

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

2. Absolute mean

$$|\bar{x}| = \left|\frac{1}{N}\sum_{i=1}^{N} x_i\right| \tag{5}$$

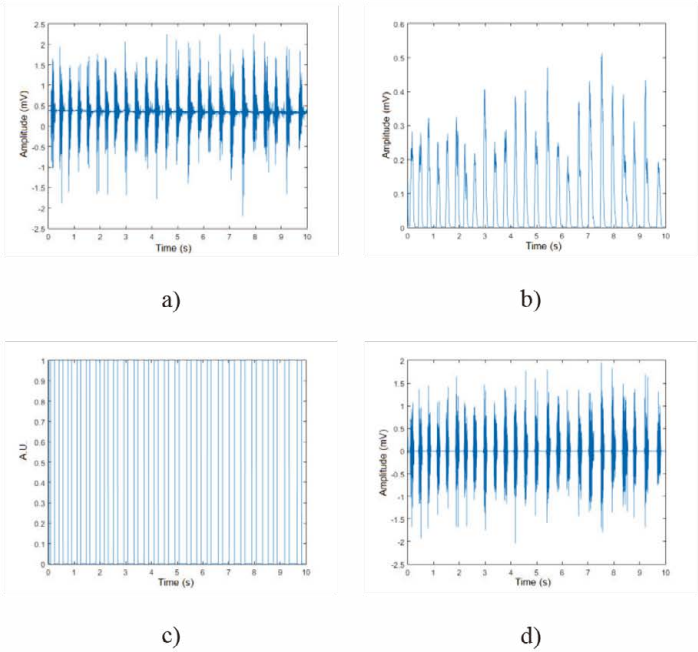

Fig. 5. Electromyographic Signal Conditioning. a) Signal acquired during the EMG recording. b) Rectification and smoothing of signal b. c) Thresholding of signal b. d) Study segments of the signal.

3. Standard Deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{6}$$

4. Variance

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{7}$$

5. RMS

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \tag{8}$$

6. Maximum Amplitude, is the maximum value of the signal among all amplitude values of the signal.

$$Amp_{max} = \max(\mathbf{x}) \tag{9}$$

7. Minimum Amplitude, is the minimum value of the signal among all amplitude values of the signal.

$$Amp_{min} = \min(\mathbf{x}) \tag{10}$$

The following 5 features are frequency domain features and consist of the sum of the magnitude spectrum coefficients obtained through the Fourier Transform or the area under the curve for 5 frequency bands into which the EMG spectrum was divided (0-100, 101-200, 201-300, 301-400, 401-500 Hz), calculated as shown in equation (11).

$$A_{bf} = \sum_{i=1}^{N}|X(f)|_i \tag{11}$$

where A_{bf} is the area under the curve in the evaluated frequency band, and i, ranging from 1 to N, represents the spectrum coefficients in the studied frequency band.

Once the features were extracted from each signal, a data classification process was performed. This classification involved using the Matlab® app, Classification Learner, which allows us to input the features of each signal to identify and classify the data behavior. This app enables the use of different classification methods such as linear regression, quadratic regression, decision trees, support vector machines (SVM), etc. In this study, an 8-fold cross-validation was applied, and the features were subjected to each classifier to determine which one achieved the best performance.

3 Results and Discussion

The classification results obtained for the features in this study showed varying performances depending on the type of classifier used. Table 2 shows the performance in classifying EMG signals from three groups (Control, Risk, and Neuropathy) for the 5 classifiers that performed best using the 12 features presented in the previous section for the EMG signal.

Table 2. Performance of the top five classifiers for EMG signal classification in Control, Risk, and Neuropathy.

Classifying algorithm	Performance
Weighted KNN	84.0 %
RUSBoosted Trees	83.3 %
Quadratic SVM	83.3 %
Cubic KNN	83.3 %
Medium Gaussian SVM	83.0 %

The results of this classification are favorable, as it is possible to separate the three groups (Control, Risk, and Neuropathy) with at least 84% accuracy. It is possible that the 16% uncertainty is due to the close similarity between the characteristics of the Risk group and the Neuropathic group, as well as with the Control group.

On the other hand, in Fig. 6, a visual separation between the groups can be observed by comparing the features of maximum amplitude (AmMax) and standard deviation. This shows that analyzing these features can be beneficial for separating and classifying the groups. Significant differences can also be observed between the Neuropathic group and the Control group.

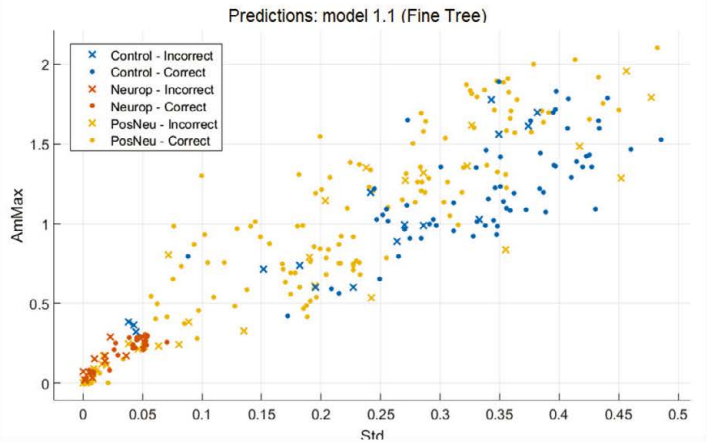

Fig. 6. Visualization of groups using the AmMax and Standard Deviation features. Three classes are distinguished: Control Subjects, Subjects with Neuropathy, and Subjects at Risk.

As can be observed, of the five best-performing algorithms presented in Table 2, the algorithm with the fifth-best performance (Medium Gaussian SVM, 83%) was not far from the algorithm in first place (Weighted KNN, 84%). Among these, there is also a decision tree-based algorithm (RUSBoostedTrees), which, along with Quadratic SVM and Cubic KNN, achieved a performance of 83.3%. Based on the above, we can say that it is possible to classify EMG signals from healthy subjects, subjects with possible neuropathy, and subjects with neuropathy with a percentage greater than 80% using the proposed signal features in this study across different classifiers. Taking into account that the Risk group (subjects at risk of developing neuropathy) shares characteristics with both the Control group (healthy subjects) and the Neuropathy group (subjects with neuropathy), we can understand why the algorithms tend to make more mistakes in correctly classifying this group, as seen in Figure 6. This study shows that it is possible to distinguish between subjects with and without neuropathy through non-invasive EMG analysis in diabetic subjects.

4 Conclusions

This work presents a methodology for detecting peripheral neuropathies using EMG, utilizing biosignal processing to characterize classification algorithms to determine the group membership of these signals. The groups are labeled, making it possible to assess the accuracy of the algorithms in determining the group to which the characterized EMG signals belong. The signals from Control (healthy), Risk (possible neuropathy), and Neuropathy subjects were classified with an accuracy of over 83% using at least five classification algorithms and 12 features. In this study, samples were only taken from 8 subjects, and the EMG activity recording was performed with a device made by

the authors. While it is possible to correctly record surface myoelectric activity with it, the methodology related to signal processing, feature extraction, and classification used in this work is the main contribution of this study. Based on this, the goal is to expand the number of subjects in the future and validate the results in neuropathy detection using EMG with low-cost equipment.

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