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Research Article

Evaluating the Reliability of Mechanomyography in Muscle Spasticity: Inter and Intra-Rater Consistency in Flexion and Extension Movements with Machine Learning Model

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ABSTRACT

Introduction: The measurement of muscle spasticity in clinical settings traditionally relies on therapists using established clinical tools. The predominant approach employed in conventional clinical assessments for assessing spasticity is the Modified Ashworth Scale (MAS), which depends on the subjective judgements of therapists. This method involves assessing spasticity by applying passive movements to joints and assigning grades based on the level of muscle resistance encountered. However, this approach often results in inconsistencies in evaluation, which may impact the overall efficiency of the rehabilitation process. Consequently, the development of the Quantitative Spasticity Assessment Technology (QSAT) Platform, which utilizes Mechanomyography (MMG) signals integrated with machine learning models to evaluate spasticity from the forearm muscles during both flexion and extension movements, can address the inconsistencies in spasticity measurement. Thirty subjects with neurological diseases participated in the data acquisition. The extracted data underwent a one-way MANOVA test to identify significant features with a p-value below 0.05, indicating statistically significant differences that were selected for the machine learning models for both movements. The KNN approach, utilising a 90/10 data split for both flexion and extension, demonstrates superior accuracy of 90.12% and 86.42% across all three datasets when compared to other algorithms. Reliability testing for both clinical assessments and QSAT measurements was conducted through inter-rater and intra-rater evaluations, revealing an exceptional Kappa value of 1.000 for the QSAT, while the clinical method exhibited poor agreement. These findings confirm the reliability of the QSAT machine learning model, highlighting strong inter-rater and intra-rater agreement. QSAT presents significant potential for improving physiotherapists' assessments of spasticity in affected limbs, providing a more reliable and objective alternative to conventional methods.

Keywords: Spasticity, Modified Ashworth Scale, Mechanomyography, Machine Learning and Reliability.

I. INTRODUCTION

Spasticity is a neurological dysfunction characteristic of upper motor neuron syndrome. It can occur due to various pathologies, such as stroke, multiple sclerosis, amyotrophic lateral sclerosis (unstable), cerebral palsy, brain injury, and spinal cord injury [1]. In 1980, Lance introduced the term "spasticity" to describe a motor disorder known as the upper motor neuron syndrome which characterized by an increase in muscle tone and exaggerated tendon jerks, which are caused by the hyperexcitability of the stretch reflex and are dependent on the velocity of movement [2], [3]. This description focuses solely on the effects of spasticity upon involuntary movements, without considering its effects on intentional motor functions. Therapists utilize a variety of stretching techniques, including both passive and active methods, with static stretching being the most employed approach [4], [5]. This technique, widely used in managing spasticity, aims to relieve discomfort, enhance functionality, maintain or improve soft tissue flexibility and joint range of motion (ROM), and regulate abnormal muscle tone.

The most common methods used in conventional clinical assessment to access the spasticity include the Modified Tardieu Scale (MTS), the Modified Ashworth Scale (MAS), and the Australian Spasticity Assessment Scale (ASAS) which relies on therapists' subjective evaluations [6], [7], [8]. While practitioners generally highly skilled, variability in categorizing the severity of spasticity remains a concern. Among the available assessment tools, MAS and ASAS are considered highly reliable for clinical spasticity evaluation [9]. The MAS, a variation of the original Ashworth Scale (AS), is frequently employed to assess spasticity by categorizing the degree of muscle resistance experienced during passive stretching [10], [11], [12]. Similarly, the ASAS designed to evaluate muscle spasticity in children with cerebral palsy, builds upon the velocity-dependent features of the Tardieu Scale (TS) and Modified Tardieu Scale (MTS), incorporating a rating system aligned with the Modified Ashworth Scale (MAS) for clinical ease, with a focus on two key elements: the specific location of the "catch" and the intensity of resistance observed after the catch [13], [14], [15]. The Tardieu Scale (TS) and its modifications The Modified Tardieu Scale (MTS) quantitatively evaluates spasticity by measuring muscle resistance to stretching at two specific velocities, slow and fast, facilitating the identification of a discernible 'catch' and the assessment of spasticity's presence and severity [16]. Additionally, therapists assess these scales to evaluate the complete slow passive range of movement (R2) and the initial resistance angle encountered during rapid passive movements (R1) to elucidate the physiological and neurological mechanisms influencing resistance to passive movements, respectively [17].

Despite the advantages of traditional clinical measurements, these methods have proven to be inadequate in reliability and validity for clinical setting, underscoring the necessity for advanced, sophisticated and objective assessment approaches [18], [19]. Conventional tone assessment methods frequently depend on subjective evaluations and manual analysis, resulting in variations in both inter-rater and intra-rater dependability [20]. While the MAS and TS offer a partially quantitative evaluation of muscular resistance during passive movement, the assessment remains insufficient in fully capturing the intricate variations in muscle tone [21]. The application of electromyography (EMG) in standard therapeutic practices signifies a modern and innovative method for neurorehabilitation in stroke recovery patients. [22]. Despite its therapeutic benefits, EMG faces significant limitations in broader applications, particularly due to its high susceptibility to external noise and resistance fluctuations, which can compromise its reliability, especially in varied environments or throughout extended data acquisition sessions, for instance when the subject is perspiring [23], [24]. Various types of transducers, including piezoelectric contact sensors, microphones, accelerometers, and laser distance sensors serve to evaluate muscle vibrations, also known as mechanical activity, as an alternative to EMG, a technique referred to as Mechanomyography (MMG) [25], [26], [27], [28]. Mechanomyography (MMG) captures the vibrations generated by muscle contractions and stretching as they travel through tissue, detectable on the skin's surface, making it a non-invasive, painless technique that healthcare professionals can use to assess spasticity and support a range of clinical objectives [29], [30]. A platform namely Quantitative Spasticity Assessment Technology (QSAT) system was designed incorporating the MMG technique which comprises two main sensors: an accelerometer, that quantifies muscle vibration (acceleration) in the biceps and triceps, and a potentiometer, that capture the upper limb's angular position through both flexion and extension movements.

The primarily objective of this study to assess the reliability of the developed QSAT model for assessing muscle spasticity, utilising Mechanomyography (MMG) signals in conjunction with Modified Ashworth Scale (MAS) levels as reference. The paper comprises four sections. Section two delineates the technique utilised, encompassing subject recruiting, conventional clinical assessment processes, the QSAT approach, and the statistical analyses applied in this study. The next section displays and analyses the results of machine learning performance and the evaluation of inter- and intra-rater reliability tests. The final section elucidates the conclusions drawn from the study's findings.

II. METHODS

A. Subjects

Thirty subjects with neurological disorders affecting the upper limb were selected for this study based on predefined criteria from the National Stroke Association of Malaysia (NASAM) and Sultan Ahmad Shah Medical Centre (SASMEC), both located in Kuantan, Pahang. Eligible subjects, aged between 18 and 80, had neurological impairments and had undergone evaluation and therapy by certified therapists. The subjects' demographic characteristics, summarized in Table 1, indicate that participants were selected among MAS levels 0, 1, 1+, 2, and 3, whereas MAS level 4 was excluded due to the lack of observable flexion and extension movements during assessment. Each subject's MAS level was measured separately for flexion and extension, as illustrated in Figure 1. This study was approved by the IIUM Research Ethics Committee (IREC 2023-025), with informed consent obtained from all subjects before participation.

Table 1: Demographic Characteristics of Subjects with Neurological Disorder Patients (N=30)

Age Distribution (Mean±SD)	59.33±12.41
Male	22
Female	08
Impacted Hand:	
Right	16
Left	14
Neurological Condition:	
Strokes	29
Cerebral Palsy	1

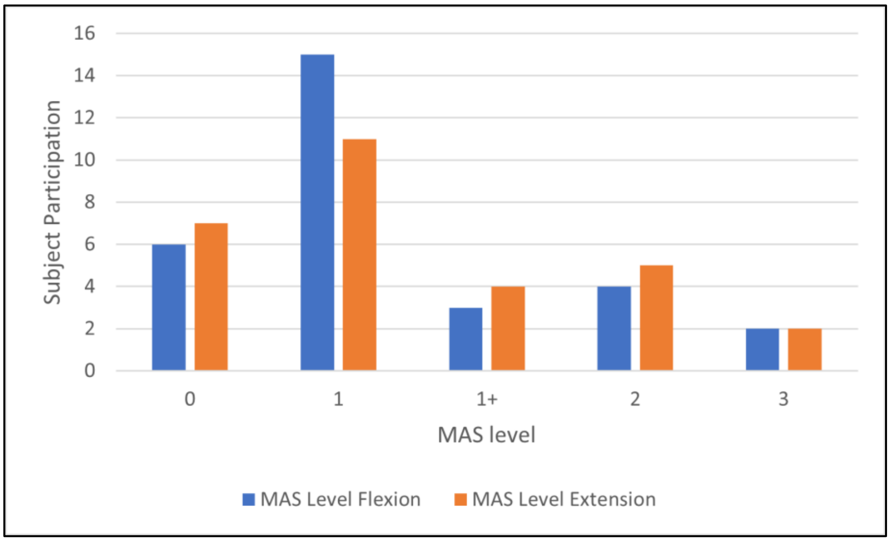

Figure 1: MAS Level Distribution

B. Conventional Clinical Assessment

Two experienced physiotherapists, familiar with the MAS procedure, were enlisted to independently assess the spasticity level of each subject. The MAS rating scale used in this study ranges from 0, 1, 1+, 2, 3, to 4 which is shown in Table 2. Scale 0 indicates the absence of increased muscle tone, categorising the individual as healthy. Scale 1 represents a slight increase in muscle tone, characterised by a catch and release with minimal resistance at the end of the range of motion. In contrast, Scale 1+ describes a similar event, but the resistance persists throughout the entire range of motion. On Scale 2, there is a more pronounced increase in muscle tone throughout most of the range of motion, although the affected limb remains mobile. Scale 3 indicates a considerable rise in muscle tone, resulting in limited movement of the afflicted limb across the range of motion. Finally, Scale 4 represents complete rigidity of the affected limb in both flexion and extension movements. The experimental procedure began with each subject positioned in a supine posture, with their arm resting beside the torso. The therapist then performed passive movements, encompassing full extension to complete flexion, evaluating the spasticity present in the corresponding joints which shown in Figure 2. Spasticity levels were assigned according to the level of muscle resistance encountered throughout passive stretching, with each therapist executed each movement three times. Subsequently, the physiotherapists assessed the subjects' spasticity levels in accordance with the Modified Ashworth Scale (MAS). The second physiotherapist then repeated these assessments, with a five-minute interval allowed between evaluations. To ensure the integrity of the results, no discussions between assessors were permitted, and all experiments were conducted independently to maintain complete blinding. All outcomes were meticulously documented and organized in a datasheet.

Figure 2: Conventional Clinical Spasticity Assessment

C. Conventional Clinical Assessment Quantitative Spasticity Assessment Technology (QSAT)

In this study, a Raspberry Pi Pico was employed as a data acquisition unit to record biological signals from both ACC-MMG sensor and potentiometer at a sampling frequency of 166.7 Hz. The biceps and triceps muscles were fitted with a tri-axial ACC-MMG accelerometer, while the upper limb was equipped with an elbow brace, which housed a potentiometer positioned at the elbow joint to ensure stability and accurate capture of angular position during the data acquisition process. This setup allowed for the simultaneous recording of single-stream potentiometer data and two-stream ACC-MMG signals, with the ACC-MMG signal recorded in three dimensions using accelerometers as MMG transducers, generating sub-signals that consists of the x, y, and z axes corresponding to the muscle fibers' longitudinal, lateral, and transverse orientations.

The experimental protocol was initiated by conducting a methodical assessment of the spasticity levels in the muscles that control the bending and straightening of the elbow joints [31]. The evaluation of muscle spasticity was conducted using the Modified Ashworth Scale (MAS), a widely recognized clinical tool for assessing muscle tone. Following the assessment, MMG signals were recorded from the biceps and triceps muscles. To ensure accurate signal acquisition, the sensors were firmly attached to the skin with double-sided adhesive tape. "Sensor 1" was positioned over the belly of the biceps muscle, while "Sensor 2" was placed on the belly of the triceps. Simultaneously, a potentiometer integrated into an elbow brace, was concurrently positioned at the joint to monitor movement. The QSAT platform was employed to conduct passive motion assessments of the elbow joint, as illustrated in Figure 3. Depending on the spasticity of the muscle group under evaluation, either flexion or extension movements were performed. Data obtained from the QSAT platform were plotted and analyzed utilizing MATLAB R2023a software (MathWorks Inc.). Various MMG signal features, including Kurtosis, Mean Average Value (MAV), Median, Peak-to-Peak Amplitude (PTP), Root Mean Square (RMS), Standard Deviation (SD), and Skewness, were extracted from the x_1, y_1, z_1 axes (biceps) and x_2, y_2, z_2 axes (triceps) for both flexion and extension movements. The extracted MMG features were subsequently mapped to corresponding MAS levels for futher analysis.

Figure 3: Configuration of the QSAT Platform for Upper Limb Measurement

D. Statistical Analysis

SPSS version 27.0.1 (IBM Inc.) was used to perform all statistical analyses. Multivariate Analysis of Variance (MANOVA) was conducted to identify significant differences in MMG signal features across various levels of muscle spasticity [32]. Features with a p-value below 0.05, indicating statistically significant variations among the dependent variables, were selected for machine learning models, and these key features were extracted from the x_1, y_1, z_1 axes of the biceps and the x_2, y_2, z_2 axes of the triceps during both flexion and extension movements. Weighted Cohen's Kappa test was employed to assess the reliability of the measurements [33]. Inter-rater reliability assessed the consistency of MAS level evaluations between two physiotherapists and the QSAT machine learning model (using the same model for comparison). Intra-rater reliability, on the other hand, was determined by having each physiotherapist and the QSAT model apply their assessments multiple times to the same dataset, ensuring the model's stability and consistency across repeated trials. Kappa values exceeding 0.80 signify excellent agreement, while those between 0.61 and 0.80 indicate substantial agreement. Moderate agreement is suggested by values ranging from 0.41 to 0.60, and fair to poor agreement is implied by values below 0.40.

III. RESULTS AND DISCUSSION

A. Machine Learning Performance Results

The study employed multiple machines learning algorithms, including Decision Tree (DT), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN), to predict spasticity levels based on the Modified Ashworth Scale (MAS) for both flexion and extension movements. These algorithms utilized 25 significant features, each with a p-value below 0.05, contributing to the x, y, and z axes of muscle movement. The results for flexion and extension predictions are detailed in Table 2, demonstrating the effectiveness of these features in assessing spasticity. The data set sample had been arranged with different percentage for the train and test to identify which algorithm have the highest accuracy result to be the selected as the model to be used in evaluation. The KNN approach, utilising a 90/10 data split for both flexion and extension, demonstrates superior accuracy of 90.12% and 86.42% across all three datasets when compared to other algorithms. The KNN classifier is an effective approach for categorizing biomechanical parameter features, especially for cases with small datasets and low-dimensional feature spaces [34], [35].

Table 2: Dataset Distribution and Algorithm Accuracy Percentage

Algorithm	Classification Accuracy Across Different Training-Testing Splits					
	Flexion			Extension		
	90-10	80-20	70-30	90-10	80-20	70-30
DT	65.43	63.89	65.08	67.90	59.72	71.43
LDA	76.54	70.83	66.67	60.49	59.72	55.56
SVM	72.84	68.06	69.84	66.67	59.72	71.43
KNN	90.12	86.11	84.13	86.42	83.33	74.60

Figures 4 and 5 illustrate the True Positive Rate (TPR) and the False Negative Rate (FNR) as derived from the confusion matrix for the KNN algorithm, utilising a 90/10 data split for both flexion and extension. The TPR exceeds the FNR in identifying high positive instances for classes 0, 1, and 3 during flexion movement, and for classes 1, 2, and 3 during extension movement, illustrating the model's significant efficacy in classifying spasticity levels. The high TPR is notably significant in this context, as accurately identifying positive cases is critical due to the severe consequences of missed diagnoses. From the confusion matrix, it turns out evident that the majority of the predictions are accurate, as seen by the larger values on the diagonal. These findings indicate that the models are generally exhibiting strong performance in accurately predicting the correct classes. Although the FNR is relatively low, it still indicates a non-negligible number of missed positive cases. There could be several potential reasons for this, including an uneven distribution of classes, a lack of distinctive characteristics, or the presence of noise in the data. This shortfall poses challenges in accurately assessing the severity of spasticity, which is essential for appropriate management and treatment. The KNN model with 90/10 data split for both flexion and extension were selected for the subsequent reliability tests, which included both inter-rater and intra-rater assessments.

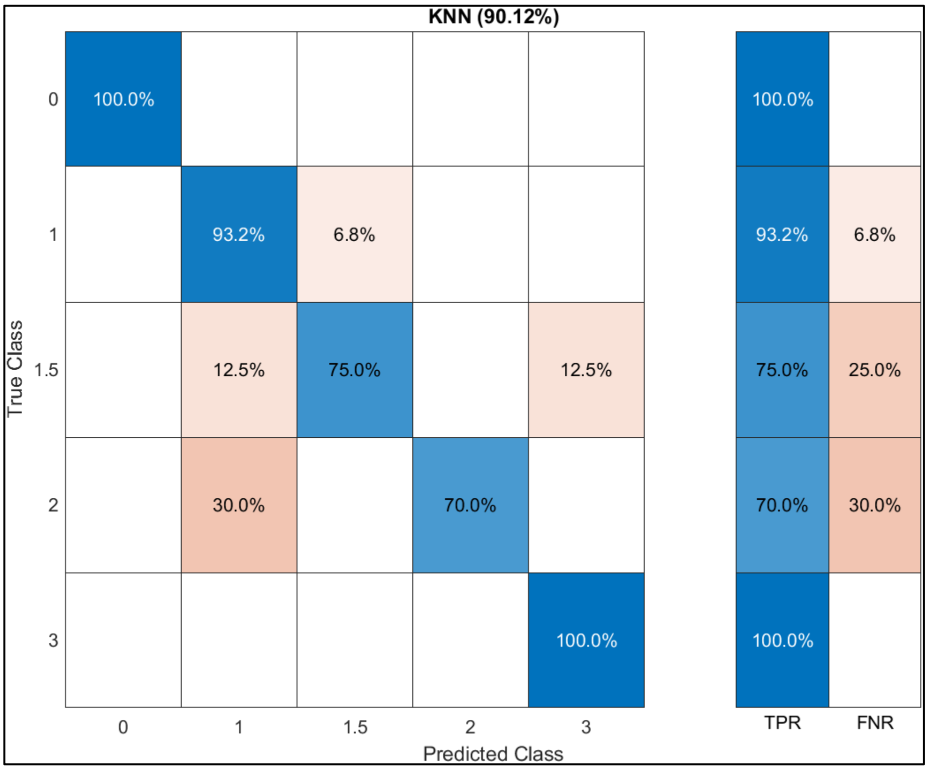

Figure 4: Confusion Matrix and Performance Metrics of KNN Model for Flexion Movement

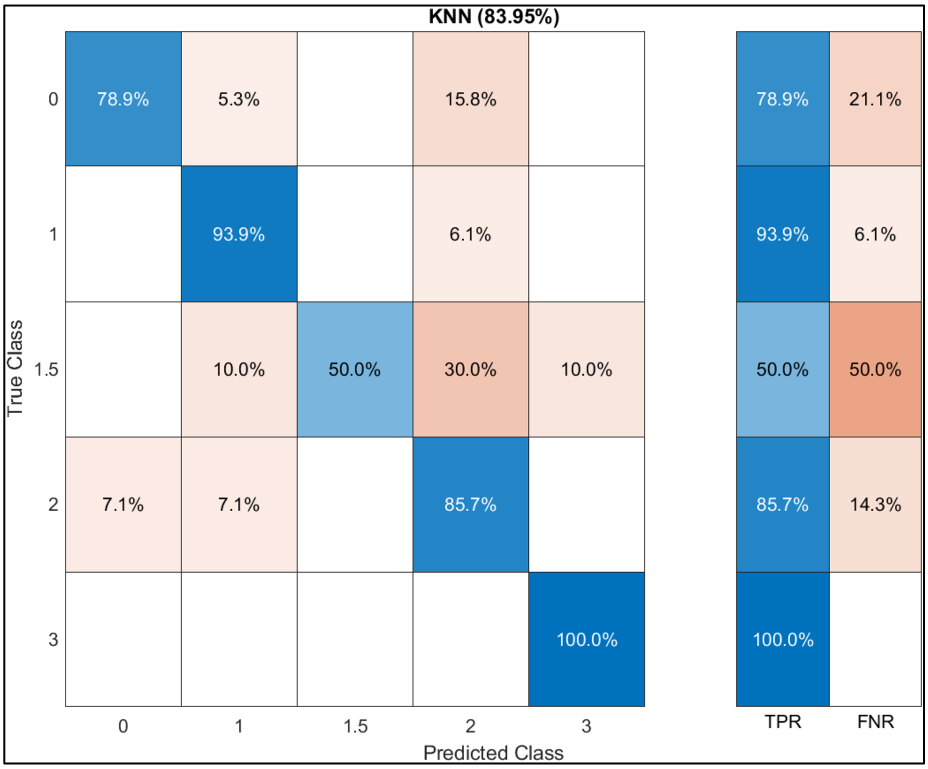

Figure 5: Confusion Matrix and Performance Metrics of KNN Model for Extension Movement

B. Evaluation of Inter and Intra Rater Reliability Results

Both physiotherapists conducted the assessment using two distinct approaches. Initially, one physiotherapist evaluated each patient by performing passive joint movements and determining the spasticity level based on the muscle resistance encountered during stretching. Subsequently, the subject's arm was secured to the QSAT platform, with one therapist positioning a hand beneath the lower arm near the wrist while the other supported the upper arm close to the shoulder. This QSAT technique was designed to be completed in under five minutes. To ensure reliability, the evaluation was conducted three times per session for both approaches. Table 3 presents the muscle spasticity scores for flexion movement, while Table 5 outlines the corresponding scores for extension movement across both assessment methods. Additionally, the inter-rater and intra-rater reliability outcomes for spasticity evaluation, comparing the clinical method with the QSAT platform, are shown in Table 4 for flexion and Table 6 for extension movements.

Table 3: Kappa Results for MAS Measurements Across Raters and Flexion QSAT Model

Reliability Types	**Rater**	**Kappa (K)**	**Standard Error**	**T Value**	**P Value**
Inter-Rater	Therapist 1 vs. Therapist 2	0.391	0.073	6.894	<0.001
	QSAT Machine Learning Model	1.000	0.000	16.426	<0.001
Intra-Rater	Therapist 1 (Trial 1 vs. Trial 2)	1.000	0.000	16.146	<0.001
	Therapist 2 (Trial 1 vs. Trial 2)	1.000	0.000	16.441	<0.001
	QSAT Machine Learning Model (Trial 1 vs. Trial 2)	1.000	0.000	16.426	<0.001

Table 4: Distribution of Average MAS Scores for Clinical and Flexion QSAT Model Methods

MAS Level	Clinical				QSAT			
	First Test (Therapist 1)	Repeat Test (Therapist 1)	First Test (Therapist 2)	Repeat Test (Therapist 2)	First Test (Model 1)	Repeat Test (Model 1)	First Test (Model 2)	Repeat Test (Model 2)
0	7	7	6	6	8	8	8	8
1	13	13	15	15	12	12	12	12
1+	4	4	3	3	6	6	6	6
2	2	2	4	4	1	1	1	1
3	4	4	2	2	3	3	3	3

Table 5: Kappa Results for MAS Measurements Across Raters and Extension QSAT Model

Reliability Types	Rater	Kappa (K)	Standard Error	T Value	P Value
Inter-Rater	Therapist 1 vs. Therapist 2	0.057	0.054	1.038	0.299
	QSAT Machine Learning Model	1.000	0.000	17.091	<0.001
Intra-Rater	Therapist 1 (Trial 1 vs. Trial 2)	1.000	0.000	17.108	<0.001
	Therapist 2 (Trial 1 vs. Trial 2)	1.000	0.000	12.996	<0.001
	QSAT Machine Learning Model (Trial 1 vs. Trial 2)	1.000	0.000	17.091	<0.001

Table 6: Distribution of Average MAS Scores for Clinical and Extension QSAT Model Methods

MAS Level	Clinical				QSAT			
	First Test (Therapist 1)	Repeat Test (Therapist 1)	First Test (Therapist 2)	Repeat Test (Therapist 2)	First Test (Model 1)	Repeat Test (Model 1)	First Test (Model 2)	Repeat Test (Model 2)
0	7	7	16	16	7	7	7	7
1	11	11	8	8	12	12	12	12
1+	4	4	6	6	4	4	4	4
2	5	5	0	0	5	5	5	5
3	2	2	0	0	2	2	2	2

The clinical approach for the flexion movement exhibited a range of agreement from low to excellent, indicated by a Kappa value (ƙ) of 0.391. Conversely, the QSAT approach demonstrated complete concordance across raters, with a Kappa value (ƙ) of 1.00, signifying exceptional consistency. The intra-rater test exhibited exceptional consistency for both approaches. The Kappa values for the clinical assessment approach, derived from measurements by both Therapist 1 and Therapist 2, as well as for the QSAT method, were both 1.000. The p-values corresponding to these Kappa values were statistically significant, indicating that the assessors' level of agreement is not attributed to random chance. For the extension movement, the clinical method showed a range of agreement from low to excellent, with a Kappa value (ҡ) of 0.057 and a non-significant p-value of 0.299. In contrast, the QSAT method exhibited perfect agreement between raters, reflected by a Kappa value (ҡ) of 1.00 and a highly significant p-value of <0.001, indicating excellent consistency. The intra-rater reliability test also demonstrated outstanding consistency for both methods. The Kappa values for the clinical assessments by Therapist 1 and Therapist 2, as well as for the QSAT method, were all 1.000, with significant p-values, confirming that the agreement was not due to random chance.

A key obstacle in neurorehabilitation is the development of inconsistent recovery plans due to the lack of agreement among physiotherapists when assessing the affected upper limb. The findings from this study indicate that the inter-rater reliability of the QSAT approach for both flexion and extension motions markedly exceed that of traditional clinical assessments. This is due to QSAT's objective approach, as it quantifies muscle vibration, which is an indicator of muscular activation, using MMG sensors. The MAS ratings acquired are exceptionally dependable and accurate. Conversely, conventional clinical evaluations rely significantly on the subjective interpretations of physiotherapists, resulting in increased variability in assessments. The repeated evaluations performed by a single physiotherapist exhibit a significant degree of intra-rater reliability, signifying that the outcomes are dependable and uniform. To improve the validity and generalisability of the findings, it is advisable to schedule a follow-up appointment within three days following the original evaluation. This will facilitate the assessment of any alterations that may have happened during the period, offering further insights into the stability and dependability of the measures.

IV. CONCLUSION

In summary, this study aimed to assess the reliability of the developed QSAT model for assessing muscle spasticity, utilising Mechanomyography (MMG) signals in conjunction with Modified Ashworth Scale (MAS) scores as reference. The primary goal was to create a new, standardized, and objective model for spasticity assessment, with the K-Nearest Neighbors (KNN) algorithm demonstrating the highest accuracy across different datasets for both flexion and extension movements. This underscores the algorithm's effectiveness in classifying biomechanical parameters, particularly in conditions where data is limited, and dimensionality is low. The findings confirm the reliability of the QSAT machine learning model, showing strong inter-rater and intra-rater agreement. Consequently, QSAT holds promise for future use in enhancing physiotherapists' evaluation of spasticity in affected limbs, offering more reliable and objective assessments. This advancement holds promise for enhancing rehabilitation outcomes by minimizing time and costs while improving the quality of care for patients. Future research should focus on validating this model through larger clinical trials and exploring its integration into routine clinical practice.

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