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Linear and Non-Linear Predictive Models in Predicting Motor Assessment Scale of Stroke Patients Using Non-Motorized Rehabilitation Device

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Abstract: Various predictive models, both linear and non-linear, such as Multiple Linear Regression (MLR), Partial Least Squares (PLS), and Artificial Neural Network (ANN), were frequently employed for predicting the clinical scores of stroke patients. Nonetheless, the effectiveness of these predictive models is somewhat impacted by how features are selected from the data to serve as inputs for the model. Hence, it's crucial to explore an ideal feature selection method to attain the most accurate prediction performance. This study primarily aims to evaluate the performance of two non-motorized three-degree-of-freedom devices, namely iRest and ReHAD using MLR, PLS and ANN predictive models and to examine the usefulness of including a hand grip function with the assessment device. The results reveal that ReHAD coupled with non-linear model (i.e. ANN) has a better prediction performance compared to iRest and at once proving that by including the hand grip function into the assessment device may increase the prediction accuracy in predicting Motor Assessment Scale (MAS) score of stroke subjects. Furthermore, these findings imply that there is a substantial association between kinematic variables and MAS scores, and as such the ANN model with a feature selection of twelve kinematic variables can predict stroke patients' MAS scores.

Keywords: Artificial neural network, grip strength, multiple linear regression, partial least square, upper limb

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1. Introduction

Stroke often leads to upper limb motor impairment, a condition that substantially curtails functional abilities and significantly diminishes the quality of life for stroke survivors [1–4]. This upper limb impairment directly affects self-sufficiency in everyday tasks, discharge destination, resuming work, emotional well-being, and overall quality of life due to motor limitations [5–7]. To address upper limb disability, it is crucial for stroke patients to engage in rehabilitation focused on the upper limb. The core objective of upper limb rehabilitation is to restore functional arm usage, enabling individuals to perform meaningful activities in their daily routines. The improved motor function also helps patients experiencing greater satisfied, heightened independence, and an overall improvement in their quality of life [8].

Various clinical scales such as Motor Assessment Scale (MAS) [9, 10], Fugl-Mayer Assessment (FMA) [11, 12], and Manual Muscle Test (MMT) [13, 14] are frequently adopted by therapists to evaluate the motor function of stroke patients throughout the rehabilitation program. Nonetheless, due to time constraints and limited resources, evaluating motor function with traditional clinical scales is challenging [15]. Moreover, the methods for scoring often exhibit subjectivity, demonstrate limited reliability, and rely significantly on the skill of proficient physiotherapists, leading to approximate evaluations of motor function [9, 16]. Over the past years, various assessment devices for upper limb stroke rehabilitation have emerged, aiming to support physiotherapists throughout the rehabilitation program [17–22]. These devices offer an accurate assessment of a motor sensory function of patients, enhancing the efficacy of the rehabilitation program [15, 23]. Kinematic variables generated by the device were employed as input predictor throughout the multivariate analysis to predict the clinical score of stroke patients [15].

Different sorts of multivariate analysis approaches can be used to extract the important part of the information from a huge dataset in order to forecast the clinical scale scores. Multiple Linear Regression (MLR), Partial Least Squares (PLS), and Artificial Neural Network (ANN) algorithms have become popular techniques for deriving a linear or non-linear input-output model from a provided dataset [24]. Nonetheless, the efficacy of the model is partially contingent upon the feature selection method employed. Hence, it is important to investigate an effective feature selection method for achieving the best prediction performance. In addition, various type of kinematic variables has been used as pivotal parameter to predict the clinical scores of stroke patients [23]. Grip strength is one of the kinematic variables required to assess upper limb performance. Therefore, it becomes necessary to investigate the potential effectiveness of integrating a hand grip function into the non-motorized assessment device.

The principal objective of this study is to evaluate the performance of two non-motorized with three-degree-of-freedom devices (iRest and ReHAD) using linear and non-linear predictive models and to examine the usefulness of including a hand grip function with the assessment device. The paper aims (i) to develop MLR, PLS, and ANN predictive models for predicting the MAS score of stroke subjects, (ii) to determine an effective feature selection method used in conjunction with predictive models for producing high prediction performance, (iii) to evaluate the prediction performance of iRest and ReHAD based on the root mean squared error (RMSE) and the coefficient of determination (R^2).

2. Research Method

The participants for this study were chosen by the occupational therapists at SOCSO Tun Razak Rehabilitation Centre using specific inclusion criteria. These criteria included individuals who had experienced a stroke, had limited arm and hand movements, and had impaired hand function that affected their ability to perform typical activities of daily living (with a minimum MAS score of 3 for upper arm function). All subjects received daily conventional physiotherapy during the rehabilitation program. The motor sensory performance of each individual was assessed using the MAS at the completion of the study. Fig. 1 illustrates the research methodology's overall framework. The original data collected from the assessment device will undergo analysis during the feature extraction phase, resulting in twelve kinematic variables. Subsequently, multivariate analysis will be employed to model the data and predict the MAS scores of each stroke subject.

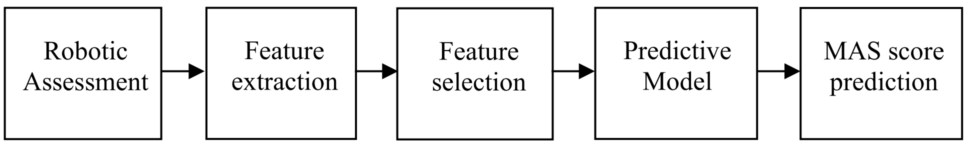

Fig. 1 - The process flows of MAS score prediction

2.1 Robotic Assessment

Two types of assessment devices, namely iRest and ReHAD were utilized in this study for assessing the upper limb performance of stroke subjects. Both assessment devices were devoid of motors and had three-degree-of-freedom, encompassing actions such as hand reaching, forearm manipulation, and hand grasping. The grasping mechanism for iRest has been designed to assess hand opening/closing movement [25]. The problem faced with iRest was the moving fixture of the grasping mechanism can opening/closing itself during forearm pronation/supination position due to gravity. Thus, it does not allow the voluntary movement of forearm manipulation. Several research endeavors have indicated a positive correlation between grip strength and both motor function and the performance in activity of daily living [26, 27]. Since grip strength is necessary for assessing the upper limb function [28], the grasping mechanism for ReHAD was designed to overcome the shortcomings of iRest by replacing the opening/closing function with the hand grip function for assessing hand grip strength of the stroke subject. Fig. 2 shows the grasping mechanism for iRest and ReHAD. This study takes into account the effect of body movement hence it will influence the performance prediction [29].

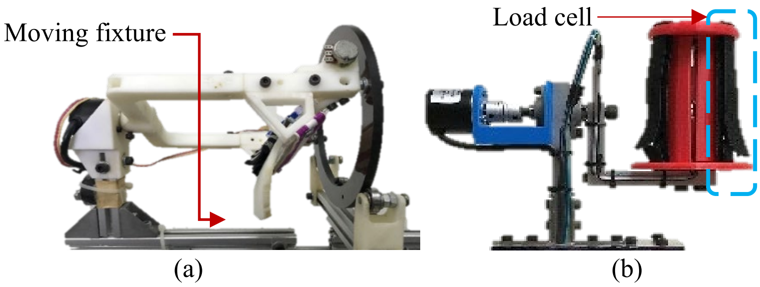

Fig. 2 - Grasping mechanism (a) iRest; (b) ReHAD

Fifty subjects who had experienced strokes (comprising 36 males and 14 females) and presented with upper limb impairment took part in a half-hour robotic assessment, where ten minutes were allocated for each assessment module. Subjects need to undergo three trials for each assessment module, starting with Draw Capital I (Draw I), Draw Diamond (Draw D), and Draw Circle (Draw C), where the experiment design implemented in this study was identical to the prior study [16, 25]. Upon completion of the assessment process, the data pertaining to each subject such as position, time and grip force were extracted from the assessment device. A dataset consisting of 150 samples was generated following the assessment process conducted on a sample of 50 stroke subjects.

2.2 Feature Extraction

The feature extraction phase was executed using MATLAB software to generate twelve kinematic variables from the raw data extracted from the assessment device. These variables encompassed reaction time, total movement time, stability time, time to peak velocity, mean velocity, peak velocity, target reached, trajectory error, hit-wall score, path ratio, grasping, and number of peaks speed. These kinematic variables were extracted because the kinematic parameters obtained through out the robotic assessment reflect the motor performance of stroke patients. The computation methods for the kinematic variables were based on the prior study [16, 30].

2.3 Feature Selection

The concept of feature selection pertains to identifying the optimal amalgamation of predictor variables that holds the greatest influence on the predictive model. A study using a 3R horizontal robot showed that by using all kinematic variables as input predictors for the ANN model was able to produce high predictive performance [31]. In addition, a study conducted utilizing Kinect employed over twelve predictors in the ANN model, yielding substantial predictive performance in estimating the FMA clinical score of stroke subjects [32]. Other studies have found that the combination of four kinematic variables exhibited sufficient strength to yield a robust regression model with favorable predictive performance [16, 33]. Moreover, a study was carried out utilizing MIT-Manus, wherein four kinematic variables were employed as predictors for the MLR model resulting the best prediction performance [34]. Other than that, a research utilized univariate regression to determine the input predictor for the multiple regression model with a p-value less than 0.2 [35]. However, only the input predictor with a p-value below 0.05 was retained for the final model, as it exhibited a statistically substantial contribution to the regression model.

Within this study, three distinct feature selection methods were observed in order to obtain the best prediction accuracy of the MAS score. Since this study extracted twelve kinematic variables from the assessment device, all twelve kinematic variables were utilized as the first feature selection method for the predictive model. Moreover, the optimal sets of four kinematic variables were employed as the secondary feature selection method for evaluating the effectiveness of the multivariate model for predicting the MAS scores. The combination was determined via the implementation of the leave-one-out cross-validation method. One point of the data was sequentially released, and the remaining data were utilized to train the predictive model. Subsequently, the RMSE was calculated contrasting the predicted MAS score of the unused data point against the actual MAS score. A set of four kinematic variables that resulted the lower RMSE value was selected using a comprehensive search of all conceivable combinations. As the third feature selection method, the combinations of kinematic variables with $p < 0.05$ have been selected for evaluating the performance of the multivariate model for MAS score prediction.

2.4 Multiple Linear Regression

Multiple Linear Regression (MLR) is the most fundamental and straightforward approach for experimental analysis and data processing in analytical contexts. It serves as a sophisticated statistical approach for elucidating correlations between multiple input predictors and a single response variable [36, 37]. The response variables y exhibit linear correlations with multiple predictor variables. The following describes the multiple linear regression model in Eq. (1).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

where, y represents the response variable, x symbolizes the predictor variables, β_0 denotes the bias, while $\beta_1, \beta_2, \ldots, \beta_n$ correspond to the coefficient of predictor variables. These values are determined through the process of training the samples. The majority of studies that have used MLR to predict upper limb performance in stroke rehabilitation have found a strong correlation between the MLR and the clinical scales [9, 33, 36]. In this study, the data sets were divided into two, which allocated 100 data sets for training and 50 data sets for testing. The training data sets were used to train the MLR model, whereas testing data sets were used to determine the accuracy of the MLR model to predict the MAS score of stroke patients.

2.5 Partial Least Squares Regression

The general idea behind Partial Least Squares (PLS) modeling is to partition the design matrix predictor X and matrix response Y as Eqs. (2) and (3). X denotes a $n \times m$ predictor matrix, and Y signifies a $n \times p$ response matrix. Additionally, matrices T and U, both with dimensions $n \times l$ represent the score projections for X and Y correspondingly. Matrices P ($m \times l$) and Q ($p \times l$) stand as orthogonal loading matrices. The algorithms will produce the PLS regression estimates B and Bo following the estimation of the loading and factor matrices T, U, P, and Q for the linear regression, as outlined in Eq. (4).

$$X = TP^T \tag{2}$$

$$Y = UQ^T \tag{3}$$

$$Y = XB + B_o \tag{4}$$

where B and B_o represent the regression coefficient of the PLS model. In this study, the regression coefficients were computed by using the MATLAB matrix routine's function. PLS components ranging from one until twelve were analyzed to optimize the accuracy of the MAS score predictions. The data sets for the PLS model were divided into training and testing samples (100 and 50 data set respectively).

2.6 Artificial Neural Network

The Artificial Neural Network (ANN) stands as the prevalent choice for non-linear prediction due to its ability to capture intricate non-linear associations between predictor variables and the response variable. The configuration of the ANN model encompasses the input layer, hidden layer, and output layer, all interlinked to one another in a complete connection. The signal was transmitted from the input layer to the output layer via the intermediary hidden layer. The connection between the nodes is known as weights, and there is an additional bias input in both the hidden and output layers. Fig. 3 depicts the feed forward back propagation of the 12-1-1 ANN model.

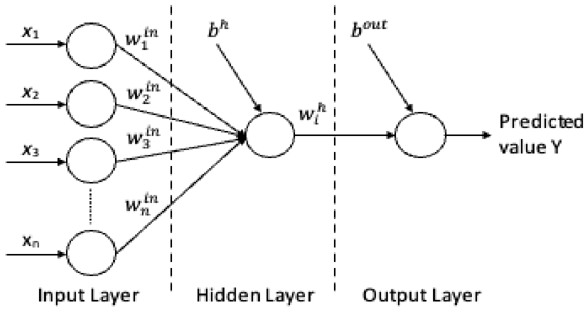

Fig. 3 - Feed forward back propagation ANN for MAS score prediction

The input of the ith node hidden layer ($HSum_h$) is calculated using Eq. (5). The output of the hidden layer node ($HSum_{hout}$) is determined using Eq. (6). The weighted sum of the output layer ($OSum_{out}$) is derived through the utilization of Eq. (7).

$$HSum_h = \sum_{i=1}^{n} x_i^{in}\, w_i^{in} + b_i^h \tag{5}$$

$$HSum_{hout} = f(HSum_h) \tag{6}$$

$$OSum_o = f\left(\sum_{i=1}^{n} x_i^h\, w_i^h + b_i^{out}\right) \tag{7}$$

where $1 \leq i \leq n$, x_i^{in} denotes the input value, w_i^{in} represents the weight of the input layer, and b_i^h stands for the bias of the input layer. The activation function for this layer is denoted as *f*. For achieving accuracy, a single hidden layer is adequate for approximating any non-linear function effectively [38]. Within this research, the exploration of hidden nodes in the hidden layer ranged from one to ten, aiming to enhance the precision of MAS score predictions. Additionally, tangent sigmoid activation function has been applied within the hidden and output layer of the ANN model. The data sets for the ANN model were divided into three including training, validation, and testing samples (100, 25, and 25 data sets respectively).

3. Result

This section addresses the comprehensive findings of this study, encompassing the outcomes of the MLR, PLS, and ANN predictive models, incorporating the three distinct feature selection techniques explored in this study. A comparison between all predictive models with the best feature selection method for iRest and ReHAD were discussed at the end of this section.

3.1 Multiple Linear Regression

The results of root mean squared error ($RMSE_{tr}$) and coefficient of determination (R_{tr}^2) of training data sets were slightly better compared to testing data sets. The performance of the MLR model was observed from the root mean squared error ($RMSE_{te}$) and coefficient of determination (R_{te}^2) of testing data sets . Table 1 and Table 2 exhibit the MLR predictive model's performance for iRest and ReHAD correspondingly. In accordance with Table 1, for each assessment module employing iRest, all feature selection methods have $RMSE_{te}$ values lower than 3.3. In the context of the first feature selection approach, which encompassed the incorporation of twelve kinematic variables in the regression analysis, the Draw I module demonstrated superior predictive precision ($RMSE_{te}$=2.6232, R_{te}^2=0.7921) on contrast to the other two modules. Furthermore, in the second feature selection approach, the prediction performance of the Draw C module ($RMSE_{te}$=3.1015, R_{te}^2=0.6934) was improved while the other two modules were dropped. In the third approach to feature selection, which involved retaining only kinematic variables with a p-value below 0.05 as predictors for the MLR model, the Draw I module showcased the most remarkable predictive capability ($RMSE_{te}$=2.5952, R_{te}^2=0.7882), trailed by the Draw C and Draw D modules. The evaluation of the MLR model with iRest demonstrated that the third feature selection method has outstanding performance, with two of the three assessment modules performing well in the regression analysis.

Table 1 - The performance of MLR model for iRest

Features selection	Module	Training		Testing	
		$RMSE_{tr}$	R_{tr}^2	$RMSE_{te}$	R_{te}^2
All kinematic variables	Draw I	2.4846	0.8001	2.6232	0.7921
	Draw D	2.6755	0.7683	2.8553	0.7374

	Draw C	2.3388	0.8228	3.2943	0.6642
Best combinations of 4 kinematic variables	Draw I	2.5763	0.7852	2.6379	0.7758
	Draw D	2.7717	0.7513	2.8968	0.7312
	Draw C	2.4422	0.8069	3.1015	0.6934
Kinematic variables with p_value < 0.05	Draw I	2.5253	0.7935	2.5952	0.7882
	Draw D	2.7072	0.7627	2.8945	0.7305
	Draw C	2.7325	0.7583	2.7544	0.7550

Table 2 - The performance of MLR model for ReHAD

Features selection	**Module**	**Training**		**Testing**	
		$RMSE_{tr}$	R^2_{tr}	**$RMSE_{te}$**	R^2_{te}
All kinematic variables	Draw I	1.4948	0.9166	2.1968	0.8221
	Draw D	1.9117	0.8636	2.5538	0.7592
	Draw C	2.0198	0.8477	2.1606	0.8276
Best combinations of 4 kinematic variables	Draw I	1.9273	0.8614	1.9591	0.8571
	Draw D	2.2883	0.8046	2.5173	0.7672
	Draw C	2.1082	0.8341	2.3366	0.7997
Kinematic variables with p_value < 0.05	Draw I	1.8975	0.8656	1.9228	0.8623
	Draw D	2.0603	0.8416	2.6136	0.7477
	Draw C	2.0404	0.8446	2.1756	0.8268

As indicated in Table 2, the Draw C module outperformed the other two modules with regard to the prediction performance ($RMSE_{te}$=2.1968, R^2_{te}=0.8221) when employing the first feature selection approach, which encompassed all kinematic variables within the regression analysis. In contrast, the Draw D module exhibited the least accurate prediction, characterized by a higher $RMSE_{te}$ value and the lowest R^2_{te} value. Under the second approach of feature selection, wherein only the top four kinematic variables were chosen as predictors for the MLR model, the Draw I module delivered the most favorable predictive outcome ($RMSE_{te}$=1.9591, R^2_{te}=0.8571). Among the many feature selection methods employed, the third approach involved retaining only kinematic variables with a p-value below 0.05 for the purpose of regression analysis. Notably, the Draw I module had the most superior predictive ability, as seen by its $RMSE_{te}$ value of 1.9228 and R^2_{te} value of 0.8623. Subsequently, the Draw C and Draw D modules followed suit in terms of prediction performance. The MLR model's prediction performance for ReHAD was evaluated, and it was observed that the third feature selection approach exhibited outstanding results. Specifically, two out of three assessment modules achieved the maximum prediction accuracy in the regression analysis. Overall, the findings of the multiple linear regression (MLR) model indicate that ReHAD exhibits superior performance in evaluating the upper limb performance of stroke subjects when compared to iRest.

3.2 Partial Least Square Regression

The performance of the PLS predictive model was evaluated based on the value of $RMSE_{te}$ and R^2_{te}. The accuracy of the Partial Least Squares (PLS) predictive model is seen in Table 3 and Table 4, which present the results for iRest and ReHAD, respectively. Most of the outcomes generated by the Partial Least Squares (PLS) prediction model exhibit greater accuracy in comparison to the Multiple Linear Regression (MLR) prediction model. However, some results are similar to the MLR prediction model due to the number of PLS components is maximum corresponding to the number of kinematic variables as an input predictor depending on the type of feature selection method.

Table 3 - The performance of PLS model for iRest

Features selection	**Module**	**PLS Comp**	**Training**		**Testing**	
			$RMSE_{tr}$	R^2_{tr}	**$RMSE_{te}$**	R^2_{te}
All kinematic variables	Draw I	3	2.4914	0.8006	2.5543	0.7991
	Draw D	4	2.6965	0.7646	2.8364	0.7409
	Draw C	2	2.6403	0.7743	2.9637	0.7177
Best combinations of 4 kinematic variables	Draw I	2	2.5890	0.7830	2.6354	0.7818
	Draw D	3	2.7718	0.7513	2.8948	0.7315
	Draw C	4	2.4422	0.8069	3.1015	0.6934
Kinematic variables with p_value < 0.05	Draw I	4	2.5258	0.7935	2.5905	0.7893
	Draw D	3	2.7681	0.7519	2.8528	0.7390
	Draw C	3	2.7143	0.7615	2.7383	0.7606

Table 4 - The performance of PLS model for ReHAD

Features selection	Module	PLS Comp	Training		Testing	
			$RMSE_{tr}$	R^2_{tr}	$RMSE_{te}$	R^2_{te}
All kinematic variables	Draw I	3	1.7525	0.8854	2.1198	0.8334
	Draw D	3	1.9924	0.8518	2.5079	0.7675
	Draw C	4	2.0388	0.8449	2.1238	0.8331
Best combinations of 4 kinematic variables	Draw I	4	1.9273	0.8614	1.9591	0.8571
	Draw D	4	2.2883	0.8046	2.5173	0.7672
	Draw C	4	2.1082	0.8341	2.3366	0.7997
Kinematic variables with p_value < 0.05	Draw I	6	1.8976	0.8656	1.9205	0.8627
	Draw D	4	2.0823	0.8382	2.5806	0.7539
	Draw C	4	2.0538	0.8426	2.1392	0.8318

According to the data presented in Table 3, the initial feature selection approach that used all kinematic variables as predictors for the Partial Least Squares (PLS) model yielded the most accurate prediction results. Specifically, the Draw I module featuring a PLS component of 3 achieved the highest prediction performance, as seen by its $RMSE_{te}$ value of 2.5543 and R^2_{te} value of 0.7991. Additionally, Draw I module also demonstrated remarkable prediction performance ($RMSE_{te}$=2.6354, R^2_{te}=0.7818) in the second feature selection approach, which involved selecting only the best four kinematic variables as predictor variables. Nevertheless, the performance of the second feature selection method, which encompasses all assessment modules, has exhibited a decline in comparison to the first feature selection method. The performance of the third feature selection approach showed improvement across all assessment modules in comparison to the second feature selection approach. Moreover, it is worth noting that Draw I exhibited the most favorable prediction outcome ($RMSE_{te}$=2.5905, R^2_{te}=0.7893), thus indicating that Draw C and Draw D modules had comparatively lower performance in terms of prediction accuracy. The PLS model's performance for iRest demonstrated that the first feature selection method yielded exceptional outcomes, with two out of the three assessment modules scoring the highest prediction accuracy in the regression analysis.

Based on Table 4, the Draw I module featuring a PLS component score of 3 demonstrates superior predictive ability ($RMSE_{te}$=2.1198, R^2_{te}=0.8334) in contrast to the other modules when utilizing the first feature selection approach. The second approach of feature selection, which selected the best set of four kinematic variables as predictors, Draw I module featuring a PLS component of 4 yielded the best performance ($RMSE_{te}$=1.9591, R^2_{te}=0.8571). The Draw C and Draw D modules also performed well in terms of prediction accuracy. There was a similarity of results for all assessment modules in the second feature selection approach with the MLR predictive model. This happened due to the number of PLS components was equal to the number of predictor inputs for the predictive model. In the context of the third feature selection approach, which exclusively incorporated kinematic variables with a p-value below 0.05 into the regression analysis, the Draw I module demonstrated the highest predictive proficiency ($RMSE_{te}$=1.9205, R^2_{te}=0.8627), trailed by the Draw C and Draw D modules. The prediction performance of the PLS model with ReHAD showed that the first feature selection approach performed remarkably well, with two out of the three assessment modules getting the best prediction accuracy in the regression analysis. Overall, the results of the PLS predictive model indicated that ReHAD displays superior prediction performance in assessing stroke subjects' upper limb performance compared to iRest.

3.3 Artificial Neural Network

The training data sets exhibited marginally better results in terms of root mean squared error ($RMSE_{tr}$) and coefficient of determination (R^2_{tr}) as compared to the testing data sets. The performance of the ANN model was examined from the value of $RMSE_{te}$ and R^2_{te} of testing data sets. Table 5 and Table 6 exhibit the ANN predictive model's performance in relation to iRest and ReHAD respectively.

Table 5 - The performance of ANN model for iRest

Features selection	Module	Hn	Training		Testing	
			$RMSE_{tr}$	R^2_{tr}	$RMSE_{te}$	R^2_{te}
All kinematic variables	Draw I	8	1.3485	0.9414	1.4108	0.9335
	Draw D	10	1.3295	0.9431	1.4687	0.9416
	Draw C	6	1.1894	0.9544	1.2593	0.9465
Best combinations of 4 kinematic variables	Draw I	10	1.2282	0.9517	1.4469	0.9435
	Draw D	8	1.5265	0.9247	1.6104	0.9135
	Draw C	10	1.3596	0.9402	1.4374	0.9306
Kinematic variables with p_value < 0.05	Draw I	6	1.4161	0.9353	1.5732	0.9201
	Draw D	3	1.2566	0.9497	1.4014	0.9338
	Draw C	9	1.4891	0.9290	1.5161	0.9224

Table 6 - The performance of ANN model for ReHAD

Features selection	Module	Hn	Training		Testing	
			$RMSE_{tr}$	R^2_{tr}	$RMSE_{te}$	R^2_{te}
All kinematic variables	Draw I	7	1.0398	0.9604	1.2234	0.9526
	Draw D	7	0.8271	0.9745	1.0520	0.9619
	Draw C	6	0.6501	0.9848	1.1044	0.9583
Best combinations of 4 kinematic variables	Draw I	7	1.3055	0.9377	1.4260	0.9296
	Draw D	10	0.9917	0.9636	1.1152	0.9570
	Draw C	7	1.2292	0.9436	1.4627	0.9253
Kinematic variables with p_value < 0.05	Draw I	10	1.2418	0.9431	1.4838	0.9250
	Draw D	10	0.9074	0.9694	1.2930	0.9428
	Draw C	7	0.9335	0.9676	1.0873	0.9606

Based on the findings shown in Table 5, it can be observed that all feature selection methods yielded $RMSE_{te}$ values below 2.0 and R^2_{te} values exceeding 0.9 for each assessment module when using iRest. In the regression study, the first feature selection approach utilized twelve kinematic variables as predictors for the ANN model. Among the three modules, the Draw C module with a hidden neuron of 6 demonstrated the most accurate prediction results, as indicated by a $RMSE_{te}$ value of 1.2593 and R^2_{te}value of 0.9465. In the second feature selection approach, the Draw C module exhibits the most favorable prediction outcome ($RMSE_{te}$=1.4374, R^2_{te}=0.9306), trailed by the Draw I and Draw D modules. However, the R^2_{te} for the Draw I module (0.9435) was higher compared to the Draw C module. For this situation, the selection of best performance was selected based on $RMSE_{te}$ since RMSE is an absolute measure of fit. When comparing all assessment modules engaged in the third feature approach method, the Draw D module with a hidden neuron of 3 has the highest prediction performance ($RMSE_{te}$=1.4014, R^2_{te}=0.9338). The performance of the ANN model for iRest shows that the first feature selection approach has higher performance by 66.67% in contrast to other two feature selection methods involved.

According to the data presented in Table 6, the Draw D module with a hidden neuron of 7 scored the highest prediction performance ($RMSE_{te}$=1.0520, R^2_{te}=0.9619) in contrast to the other two modules in the first feature selection method. The second method of feature selection, which selected the best four kinematic variables as predictors, Draw D module with a hidden neuron of 10 yielded the best performance ($RMSE_{te}$=1.1152, R^2_{te}=0.9570). In contrast to the other assessment modules employed, the Draw C module exhibits the poorest performance, as evidenced by its notably lower values of $RMSE_{te}$ and R^2_{te}. However, the Draw C module with a hidden neuron of 7 demonstrates remarkable predictive capabilities ($RMSE_{te}$=1.0873, R^2_{te}=0.9606) in the third feature selection method trailed by Draw D and Draw I modules. The findings of the ANN model's performance for ReHAD indicate that the first feature selection method exhibited exceptional performance. Specifically, 66.67% of the assessment module scored the highest prediction results, surpassing the outcomes achieved by the other two feature selection approach employed in the study. In general, the outcomes from the ANN predictive model indicate that ReHAD exhibits admirable performance in evaluating upper limb performance among stroke patients, as compared to iRest.

4. Discussion

The feature selection method plays an important role in improving the predictive accuracy of the predictive models. In this study, three distinct feature selection approaches are utilized to identify the optimal prediction accuracy for the MAS score. The findings of the predictive analysis highlight that the first feature selection approach, which incorporates twelve kinematic variables in the regression analysis, has superior performance with a 56% advantage over alternative methods. This is due to the fact that all of the kinematic variables that were recorded throughout the assessment contribute to highlight significant information regarding the motor performance of the stroke subject [23]. Each kinematic variable holds its own distinct substantial input for analyzing the upper limb performance based on the three basic hand functions (hand reaching, forearm manipulation, and grasping). Therefore, it is noteworthy that incorporating all twelve kinematic variables as input predictors in the predictive model could potentially enhance the precision in predicting the MAS score of stroke subjects. Table 7 shows the performance of all predictive models for ReHAD.

Table 7 - The performance of predictive models with the first feature selection method for ReHAD

	MLR			PLS			ANN		
	Draw I	**Draw D**	**Draw C**	**Draw I**	**Draw D**	**Draw C**	**Draw I**	**Draw D**	**Draw C**
RMSE	2.1968	2.5538	2.1606	2.1198	2.5079	2.1238	1.2234	1.0520	1.1044
R^2	0.8221	0.7592	0.8276	0.8334	0.7675	0.8331	0.9526	0.9619	0.9583

In this study, two types of linear predictive models (MLR and PLS) and a non-linear predictive model (ANN) have been used to predict MAS scores. The results demonstrate that the performance of the PLS predictive model is marginally better than that of the MLR predictive model. The use of eigenvectors for the predictor variables ensures that the corresponding scores not only fully explain the variance of the predictor variables but also have a high correlation with the response variables, which gives PLS predictive model an advantage over MLR predictive model. However, the outcomes also corroborate the conclusions drawn in a prior study that the ANN predictive model outperformed the PLS predictive model in terms of prediction performance [39]. This could be because of the presence of non-linear information within the kinematic variables. Furthermore, the ANN predictive model exhibits a higher prediction accuracy due to its inherent ability to approximate the non-linearity of the system, which is not possible with the PLS model since it is constrained by linearity [40]. This study indicates that the ANN predictive model has better prediction performance compared to MLR and PLS predictive models for both iRest and ReHAD assessment devices. Besides, the MAS score and predicted MAS score have statistically significant ($p < 0.05$) correlations in all cases.

Several studies have indicated a positive correlation between grip strength and motor function, as well as performance in activity of daily living [26, 27]. In MAS, there are some upper limb activities under the hand movement section that require the stroke subject to lift some object such as a cylindrical object, a 5-inch ball, and a polystyrene cup. A certain amount of hand grip strength is required in order to be able to lift the objects. The implementation of the hand grip function in the grasping mechanism makes ReHAD different from iRest, where the grasping mechanism for ReHAD can be used to assess the hand grip force of the stroke subject. Observing Table 6 and Table 7, the findings suggest that ReHAD combined with the ANN predictive model, utilizing all twelve kinematic variables as predictors, exhibits greater resilience in evaluating novel and unobserved test sets samples of kinematic variables. It had been evaluated through the lower value of $RMSE_{te}$ and higher value of R_{te}^2. Moreover, the results of the predictive analysis underscore that by including the hand grip function in the non-motorized three-degree-of-freedom assessment device, may increase the prediction accuracy in predicting the MAS score of stroke subjects.

The results reported herein should be considered in the light of some limitations. This study focuses only on the linear and non-linear predictive models for predicting the clinical score of the stroke subjects. Other types of dedicated predictive models should be examined in order to achieve the best prediction performance on predicting the MAS score. The uses of the hybrid predictive model such as MLR combined with ANN (MLR-ANN) and PLS combined with ANN (PLS-ANN) that considering the linear and non-linearity of the data should be investigated in further studies with the larger sample dataset of stroke patients.

5. Conclusions

A study was carried out utilizing two assessment devices, namely iRest and ReHAD for the purpose of predicting clinical scale scores through MLR, PLS, and ANN predictive models. To summarize, choosing an appropriate feature selection method is important for enhancing the predictive accuracy of the predictive model. Findings show that the feature selection of all kinematic variables as predictors for the predictive model yields commendable prediction performance for both devices. Notably, iRest excels with the Draw C module ($RMSE_{te}$=1.2593, R_{te}^2=0.9465) while ReHAD showcased its peak performance with the Draw D module ($RMSE_{te}$=1.0520, R_{te}^2=0.9619). In addition, the results reveal that ReHAD coupled with ANN predictive model has a better performance of prediction compared to iRest for most assessment modules and at once proving that by including the hand grip function into the non-motorized three-degree-of-freedom assessment device could improve the prediction accuracy in predicting MAS score of stroke subjects.

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References

[1] Ferreira, F. M. R. M., Chaves, M. E. A., Oliveira, V. C., Van Petten, A. M. V. N., & Vimieiro, C. B. S. (2018). Effectiveness of robot therapy on body function and structure in people with limited upper limb function: A systematic review and meta-analysis. Public Library of Science, 13(7), e0200330. https://doi.org/10.1371/journal.pone.0200330

[2] Ang, B. W. K., & Yeow, C. (2019). Design and Characterization of a 3D Printed Soft Robotic Wrist Sleeve with 2 DoF for Stroke Rehabilitation. In 2019 2nd IEEE International Conference on Soft Robotics (RoboSoft) (pp. 577–582). https://doi.org/10.1109/ROBOSOFT.2019.8722771

[3] Zimmermann, Y., Forino, A., Riener, R., & Hutter, M. (2019). ANYexo: A Versatile and Dynamic Upper-Limb Rehabilitation Robot. IEEE Robotics and Automation Letters, 4(4), 3649–3656. https://doi.org/10.1109/LRA.2019.2926958

[4] Chen, Z., Wang, C., Fan, W., Gu, M., Yasin, G., Xiao, S., Huang, J., & Huang, X. (2020). Robot-Assisted Arm Training versus Therapist-Mediated Training after Stroke: A systematic review and meta-analysis. Journal of Healthcare Engineering, 1–10. https://doi.org/10.1155/2020/8810867

[5] Signal, N. E. J., McLaren, R., Rashid, U., Vandal, A., King, M., Almesfer, F., Henderson, J., & Taylor, D. (2020). Haptic Nudges Increase Affected Upper Limb Movement During Inpatient Stroke Rehabilitation: Multiple-Period Randomized Crossover Study. JMIR Mhealth Uhealth, 8(7), e17036. https://doi.org/10.2196/17036

[6] Morris, J. H., van Wijck, F., Joice, S., & Donaghy, M. (2013). Predicting health related quality of life 6 months after stroke: the role of anxiety and upper limb dysfunction. Disability and Rehabilitation, 35(4), 291–299. https://doi.org/10.3109/09638288.2012.691942

[7] Wang, Y.-C., Kapellusch, J., & Garg, A. (2014). Important factors influencing the return to work after stroke. Work, 47, 553–559. https://doi.org/10.3233/WOR-131627

[8] Barbara, B., Y., C. J., W., D. P., J., G. J., D., G. G., C., K. R., Kerri, L., Dean, R., & Richard, Z. (2005). Veterans Affairs/Department of Defense Clinical Practice Guideline for the Management of Adult Stroke Rehabilitation Care. Stroke, 36(9), 2049–2056. https://doi.org/10.1161/01.STR.0000180432.73724.AD

[9] Rahman, H. A. (2016). Non-motorized Three Degree of Freedom Assessment Tool for Stroke Patients. Universiti Teknologi Malaysia.

[10] Barker, R. N., Brauer, S. G., & Carson, R. G. (2008). Training of Reaching in Stroke Survivors With Severe and Chronic Upper Limb Paresis Using a Novel Nonrobotic Device. Stroke, 39(6), 1800–1807. https://doi.org/10.1161/STROKEAHA.107.498485

[11] Colombo, R., Pisano, F., Delconte, C., Mazzone, A., Grioni, G., Castagna, M., Bazzini, G., Imarisio, C., Maggioni, G., & Pistarini, C. (2017). Comparison of exercise training effect with different robotic devices for upper limb rehabilitation: a retrospective study. Eur J Phys Rehabil Med, 53(2), 240–248. https://doi.org/10.23736/s1973-9087.16.04297-0

[12] Rech, K. D., Salazar, A. P., Marchese, R. R., Schifino, G., Cimolin, V., & Pagnussat, A. S. (2020). Fugl-Meyer Assessment Scores Are Related With Kinematic Measures in People with Chronic Hemiparesis after Stroke. Journal of Stroke and Cerebrovascular Diseases, 29(1). https://doi.org/10.1016/j.jstrokecerebrovasdis.2019.104463

[13] Ciesla, N., Dinglas, V., Fan, E., Kho, M., Kuramoto, J., & Needham, D. (2011). Manual Muscle Testing: A Method of Measuring Extremity Muscle Strength Applied to Critically Ill Patients. Journal of visualized experiments : JoVE, 50. https://doi.org/10.3791/2632

[14] Bohannon, R. W. (2019). Considerations and Practical Options for Measuring Muscle Strength: A Narrative Review. BioMed Research International, 2019, 8194537. https://doi.org/10.1155/2019/8194537

[15] Tran, V. D., Dario, P., & Mazzoleni, S. (2018). Kinematic measures for upper limb robot-assisted therapy following stroke and correlations with clinical outcome measures: A review. Med Eng Phys, 53, 13–31. https://doi.org/10.1016/j.medengphy.2017.12.005

[16] Abdul Rahman, H., Khor, K. X., Yeong, C. F., Su, E. L. M., & Narayanan, A. L. T. (2017). The potential of iRest in measuring the hand function performance of stroke patients. Bio-medical materials and engineering, 28(2), 105–116. https://doi.org/10.3233/BME-171660

[17] Ferreira, F. M. R. M., Rúbio, G. de P., Brandão, F. H. de L., Mata, A. M. da, Avellar, N. B. C. de, Bonfim, J. P. F., Tonelli, L. G., Silva, T. G., Dutra, R. M. A., Petten, A. M. V. N. Van, & Vimieiro, C. B. S. (2020). Robotic Orthosis for Upper Limb Rehabilitation. Proceedings, 64(1), 10. https://doi.org/10.3390/IeCAT2020-08519

[18] Zhang, C., Li-Tsang, C. W., & Au, R. K. (2017). Robotic approaches for the rehabilitation of upper limb recovery after stroke: a systematic review and meta-analysis. International journal of rehabilitation research, 40(1), 19–28. https://doi.org/10.1097/mrr.0000000000000204

[19] Mehrholz, J., Pohl, M., Platz, T., Kugler, J., & Elsner, B. (2015). Electromechanical and robot-assisted arm training for improving activities of daily living, arm function, and arm muscle strength after stroke. Cochrane database of systematic reviews, (11), Cd006876. https://doi.org/10.1002/14651858.CD006876.pub4

[20] Veerbeek, J. M., Langbroek-Amersfoort, A. C., van Wegen, E. E., Meskers, C. G., & Kwakkel, G. (2017). Effects of Robot-Assisted Therapy for the Upper Limb After Stroke. Neurorehabilitation and neural repair, 31(2), 107–121. https://doi.org/10.1177/1545968316666957

[21] Bertani, R., Melegari, C., De Cola, M. C., Bramanti, A., Bramanti, P., & Calabro, R. S. (2017). Effects of robot-assisted upper limb rehabilitation in stroke patients: a systematic review with meta-analysis. Neurological sciences, 38(9), 1561–1569. https://doi.org/10.1007/s10072-017-2995-5

[22] Mazlan, S., Abdul Rahman, H., & Hanafi, D. (2020). A Review of Upper Limb Rehabilitation Robot. Journal of Tomography System and Sensor Application, 2(1), 1–8.

[23] Mazlan, S., Abdul Rahman, H., Fai, Y., Ibrahim, B., & Huq, M. (2020). Kinematic variables for upper limb rehabilitation robot and correlations with clinical scales: A review. Bulletin of Electrical Engineering and Informatics, 9(1), 75–82. https://doi.org/10.11591/eei.v9i1.1856

[24] Muhamad Safiih, L., Ramlee, M., Gunalan, S., Zainuddin, N., Zakariya, R., Idris, M., & Khalil, I. (2016). Improved the Prediction of Multiple Linear Regression Model Performance Using the Hybrid Approach: A Case Study of Chlorophyll-a at the Offshore Kuala Terengganu, Terengganu. Open Journal of Statistics, 6, 789–804. https://doi.org/10.4236/ojs.2016.65065

[25] Rahman, H. A., Narayanan, A. L. T., Xiang, K. K., Ming, E. S. L., Fai, Y. C., & Khan, Q. I. (2015). iRest: Interactive rehabilitation and assessment tool. 2015 10th Asian Control Conference (ASCC), 1–6. https://doi.org/10.1109/ASCC.2015.7244656

[26] Stock, R., Thrane, G., Askim, T., Anke, A., & Mork, P. J. (2019). Development of grip strength during the first year after stroke. Journal of rehabilitation medicine, 51(4), 248–256. https://doi.org/10.2340/16501977-2530

[27] Martins, J. C., Aguiar, L. T., Lara, E. M., Teixeira-Salmela, L. F., & Faria, C. D. C. M. (2015). Assessment of grip strength with the modified sphygmomanometer test: association between upper limb global strength and motor function. Brazilian journal of physical therapy, 19(6), 498–506. https://doi.org/10.1590/bjpt-rbf.2014.0118

[28] Kim, D. (2016). The effects of hand strength on upper extremity function and activities of daily living in stroke patients, with a focus on right hemiplegia. Journal of physical therapy science, 28(9), 2565–2567. https://doi.org/10.1589/jpts.28.2565

[29] Mazlan, S. (2021). Effect of Shoulder Movement on Assessing Upper Limb Performance of Stroke Patient, 239–244.

[30] Mazlan, S., Abdul Rahman, H., Ksm KaderIbrahim, B. S., Huq, M. S., & Che Fai, Y. (2022). Non-motorized Rehabilitation Device for Performance Assessment in Upper Limb Stroke Rehabilitation: A Pilot Study. International Journal of Integrated Engineering, 14(4), 323–331. https://doi.org/10.30880/ijie.2022.14.04.024

[31] Fikri, M. A., Abdullah, S. C., & Ramli, M. H. M. (2014). Arm Exoskeleton for Rehabilitation Following Stroke by Learning Algorithm Prediction. Procedia Computer Science, 42, 357–364. https://doi.org/10.1016/j.procs.2014.11.074

[32] Kim, W.-S., Cho, S., Baek, D., Bang, H., & Paik, N.-J. (2016). Upper Extremity Functional Evaluation by Fugl-Meyer Assessment Scoring Using Depth-Sensing Camera in Hemiplegic Stroke Patients. PLOS ONE, 11(7), e0158640. https://doi.org/10.1371/journal.pone.0158640

[33] Zariffa, J., Kapadia, N., Kramer, J. L. K., Taylor, P., Alizadeh-Meghrazi, M., Zivanovic, V., Albisser, U., Willms, R., Townson, A., Curt, A., Popovic, M. R., & Steeves, J. D. (2012). Relationship Between Clinical Assessments of Function and Measurements From an Upper-Limb Robotic Rehabilitation Device in Cervical Spinal Cord Injury. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 20(3), 341–350. https://doi.org/10.1109/TNSRE.2011.2181537

[34] Bosecker, C., Dipietro, L., Volpe, B., & Igo Krebs, H. (2009). Kinematic Robot-Based Evaluation Scales and Clinical Counterparts to Measure Upper Limb Motor Performance in Patients With Chronic Stroke. Neurorehabilitation and Neural Repair, 24(1), 62–69. https://doi.org/10.1177/1545968309343214

[35] Hussain, N., Sunnerhagen, K. S., & Alt Murphy, M. (2019). End-point kinematics using virtual reality explaining upper limb impairment and activity capacity in stroke. Journal of NeuroEngineering and Rehabilitation, 16(1), 82. https://doi.org/10.1186/s12984-019-0551-7

[36] Miler-Jerković, V., Djurić-Jovičić, M., Perović-Belić, M., Ječmenica-Lukić, M., Petrović, I. N., Radovanović, S. M., Kostić, V. S., & Popović, M. B. (2014). Multiple regression analysis of repetitive finger tapping parameters. 2014 22nd Telecommunications Forum Telfor (TELFOR), 537–540. https://doi.org/10.1109/TELFOR.2014.7034465

[37] Mazlan, S., Rahman, H. A., Kader, B. S. K., Yeong, C. F., & Alhusni, N. A. M. R. (2021). Multiple Linear Regression in Predicting Motor Assessment Scale of Stroke Patients. International Journal of Integrated Engineering, 13(6), 330–338. https://doi.org/10.30880/ijie.2021.13.06.029

[38] Maya Gopal, P. S., & Bhargavi, R. (2019). A novel approach for efficient crop yield prediction. Computers and Electronics in Agriculture, 165, 104968. https://doi.org/10.1016/j.compag.2019.104968

[39] Effendy, M. N. (2018). Predictive Models In Near-Infrared Spectroscopic Analysis For Blood Hemoglobin Prediction. Universiti Tun Hussein Onn Malaysia.

[40] Rongtong, B., Suwonsichon, T., Ritthiruangdej, P., & Kasemsumran, S. (2018). Determination of sulfur dioxide content in osmotically dehydrated papaya and its classification by near infrared spectroscopy. Journal of Near Infrared Spectroscopy, 26(6), 359–368. https://doi.org/10.1177/0967033518808054