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Non-motorised Rehabilitation Device for Performance Assessment in Upper Limb Stroke Rehabilitation: A Pilot Study

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Abstract: Stroke patients with upper limb disability restricted to carry out their activities of daily living. The patient needs a motivation to recover from a stroke and the patient also needs to go through a rehabilitation process at the same time. The conventional rehabilitation process scoring systems are always subjective, lack reliability and relies heavily on the ability of the trained physiotherapist that providing only rough estimates on motor function. On the other hand, robot-based assessments are objective, repeatable, and could potentially reduce the assessment time. Therefore, a simple non-motorized device was developed as a tool to objectively assess hand function of stroke patients. This study was carried out to investigate the suitability of using the developed device with stroke patient populations and to evaluate the performance of clinical scores prediction of the stroke patients. A total of five patients with upper limb disability following stroke consented to take part in this study. Twelve predictive variables were investigated, relating to the total movement time, velocity, strategy, accuracy, and smoothness from three robotic assessment modules which are Draw I, Draw Diamond and Draw Circle. The hardware for measuring elbow angle has been developed to measure the shoulder movement performed by patient during the assessment process. In addition to that, the shoulder movement calculation method has been proposed and validated. The findings indicate that the performance of prediction for all assessment modules has been increased after implementing the shoulder movement calculation. It is recommended this calculation method to be used in conjunction with kinematic variables to carry out the data acquisition process in the future for improvement of effectiveness and accuracy of the robotic assessment.

Keywords: Rehabilitation, assessment, stroke, upper limb, robotic

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1. Introduction

Impairment of the upper limb motor is one of the most common functions affected by stroke [1], can lead to function limitations and dramatically reduce the quality of life of stroke patients [2]. Due to motor impairment, stroke patients with upper limb disability are restricted to perform their daily life activities. In order to recover from a stroke, the patient needs to be motivated and at the same time the patient also needs to undergo a rehabilitation process. The aims of the rehabilitation process are to improve the functional use of the upper limb and to reduce motor impairment for the enhancement the quality of life so that this stroke patient able to perform productive daily activities [1,3].

Conventionally, clinical scales such as Fugl-Mayer (FMA) [4], Motor Assessment Scale (MAS) [5] or Manual Muscle Test (MMT) is generally used by the physiotherapist to evaluate motor function during the rehabilitation process. However, the assessment of the motor function of stroke patients using conventional clinical scales is difficult due to time and resources limitations [3]. In addition, the scoring systems are often subjective, lack of reliability and relies heavily on the ability of the experienced physiotherapist to provide only rough estimates of motor function [5,6]. That makes it arduous to quantify disability and impairment objectively. Furthermore, their low sensitivity makes it arduous to detect small changes in motor function recovery. Precise and objective measurement of the motor function is therefore needed for monitoring and quantifying the patient's progress all through the rehabilitation process.

Voluntary or free-living activity may be carried out by subjects using wearable sensors and motion capture devices without consciously engaging in the use of assistive or resistive force, hence providing more ecological and rich data related to disability [7]. Therefore, the voluntary movement perform by the expense of the subject itself can be collected during the assessment process. Besides, by using robotic device, the actuator should be back-drivable or a good control algorithm is required to allow the subject to make voluntary movements. The affordable motion capture systems or an non-actuated rehabilitation device can provide an inexpensive and practical way of conducting clinically validated assessments [8–10].

Many types of upper limb robotic device or rehabilitators for stroke rehabilitation have been developed to assist physiotherapists during rehabilitation program. The systematic reviews on the effects of robotic rehabilitator within the stroke population have been increased in recent years [11–15]. These robotic rehabilitators provide precise measurement of the sensory motor performance of the patient, which can positively influence the rehabilitation result [11]. Generally, a robotic rehabilitation system with a large number of degree of freedom (DOF) is required in order to train and assess the upper limb functional movement. However, the more complex the mechanical design, the device become more costly, less reliable and it has fewer number of potential users [5]. Therefore, a simple nonmotorized device was developed to represent the subject’s voluntary movement while playing an interactive game that can be used as a device to objectively assess hand function of stroke patients.

This paper focuses on pilot studies that have been conducted using developed rehabilitation device and suggestions for future data analysis improvements. The first objective of this study is to evaluate the kinematic variables of the upper limb assessment using the rehabilitation device with stroke patient populations. The second objective is to identify and validate the shoulder movement of upper limb while using the rehabilitation device. The third objective is to evaluate the performance of clinical scores prediction before and after implementing the shoulder movement of the stroke subjects. The outcomes of this study could be used to improve data analysis among stroke patient’s population in the future for predicting the clinical scales score.

2. Research Method

This research was conducted according to the several procedures that have been used by previous researchers [6]. Information on subjects, set-up procedure and kinematic variables has been discussed in this section. In addition, the methods used for calculating shoulder movements and the methods to evaluate the performance of assessment was discussed in detail at the end of this section.

2.1 Subjects

A total of five patients with upper limb disability following stroke consented to participate in this study. There were four males and one female, aged between 23 to 54 years. Four out of five participants were right-hand dominant. The demographic profile of stroke patients is shown in Table 1. Inclusion criteria for this study is the stroke patients who only capable of limited hand and arm movements but suffer from impaired hand function that hinders normal everyday life activities. The MAS score given by therapist for upper limb function at least 2. Exclusion criteria were the existence of musculoskeletal or neurological disability that could impair the function of the arm. Every subject had been told of the intent and instructions for the experiment before the experiment started. The research and development team of SOCSO Tun Razak Rehabilitation Centre approved all the research procedures applied in this study.

Table 1 - Demographic Data of Stroke Patients

Subject	Gender	Age	Lesion Side	MAS
P 1	M	54	R	18
P 2	M	41	R	13
P 3	F	47	R	10
P 4	M	23	L	8
P 5	M	46	R	3

Abbreviations: P, Patient; M, Male; F, Female; R, Right; L, Left; MAS, Motor Assessment Scale;

2.2 Set-up and Procedure

Subjects were selected by the therapists in Perkeso Tun Razak Rehabilitation Center Melaka. The selections of the subjects were based on the inclusion criteria of this study. All subjects received conventional therapy everyday throughout the rehabilitation process. The upper limb function of each subject was evaluated by physiotherapist at the end of the study using the MAS. Fig. 1 shows the experiment setup during the robotic assessment.

(a) (b)

Fig. 1 - The experiment setup during the robotic assessment; (a) Left hand; (b) right hand

Subjects participated in three robotic assessments that lasted 30 minutes, allocated 10 minutes for each assessment module. The experiment set-up as the previous study has been used, where the assessment began with Draw I module, Draw Diamond module and Draw Circle module in sequences [6,16]. The grasping mechanism for this device were used to assess the hand grip force which are different from the previous device that used to assess hand opening and closing movement. Subjects were asked to grasp the handle of the assessment device with their affected hands and were secured with Velcro band. Each subject makes a total of 9 movements to complete the study: 3 for Draw I, 3 for Draw Diamond and 3 for Draw Circle modules.

2.3 Kinematic Variables

The kinematic variables were calculated using MATLAB software. Twelve kinematic variables were extracted from the rehabilitation device: Total movement time, stability time, reaction time, mean velocity, peak velocity, time to peak velocity, hit-wall score, path ratio, trajectory error, target reached, grasping, number of peaks speed. All the calculation for the kinematic variables were referred from the previous study [6]. Table 2 shows the properties of the twelve kinematic variables used in this study.

Table 2 - Properties of The Kinematic Variables

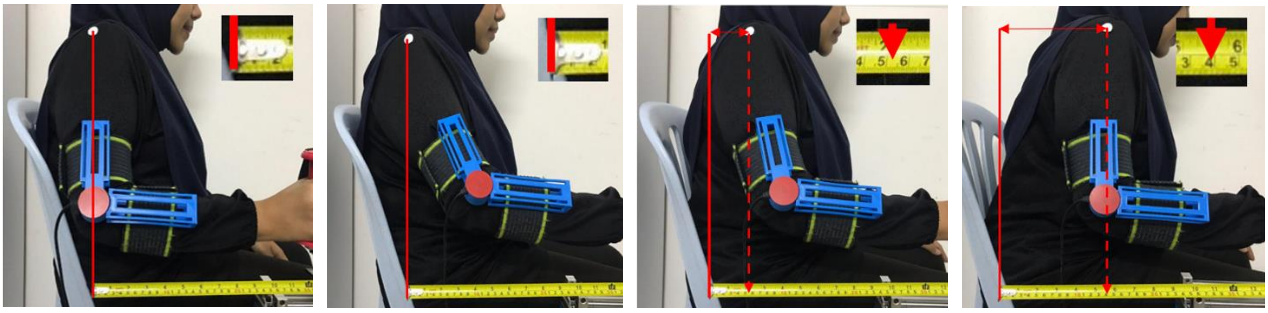
Kinematic variables	Definition
Total movement time	Elapsed time from movement onset to movement offset.
Stability time	Time required to make fine adjustments once the target position reached for the first time.
Reaction time	Time between illumination of the target and movement onset.
Mean velocity	Mean tangential speed from movement onset to offset using combined linear reaching and forearm rotation movements.
Peak velocity	Maximum instantaneous velocity during the movement.
Time to peak velocity	Percentage of the time to reach the peak velocity.
Hit-wall score	Percentage of elapsed time for the green dot to touch the grey background.
Path ratio	Ratio between the total distance travelled from movement onset to movement offset and task distance.

Trajectory error	Summation of the mean deviation from the path line connecting the targets, starting distance error and nearest distance error. This variable was normalized by distance travelled.
Target reached	Total number of targets that the subject successfully reached.
Grasping	Hand grip force applied by the subject during the assessment process.
Number of peaks speed	The distance travelled and the number of data has normalized the number of peaks in the velocity profile.

2.4 Shoulder Movement

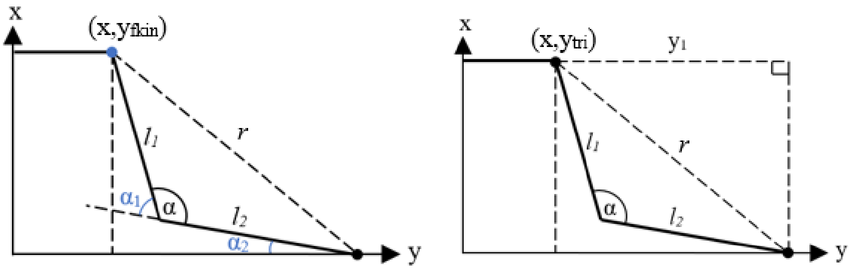
The range of reaching movement to be covered by the subject in the assessment module was from 0 to 150 mm. As in the experimental protocol, subjects had to move their arms without moving their shoulders. Stroke patients have difficulty performing reaching movements while maintaining their shoulder position. They used available motor strategies to reach their target position in order to compensate for the weakness in their upper limbs [6,17,18]. During reaching movement, stroke subjects attempt to move their shoulder to reach the target position. This shoulder movement can cause the data for reaching movement to be invalid for use in analysis. Therefore, a device has been developed for measuring the elbow angle of the patient arm during performing the assessment module. The measurement of elbow angle is intended to calculate the shoulder movement performed by the patient using mathematical equations. A potentiometer was placed in the device for measuring the elbow angle.

Experiment was conducted using the device to measure the distance of shoulder movement using measurement tape. Then, the distance of the shoulder movement was validated by forward kinematic equations and trigonometry equations. Data from one healthy subject was used in this experiment. The experiment protocol was the same as the previous experiment where the subject need to seat on the high back seated chair during the assessment. Subject arm length is measured before starting the assessment for the use in mathematical equations. Fig. 2 shows the measurement of the shoulder movement during performing the assessment process using assessment device. The measuring tape was attached as fixed position with the device's base. Fig. 3 shows the schematic of upper limb joint angle for forward kinematic and trigonometry model.



(a) (b) (c) (d)

Fig. 2 - The shoulder positions during reaching movement: (a) Normal (0mm); (b) normal (150mm); (c) small compensate (150mm); (d) large compensate (150mm)



(a) (b)

Fig. 3 - Schematic of upper limb joint angle; (a) forward kinematic; (b) trigonometry model

The hand position had been extracted from the rehabilitation device in term of x and y axis. Position of x value represents hand manipulation (pronation and supination) while y value represents hand reaching movement. Since this experiment is only to identify the distance of shoulder movement (reaching movement), x value assumes to be zero. l_1 and l_2 represent the arm length of the subject. The arm length was measured before performing the task. Length r can be determined using known l_1, l_2 and angle α. Length r is given by Eq. (1).

$$r = \sqrt{l_1^2 + l_2^2 - 2\,l_1^2\,l_2^2 \cos\alpha} \tag{1}$$

The value of α_1 and α_2 can be identified by the known angle α. The position of the shoulder (y-axis) can be calculated using forward kinematic in Eq. (2).

$$y_{fkin} = \left(y_{game} + l_2\right) - \left[l_1 \cos\left(\alpha_1 + \alpha_2\right) + l_2 \cos\alpha_2\right] \tag{2}$$

The y_1 represent the actual reaching distance performed by the subject using trigonometry calculation. The value y_1 can be calculated using Eq. (3).

$$y_1 = r * \cos\left[\sin^{-1}\left(\frac{l_1}{r}\right)\right] \tag{3}$$

The y_{tri} define as the compensatory movement perform by the patient during the assessment. The value of y_{tri} can be identified using Eq. (4).

$$y_{tri} = \left(y_{game} + l_2\right) - y_1 \tag{4}$$

2.5 Performance of Assessment

Multiple Linear Regression (MLR) approaches is the basic and simple method for data processing in analytical data [19]. MLR is a powerful statistical tool finding relationships between one dependent and multiple independent variables [20–22]. Several studies shows that four kinematic variables were high enough to result a good predictive performance of a regression model [6,23]. Therefore, the best four combination of the kinematic variables has been selected as the feature selection method in order to evaluate the performance of the linear regression model for predicting the clinical scores. The best combination of four kinematic variables was determined using leave one out cross validation (LOOCV) approach. One data point was released in turn, the remaining data were used to fit the predictive model. These kinematic variables were used as the independent variables for MLR model to predict the MAS score of the stroke patients. Each subject performed 3 trials for each assessment module. Fifteen data set of the stroke subjects were divided into training and validation data set. The predictive accuracy of the assessment was evaluated based on root mean squared error (RMSE) and coefficient of determination (R^2).

3. Results and Discussion

This section discusses about the results of kinematic variables of the stroke subjects and the results of shoulder movement performed by healthy subject using the proposed calculation method. In addition, the performance of assessment using MLR model were discussed in detail at the end of this section including before and after implementing the shoulder movement of the stroke subjects.

3.1 Kinematic Variables

The extracted data from the rehabilitation device has been calculated and analysed. All kinematic data of stroke subjects were compared with healthy subjects. Fig. 4 shows the hand path covered by the subjects for each assessment module. Only P1 was able to perform all the required assessment task close to healthy subject. In addition, P2 hand paths were fairly straight with small corrective movements. In contrast, the hand paths for P3, P4 and P5 were highly complicated and often required extensive corrective movements. Besides, the hand paths of P3 in all robotic assessment modules revealed that P3 had difficulty to follow the desired path in order to reach the target position that involving forearm pronation and supination. P5 movement trajectories for Draw Circle was highly erratic and showed that P5 was unable to manipulate the hand reaching, pronation and supination movement to follow the desired path of the assessment module. All kinematic variables extracted from the assessment module are recorded in Table 3.

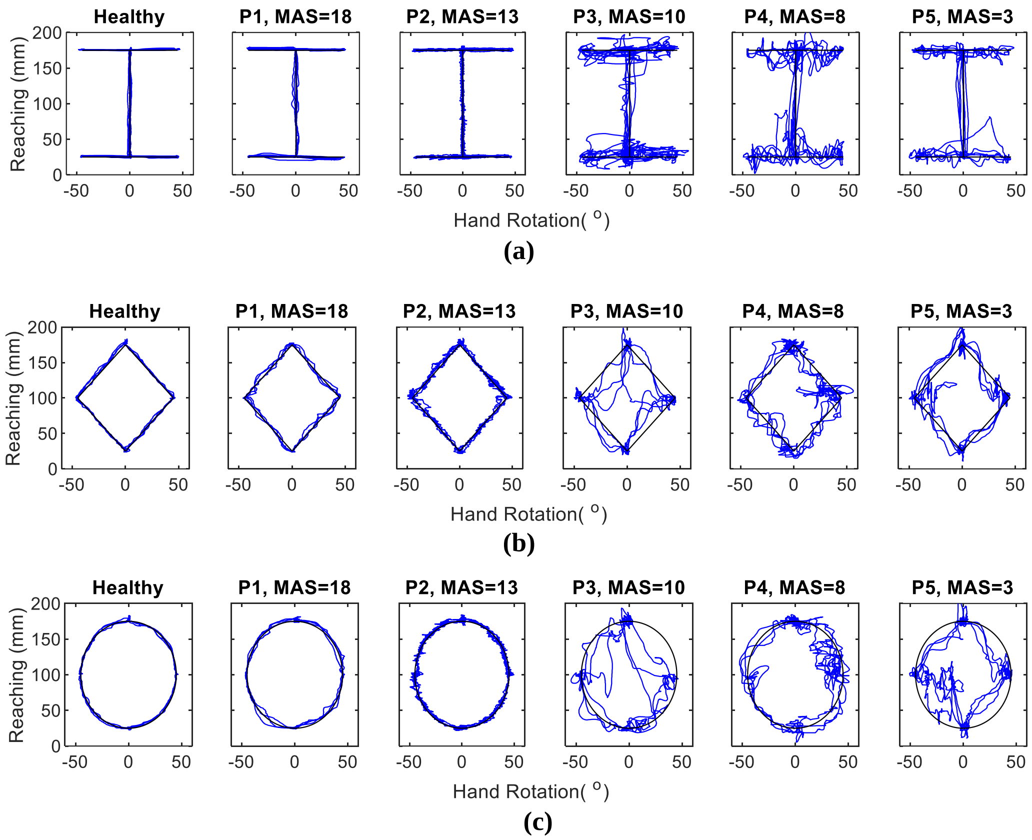


Fig. 4 - Hand paths covered by a healthy subject and five stroke patients to complete the three robotic assessment modules in descending order of upper limb MAS; (a) Draw I; (b) Draw Diamond; (c) Draw Circle

Table 3 - Kinematic Data for Robotic Assessment Module

Kinematic Variables	Healthy	P 1	P 2	P 3	P 4	P 5
Movement Time and Velocity						
Total Movement Time	23.39	25.39	53.13	51.26	45.59	47.72
Stability Time	99.15	98.25	44.53	13.38	42.25	39.07
Reaction Time	1.30	1.35	0.3	0.41	1.61	1.46
Mean Velocity	269.84	224.15	110.96	107.87	155.73	143.35
Peak Velocity	768.61	527.51	514	1062.62	781.19	1086.84
Movement Strategy						
Time to PV	31.84	33.81	18.80	24.53	28.73	26.11
Movement Accuracy						
Hit Wall Score	98.65	94.78	99.85	63.3	71.97	59.66
Path Ratio	114.48	17.74	17.74	17.81	17.74	17.74
Trajectory Error	11.06	12.41	27.13	122.50	145.49	106.26
Target Reached	8	8	8	8	7	7.33
Grasping	100	100	87.63	92.15	86.52	87.53
Smoothness						
Number of Peaks Speed	0.00064	0.00067	0.00071	0.00036	0.00055	0.00037

Based on the kinematic variables tabulated in Table 3 which represent Draw I assessment modules, P1 obtained the closest data to a healthy subject for most of the kinematic variables and has been given the highest MAS score among the other patients by the therapist. However, some kinematic variables readings were not consistent with their MAS score. For examples, it can be seen through the movement pattern of the patients. P5 scored the lowest trajectory error compared to P3 and P4. But the MAS score given by physiotherapy for P5 is lower than P3 and P4. This might be happened due to the performance inequality by subject for each assessment trial. The assessment tasks include only linear reaching, forearm pronation/supination movement and hand grasping force. The stroke patients had trouble performing some of these movements because of disability and therefore activated other movements that were not related to the tasks. For example, they activated elbow, wrist flexion/extension and body movements to help them reach the target. The result from this study shows there were some conflicts between robot score and MAS score given by the therapies. This maybe cause by the movement of the patient's shoulder during performing the assessment using rehabilitation device. The extracted data form rehabilitation device shows that the patient's arm has reached a maximum reaching distance of 150 mm, instead the patient can only move the arm less than 150 mm. This happens because patients compensate their upper limb by moving their shoulder in order to reach the 150 mm target.

3.2 Shoulder Movement

Experiment has been conducted to measure the distance of shoulder's movement or compensatory movement using measurement tape. Then, the distance of the movement is validated by forward kinematic equations and trigonometry equations. Table 4 shows the compensatory distance during reaching movement performed by a healthy subject. The results show the value of the shoulder movement distance that has been calculated by forward kinematic and trigonometry equation are the same. As stipulated in the experiment protocol, the subject should perform reaching activities by simply moving the arms without moving the shoulders. As a result, normal movement without compensating the shoulder position is constant at 0 mm either from the measurement tape reading or from mathematical calculations. Furthermore, the value from measuring tape were closed to the value from mathematical equation as the subject balances the upper limb during reaching movement at 150 mm.

Table 4 - Shoulder Movement Distance During Reaching Movement

y_{game} (mm)	α (º)	Shoulder Movement Distance		
		y_{ex} (mm)	y_{fkin} (mm)	y_{tri} (mm)
0	90	0	0	0
150	140.6	0	0	0
150	116.9	55	54.6	54.6
150	92.6	139	138.8	138.8

Abbreviations: $Reach_{game}$, Game reaching position; α, Elbow angle; y_{ex}, y-axis during experiment; y_{fkin}, y-axis calculated using forward kinematic; y_{tri}, y-axis calculated using trigonometry;

As a result, this shows that the shoulder movement reading in this experiment has been validated by the mathematical equation. Since these two mathematical equations produce the same value, one of these equations can be used data analysis in the future. In addition, by knowing the shoulder movement distance during the assessment process, the actual value of the reaching movement performed by the subject can also be known. Therefore, by implementing this calculation method, the kinematic variables can be calculated using the actual value of the reaching movement performed by patients as well as improving the prediction of the clinical scores.

3.3 Performance of Assessment

The best combination of kinematic variables was determined using LOOCV approach. The error between the estimated value of the unused data point and the actual value was calculated as root mean square error of LOOCV ($RMSE_{cv}$). The combination that produced the least $RMSE_{cv}$ value was selected using an exhaustive search of all possible combinations. The $RMSE_{cv}$ values derived from LOOCV process tabulated in Table 5 and Table 6 below.

Table 5 - Combination of Kinematic Variables Before Implementing Shoulder Movement

Comb. of variables	Draw I		Draw Diamond		Draw Circle	
	Kinematic variables	$RMSE_{cv}$	Kinematic variables	$RMSE_{cv}$	Kinematic variables	$RMSE_{cv}$
4	Movement time, Stability time, Peak velocity, Grasping	1.6857	Stability time, Peak velocity, Time to peak velocity, Trajectory error	1.3530	Stability time, Reaction time, Mean velocity, Target Reached	1.8077

Table 6 - Combination of Kinematic Variables After Implementing Shoulder Movement

Comb. of variables	Draw I		Draw Diamond		Draw Circle	
	Kinematic variables	$RMSE_{cv}$	Kinematic variables	$RMSE_{cv}$	Kinematic variables	$RMSE_{cv}$
4	Stability time, Peak velocity, Hit-wall score, Trajectory error	1.1084	Stability time, Peak velocity, Number of peaks speed, Target Reached	1.1560	Stability time, Reaction time, Hit-wall score, Number of peaks speed	1.2430

Based on Table 5 and Table 6, the LOOCV results show that $RMSE_{cv}$ values were smaller for all assessment modules after implementing shoulder movement calculation. The selected four kinematic variables will be used as the input predictors for MLR predictive model, and the performance of the assessment was observed based on the value of $RMSE_v$ and R^2. The performance of the MLR predictive model shown in Table 7 and Table 8 for before and after implementing the shoulder movement respectively.

Table 7 - Performance of Assessment Before Implementing Shoulder Movement

Assessment Module	Data Set		Correlation Coefficient		RMSE	
	Training	Validation	R_t^2	R_v^2	$RMSE_t$	$RMSE_v$
Draw I	10	5	0.9618	0.9226	0.9782	1.4472
Draw Diamond	10	5	0.9618	0.9248	0.9783	1.3794
Draw Circle	10	5	0.9519	0.9010	1.0970	1.7188

Abbreviations: R_t^2, Correlation coefficient of training; R_v^2, Correlation coefficient of validation; $RMSE_t$, Root Mean Squared Error of training; $RMSE_v$, Root Mean Squared Error of validation;

Table 8 - Performance of Assessment After Implementing Shoulder Movement

Assessment Module	Data Set		Correlation Coefficient		RMSE	
	Training	Validation	R_t^2	R_v^2	$RMSE_t$	$RMSE_v$
Draw I	10	5	0.9880	0.9563	0.5478	1.2984
Draw Diamond	10	5	0.9832	0.9510	0.6490	1.2768
Draw Circle	10	5	0.9772	0.9458	0.7557	1.1886

Abbreviations: R_t^2, Correlation coefficient of training; R_v^2, Correlation coefficient of validation; $RMSE_t$, Root Mean Squared Error of training; $RMSE_v$, Root Mean Squared Error of validation;

Based on Table 7, Draw Diamond module scored the best prediction result ($RMSE_v$=1.3794, R_v^2 =0.9248) followed by Draw I module ($RMSE_v$=1.4472, R_v^2 =0.9226) and Draw Circle module ($RMSE_v$=1.7188, R_v^2 =0.9010). Based on Table 8, Draw Circle module scored the best prediction result ($RMSE_v$=1.1886, R_v^2 =0.9458) followed by Draw Diamond module ($RMSE_v$=1.2768, R_v^2 =0.9510) and Draw I module ($RMSE_v$=1.2984, R_v^2 =0.9563). Comparison between the performance of prediction before and after implementing shoulder movement calculation showed that the performance of Draw I modules has increased 10.28% of $RMSE_v$ value and 3.65% of R_v^2 value after implementing the shoulder movement calculation. In addition, the performance of prediction for Draw Diamond module has improved by 7.44% of $RMSE_v$ value and 2.83% of R_v^2 value while the performance of prediction for Draw Circle module also has improved by 30.85% of $RMSE_v$ value and 4.97% of R_v^2 value after implementing the shoulder movement calculation. The results show that the performance of prediction for all assessment modules have better prediction accuracy after implementing the shoulder movement calculation. This shows that by implementing the shoulder movement calculation method to identify kinematic variables based on the actual value of the reaching movement may improve the prediction of the clinical scores.

4. Conclusion

A study has been conducted using developed assessment devices to predict the clinical scale score using Multiple Linear Regression (MLR). Furthermore, the hardware for measuring elbow angle have been developed in order to calculate the shoulder movement perform by patient during the assessment process. In addition to that, the shoulder movement calculation method has been proposed and validated. The results show that the performance of prediction for all assessment modules have been increased after implementing the shoulder movement calculation. It is recommended this calculation method to be used in conjunction with kinematic variables to increase the effectiveness and accuracy of the robotic assessment. Larger data sets are also needed for more representative findings in predicting clinical scores.

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