Leveraging Mechanomyography Signal for Quantitative Muscle Spasticity Assessment of Upper Limb in Neurological Disorders Using Machine Learning

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***Abstract*—Upper motor neuron syndrome is characterised by spasticity, which represents a neurological disability that can be found in several disorders such as cerebral palsy, amyotrophic lateral sclerosis, stroke, brain injury, and spinal cord injury. Muscle spasticity is always assessed by therapists using conventional methods involving passive movement and assigning spasticity grades to the relevant joints based on the degree of muscle resistance which leads to inconsistency in assessment and could affect the efficiency of the rehabilitation process. To address this problem, the study proposed to develop a muscle spasticity model using Mechanomyography (MMG) signals from the forearm muscles. The muscle spasticity model leveraged based on the Modified Ashworth Scale and focus on flexion and extension movements of the forearm. Thirty subjects who satisfied the requirements and provided consent were recruited to participate in the data collection. The data underwent a pre-processing stage and was subsequently analysed prior to the extraction of features. The dataset consists of forty-eight extracted features from the three-direction x, y, z axes (for both biceps and triceps muscle), corresponding to the longitudinal, lateral, and transverse orientations relative to the muscle fibers. Significant features selection was conducted to analyse if overall significant difference showed in the combined set of these features across the different spasticity levels. The test results determined the selection of twenty-five features from a total of forty-eight which be used to train an optimum classifier algorithm for the purpose of quantifying the level of muscle spasticity. Linear Discriminant Analysis (LDA), Decision Trees (DTs), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) algorithms have been employed to achieve better accuracy in quantifying the muscle spasticity level. The KNN-based classifier achieved the highest performance, with an accuracy of 91.29% with k=15, surpassing the accuracy of other classifiers. This leads to consistency in spasticity evaluation, hence offering optimum rehabilitation strategies.**

Keywords*—*Spasticity; mechanomyography; Modified Ashworth Scale; machine learning

I. Introduction

A stroke is a sudden and chronic loss of neurological function caused by infarction or haemorrhage in the brain, spinal cord, or retina, resulting in impaired motor function and significant restrictions in performing everyday tasks and overall well-being [1]. Most stroke patients experience movement difficulties, with approximately 30% of those affected experiencing spasticity [2]. Moreover, stroke remains the second most prevalent cause of fatality and the primary cause of impairment on a global scale, making it the third leading cause of death and disability worldwide [3], [4], [5]. On a global scale the prevalence of stroke has grown in correlation with the process of modemisation, modifications in lifestyle, and a growing population of older individuals [6].

Upper motor neuron syndrome has been defined by spasticity, a neurological impairment that occurs in a variety of conditions, including cerebral palsy, amyotrophic lateral sclerosis, stroke, brain injury, and spinal cord injury [7]. Lance introduced the term "spasticity" in 1980 to define the upper motor neuron syndrome, a motor disorder marked by increased muscle tone and exaggerated tendon jerks that rely on movement velocity and result from the hyperexcitability of the stretch reaction [8], [9]. This description exclusively emphasises the impact of spasticity on involuntary movements, disregarding its effect on deliberate behaviours. The Modified Ashworth Scale (MAS) and the Australian Spasticity Assessment Scale (ASAS) are widely recognised as the most reliable methods for evaluating spasticity in clinical settings, with the MAS being a frequently employed tool in stroke rehabilitation [10], [11].

In addition, there are several other clinical tools available for assessing spasticity, such as Spinal Cord Assessment Tool for Spastic Reflexes (SCATS), Fugl-Meyer Assessment (FMA), Penn Spasm Frequency Scale (PSFS), and Modified Tardieu Scale (MTS) [12], [13]. However, these tools are less accurate compared to the MAS and ASAS. Furthermore, the conventional method that has been used to assess spasticity nowadays involves subjective measurement by the therapists [14]. Although, the therapists already been trained well in assessing the spasticity using MAS tool measurement, there might be a possibility of difference in identify the spasticity level. The variability can disturb the effectiveness of the rehabilitation process for the neurological disorder patients.

During the procedural application of the MAS, the therapist executes passive movement and assigns spasticity grades to the relevant joints based on the degree of muscle resistance experienced during passive stretching [15], [16].

The main objective of this study is to validate Mechanomyography (MMG) as a reliable signal by comparing the accuracy of various machine learning algorithms and demonstrate its clinical applicability in objective measurement. This study highlights the effectiveness of combining mechanomyography with machine learning as a superior approach for evaluating muscular spasticity in patients with upper limb neurological disorders.

The main contributions of this study include the introduction of MMG as a new and unbiased instrument for evaluating muscular spasticity, which has the potential to enhance current subjective approaches. The research also evaluates various machine learning algorithms to determine the best models for analysing MMG data, thereby improving the accuracy and consistency of spasticity assessments. Additionally, the study illustrates the practical applicability of MMG in clinical settings, highlighting its potential to standardize evaluations, optimize rehabilitation strategies, and ultimately improve patient outcomes. These contributions have substantial significance for the field of neurorehabilitation as it establishes an accurate and unbiased technique for evaluating spasticity, which can lead to enhanced diagnostic precision, individualized treatment strategies, and potentially improved long-term results for patients with upper limb neurological diseases.

The structure of the article is as follow: Section II describe on characteristics of electromyography and mechanomyography on clinical evaluation. Section III presents a comprehensive summary of the research carried out by researchers in the topic throughout the years. Section IV provide detailed explanations on the selection of subjects, the experimental setup, and the pre-processing and analysis of the data. Section V provides an explanation of the machine learning algorithms. Section VI provided and deliberated upon the experimental findings and the subsequent section explain the conclusion of the study findings.

II. Electromyography and Mechanomyography

The utilization of electromyography (EMG) in routine therapeutic procedures represents a contemporary and pioneering approach to neurorehabilitation for individuals recovering from a stroke [17]. EMG has been used to record electrical muscle activity for quite some time, though it's currently limited to therapeutic purposes [18]. Additionally, EMG can be highly susceptible to interference from noise and variations in resistance, rendering it unreliable in diverse settings or during prolonged data collection, such as when an individual starts sweating [19], [20]. At the same time, the use of EMG sensors necessitates time-consuming skin preparation, including disinfection and abrasive paste application, along with electrode placement on multiple leg muscles which requires an expert environment for accurate sensor positioning and signal interpretation [21]. Mechanomyography (MMG) serves as an alternative or mechanical counterpart to EMG by quantifying muscle vibrations, or mechanical activity generated by active muscle, using sensors such as microphones or accelerometers [22], [23]. The invention of piezoelectric, microphone, and accelerometers demonstrated the adequate detection of mechanical signals from the surface of skeletal muscles at low frequencies, known as MMG signals that tend to be contaminated by electrical noise [24], [25]. MMG provides a method that enables the detection and measurement of vibrations resulting from muscle contractions and stretching [26]. These vibrations propagate through the tissue and can be detected on the surface of the skin.

The characteristics of a reliable MMG transducer typically include high sensitivity within the muscle vibrational frequency range of 2 Hz to 100 Hz, low sensitivity to random noise, ease and standardization of sensor attachment, biocompatibility, suitability for clinical environments, and cost-effectiveness compared to other clinical assessment techniques [27]. Compared to EMG, MMG has not yet gained widespread acceptance, particularly in clinical settings. Despite not yet achieving widespread acceptance, particularly in clinical settings, MMG holds significant potential for various applications. These include controlling prosthetic devices, recognizing gestures in human-machine interfaces (HMIs), and studying the underlying physiological mechanisms of the neuromuscular system in scientific research [28]. Additionally, MMG offers greater convenience than EMG as it being highly responsive to skin conditions and reliable performance in dynamic settings, reducing the necessity for frequent cleaning, drying, and optimal skin condition maintenance throughout usage [29], [30]. MMG responses can be utilized in various medical contexts, including the clinical evaluation of neuromuscular tissue, biofeedback rehabilitation, and neural/myoelectric prosthetic control.

III. Related Works on Machine Learning

Machine learning has become a popular data analytics technology that uses statistical methods to analyze observed data and make predictions or classify new data [31]. Multiple studies have investigated the effectiveness of machine learning in improving the provision of rehabilitation services, showcasing its capacity to enhance patient outcomes and improve clinical procedures.

For instance, Puzi et al. [32] developed An Automatic Muscle Spasticity Assessment System (AMSAS) to evaluate the muscle spasticity, specifically emphasizing the utilization of machine learning methods. The torque and angle signals generated by the arm muscles were examined to classify levels of spasticity according to the Modified Ashworth Scale (MAS). Twenty-five patients with varied degrees of spasticity were analysed, and seven features were retrieved. A Linear Support Vector Machine (SVM) classifier with four specified characteristics got the maximum accuracy of 84% when classifying spasticity levels. The variables of Three-Way Decision (TWD) including the first and second halves of the region, catch position, and post-catch stiffness, were found to have a significant association with MAS levels.

In another study, Puzi et al. [33] presented a new classifier that uses clinical data from the affected upper limb to accurately measure levels of muscle spasticity. The study proposes a methodical quantification strategy that utilizes the Modified Ashworth Scale (MAS) in conjunction with a one-way ANOVA test to assess the extent to which these features accurately predicted test scores. subsequently, four important features were determined as the most significant for creating efficient classification models and were employed in the training process. The study showcased that the Support Vector Machine (SVM) classifier surpassed the Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier, with an accuracy rate of 88.0%.

Additionally, Liu et al. [34] investigated on muscle spasticity, specifically targeting the wrist flexor and extensor muscles. The methods employed in this study utilise MMG signals to identify periods of muscular activity in real-time gesture recognition, which is essential for diagnosing muscle spasticity. Additionally, it has been utilised to offer significant observations on muscle exhaustion and torque, proving their potential in evaluating muscle spasticity. The study involved assessing eight distinct and atypical gestures, which included clapping, flicking the index finger, snapping the finger, flipping a coin, shooting, extending the wrist, bending the wrist, and creating a fist. The K-nearest neighbours (KNN) algorithm, with a value of K set to 7, achieved the maximum classification accuracy of 94.56% for the eight gestures.

Furthermore, Kim et al. [31] conducted a study aimed at assessing elbow spasticity by the application of machine learning techniques. This was achieved by employing sophisticated machine learning algorithms to meticulously analyse acceleration and rotation characteristics derived from the injured elbow's side. The acceleration and rotation properties of the elbows of affected patients have been examined to determine the degree of spastic movement, similar to the way the modified Ashworth scale (MAS) score was used. Achieving an accuracy of up to 95.4%, a random forest (RF) algorithm was used to classify spasticity. The learning problem was classified as supervised since the signals correlated with MAS scores, as evaluated by therapists. Additional features were extracted and incorporated into the existing feature set, resulting in enhanced classification performance.

These studies collectively illustrate the potential of machine learning in the precise assessment and classification of muscle spasticity, offering significant advancements in the field of rehabilitation.

IV. Methodology

A. Subjects

30 post-stroke subjects with upper limb spasticity participated in the study. This study has obtained approval by the Research Ethics Committee of the International Islamic University Malaysia (IIUM) under the identification number IREC 2023-025. Specifically, the subjects were diagnosed with spasticity in upper limbs (UL), with an age range of 18 to 80 years recruited from Sultan Ahmad Shah Medical Centre (SASMEC) and National Stroke Association of Malaysia (NASAM). The informed consent has been provided by the subjects prior to participation, and the study adhered to strict data protection procedures, ensuring that all subject information was managed in accordance with applicable data privacy regulations. The subjects recruited for this research were chosen from MAS levels 0, 1, 1+, 2, and 3. The MAS level 4 was omitted due to the absence of any noticeable bending and straightening movements during the evaluation. The pilot examination was conducted by experienced therapists to evaluate the subjects movement capability and identify potential issues that can be addressed for the upcoming data collection. The demographic characteristics of the research subjects were detailed in Table I. MAS scores ranging from 0 to 3 were determined for the participants' affected muscles. Five groups were formed from the volunteers: MAS-0 (N=5), MAS-1 (N=16), MAS-1+ (N=3), MAS-2 (N=4) and MAS-3(N=2).

TABLE I. Demographic Data of the Patients (Divided into Four Groups)

Mas Level	Numbers (N)	Genders (M/F)	Affected Hand (Left/Right)	Age (Year)
0	6	3/3	2/4	44.3 ± 18.4
1	15	11/5	7/8	62.7 ± 10.1
1+	3	3/0	2/1	56.0 ± 7.5
2	4	3/1	1/3	50.0 ± 9.5
3	2	2/0	2/0	38.7 ± 19.1

B. QSAT Platform

A new platform called as Quantitative Spasticity Assessment Technology (QSAT) has been developed based on the Mechanomyography (MMG) technique to overcome the inconsistency measurement of spasticity as depicted in Fig. 1. The platform incorporates two primary sensors: an accelerometer Mechanomyography (ACC-MMG), which measures muscle vibrations in the biceps and triceps, and a potentiometer, which assesses the angular position of the upper limb during flexion and extension movements. Through the measurement of patients' biological signals, the extracted features have been examined for their correlation with MAS using machine learning. The utilization of platform measurements mapped to MAS levels enhances the evaluation of spasticity and streamlines the clinical workflows of therapists.

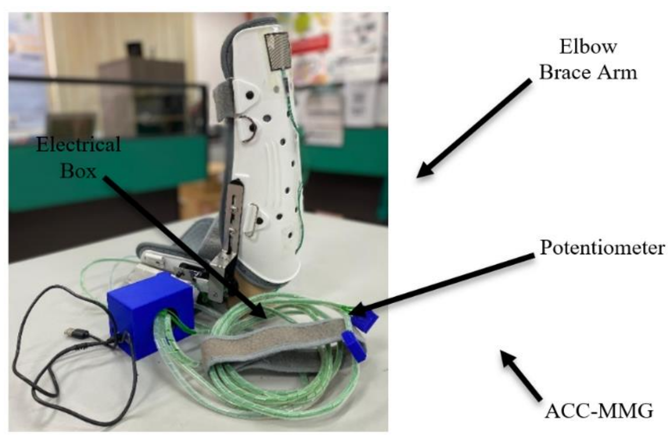
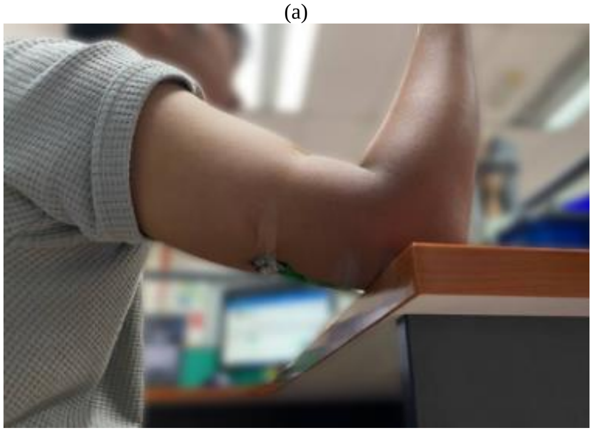


Fig. 1. QSAT System with labels.

C. Data Acquisition and Experimental Setup

In this study, a commercial biological signal acquisition system (Raspberry Pi Pico) was used to record ACC-MMG signals (ADXL345, Digital Devices, full-scale range = ± 2 g to ± 16 g; typical frequency responses = 0.1 to 3200 Hz; sensitivity = 3.9 mg/LSB; size = 3 mm x 5 mm x 1 mm)) and potentiometer data, both sampled at a rate of 166.7 Hz. Each muscle group, including the biceps and triceps, was equipped with a tri-axial ACC-MMG accelerometer and a potentiometer, which were integrated within an elbow brace arm. This configuration enabled single-channel potentiometer recording alongside simultaneous two-channel ACC-MMG recording. The ACC-MMG signal, captured three-dimensionally by the accelerometers, included three distinct sub-signals corresponding to the x, y, and z axes. Consequently, one channel was designated for potentiometer data, while two channels were dedicated to ACC-MMG signal acquisition, with all data recorded concurrently. The ACC-MMG signals along the muscle axes were captured using three distinct tri-axial accelerometers. These accelerometers were oriented along the x, y, and z axes, corresponding to the longitudinal, lateral, and transverse orientations relative to the muscle fibers, respectively, as illustrated in Fig. 2.

(a)



(b)

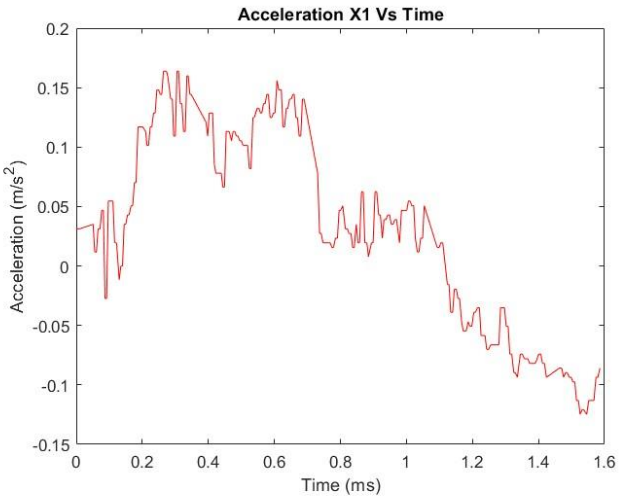
Fig. 2. ACC-MMG Sensor placement: (a) On the Biceps and (b) On the triceps.

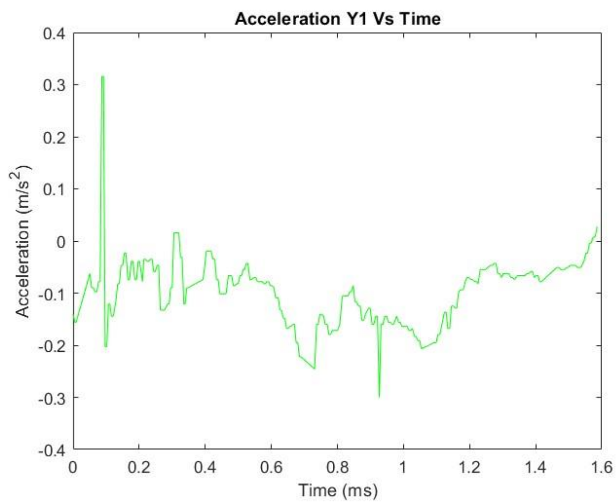
The experimental protocol began with each subject directed to lie down in the supine position with their arm positioned alongside their body. This evaluation was carried out using the Modified Ashworth Scale (MAS) as the clinical tool for assessment. During the implementation of the MAS, the therapist performs passive movements and assigns spasticity grades to the corresponding joints depending on the level of muscular resistance observed during passive stretching. After the session, the ACC-MMG signal of biceps and triceps was recorded. The sensors were affixed to the skin in a secure manner through the utilization of double-sided tape. "Sensor 1" was placed on the biceps muscle's belly, while "Sensor 2" was positioned on the triceps muscle's belly. The sensor's x-axis was aligned with the direction of muscle fiber contraction while z-axis was touched directly to the skin surface. At the same time, the potentiometer with elbow brace arm support was attached to the elbow joint. The QSAT experiment began by assessing the subject's arm through the placement of one therapist's hand beneath the lower arm in proximity to the wrist, while the other hand gave stability to the upper arm near the shoulder, as illustrated in Fig. 3. The subject's arm underwent three repetitions of a movement, transitioning from full extension (0°) to full flexion (135°) for a duration of two seconds each time. All results have been recorded and organized in an Excel datasheet.

Fig. 3. Setup of QSAT Platform measures for upper limb.

D. Data Analysis and Feature Extraction

Signal preprocessing was conducted using MATLAB R2023a software (MathWorks Inc.). The ACC-MMG and potentiometer data collected throughout the experiments underwent initial preprocessing to ensure precision and reliability. Based on the analysis of the raw data, the signals exhibited minimal noise interference, indicating that filtering was unnecessary. The continuous data was then divided into epochs corresponding to each movement cycle, ranging from full extension (0°) to complete flexion (135°) of the elbow. The potentiometer data provided distinct markers indicating the beginning and end of each movement cycle. Fig. 4 shows a graph that presents the time-series plots of the ACC-MMG signals along the x_1, y_1, z_1 axes (for the biceps) and the x_2, y_2, z_2 axes (for the triceps), together with the potentiometer readings. The resulting graph visually represents the patterns of muscle fibres vibration along all three spatial directions and joint motions during flexion. The ACC-MMG signals had distinct amplitude and frequency characteristics for each axis, aligning with the longitudinal, lateral, and transverse orientations of muscle fibres. Significant differences in muscle activity patterns can be observed when comparing the ACC-MMG signals of the biceps and triceps while the potentiometer readings, indicating joint angles, align with the ACC-MMG signals, validating the observed movement cycles.


Acceleration X1 Vs Time
Acceleration (m/s2)
Time (ms)
(a)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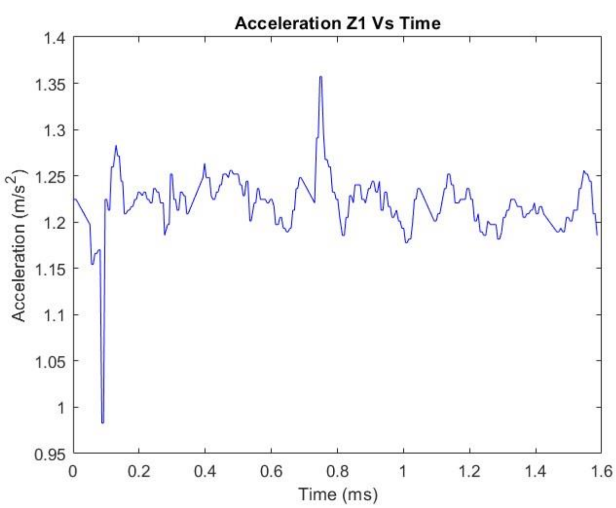
Acceleration Z1 Vs Time
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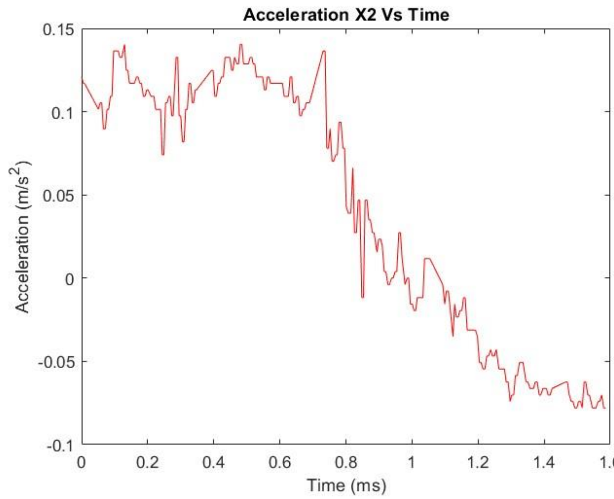
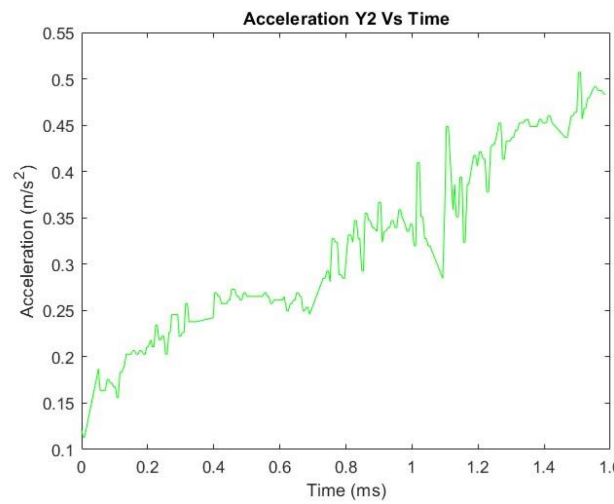
(c)


Acceleration X2 Vs Time
Acceleration (m/s2)
Time (ms)
(d)


Acceleration Y2 Vs Time
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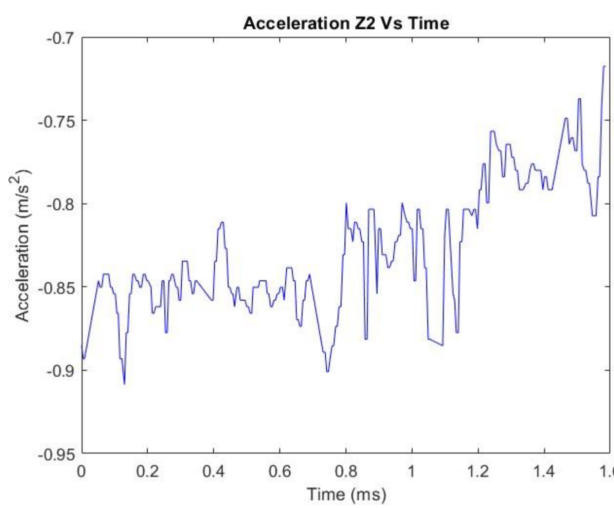
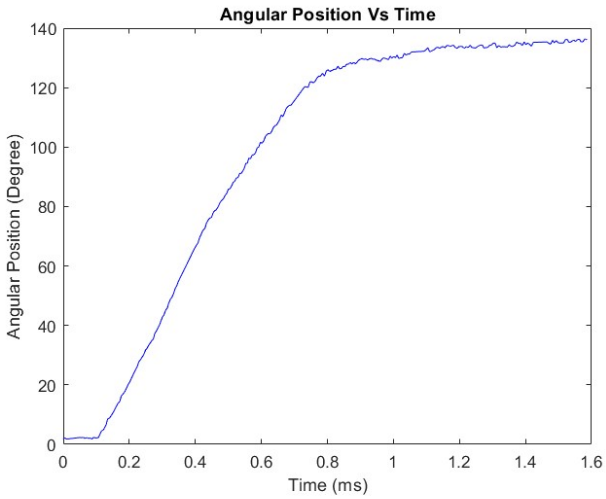
Time (ms)
(e)


Acceleration Z2 Vs Time
Acceleration (m/s2)
Time (ms)
(f)



(g)

Fig. 4. Muscle vibrations of the biceps (a, b, c) and triceps (d, e, f), and the angular position (g) during flexion for patient 30.

A specialised algorithm was developed to extract significant features from the ACC-MMG signals. The features selected for analysis included Root Mean Square (RMS), Peak to Peak Amplitude (PTP), Max, Min, Mean Average Value (MAV), Standard Deviation (SD), Skewness (S), and Kurtosis (K). During the feature extraction stage, time-domain features were extracted for the x_1, y_1, z_1 axes (for the biceps) and the x_2, y_2, z_2 axes (for the triceps), corresponding to the longitudinal, lateral, and transverse orientations relative to the muscle fibers. The obtained features were tabulated into a dataset. The equation that determines each extracted feature are as follows:

$$RMS = \sqrt{\frac{1}{n}\sum_i x_i^2} \tag{1}$$

$$PTP = Max - Min \tag{2}$$

$$Max = maximum\ of\ the\ terms \tag{3}$$

$$Min = minimum\ of\ the\ terms \tag{4}$$

$$MAV = \frac{sum\ of\ the\ terms}{number\ of\ terms} \tag{5}$$

$$SD = \frac{\sum(x_i - MAV)^2}{n} \tag{6}$$

$$S = \frac{\sum_i^n (x_i - MAV)^3}{(n-1)\, SD^3} \tag{7}$$

$$K = \frac{n\,(n+1)}{(n-1)(n-2)(n-3)} \times \sum\left(\frac{x_i - MAV}{SD}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{8}$$

The RMS is a metric that quantifies the amplitude of a signal, serving as an indicator of the intensity of muscular contractions or tension of the upper limbs [2], [35]. MAV of MMG signals serves as an indicator of the muscular strength and endurance of the specific muscle in concern [36]. It symbolizes the power, and the energy generated by the muscle. SD were computed for the ACC-MMG signals in the x, y, and z axes, providing insights into the average muscle activity and its variability. Complementing these metrics, the PTP value measures the extent of a signal by determining the disparity between its highest positive peak and its lowest negative peak of vibration amplitude during a specific timeframe, thereby representing the magnitude spectrum of muscular oscillations or motions within the ACC-MMG signals. Additionally, skewness and kurtosis were calculated to offer a deeper understanding of the properties of muscle signal distributions, thus enhancing the comprehension of muscle activity and its variability.

For this study, a total of 90 datasets were collected from 30 subjects in order to train the muscular spasticity classifier. The one-way MANOVA test was utilised with SPSS 27.0.1 (IBM Inc.) to minimise dependent and redundant features through significant feature analysis. The statistical test selected was a one-way MANOVA due to the presence of multiple continuous dependent variables in independent groups [37]. The features were testing using the technique to examine the significant difference in mean value between the groups. The results from the one-way MANOVA test, including significant values and corresponding p-values, are presented in Table II. A rejection threshold was set at $p < 0.05$ to identify significant differences in the dependent variables. The null hypothesis for ANOVA posited that no difference existed in mean values among the groups. As the p-values of the features listed in Table II were less than 0.05, the null hypothesis was effectively rejected. Consequently, these twenty-five optimal features were selected to train the classifiers for classifying the level of muscle spasticity.

TABLE II. SIGNIFICANT VALUE OF FEATURES

Features	**P Values**
$MAVx_1$	0.000
$MAVy_1$	0.000
$MAVz_1$	0.000
SDz_1	0.001
$PTPy_1$	0.013
$Maxx_1$	0.000
$Maxy_1$	0.003
$Maxz_1$	0.000
$Minx_1$	0.000
$Miny_1$	0.000
$Minz_1$	0.000
Sx_1	0.001
Ky_1	0.020
$RMSx_1$	0.004
$RMSy_1$	0.000
$RMSz_1$	0.000
$MAVy_2$	0.000
$MAVz_2$	0.006
SDz_2	0.042
$Maxy_2$	0.000
$Maxz_2$	0.011
$Miny_2$	0.000
$Minz_2$	0.003
$RMSy_2$	0.000
$RMSz_2$	0.002

E. Machine Learning Algorithm

Machine-learning classifiers were utilised to automatically infer a prediction function from labelled data derived from inertial signals obtained during passive stretching. The therapist provided MAS ratings to annotate these inertial signals, thus structuring the task as a supervised learning problem. Most offline approaches rely on supervised Machine Learning (ML) models for activity recognition, such as Support Vector Machine (SVM), Decision Trees (DTs), K-Nearest Neighbors (KNN) and Linear Discriminant Analysis (LDA) [31], [38]. Supervised machine-learning algorithms have the benefit over unsupervised methods of being able to assign appropriate labels to training data based on preset classes, thereby avoiding the need to create "artificial" groups [39].

SVM known as a collection of supervised learning techniques employed for the purposes of classification and regression [40], [41]. For a classification problem, SVM seeks to identify the separating hyperplanes that maximize the margin between sets of data points in an n-dimensional space, where each data point belongs to one of the available classes. This will guarantee a strong ability to make accurate predictions in various situations, assuming that the target function remains stable between the training and testing data. SVM are primarily used when the data cannot be separated by a straight line in their current domain [42]. SVM applies a transformation to the input data points, mapping them to a feature space where they can be separated by a linear boundary. Essentially, it separates the classes by incorporating support vectors to optimize the separation between samples belonging to distinct classes. Therefore, it is also known as large-margin categorization.

DTs is a structured representation of a decision-making process used to determine the class of a given instance [43]. Every node in the tree represents either a class label or a particular test that divides the instance space according to the potential results of that test. Every subset of partitions corresponds to a subproblem of classification, which is then resolved by a subtree. The terminal nodes of the decision tree include the class labels. To categorize an instance, one must follow a path from the starting point of the tree to one of its end nodes, taking into account the results of the tests at each step of the process.

KNN classifier is a method used to categorise unlabelled data by assigning them to the class of the most comparable labelled samples. Observational characteristics are gathered for both the training and test datasets [44]. The intuition behind Nearest Neighbor Classification is straightforward. It often proves beneficial to consider multiple neighbors, leading to the more commonly utilized K-Nearest Neighbor (KNN) Classification, where the class of an instance is determined based on the k nearest neighbors [45]. Besides that, LDA is also highly popular technique used to extract distinctive features for the purpose of pattern classification [46]. Linear Discriminant Analysis (LDA) leverages label information to acquire a discriminant projection that effectively increases the separation between different classes and decreases the distance within each class, hence enhancing the accuracy of classification. Several extensions of LDA have been established to improve performance and efficiency. The traditional Linear Discriminant Analysis (LDA) model typically assigns a Gaussian density to each class, assuming that all classes have an identical covariance matrix [47]. LDA is closely associated with ANOVA (analysis of variance) and regression analysis, since each attempt to represent a dependent variable as a linear combination of other traits or data.

Two dataset has been prepared and structured for muscle spasticity model development. The first data utilized all available features, while the second dataset incorporated only the significant features identified through a one-way MANOVA test. Each dataset datasets were divided into training and testing sets with ratios of 90/10, 80/20, and 70/30. In the 90/10 split, 90% of the data was used for training the model while the remaining 10% was reserved for testing. Similar procedures were followed for the 80/20 and 70/30 splits. These different partitions were used to evaluate the models' robustness and generalization capabilities. The optimal algorithm underwent k-fold cross-validation, where it was trained and tested with k values of 5, 10 and 15 to evaluate the stability of the models across different partitioning schemes. The performance of the machine learning algorithms was assessed using confusion matrices, accuracy, and training length. The percentage of correctly predicted samples to the total number of samples represents the definition of accuracy. A True Positive (TP) outcome occurs when the model accurately predicts the positive class while a True Negative (TN) refers to an outcome where the model accurately predicts the negative class. likewise, a False Positive (FP) occurs when the model wrongly predicts the positive class, whereas a False Negative (FN) occurs when the model incorrectly predicts the negative class. Equation 9 can be used to compute the accuracy by considering the values of TP (true positive), TN (true negative), FN (false negative), and FP (false positive) [48].

$$Accuracy = \frac{T_p + T_N}{T_p + T_N + FP + FN} \tag{9}$$

A confusion matrix comprises a square matrix displaying the general classification model performance. The rows of the confusion matrix show actual instances of class labels, whereas the columns show instances of predicted class labels. For each trial, the diagonal components of this matrix will indicate how many times the predicted label matches the actual label. For assessing how effectively the model classified data, the confusion matrix acts as a useful indicator.

V. Results and Discussion

The accuracy performance of the algorithms influenced by different training and testing splits which presented in Table III. It also compares the accuracy based on features selected for training and testing, yielding varying results. Dataset with all features and significant features for the 90/10 split showed highest accuracy compared to other data ratios. However, most researchers recommend using a 70/30 split for smaller datasets [49]. Dataset with all features shown that KNN algorithm achieved an accuracy of 83.95%, outperforms the others algorithm. Notably, the KNN algorithm demonstrated an even higher accuracy of 90.12% when using significant features, indicating that the use of significant features enhances the model's performance.

TABLE III. PERCENTAGE OF DATA SET AND ACCURACY WITH ALL FEATURES AND SIGNIFICANT FEATURES

Algorithm	Training and Testing Split Percentage of Accuracy					
	All Features			*Significant Features*		
	90-10	80-20	70-30	90-10	80-20	70-30
DT	64.20	65.28	55.56	65.43	63.89	65.08
LDA	69.14	59.72	46.03	76.54	70.83	66.67
SVM	65.43	69.44	60.32	72.84	68.06	69.84
KNN	83.95	80.56	66.67	90.12	86.11	84.13

The confusion matrix findings shows that the accuracy of KNN algorithm for all features and significant features which presented in Fig. 5 and Fig. 6. The True Positive Rate (TPR) and the False Negative Rate (FNR) are shown in a confusion matrix in KNN algorithms. The rows and columns of the matrix represent the predicted and actual classes for the MAS levels 0, 1, 1.5 (1+), 2, and 3, respectively. Comparing the accuracy of the KNN classifier using all features and significant features reveals important insights. KNN algorithm with all features achieves an overall accuracy of 83.95%, demonstrating superior performance, particularly in correctly identifying the extreme classes (0 and 3) and maintaining high true positive rates across most classes. However, when using the dataset with significant features, the KNN algorithm's overall accuracy increases to 90.12%. This improvement is evident in its enhanced ability to correctly identify not only the extreme classes (0 and 3) but also intermediate classes 1. It also showed increase in true positive rates across classes 1.5 compared to KNN algorithm using all features. This comparison highlights the effectiveness of using significant features in improving the classification accuracy of the KNN model. Futhermore, comparing with both dataset, significant features proving to be most optimum accuracy.

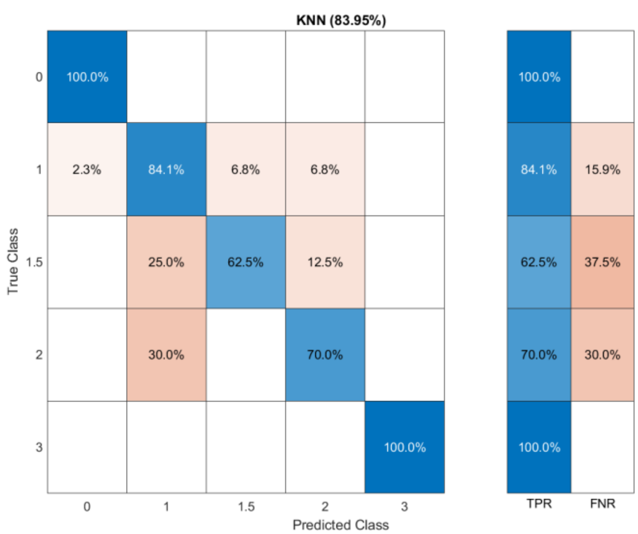


Fig. 5. Confusion matrix for KNN using all features.

Table IV presents the training durations for several machine learning algorithms, illustrating that the use of significant features consistently reduces training time compared to using all features. Specifically, the training time for the Decision Trees (DTs) algorithm decreased from 4.27 seconds to 3.24 seconds. The Linear Discriminant Analysis (LDA) algorithm's training time was reduced from 1.13 seconds to 0.91 seconds. The Support Vector Machine (SVM) algorithm showed a reduction in training time from 4.35 seconds to 3.75 seconds. Similarly, the K-Nearest Neighbors (KNN) algorithm experienced a decrease in training time from 3.03 seconds to 2.46 seconds. Among the algorithms evaluated, the Decision Trees (DTs) algorithm exhibited the most significant reduction in training time based on the percentage difference with 24.12% due to algorithm structured. The notable decrease in training time emphasises the efficiency improvements obtained by prioritising the most pertinent features, thereby illustrating the advantages of feature selection in machine learning models. Moreover, utilising crucial features simplifies the training process by decreasing the complexity and size of the dataset, enabling machine learning algorithms to function more effectively and attain quicker convergence [47].

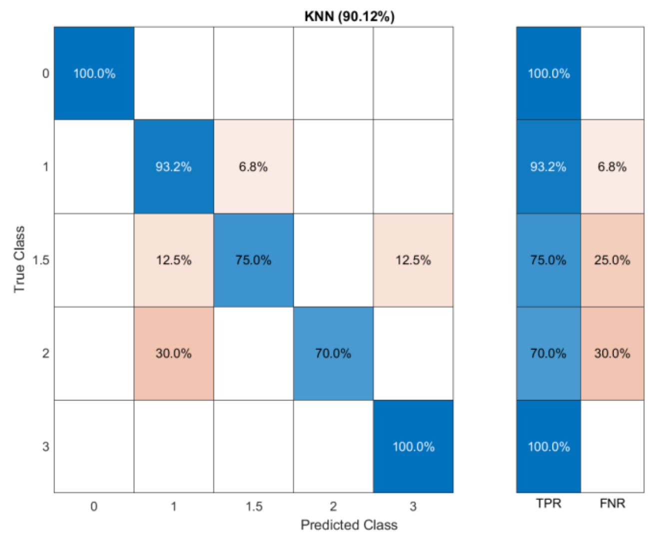


Fig. 6. Confusion matrix for KNN using significant features.

TABLE IV. TRAINING TIME OF ALL ALGORITHM WITH ALL FEATURES AND SIGNIFICANT FEATURES

Table Head	Training Time (seconds)		Percentage Difference (%)
	All Features	*Significant Features*	
DT	4.27	3.24	24.12
LDA	1.13	0.91	19.47
SVM	4.35	3.75	13.79
KNN	3.03	2.46	18.81

Machine learning models trained on datasets with significant features identified through a one-way MANOVA test consistently showed higher accuracy across all data split tests compared to those using all available features. This underscores the impact of feature selection on model performance, demonstrating that models trained on statistically significant features often outperform those using all features. This highlights the importance of feature selection in enhancing model accuracy and efficiency. Furthermore, the efficacy and efficiency of a machine learning solution are contingent upon the inherent qualities and attributes of the data, as well as the proficiency of the learning algorithms [47]. Among the algorithms, KNN exhibited the highest accuracy across all datasets. The KNN classifier proves to be the optimal method for classifying biomechanical parameter features, particularly in scenarios with limited datasets and low dimensionality [50], [51].

A. Comparative Performance Analysis of Classifier Algorithms

The KNN algorithm using significant features was evaluated and compared in a 90/10 split using k-fold cross-validation with k values of 5, 10, and 15. This methodology enabled a thorough evaluation of the performance of KNN algorithm by dividing the dataset into k subsets, or folds, in a systematic manner. The algorithm underwent k-fold cross-validation, where it was trained and tested k times. In each iteration, a different fold was used as the validation set, while the remaining k-1 folds were utilised for training. Varying the value of k allowed for an examination of the models' stability and robustness across different partitioning schemes, providing a thorough evaluation of their predictive capabilities and overall performance in diverse scenarios. Table V illustrates the comprehensive comparison of accuracy in classifying various levels of spasticity, based on the output of MAS levels. The accuracy of KNN algorithm showed a decreased when the number of folds increased from 5 to 10. However, KNN algorithm demonstrates optimum accuracy with k= 15 at 91.29%.

Based on the result, there is no direct correlation between adjusting the value of K in k-fold cross-validation and the accuracy of machine learning algorithms [52]. Hence, while choosing the value of k, it is important to exercise caution as a lower k value entails decreased computing cost, reduced variance, but increased bias. Conversely, a larger value of k is more computationally demanding but exhibits greater variability and reduced bias. Therefore, the value of k must be chosen such that the size of each validation set is sufficient to ensure a reliable assessment of the model's performance. In conclusion, the KNN algorithm with significant features demonstrated superior performance in objectively evaluating the level of muscle spasticity.

TABLE V. PERFORMANCE OF KNN ALGORITHM WITH DIFFERENT VALUE OF K-FOLDS

k-folds	Percentage of Accuracy
5	90.12
10	88.89
15	91.29

B. Clinical Implementation and Integration

A systematic approach would be beneficial for the successful incorporation of mechanomyography (MMG) technology into current spasticity management treatments. MMG evaluations can serve as an addition to older methods like the Modified Ashworth Scale (MAS) and the Australian Spasticity Assessment Scale (ASAS). MMG can enhance the reliability and consistency of spasticity level evaluations by offering unbiased data that can validate and improve the subjective assessments currently employed.

As trust in the technology increases, MMG might be progressively integrated as a principal evaluation tool. This would require the development of standardised protocols that integrate MMG measurements into clinical decision-making processes. For instance, MMG data can be utilised to modify treatment strategies, track the development of spasticity over a period, and assess the efficacy of therapies. Integrating MMG with current electronic health record (EHR) systems could enhance efficiency by enabling doctors to conveniently access and analyse MMG data in conjunction with other patient information.

Comprehensive training for therapists is crucial for ensuring the effective utilisation of MMG technology in clinical contexts. This training should include both the technical aspects of utilising MMG devices, and the analysis of data produced by the machine learning models. It is important for therapists to receive training to comprehend the importance of MMG signals, specifically the time and frequency domain characteristics considered essential for precise assessment of spasticity.

Furthermore, therapists must acquire knowledge of the machine learning algorithms employed to analyse MMG data. This entails comprehending the mechanisms by which these models generate predictions, interpreting the significance of the primary output metrics, and incorporating these insights into clinical practice. Hands-on training, supported by user-friendly software interfaces, will further enhance therapists' proficiency in utilizing MMG technology effectively.

C. Limitation of Study

While this study demonstrates the potential of mechanomyography (MMG) in assessing muscle spasticity, several limitations should be considered. Initially, while MMG is proficient in assessing muscle vibrations within the frequency range of 2 to 100 Hz, enhancing the sampling rate could enhance the precision of the data. Increasing the sampling rates can catch finer details of the muscle signals, perhaps improving the accuracy of the assessments and offering a more thorough comprehension of muscle spasticity.

Moreover, the study primarily utilises time domain variables for analysis. Although these features provide information, it may not comprehensively capture all the complexities that comprise MMG signals. In contrast, frequency domain features may identify additional patterns and behaviours that are not evident in the temporal domain. By including frequency domain analysis, a more comprehensive and precise depiction of muscle vibrations can be achieved. This has the potential to enhance the performance of models and enable more dependable evaluations of spasticity.

D. Future Research

A precise assessment of muscle spasticity is essential for the effective treatment and control of neurological diseases in patients. Although mechanomyography (MMG) has potential as a technique for assessing spasticity, its present uses mostly rely on extracting time-domain characteristics from MMG data. To completely maximise the potential of MMG and enhance its practical application in clinical settings, future research should prioritise several crucial areas of development.

Exploring advanced optimisation approaches and ensemble methods can greatly improve the accuracy and reliability of predictive models used in spasticity assessment. Techniques such as hyperparameter tuning, ensemble learning, and deep learning approaches could offer significant improvements in interpreting MMG data and assessing spasticity levels. Besides that, the exploration of ensemble methods offers another promising avenue for improving model performance. By combining the predictions of multiple algorithms, ensemble techniques such as bagging, boosting, or stacking could reduce variance, mitigate overfitting, and increase the overall predictive power of the models. These methods could enhance the model's ability to generalize across different patient populations and clinical settings, thereby improving the robustness of spasticity predictions.

Moreover, the integration of advanced deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), could enhance the automated extraction of detailed and significant characteristics from the MMG signals. These models have demonstrated considerable efficacy in various biomedical signal processing contexts, as they are adept at identifying intricate patterns and relationships within the data that might be overlooked by traditional feature extraction methods. While this study primarily utilizes time domain features extracted from MMG signals, there remains significant potential to enhance model performance through more sophisticated feature engineering approaches. For instance, increasing the sampling rate of MMG data could capture finer details of the signal, thereby enabling the application of frequency domain extraction methods. Such techniques would provide a more nuanced analysis of the MMG signals, potentially uncovering features that are not detectable in the time domain alone.

By integrating these advanced techniques, the precision and robustness of spasticity assessments could be substantially improved, leading to more accurate and reliable predictions. Future research should investigate these avenues to further enhance the clinical utility of MMG in the objective assessment of muscle spasticity.

VI. Conclusion

Essentially, the purpose of this study was to address the problem of subjective and inconsistent evaluation of muscle spasticity in patients with neurological diseases. The objective was to validate MMG as a reliable signal by comparing the accuracy of various machine learning algorithms and demonstrate its clinal applicability in objective measurement. The study demonstrated the efficacy of employing different machine learning algorithms, such as Decision Trees (DTs), Support Vector Machines (SVM), and K-Nearest Neighbours (KNN), for accurately predicting degrees of spasticity. The KNN algorithm, using both all features and significant features, achieved optimal accuracy in the 90/10 split. Specifically, KNN with significant features demonstrated the highest accuracy at 91.29% with k=15, outperforming the use of all features, highlighting its effectiveness in categorizing biomechanical parameters. This technological development has the potential to greatly improve rehabilitation processes by offering more accurate and unbiased evaluations of spasticity. Moreover, it has the potential to decrease related expenses and time, ultimately resulting in an enhancement in the standard of treatment for impacted patients.

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