IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 7 January 2025, accepted 28 January 2025, date of publication 31 January 2025, date of current version 19 February 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3537619

RESEARCH ARTICLE

Analyzing Activity of Daily Living Data Utilizing Motor Activity Log Toward Quantitative Scoring System

MOHD AZRI BIN ABD MUTALIB[1], NORSINNIRA ZAINUL AZLAN[2], (Member, IEEE), NOR MOHD HAZIQ NORSAHPERI[3], AND IBRAHIM HAFIZU HASSAN[4]

[1]Machine Design Section, Machinery Technology Centre, SIRIM Berhad, Rasa, Selangor 44200, Malaysia
[2]Department of Mechatronics Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Kuala Lumpur 53100, Malaysia
[3]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor 43400, Malaysia
[4]Department of Mechatronics Engineering, Ahmadu Bello University, Zaria 810211, Nigeria

Corresponding author: Norsinnira Zainul Azlan (sinnira@iium.edu.my)

This work was supported in part by the Ministry of Higher Education (MoHE) Malaysia through the Fundamental Research Grant Scheme under Grant FRGS/1/2021/TK0/UIAM/02/10.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by IIUM Research Ethics Committee (IREC) under Application No. IREC 2023-078, and performed in line with the International Conference of Harmonization Good Clinical Practice Guidelines (ICH-GCP), Malaysia Good Clinical Practice Guidelines and Council for International Organizations of Medical Sciences (CIOMS) International Ethical Guidelines.

ABSTRACT Assessment of stroke severity and recovery progress relies on a therapist's rating or score. It is typically administered manually with subjective input from therapists. This method is exposed to inconsistency, particularly when involving different therapists which depends on their own experiences and expertise. This paper presents a study on one-way ANOVA analysis to investigate the impact of force, forearm and elbow movement, Activity of Daily Living (ADL) equipment motion, and time duration on the MAL score during the execution of ADLs. A Motor Activity Log (MAL) is employed as the standard clinical assessment benchmark, where ten ADLs have been selected from the MAL standard for data collection purposes involving 30 healthy individuals and 56 stroke patients. The analyses are divided into two which are Analysis 1) focuses on the data with therapist rating 5, while Analysis 2) considers the data with therapist ratings ranging from 1 to 5. Data inputs including force, forearm and elbow movement, ADLs equipment motion, and activity time duration have been collected using sensors of force, distance, Inertial Measurement Unit (IMU), and encoders. Output data in MAL scores are obtained manually from therapists using the current methodology. The results indicate significant differences in 19 out of 40 cases for Analysis 1) and 85 out of 100 cases for Analysis 2). This paper contributes towards an objective and accurate automatic scoring system for a more consistent and efficient assessment of stroke patients' performance and recovery progress.

INDEX TERMS Activity of daily living, ANOVA analysis, motor activity log, occupational therapy, stroke rehabilitation.

I. INTRODUCTION

Stroke, also known as brain attack, occurs when blood flow to the brain is disrupted or stopped, leading to brain cell death and potential brain damage [1], [2]. There are two main types of strokes which are ischemic and hemorrhagic.

1) Ischemic Stroke: This type of stroke is caused by a blocked artery in the brain, often due to blood clots or other particles. It accounts for most strokes and can lead to long-term disability or even death [3], [4], [5].
2) Hemorrhagic Stroke: This type of stroke occurs when an artery in the brain leaks blood or ruptures, putting too much pressure on brain cells and causing damage. High blood pressure and aneurysms are common causes of hemorrhagic strokes [6], [7].

The associate editor coordinating the review of this manuscript and approving it for publication was Diego Bellan.

Risk factors for stroke include high blood pressure, heart disease, diabetes, smoking, high cholesterol, obesity, lack of exercise, and excessive alcohol use [8]. Some of these risk factors can be changed, treated, or medically managed to reduce the likelihood of a stroke [9]. Symptoms of a stroke can vary depending on the affected brain area, but they often include facial drooping, arm weakness, and speech difficulty [10]. Early detection and treatment of stroke symptoms are crucial, as they can significantly improve patient treatment outcomes and reduce the risk of long-term disability [11].

Stroke assessment is a procedure employed to examine the intensity and implications of a stroke on a patient's health. These measurement tools aid therapists in recognising and evaluating stroke symptoms, a critical factor in determining suitable treatment and enhancing patient outcomes [12]. Importantly, the approach varies for each patient, subject to the extent of their stroke. The evaluation of motor function in post-stroke patients is typically conducted manually by therapists [13]. However, manual assessment encounters several challenges, as it is inherently subjective and heavily reliant on the therapist's individual experiences [14].

The current qualitative approach requires enhancement through the incorporation of quantitative methods. Integrating sensors alongside standard clinical assessments represents a current research direction aimed at addressing this need. Wang et al., [15] utilised reflective marker sensors to measure kinematic and muscular levels in 15 healthy subjects and 15 stroke patients, employing the Brunnstrom, Fugl-Meyer Assessment (FMA), and Modified Ashworth Scale (MAS) clinical scales. Reflective marker sensors are also being used by Błaszczyszyn et al., [16] to measure X, Y, and Z hand coordinates in a time series 3D trajectory on 54 subjects, involving 35 stroke patients and 19 healthy subjects, basing their research on the Frenchay Arm Test (FAT) clinical scale. Boukhennoufa et al., [17] utilised IMU sensors to measure tri-axial linear acceleration and tri-axial angular velocity at a frequency of 50Hz, collecting data from 30 healthy subjects.

Li et al., [18] utilised sEMG sensors to measure muscle synergies, which consist of synergy vectors and synergy activation. Their research is based on the Brunnstrom, FMA, and MAS clinical scales, collected data from 20 subjects, including 10 healthy individuals and 10 stroke patients. Bisio et al., [19] used a motion capture (MoCap) system called SmartPANTS to measure three Cartesian coordinates, limb rotation, and force, with pilot data from one healthy subject. Additionally, Weiss and Daniele [20], Ma et al., [21], Moore et al., [22], Li et al., [23], and Chen et al., [24] utilised camera or image processing methods to measure parameters such as the position, direction, and length of fingers, hand extent of reach and movement speed, body motion, and hand gestures, respectively.

Table 1 illustrates recent studies undertaken toward this objective. Despite these efforts, to the best of the author's knowledge, there have been few dedicated studies employing sensors to assess post-stroke patients performing Activities of Daily Living (ADL). Practicing ADL effectively improves fine and gross motor skills, coordination, and balance, which are frequently impacted by a stroke [25], [26].

Therefore, this paper presents an analysis of human arm and equipment motion data utilising Motor Activity Log (MAL) assessment towards a quantitative scoring system. The MAL is directly associated with the selected ADL. The detailed explanation about MAL assessment will be elaborated in Section III. Parameters of force, forearm and elbow movement, ADL equipment motion, and time taken to complete the activity are identified as the input measurement for the stroke assessment [27], [28], [29]. Data collection involving stroke patients and healthy individuals has been conducted for this purpose. Two sets of one-way ANOVA analyses have been performed to investigate the influence of the measured parameters on the output, specifically the MAL score obtained from therapist ratings during subject engagement in ADLs [30], [31], [32]. Analysis (i) focuses on the data with therapist rating 5, involving healthy individuals and stroke patients. The aim of Analysis (i) is to examine

TABLE 1. Recent study focuses on strokes quantitative assessment by integrating sensor.

Researcher	Sensor Type	Measured Parameter	Subjects	Clinical Assessment Scale
Wang *et al.*,[15]	Reflective marker	Kinematic and muscular level	15 Healthy subjects 15 Stroke patients	Brunnstorm, FMA, MAS
Błaszczyszyn *et al.*,[16]		x, y, and z hand coordinates in time series 3D trajectory	19 Healthy subjects 35 Stroke patients	FAT
Boukhennoufa *et al.*,[17]	IMU	Tri-axial linear acceleration and tri-axial angular velocity at a frequency of 50Hz	30 Healthy subjects	Nil
X. Li et al.,[18]	sEMG	Muscle synergies consist of synergy vectors and synergy activation	10 Healthy subjects 10 Stroke patients	Brunnstorm, FMA, MAS
Bisio *et al.*,[19]	MoCap (SmartPANTS)	Three Cartesian coordinates, limb rotation and force	1 Healthy subject	Nil
Weiss *et al.*,[20]	Camera or Image processing	Position, direction and length of the finger	3 Stroke patients	Nil
Ma *et al.*,[21]		Hand extent of reach and movement speed	1 Healthy subject 1 Stroke patients	Nil
Moore *et al.*,[22]		Body motion	1 Stroke subject	Nil
Li *et al.*,[23]		Hand gestures	50 Stroke subjects	Brunnstorm, FMA
Chen *et al.*, [24]		Hand gestures	79 Stroke subjects	FMA

whether there are significant differences between the healthy individuals and the patients who are rated as 5 in the therapist data groups. Analysis (ii) considers the data with therapist ratings ranging from 1 to 5, aiming to investigate whether there are significant differences to the input parameters among scores. Both analyses are conducted to confirm whether the collected data are aligned with the standard MAL assessment.

The paper is structured as follows: Section II describes ANOVA Analysis, with an elaboration of the processes on the collected data. Section III presents the data collection equipment setup, providing a detailed explanation of the ADL selection, the recorded parameters, the sensors utilised, and the data logger employed. Section IV presents the results from the analysed data while Section V discusses the results obtained in the previous section. Finally, Section VI concludes the overall work in this paper, summarising the key insights and suggesting the potential research areas in the future.

II. ONE-WAY ANOVA ANALYSIS

One-Way ANOVA analysis is a valuable statistical tool, making it a preferred choice in research data analysis [28], [33]. The ability to conduct a comparison of multiple groups simultaneously and provide a comprehensive analysis in a single test are among its advantages [34], [35]. Additionally, the one-way ANOVA analysis helps in identifying statistically significant differences between group means and enabling researchers to determine if variations are genuine effects by calculating the p-value [36]. In this paper, the IBM SPSS Statistics Version 27 software is employed for one-way ANOVA analysis. The objective of this analysis is to compare input sensor readings from the different therapist ratings group. This comparison aims to examine the characteristics of the collected input sensor data before computing therapist ratings, ensuring alignment with the standard MAL assessment.

Two sets of data have been collected for this purpose. One from healthy individuals and the other from stroke patients. Based on these datasets, there is an overlap in the healthy individual's patients who score of 5 data. Stroke subjects, who perform activities well, are assigned a score of 5 by the therapist and all healthy subjects are set to be score 5. Therefore, ANOVA Analysis (i) is conducted to determine whether a significant difference exists between these groups. The hypothesis for Analysis (i) suggests that there is no significant difference between the groups, indicated by a p-value greater than 0.05. This is because, according to MAL score ratings, stroke subjects who score 5 can perform as well as healthy subjects.

The score distribution for stroke patients performing ADLs task varies in the range of 0 to 5. ANOVA Analysis (ii) aims to determine significant differences among input parameters for stroke patients with scores ranging from 1 to 5. Data with a score of 0 is excluded due to inconsistencies, such as excessively high or low force parameters and various movements performed without success. Some subjects take too long before giving up, while others quit early. This variability introduces confusion in computation.

TABLE 2. One-way ANOVA analysis conducted.

ANOVA	Group	Hypothesis
Analysis (i)	Healthy subjects and stroke patients who scored 5 for AOU and QOM	No significant difference, $p \geq 0.05$
Analysis (ii)	Stroke patient for score 1 to 5. Data for score 0 are excluded due to inconsistency.	Significant difference, $p \leq 0.05$.

TABLE 3. The MAL score rating for AOU [41].

Score	Amount of Use (AOU)	Assigned Terminology
0	The weaker arm was not used at all for that activity.	Never
1	Occasionally used the weaker arm, but only very rarely.	Very Rarely
2	Sometimes used the weaker arm but did the activity most of the time with the stronger arm.	Rarely
3	Used the weaker arm about half as much as before the stroke.	½ of Healthy Subject
4	Used the weaker arm almost as much as before the stroke	¾ of Healthy Subject
5	Used the weaker arm as often as before the stroke.	As per Healthy Subject

The hypothesis for ANOVA Analysis (ii) is there is a significant difference among scores, as indicated by a p-value lower than 0.05. This is grounded in the belief that each MAL score level should exhibit distinct parameter readings, leading to a significant difference. The analysis of the one-way ANOVA conducted on the collected data are simplified in Table 2.

III. DATA COLLECTION EQUIPMENT SETUP

Stroke assessment is a medical evaluation employed to gauge and diagnose the severity of a stroke patient and monitor their recovery progress. Physical examination stands out as a key component within this assessment. Various standard clinical stroke assessment scales are utilised as part of the physical examination, depending on the preference of therapists or doctors. These standards undergo continuous improvement and are updated over time to align with the current needs and advancements in medical technology.

The MAL [37] is an established tool widely recognised in assessing the quantity and quality of arm use in daily activities among stroke survivors. Its proven valid and relevance to evaluate upper limb function make it a keystone for measuring rehabilitation outcomes in post-stroke populations [38], [39], [40]. MAL assesses two key dimensions: Amount of Use (AOU), which quantifies the capacity of limb usage, and Quality of Movement (QOM), which evaluates the quality

TABLE 4. The MAL score rating for QOM [41].

Score	Quality of Movement (QOM)	Assigned Terminology
0	The weaker arm was not used at all for that activity	Never
1	The weaker arm was moved during the activity but was not very helpful.	Very Rarely
2	The weaker arm was of some use during the activity but needed some help from the stronger arm but moved very slowly or with difficulty.	Rarely
3	The weaker arm was used for that activity, but the movements were slow or were made only with some effort.	Fair
4	The movements made by the weaker arm for the activity were almost normal but not quite as fast or accurate as normal	Almost Normal
5	The ability to use the weaker arm for that activity was as good as before the stroke.	Normal

with which the limb is utilised in real-life scenarios. Ratings range from 0 to 5, as detailed in Tables 3 and 4, respectively, which outline the scoring criteria and assigned terminology in this study.

The MAL is utilised in this research due to its extensive adoption in post-stroke rehabilitation studies and its direct applicability in assessing ADL for functional recovery. Ten ADLs are carefully selected from the MAL-30 and MAL-45 scales, with the selection process thoroughly aligned with the research objectives. This process is conducted under the guidance of experienced therapists from the Hospital Selayang Rehabilitation Centre, Sultan Ahmad Shah Medical Centre (SASMEC), and Daehan Rehabilitation Hospital Putrajaya, ensuring the chosen ADLs are clinically relevant and representative of patients' daily living needs. These 10 ADLs are also chosen for their suitability to be quantified using five input parameters, Force, Rot-α, Rot-β, Equipment Motion, and Time to enable comprehensive analysis and modelling in the context of rehabilitation. In contrast, ADLs such as toileting, dressing, and writing are excluded, as they are not conducive to evaluation using these input parameters. The 10 selected ADLs and their terminology used in this paper are drawn in Table 5.

Data for the ANOVA analysis are collected while subjects engage in ADLs as listed in Table 5, imitating the real-life activities in daily living. The assessment of stroke patients is particularly dependent on quantifying the force exerted by the patient and the time needed to complete specific tasks. Additional relevant parameters, which are the forearm pronation or supination, elbow flexion or extension and ADLs equipment motion are also collected to strengthen this study.

Force-sensing resistor (FSR) type force sensors are utilised across all ten ADLs to measure the force exerted by subjects

TABLE 5. ADLs and the assigned terminology [37].

No	Item of MAL	Assigned Terminology
1	Engage and release plug top	3 Pin Plug
2	Turning on a light switch	Switch
3	Turning a fan regulator	Fan Regulator
4	Turning a water faucet	Water Faucet
5	Turning a doorknob	Doorknob
6	Opening a drawer	Drawer
7	Opening a door	Door
8	Combing a hair	Comb
9	Using a spoon for eating	Spoon
10	Brushing a tooth	Toothbrush

during these activities. Fig. 1 illustrates the arrangement of the force sensors attached to the ADLs Doorknob and Water Faucet. FSR is a resistive pressure sensor that changes its electrical resistance in response to applied force or pressure. The construction made from a polymer thick film (PTF) that contains conductive particles makes the sensor highly flexible [42]. The film is well-suited for integration into various surfaces on ADLs. This sensor delivers measurement in Newton as the participants applied force while performing the ADLs, enabling precise quantification of the force exerted during ADLs.

The ADLs equipment motion parameter aims to record the movement and gather information about the completion of the ADLs task performed by the subject. Not all subjects can execute ADLs entirely, especially the new stroke patients. Various sensors are installed on the ADLs equipment depending on the motion involved. For Water Faucet and Door, 360-degree rotary encoders are employed. Fig. 2 illustrates the attachment of the encoder to the Water Faucet ADL. These sensors convert angular motion into digital signals, enabling accurate tracking position of the water faucet lever rotation and the degree of door opening initiated by the subject. In the case of the Doorknob activity, a Time-of-Flight (ToF) VL53L0X range sensor is utilised as shown in Fig. 3. The readings obtained are within the 0mm to 15mm range, where 0mm signifies no knob rotation and 15mm corresponds to a complete turn. The Drawer activity utilises an ultrasonic distance sensor to measure the drawer's opening in millimeter (mm). The recorded distance increases with a larger drawer opening. No additional sensors are required for the 3 Pin Plug, Switch, and Fan Regulator, as motion is tracked through digital signals with the completion of the task. A value of 0 indicates that the subject has not successfully completed the ADLs task, while a value of 1 signifies completion. Finally, for Toothbrush, Spoon, and Comb, the motions are not sensed through equipment-mounted sensors; instead, they are referenced to Inertial Measurement Unit (IMU) sensors that are attached to the subject's arm.

The subject's arm movement is measured using an Inertial Measurement Unit (IMU) sensor, a method also used by [43] and [44] in their research on daily gesture and ADL recognition. The sensor is securely housed in a box

(a) (b)

FIGURE 1. The integration of the FSR Force Sensor for (a) Doorknob and (b) Water Faucet ADLs.

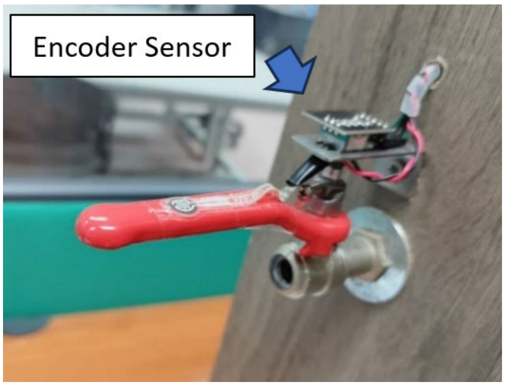

FIGURE 2. The integration of the encoder sensor to the Water Faucet ADL.

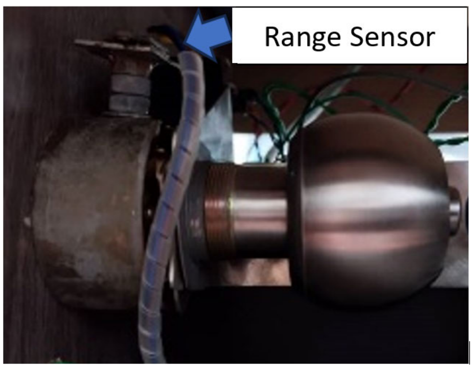

FIGURE 3. The integration of the range sensor for the Doorknob ADL.

and worn like a wristwatch, as shown in Fig. 4. This setup minimizes discomfort associated with electronic equipment for participants and has proven effective, as demonstrated by [45]. The MPU6050 3-axis accelerometer and gyroscope module IMU measures the forearm pronation or supination and elbow flexion or extension, labelled as Rot-α and Rot-β, respectively, as depicted in Fig. 5. The initial force reading provides a baseline of 0° and the maximum rotation can be measured up to 90°, in accordance with the requirements in performing ADLs. The key advantage of this sensor is its ability to simultaneously capture rotation in two directions.

The overall sensors utilised in this study are summarised in Table 6.

The time parameters are captured using the data logger. All input parameters are read at the intervals of 500 milliseconds this means two data points are stamped per second. This application is designed to capture parameters for post-stroke patients which generally have slower movement than healthy individuals. This cycle time provides the most consistent and reliable data stamps based on the equipment setup calibration. The sampling frequency are the same for all the sensors. This data logger is integrated with the ESP32 Wrover B micro-controller, which plays a role in coordinating all sensors. It allows for WiFi functionality, serving as a gateway for potential Internet of Things (IoT) applications in the future. This strategic inclusion enables seamless connectivity and communication, opening possibilities for remote monitoring, data analysis, and other IoT-related functionalities that are necessary for future work. The ESP32 Wrover B serves as a versatile and robust central hub, facilitating the integration and synchronisation of various sensor data.

FIGURE 4. IMU sensor mimics wristwatch for measuring arm movement.

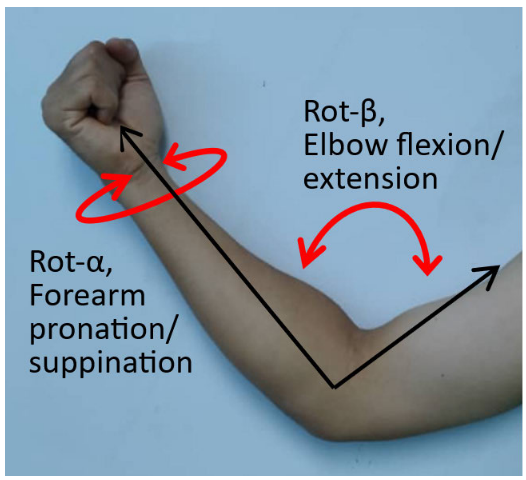

FIGURE 5. The forearm pronation or supination and elbow flexion or extension donated as Rot-α and Rot-β respectively.

This equipment setup, when compared with methods used by recent researchers as shown in Table 1, appears to be more effective. The reflective marker setup by Wang et al., [15] and Błaszczyszyn et al., [16] can cause significant discomfort

TABLE 6. Summerised of overall sensors utilised in this study.

No	ADLs	Parameter/ Sensor Utilises				
		Force	Rot-α	Rot-β	Equipment Motion	Time
1	3 Pin Plug	FSR Force Sensor	IMU Sensor	IMU Sensor	Digital Input	Data Logger
2	Switch	FSR Force Sensor	IMU Sensor	IMU Sensor	Digital Input	Data Logger
3	Fan Regulator	FSR Force Sensor	IMU Sensor	IMU Sensor	Digital Input	Data Logger
4	Water Faucet	FSR Force Sensor	IMU Sensor	IMU Sensor	Encoder	Data Logger
5	Doorknob	FSR Force Sensor	IMU Sensor	IMU Sensor	Range Sensor	Data Logger
6	Drawer	FSR Force Sensor	IMU Sensor	IMU Sensor	Distance Sensor	Data Logger
7	Door	FSR Force Sensor	IMU Sensor	IMU Sensor	Encoder	Data Logger
8	Comb	FSR Force Sensor	IMU Sensor	IMU Sensor	-	Data Logger
9	Spoon	FSR Force Sensor	IMU Sensor	IMU Sensor	-	Data Logger
10	Toothbrush	FSR Force Sensor	IMU Sensor	IMU Sensor	-	Data Logger

for subjects, especially stroke patients, due to the numerous sensors and tangled wires attached to the body. The use of IMUs by Boukhennoufa et al., [17], without accompanying force and motion sensors for each ADL, limits the assessment by overlooking fine motor skills such as grip. Similarly, the MoCap system used by Bisio et al., [19] provides only movement data without capturing force and equipment motion. Moreover, the camera-based methods with image processing applied by Weiss and Daniele [20], Ma et al., [21], Moore et al., [22], Li et al., [23], and Chen et al., [24] involve high costs for camera equipment and do not account for fine motor performance.

In the authors' view, this equipment setup is the most effective and remains unexplored by other researchers, as it integrates a quantitative scoring system aligned with MAL assessment. This setup provides therapists with more consistent and objective measures of improvement in specific daily tasks. Additionally, the simplicity and cost-effectiveness of this setup could encourage wider adoption in clinical and home-based environments, especially compared to more complex sensor systems.

For the data collection procedure, the subjects sit on an adjustable seat to ensure their comfort. Prior to data recording, subjects are advised to familiarise themselves with the ADLs tasks through a short briefing and trial sessions. It is essential to note that not every participant are inclined or suitable for these trials. Healthy subjects often find these activities align with their daily routines and do not express much interest in the trial sessions. Conversely, subjects who are recovering from a stroke may experience fatigue during these attempts. As a result, trial opportunities are extended to participants who genuinely express their interest and are deemed appropriate for such sessions.

The data collection comprises two groups of subjects: 30 randomly selected healthy individuals from the Machinery Technology Centre of SIRIM Berhad in Rasa, Selangor and 56 stroke survivors from Sultan Ahmad Shah Medical Centre (SASMEC), Kuantan, Pahang. The IIUM Research Ethics Committee (IREC) has approved data collection from under the approval number IREC 2023-078.

Professional therapists provide rating scores for the patients. Each stroke patient is paired with the therapist who closely collaborates with them to understand their constraints better and monitor their progress. The therapist's expertise and familiarity with their patients significantly contribute to the reliability and validity of MAL score assessments. Fig. 6 shows the summary of the data collection process flow.

The data logger records the input data from sensors attached to the selected ADLs at an interval of 500 milliseconds. These recorded input data includes the force exerted (Force) by the subject while performing the ADLs, forearm and elbow rotation donated as Rot-α and Rot-β respectively as listed in Table 6, ADLs equipment motion (Motion) and time taken (Time) to complete the ADLs. The output data, namely the MAL score in AOU and QOM rating are provided by therapists. These ratings are assigned based on the subject's performance during the execution of ADLs. The subject's performance improves indicates the score increases, starting from 0 for subjects unable to perform the activity or receiving a "Never" score for AOU and QOM. The scale progresses up to 5, where the subject successfully performs the ADL similar to a healthy individual for AOU and achieves a normal QOM. A subject is considered fully recovered when consistently receiving a score of 5 for both AOU and QOM.

The collected data is then organised to facilitate subsequent analysis. The maximum parameters for the Force, Rot-α, Rot-β, and Time data are extracted, as they indicate the subject's maximum capability in completing a specific ADL task. At this stage, the rest time and error time during data collection are filtered out. The average data are utilised in the analysis for subjects who have successfully performed 2 or 3 repetitions of the ADLs. For subject's incapable of performing more than one cycle in the ADL task, the data from that single instance are considered. Then, all input data undergoes normalisation using a Normalisation Function. The normalisation function is a statistical process for transforming data to a standard or common scale. The Min-Max Normalisation Function is utilised to ensure all data are within the range of 0 to 1. All data including force, angle, distance, and time are standardised to the same scale after this process. Normalisation helps to prevent numerical instability in the computations, particularly when dealing with diverse and extensive datasets. The formula for the Min-Max

Normalisation Function is as follows [46], [47]:

$$X_{Normalised} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where $X_{Normalised}$ is the data value after normalisation function, X is the current data value, X_{min} is the minimum value in the dataset and X_{max} is the maximum value in the dataset.

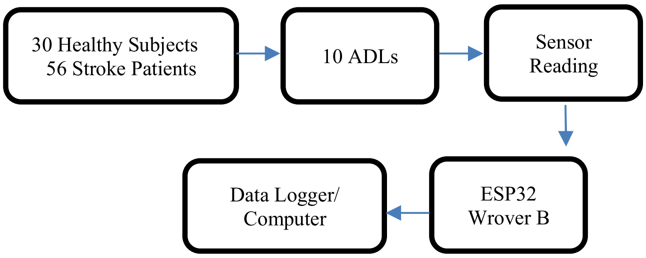

FIGURE 6. Data collection process flow.

Next, the normalised data is exported to IBM SPSS Statistics Version 27 software for one-way ANOVA analysis.

IV. RESULT

Two sets of One-way ANOVA analyses, Analysis (i) and Analysis (ii), have been performed on the collected data. As described in Section II, for Analysis (i), only healthy subjects and stroke patients who scored 5 are involved. Consequently, the number of subjects, N, participating in the analysis for each activity varied based on the number of score 5 instances for stroke patients. For healthy subjects, the count remained consistent at 30 subjects for each ADL. The results of the One-way ANOVA for Analysis (i) are presented in Table 7.

The computed averages (Mean) and standard deviations (Std. Dev) are derived from normalised data using the Min-Max Normalisation method. 'Sig.' stands for the significance value, also known as the p-value. A p-value of 0.05 is utilised as the threshold. Data is considered significantly different if the p-value is less than 0.05 ($p \leq 0.05$), indicated in bold for clarity. Analysis (i) cannot be conducted on the input ADLs equipment motion (Motion) and the output parameters AOU and QOM data because all the data for these groups has a value of 5.

Table 8 presents the results for Analysis (ii). Similar to Analysis (i), the number of subjects, N, varies for each activity. This is due to the exclusion of subjects scoring 0 from the analysis, as data from such subjects are found to be inconsistent and unsuitable for analysis. One-way ANOVA calculations for the Motion parameter for the Water Faucet activity could not be performed as all data involved in Analysis (ii) indicates that all subjects could fully complete this activity. So, all of them would have the same score of 5 for this activity.

Calculations for Analysis (ii) are also unfeasible for the Comb, Spoon, and Toothbrush activities because these activities solely depend on the forearm pronation or supination and elbow flexion or extension (Rot-α and Rot-β) without input from ADLs motion.

TABLE 7. One-way ANOVA for Analysis (i).

ADL	Parameter	Group	N	Mean	Std. Dev	Sig./ p-value
3 Pin Plug	Force	Healthy	30	0.46	0.3	**0.037**
		Stroke	8	0.22	0.14	
	Rot-α	Healthy	30	0.52	0.25	0.66
		Stroke	8	0.48	0.12	
	Rot-β	Healthy	30	0.39	0.27	0.83
		Stroke	8	0.41	0.22	
	Time	Healthy	30	0.61	0.21	0.087
		Stroke	8	0.76	0.21	
Switch	Force	Healthy	30	0.36	0.21	0.161
		Stroke	16	0.27	0.23	
	Rot-α	Healthy	30	0.09	0.08	0.069
		Stroke	16	0.18	0.23	
	Rot-β	Healthy	30	0.08	0.08	**0.031**
		Stroke	16	0.19	0.26	
	Time	Healthy	30	0.39	0.22	0.754
		Stroke	16	0.37	0.28	
Fan Regulator	Force	Healthy	30	0.75	0.14	**0.01**
		Stroke	8	0.22	0.21	
	Rot-α	Healthy	30	0.56	0.28	0.055
		Stroke	8	0.34	0.28	
	Rot-β	Healthy	30	0.47	0.25	**0.043**
		Stroke	8	0.27	0.2	
	Time	Healthy	30	0.29	0.23	0.388
		Stroke	8	0.38	0.27	
Water Faucet	Force	Healthy	30	0.48	0.24	**0.01**
		Stroke	14	0.2	0.15	
	Rot-α	Healthy	30	0.07	0.12	**0.018**
		Stroke	14	0.23	0.31	
	Rot-β	Healthy	30	0.07	0.05	**0.048**
		Stroke	14	0.17	0.25	
	Time	Healthy	30	0.36	0.22	0.587
		Stroke	14	0.33	0.16	
Doorknob	Force	Healthy	30	0.72	0.15	**0.01**
		Stroke	15	0.33	0.21	
	Rot-α	Healthy	30	0.4	0.2	0.328
		Stroke	15	0.33	0.27	
	Rot-β	Healthy	30	0.17	0.18	**0.029**
		Stroke	15	0.32	0.27	
	Time	Healthy	30	0.3	0.18	**0.031**
		Stroke	15	0.46	0.31	
Drawer	Force	Healthy	30	0.48	0.3	0.235
		Stroke	11	0.36	0.24	
	Rot-α	Healthy	30	0.35	0.23	**0.016**
		Stroke	11	0.56	0.24	
	Rot-β	Healthy	30	0.27	0.18	0.212
		Stroke	11	0.37	0.33	
	Time	Healthy	30	0.42	0.26	0.268
		Stroke	11	0.32	0.24	
Door	Force	Healthy	30	0.36	0.24	0.086
		Stroke	9	0.21	0.14	
	Rot-α	Healthy	30	0.33	0.25	0.123
		Stroke	9	0.49	0.37	
	Rot-β	Healthy	30	0.32	0.2	0.138
		Stroke	9	0.46	0.33	
	Time	Healthy	30	0.21	0.21	0.941
		Stroke	9	0.22	0.21	
Spoon	Force	Healthy	30	0.36	0.25	**0.013**
		Stroke	13	0.17	0.11	
	Rot-α	Healthy	30	0.25	0.19	0.507
		Stroke	13	0.29	0.16	
	Rot-β	Healthy	30	0.22	0.22	0.728
		Stroke	13	0.2	0.15	
	Time	Healthy	30	0.23	0.18	**0.041**
		Stroke	13	0.37	0.25	

TABLE 7. ***(Continued.)*** **One-way ANOVA for Analysis (i).**

Comb	Force	Healthy	30	0.32	0.22	0.115
		Stroke	12	0.21	0.18	
	Rot-α	Healthy	30	0.27	0.15	**0.031**
		Stroke	12	0.41	0.24	
	Rot-β	Healthy	30	0.26	0.19	0.082
		Stroke	12	0.39	0.25	
	Time	Healthy	30	0.28	0.24	**0.05**
		Stroke	12	0.52	0.23	
Toothbrush	Force	Healthy	30	0.57	0.26	**0.001**
		Stroke	13	0.29	0.25	
	Rot-α	Healthy	30	0.27	0.18	**0.001**
		Stroke	13	0.55	0.28	
	Rot-β	Healthy	30	0.21	0.2	**0.001**
		Stroke	13	0.47	0.26	
	Time	Healthy	30	0.24	0.18	**0.01**
		Stroke	13	0.42	0.24	

V. DISCUSSION

Based on the results of Analysis (i) in Table 7, it has been found that 19 out of 40 ANOVA p-values are less than 0.05. This indicates that nearly half or 47.5% of the analysed data shows a significant difference. Table 9 is the summary of Table 7 focusing only on p-values. 6 out of 10 tasks for Force, 4 out of 10 ADLs for Rot-α, 5 out of 10 tasks for Rot-β, and 4 out of 10 activities for Time show p-values less than 0.05. These findings do not contradict the hypothesis stating that the dataset should not show significant differences. More than half of the dataset does not exhibit a significant difference, which aligns with the hypothesis based on the MAL assessment and remains acceptable.

Subsequently, the results of Analysis (i) are discussed based on their Estimated Marginal Means (EMM) viewpoint to provide understanding of the effects of input variables which are Force, Rot-α, Rot-β, and Time on the dataset groups of healthy individuals and stroke patients. This analysis helps identify which inputs are driving the variations in the output. Only data for the ADL parameters showing significant differences are included in the figures due to their substantial impact on the dependent variable. For example, in Fig. 7, only the 3 Pin Plug, Fan Regulator, Water Faucet, Doorknob, Spoon, and Toothbrush show significant differences in the ANOVA analysis, with a p-value less than 0.05, as recorded in Table 9. This means that only these six ADLs influence the variations of the output (Force) and are included in Fig. 7. The same concept applies to Figs. 8 to 15.

The EMM for Force parameter in Analysis (i) as illustrated in Fig. 7 shows that healthy subjects consistently apply higher force compared to stroke patients. This is in line with literature findings on the weakened strength of stroked patients. Figs. 8 and 9 display the EMM for subject arm movement parameters, Rot-α and Rot-β, which are recorded simultaneously. Most activities with a significant dataset show that stroke patients exhibit a larger range of motion compared to healthy subjects during ADLs, except for the Fan Regulator activity in Rot-β.

Stroke patients tend to perform more steps to complete activities, associated with the Force factor, where their weakened strength leads to more steps compared to healthy subjects. This trend is observed in activities like Fan Regulator, where healthy subjects tend to complete the task in one large rotation, while stroke patients prefer multiple smaller rotations. Thus, the arm movement margin is higher in healthy subjects than stroke patients.

Fig. 10 illustrates the EMM for the Time parameter. As expected, stroke patients take a longer time to complete ADLs compared to healthy subjects, which is in alignment with the natural observation where stroke patients take a longer time to complete tasks due to their inability.

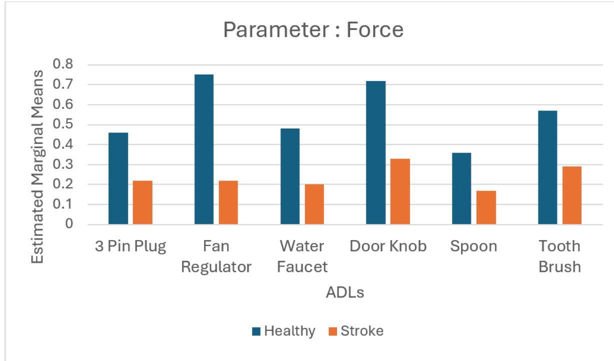

FIGURE 7. **EMM for Force parameter in Analysis (i).**

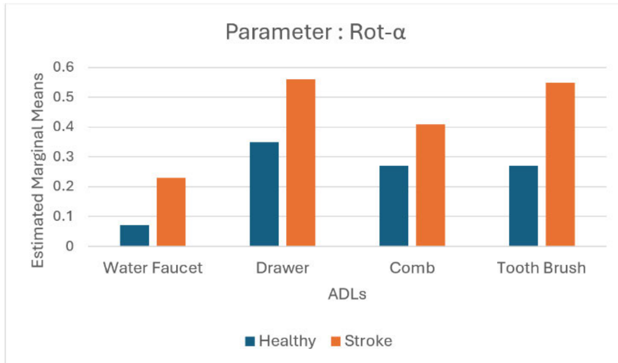

FIGURE 8. **EMM for Rot-α parameter in Analysis (i).**

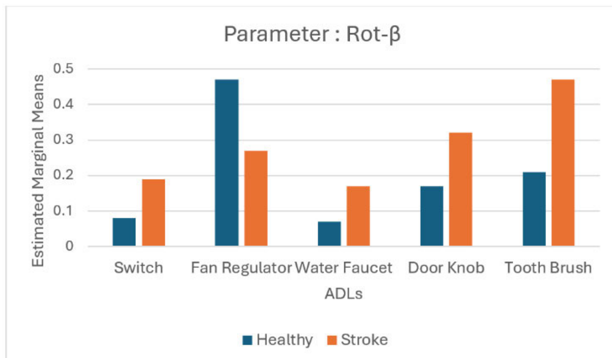

FIGURE 9. **EMM for Rot-β parameter in Analysis (i).**

TABLE 8. One-way ANOVA for Analysis (ii).

ADL	Parameter	N	AOU											N	QOM										
			Mean					Std. Dev					Sig./ p-value		Mean					Std. Dev					Sig./ p-value
			1	2	3	4	5	1	2	3	4	5			1	2	3	4	5	1	2	3	4	5	
	Force		0.20	0.16	0.35	0.40	0.59	0.22	0.08	0.15	0.22	0.21	0.01		0.19	0.15	0.31	0.40	0.62	0.28	0.08	0.17	0.21	0.19	0.001
	Rot-α		0.22	0.39	0.69	0.43	0.36	0.27	0.14	0.26	0.13	0.15	0.003		0.44	0.27	0.38	0.44	0.37	0.22	0.25	0.15	0.22	0.15	0.488
3 Pin Plug	Rot-β	69	0.33	0.37	0.47	0.37	0.24	0.35	0.24	0.27	0.17	0.12	0.033	74	0.55	0.25	0.43	0.33	0.24	0.32	0.33	0.21	0.20	0.12	0.001
	Motion		0.60	1.00	1.00	1.00	1.00	0.55	0.00	0.00	0.00	0.00	0.001		0.38	0.67	1.00	1.00	1.00	0.52	0.58	0.00	0.00	0.00	0.001
	Time		0.23	0.44	0.27	0.22	0.12	0.26	0.20	0.07	0.09	0.06	0.001		0.38	0.32	0.28	0.21	0.11	0.23	0.32	0.14	0.06	0.45	0.001
	Force		0.13	0.28	0.13	0.28	0.19	0.01	-	0.08	0.30	0.12	0.224		0.18	0.09	0.14	0.28	0.19	0.09	0.04	0.10	0.27	0.12	0.119
	Rot-α		0.31	0.21	0.30	0.15	0.13	0.22	-	0.17	0.12	0.15	0.02		0.27	0.18	0.25	0.21	0.11	0.22	0.13	0.16	0.17	0.14	0.029
Switch	Rot-β	77	0.36	0.23	0.30	0.16	0.12	0.41	-	0.26	0.14	0.15	0.025	79	0.38	0.18	0.25	0.20	0.11	0.40	0.15	0.22	0.16	0.15	0.017
	Motion		0.33	1.00	1.00	1.00	1.00	0.58	-	0.00	0.00	0.00	0.001		0.33	1.00	0.75	1.00	1.00	0.58	0.00	0.46	0.00	0.00	0.001
	Time		0.09	0.38	0.18	0.07	0.05	0.02	-	0.10	0.03	0.04	0.001		0.19	0.19	0.15	0.09	0.04	0.17	0.12	0.09	0.04	0.02	0.001
	Force		0.27	0.40	0.45	0.44	0.73	0.31	0.15	0.16	0.16	0.20	0.001		0.20	0.41	0.33	0.47	0.73	0.30	0.15	0.12	0.16	0.20	0.001
	Rot-α		0.28	0.51	0.26	0.38	0.47	0.22	0.36	0.22	0.19	0.16	0.019		0.31	0.29	0.38	0.31	0.48	0.20	0.32	0.23	0.18	0.15	0.019
Fan Regulator	Rot-β	67	0.34	0.41	0.27	0.31	0.35	0.28	0.40	0.11	0.15	0.15	0.741	70	0.41	0.31	0.29	0.28	0.36	0.27	0.32	0.13	0.14	0.15	0.541
	Motion		0.23	0.55	0.83	0.98	1.00	0.41	0.19	0.24	0.06	0.00	0.001		0.17	0.40	0.85	1.00	1.00	0.37	0.23	0.21	0.00	0.00	0.001
	Time		0.24	0.27	0.33	0.29	0.14	0.18	0.04	0.10	0.25	0.05	0.001		0.24	0.25	0.39	0.22	0.15	0.17	0.10	0.27	0.06	0.06	0.001
	Force		0.09	0.22	0.37	0.34	0.39	0.02	0.13	0.26	0.27	0.22	0.168		0.18	0.12	0.28	0.37	0.41	0.13	0.04	0.18	0.27	0.22	0.014
	Rot-α		0.55	0.52	0.35	0.27	0.16	0.36	0.33	0.13	0.21	0.22	0.002		0.67	0.42	0.39	0.28	0.11	0.21	0.34	0.19	0.20	0.16	0.001
Water Faucet	Rot-β	80	0.49	0.69	0.28	0.18	0.13	0.30	0.51	0.21	0.19	0.18	0.001	82	0.67	0.46	0.30	0.18	0.10	0.27	0.39	0.23	0.18	0.13	0.001
	Motion		1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	-		1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	-
	Time		0.30	0.67	0.23	0.21	0.10	0.10	0.29	0.17	0.09	0.08	0.001		0.39	0.45	0.25	0.21	0.08	0.12	0.30	0.17	0.09	0.04	0.001
	Force		0.23	0.23	0.45	0.47	0.64	0.16	-	0.19	0.21	0.21	0.001		0.15	0.34	0.27	0.46	0.67	0.16	0.32	0.16	0.18	0.20	0.001
	Rot-α		0.67	0.89	0.11	0.35	0.48	0.25	-	0.09	0.23	0.18	0.001		0.60	0.42	0.26	0.35	0.49	0.30	0.19	0.39	0.20	0.18	0.031
Doorknob	Rot-β	71	0.54	0.20	0.15	0.25	0.11	0.21	-	0.17	0.15	0.10	0.001	76	0.47	0.26	0.17	0.20	0.11	0.32	0.21	0.21	0.15	0.11	0.001
	Motion		0.63	1.00	1.00	1.00	1.00	0.44	-	0.00	0.00	0.00	0.001		0.41	0.82	0.85	1.00	1.00	0.42	0.37	0.30	0.00	0.00	0.001
	Time		0.32	0.32	0.20	0.15	0.06	0.17	-	0.14	0.08	0.04	0.001		0.33	0.25	0.20	0.13	0.05	0.21	0.03	0.22	0.09	0.03	0.001
	Force		0.13	0.09	0.28	0.26	0.46	0.04	0.13	0.24	0.16	0.26	0.005		0.09	0.23	0.27	0.27	0.48	0.07	0.21	0.21	0.15	0.27	0.001
	Rot-α		0.57	0.46	0.22	0.28	0.21	0.38	0.18	0.07	0.15	0.15	0.002		0.46	0.42	0.39	0.24	0.19	0.38	0.24	0.12	0.11	0.18	0.001
Drawer	Rot-β	77	0.35	0.41	0.17	0.16	0.20	0.15	0.45	0.11	0.18	0.19	0.262	81	0.27	0.62	0.29	0.16	0.16	0.19	0.30	0.29	0.16	0.11	0.001
	Motion		1.00	0.50	1.00	0.99	1.00	0.00	0.71	0.00	0.04	0.00	0.001		0.75	0.84	0.92	0.99	1.00	0.50	0.30	0.16	0.04	0.00	0.002
	Time		0.73	0.34	0.42	0.26	0.19	0.24	0.10	0.12	0.06	0.10	0.001		0.63	0.44	0.35	0.27	0.16	0.27	0.11	0.14	0.07	0.05	0.001
	Force		0.21	0.27	0.29	0.22	0.36	0.16	0.21	0.18	0.12	0.21	0.097		0.13	0.24	0.21	0.21	0.40	0.09	0.16	0.14	0.11	0.20	0.001
	Rot-α		0.59	0.32	0.51	0.33	0.24	0.27	0.18	0.31	0.24	0.18	0.005		0.47	0.37	0.59	0.28	0.23	0.32	0.22	0.31	0.18	0.17	0.001
Door	Rot-β	77	0.53	0.31	0.49	0.22	0.18	0.22	0.03	0.39	0.20	0.90	0.001	81	0.45	0.33	0.43	0.20	0.17	0.23	0.12	0.32	0.17	0.09	0.001
	Motion		1.00	0.83	1.00	1.00	1.00	0.00	0.29	0.00	0.00	0.00	0.001		0.88	0.91	0.94	0.99	1.00	0.25	0.24	0.12	0.04	0.00	0.015
	Time		0.86	0.42	0.56	0.30	0.21	0.12	0.17	0.22	0.15	0.17	0.001		0.71	0.59	0.52	0.27	0.17	0.33	0.18	0.20	0.11	0.09	0.001
	Force		0.12	0.39	0.20	0.22	0.35	0.17	0.34	0.17	0.18	0.21	0.036		0.09	0.23	0.09	0.20	0.31	0.08	0.20	0.09	0.20	021	0.013
	Rot-α		0.47	0.21	0.27	0.28	0.27	0.30	0.16	0.11	0.21	0.18	0.22		0.32	0.39	0.13	0.30	0.30	0.19	0.23	0.08	0.26	0.18	0.182
Spoon	Rot-β	77	0.47	0.18	0.20	0.23	0.15	0.22	0.15	0.10	0.18	0.12	0.001	82	0.41	0.35	0.24	0.25	0.20	0.26	0.29	0.20	0.16	0.13	0.034
	Motion		-	-	-	-	-	-	-	-	-	-	-		-	-	-	-	-	-	-	-	-	-	-
	Time		0.28	0.28	0.33	0.21	0.05	0.14	0.22	0.21	0.12	0.04	0.001		0.51	0.44	0.24	0.22	0.09	0.25	0.24	0.16	0.22	0.07	0.001
	Force		0.12	0.23	0.16	0.18	0.30	0.10	0.25	0.20	0.19	0.21	0.086		0.05	0.36	0.22	0.23	0.36	0.02	0.29	0.16	0.17	0.22	0.008
	Rot-α		0.36	0.37	0.19	0.30	0.30	0.19	0.28	0.17	0.27	0.18	0.434		0.27	0.31	0.29	0.29	0.27	0.12	0.26	0.08	0.21	0.18	0.978
Comb	Rot-β	79	0.39	0.46	0.20	0.25	0.20	0.30	0.34	0.16	0.17	0.13	0.009	80	0.38	0.26	0.22	0.22	0.15	0.24	0.20	0.08	0.18	0.12	0.013
	Motion		-	-	-	-	-	-	-	-	-	-	-		-	-	-	-	-	-	-	-	-	-	-
	Time		0.53	0.29	0.27	0.24	0.09	0.27	0.11	0.21	0.24	0.6	0.001		0.35	0.33	0.47	0.19	0.05	0.34	0.22	0.14	0.12	0.04	0.001
	Force		0.06	0.20	0.19	0.29	0.52	0.05	0.20	0.13	0.18	0.27	0.001		0.06	0.20	0.15	0.28	0.53	0.03	0.16	0.11	0.17	0.27	0.001
	Rot-α		0.57	0.34	0.33	0.33	0.28	0.38	0.19	0.17	0.23	0.19	0.081		0.34	0.41	0.41	0.31	0.28	0.09	0.29	0.24	0.22	0.19	0.372
Toothbrush	Rot-β	79	0.61	0.56	0.23	0.30	0.25	0.33	0.33	0.10	0.19	0.22	0.001	82	0.64	0.45	0.24	0.33	0.24	0.29	0.32	0.15	0.21	0.20	0.001
	Motion		-	-	-	-	-	-	-	-	-	-	-		-	-	-	-	-	-	-	-	-	-	-
	Time		0.34	0.32	0.33	0.26	0.08	0.13	0.17	0.28	0.14	0.05	0.001		0.34	0.38	0.48	0.24	0.08	0.18	0.19	0.31	0.14	0.05	0.001

TABLE 9. Analysis (i) p-value.

ADL	Force	Rot-α	Rot-β	Time
3 Pin Plug	**0.037**	0.66	0.83	0.087
Switch	0.161	0.069	**0.031**	0.754
Fan Regulator	**0.01**	0.055	**0.043**	0.388
Water Faucet	**0.01**	**0.018**	**0.048**	0.587
Doorknob	**0.01**	0.328	**0.029**	**0.031**
Drawer	0.235	**0.016**	0.212	0.268
Door	0.086	0.123	0.138	0.941
Spoon	**0.013**	0.507	0.728	**0.041**
Comb	0.115	**0.031**	0.082	**0.05**
Toothbrush	**0.001**	**0.001**	**0.001**	**0.01**

For Analysis (ii), ANOVA results in Table 8 show that 15 out of 100 recorded p-values are greater than 0.05. Thus, 85% results indicate a significant difference, consistent with the hypothesis. The Doorknob activity is observed to display significant differences across all parameter data, as shown in Table 8. In contrast, other ADLs show one to three parameters that do not indicate significant differences. However, this variation is reasoned acceptable for real-life applications due to potential environmental errors.

For the EMM viewpoint, from the one-way ANOVA results shown in Table 8, it is observed that 15 out of the Force dataset exhibit significant differences. Fig. 11 depicts the EMM graph for the Force dataset in Analysis (ii). The mean for the Force parameter with a MAL score of 5 is highest for all activities except AOU Spoon and QOM Comb. This aligns with the MAL assessment standard where lower scorer stroke patients exert less force in completing ADL tasks compared to recovering patients with higher scores. However, exceptions occur for the mean of AOU Spoon and QOM Comb, where the mean with a score of 2 indicates higher readings and is equal to the mean score of 5 for the respective ADLs. This is because the MAL score considers not only the Force factor but also all other input factors, such as completion of ADLs task, and the time taken to complete the activities.

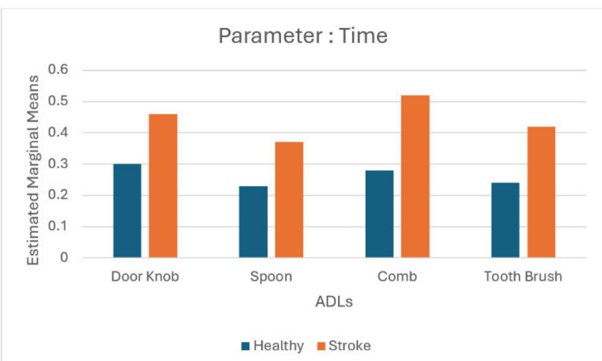

FIGURE 10. EMM for Time parameter in Analysis (i).

For the Rot-α dataset, a total of 13 datasets exhibits significant differences, whereas for the Rot-β dataset, there are 17 datasets showing significant differences, as depicted in Figs. 12 and 13 respectively. Both input parameters represent the subject's arm movement during ADL task execution and recorded simultaneously. The mean graphs in Figs. 12 and 13 display different trends that are not consistent for each activity. However, when examining the mean for MAL scores of 1 and 5 only, it is noticeable that most of them show a decrease, where stroke patients with a score of 1 exhibit a wider range of movement compared to those with a score of 5. To the best of the author's knowledge, this finding has yet been documented in any literature review. However, exceptions occur in the EMM for AOU and QOM for Fan Regulator activity in the Rot-α dataset. As observed in Analysis (i), recovering stroke patients with higher scores tend to complete the task with one large rotation, in line with their abilities. Meanwhile, stroke patients with lower scores prefer to make smaller rotations and pause for rest at each fan speed. Exceptions also occur in the EMM for QOM Toothbrush in the Rot-β dataset. Based on observations during data collection, stroke patients with higher scores show more interest in genuinely imitating their toothbrushing activity and perform a larger range of arm movement compared to those with lower scores due to their limitations.

Fig. 14 illustrates the EMM for the Motion parameter. A total of 12 datasets shows significant differences for the Motion parameter in Analysis (ii). The graph indicates that most of the mean scores reach or approach a value of 1 as the MAL score increases. A mean value of 1 indicates that the subject successfully performs the ADL task. The dataset QOM Fan Regulator displays a different pattern, where all means of MAL scores are below 0.5. This is because the QOM refers to the quality of movement. Although AOU Fan Regulator shows an increasing trend up to the value of 1 at MAL score 5, in terms of the quality of task completion, it is still assessed as low. This aligns with the MAL assessment standard where stroke patients are expected to demonstrate poor movement quality. Additionally, the Fan Regulator activity proves to be challenging for stroke patients and is a good choice for assessment purposes.

It is observed that 20 out of the Time dataset demonstrate significant differences as indicated in Table 8. Fig. 15 shows the EMM graph for the Time dataset in Analysis (ii). Most of EMM graphs are not consistent for mean MAL scores of 1 and 2. However, for MAL scores 3, 4, and 5, a decreasing trend can be observed. This aligns with the MAL standard assessment, where the higher score or the more recovered the stroke subject, the shorter the time required to complete the ADL task. The inconsistency in means for scores 1 and 2 is due to the related Motion parameter results where most subjects fail to complete ADLs task and surrender early, resulting in low recorded times. The mean graph for the QOM Toothbrush shows a different pattern which is increasing across scores.

Referring to the Rot-β results, this activity indicates that subjects perform a larger range of motion across scores, requiring more time to complete.

The inconsistencies in the ANOVA results across different ADLs are attributed to several factors. The nature of each

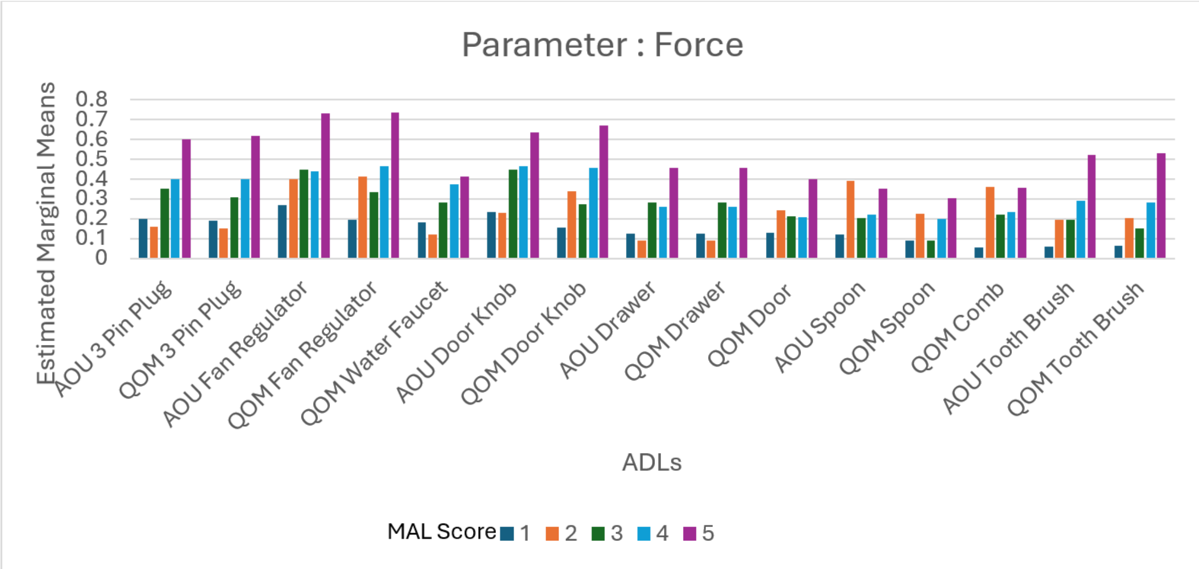

FIGURE 11. EMM for Force parameter in Analysis (ii).

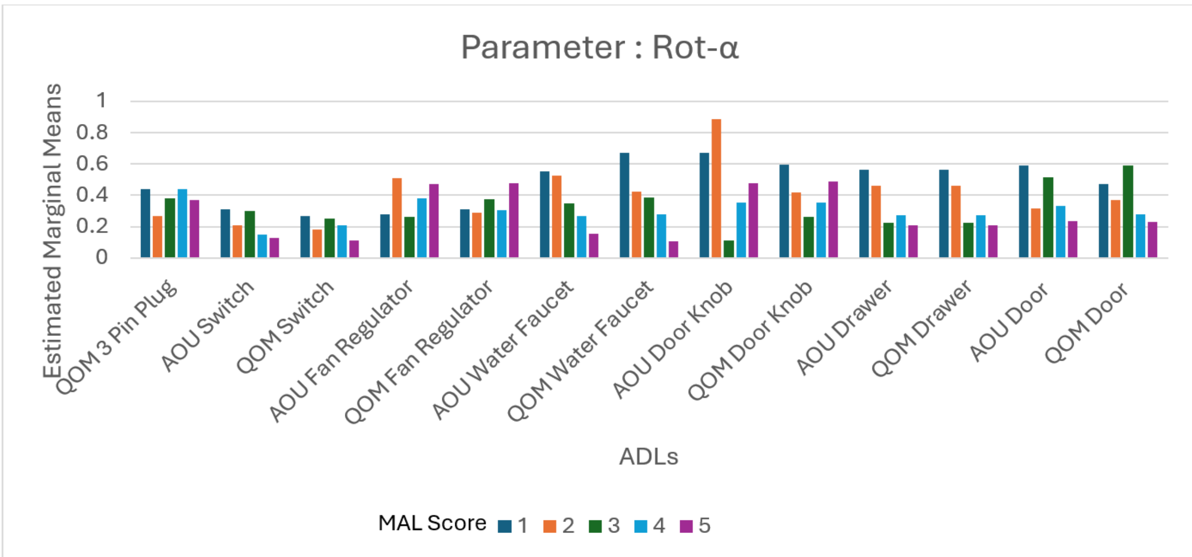

FIGURE 12. EMM for Rot-α parameter in Analysis (ii).

ADL itself plays an important role in performance impact. ADLs that require more complex movements or force generation show significant differences in certain parameters (e.g., Force, Rot-α, Rot-β). Conversely, ADLs that involve simpler or more routine tasks do not exhibit the same degree of variation in the same parameters, leading to non-significant results. Besides, the individual variability among patients, such as differences in severity of stroke and functional ability also contribute to the inconsistencies. For instance, certain patients exhibit significant impairments in one input factor (e.g., Force) while others may show improvements in other factors like arm movement or time. This variability can affect the significance of each parameter across different ADLs.

Furthermore, the design and structure of the ADLs themselves also influence the results. Some ADLs are inherently more dependent on specific parameters, such as force or rotational movement, while others rely on a combination of inputs, making it more challenging for certain parameters to emerge as significant. For example, an ADL involving fine motor skills (e.g., Water Faucet and Doorknob) rely heavily on rotational movements than force, leading to significant results for one parameter and non-significant results for others. To provide a clearer interpretation of the findings,

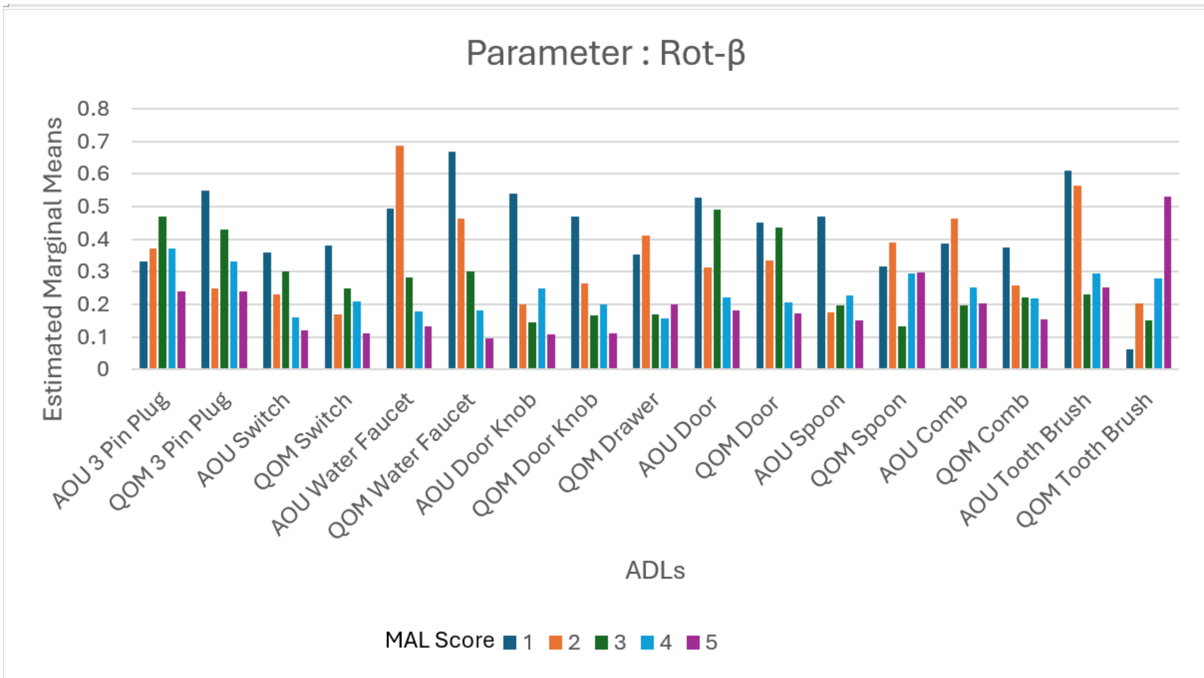

FIGURE 13. EMM for Rot-β parameter in Analysis (ii).

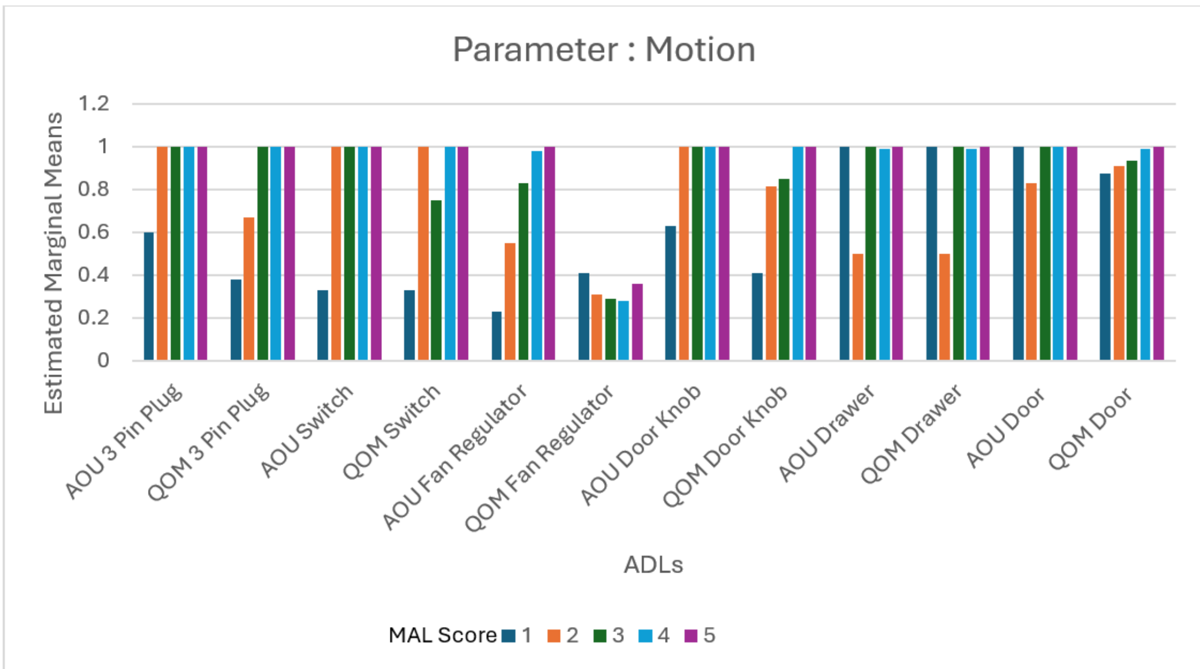

FIGURE 14. EMM for Motion parameter in Analysis (ii).

it is important to consider both, task complexity and patient attributes. The parameters that are found to be significant in some ADLs highlight their specific relevance to those tasks, while non-significant results in others suggest that these parameters may not be as critical in those contexts.

In this study, utilising one best parameter for analysing the ADL is impossible since it does not provide enough information on the subject's and equipment motion in performing the activities. A combination of the three or four selected parameters needs to be considered for analysing the

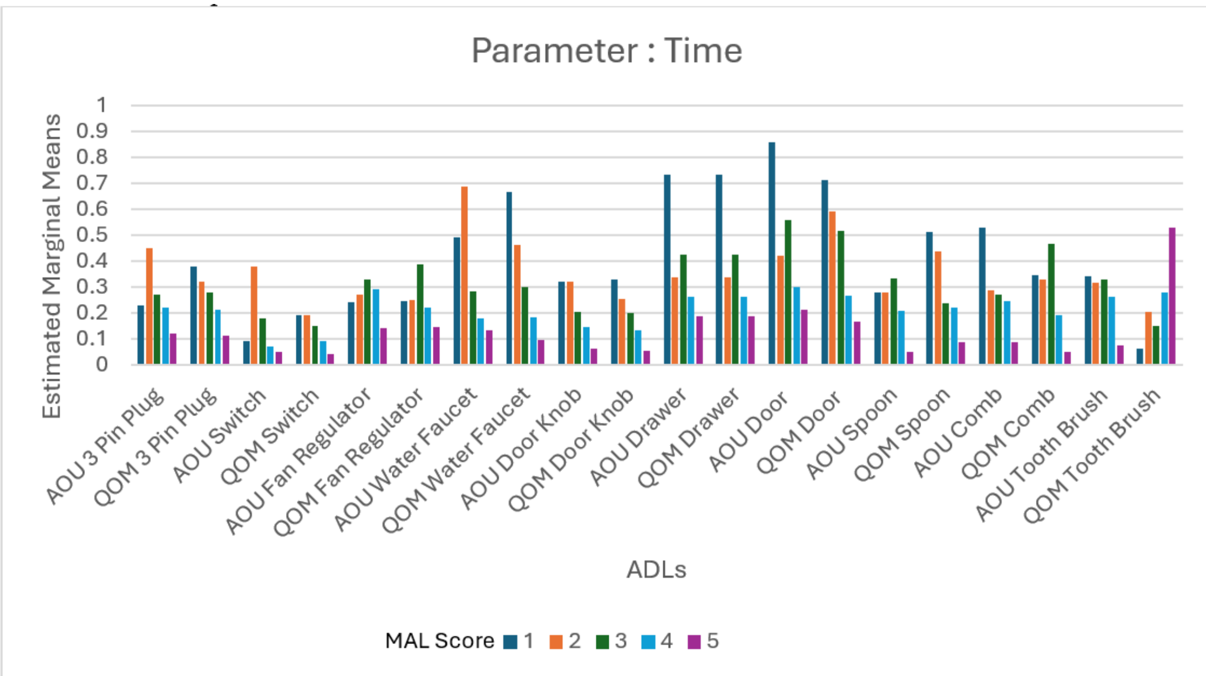

FIGURE 15. EMM for Time parameter in Analysis (ii).

ADL, depending on the specific task. This is because the two sets of one-way ANOVA analysis show the significance of Force, Rot-α, Rot-β, and Time parameters in assessing stroke patients. The Motion parameters seemed to be less influential for the analysis process, and Motion data can be excluded from the analysis. However, they still hold importance in evaluating a subject's success in completing the ADL tasks.

Sensor-based in stroke rehabilitation has become a significant area of research, with various methods utilising sensors to monitor recovery. These approaches typically focus on specific parameters, such as joint movement, muscle activity, or motion tracking. While these methods offer valuable insights, many fall short in fully capturing functional ability, particularly when assessing ADLs. They often lack integration of multiple factors or fail to account for the complexities inherent in real-life tasks. Table 10 compares our proposed method to other studies integrating sensor-based approaches, highlighting the key differences and advancements.

Porciuncula et al. [48] utilised IMUs combined with advanced signal processing to recognise activities and analyse biomechanical features, focusing on detecting pathological motor features and compensatory movements.

Picerno et al. [49] used MIMUs for assessing reach-to-grasp kinematics, offering a non-intrusive solution that could be applied to bedridden patients. Bailey et al. [50] employed accelerometers to quantify upper limb activity hours and activity ratios, linking these metrics with motor dysfunction and ADL dependency. While these methods provided useful insights into specific aspects of stroke recovery, they are limited in terms of task diversity and real-world applicability.

Our method introduces a novel measure designed to provide a more comprehensive assessment of functional ability. By incorporating force, joint angle, ADL equipment motion and time data, our approach captures a complete picture of functional performance. The method considers task, object, and hand characteristics, offering a thorough analysis of functional ability across different contexts. Additionally, by integrating 10 clinically validated ADLs from the MAL with ANOVA, our method allows for the statistical evaluation of motor control variations and functional abilities across a wide range of tasks, making it more adaptable to individual patient needs. What differentiates our approach is its broader scope, incorporating multiple dynamic variables such as time, force, and movement patterns. This multidimensional approach enhances the clinical relevance of our method, making it more adaptable to the varying functional abilities of post-stroke patients. Unlike traditional methods that focus on limited tasks or measurements, our method integrates a wider range of factors, offering deeper insights into rehabilitation outcomes.

The ANOVA results reveal significant differences in functional abilities across class variations and between healthy individuals and post-stroke patients. Complex activities, such as Fan Regulator or Water Faucet, require greater force and arm movement, highlighting the need to prioritise ADLs based on class levels. This ensures therapy targets tasks that align with each patient's needs, enhancing rehabilitation outcomes. Force emerged as the most critical input factor, showing significant differences across six of the ten ADLs. This finding underscores its importance as a primary focus

TABLE 10. The comparison of other studies that integrate sensor-based approaches with our proposed method.

Study/Method	Sensors	ADLs Covered	Evaluation Metric	Key Findings	Novelty of Our Approach
Porciuncula *et al.* [48]	IMUs + Advanced Signal Processing	Various activities	Biomechanical Features, AR	High sensitivity in detecting pathological motor features and compensatory movements.	Focuses on ADLs relevant to clinical practice, employing MAL as a structured task selection framework.
Picerno *et al.* [49]	Magnetic and Inertial Measurement Units (MIMUs)	Reach-to-grasp kinematic s	Kinematic Metrics (e.g., ROM, Bias)	Validated accurate, non-intrusive assessment of reach-to-grasp in stroke patients.	Broader task diversity and statistical analysis with ANOVA compared to focus on reach-to-grasp.
Bailey *et al.* [50]	Accelerometers	Various ADLs (not explicitly listed)	Hours of UL Activity; Activity Ratio	Activity ratio strongly correlated with motor dysfunction and ADL dependency.	Focuses on 10 specific MAL-based ADLs, offering detailed ANOVA insights for diverse motor patterns.
Our method	Force, equipment motion, IMUs	10 MAL Based ADLs	ANOVA	Provides significant insights into motor control variations across diverse ADLs and stroke-specific impairments.	Combines robust statistical validation, diverse and clinically relevant tasks, and real-world evaluation possibilities.

in rehabilitation. Therapists can use this insight to design programs that prioritise force generation before addressing secondary factors like arm movement and task completion time. By tailoring therapy to each patient's functional ability and recovery stage, therapists can deliver focused, evidence-based interventions. This personalised approach accelerates recovery and optimises rehabilitation outcomes, ensuring effective and impactful treatment.

This research aims to provide a quantifiable and objective measure of upper extremity functional ability to assist therapists in monitoring progress, evaluating therapy effectiveness, and personalising rehabilitation strategies. By analysing key metrics such as force and joint angular displacement, it provides valuable insights to enhance therapeutic outcomes. The integration of IoT-ready devices, like the ESP32, enables real-time data collection and feedback during home-based rehabilitation. These devices allow therapists to monitor patient performance during ADLs, provide immediate feedback to encourage exercise adherence, and facilitate remote monitoring. Therapists can analyse trends and adjust treatment plans without requiring in-person visits, ensuring consistent, evidence-based care while reducing access barriers. In clinical settings, the functional ability metric serves as a decision-support tool, offering detailed performance data to identify impairments, target specific interventions, standardise evaluations, and support research and clinical trials. By combining objective assessments, real-time feedback, and remote monitoring, this approach bridges clinical rehabilitation with home-based care, improving therapy outcomes, reducing healthcare costs, and expanding access to effective rehabilitation services.

VI. CONCLUSION

This paper presents the outcomes of analysing ADLs data utilising MAL assessment towards quantitative scoring system. A set of ten ADLs is chosen from the MAL assessment standard and employed for data collection. Data has been collected from 86 subjects, consisting of 56 stroke patients and 30 healthy subjects. The forces, encoders, distances and IMU sensors are installed on the ADL devices and the subjects' arm used to collect the input parameters data including the force exerted, arm rotation around α and β direction, ADLs equipment motion and time taken to complete the ADLs task. Certified therapists provided the MAL scores for the output parameters in AOU and QOM.

Future work will focus on developing an equation to automatically describe a patient's ability or recovery progress based on MAL scoring, incorporating these results as an assessment tool in hospitals and rehabilitation centers. The ANOVA findings could contribute to a more objective, measurable approach for monitoring recovery, complementing the subjective assessments typically made by therapists. This approach would enhance traditional qualitative evaluations with a consistent, data-driven method. Additionally, this technique would support home-based rehabilitation, allowing assessments to be conducted without a therapist's presence. An ADL-focused assessment system for both clinical and home use could empower patients to monitor their own recovery, encourage daily practice, and enable therapists to assess progress remotely.

ACKNOWLEDGMENT

The authors would like to extend their appreciation to Sultan Ahmad Shah Medical Centre (SASMEC) for facilitating the data collection involving stroke patients at their rehabilitation center.

REFERENCES

[1] P. Langhorne, J. Bernhardt, and G. Kwakkel, "Stroke rehabilitation," *Lancet*, vol. 377, no. 9778, pp. 1693–1702, May 2011, doi: 10.1016/S0140-6736(11)60325-5.

[2] E. H. Lo, M. A. Moskowitz, and T. P. Jacobs, "Exciting, radical, suicidal: How brain cells die after stroke," *Stroke*, vol. 36, no. 2, pp. 189–192, Feb. 2005, doi: 10.1161/01.str.0000153069.96296.fd.

[3] M. L. Corrigan, A. A. Escuro, and D. F. Kirby, *Handbook of Clinical Nutrition and Stroke*. Nutrition and Health, Humana Press, 2013, pp. 1–310, doi: 10.1007/978-1-62703-380-0.

[4] K. Petty, B. P. Lemkuil, and B. Gierl, "Acute ischemic stroke," *Anesthesiology Clinics*, vol. 39, no. 1, pp. 113–125, Mar. 2021, doi: 10.1016/j.anclin.2020.11.002.

[5] S. D. Smith and C. J. Eskey, "Hemorrhagic stroke," *Radiologic Clinics North Amer.*, vol. 49, no. 1, pp. 27–45, Jan. 2011, doi: 10.1016/j.rcl.2010.07.011.

[6] D. M. Reker, B. B. Hamilton, P. W. Duncan, and S. Jennifer, "Stroke: Who's counting what?" *J. Rehabil. Res. Develop.*, vol. 38, no. 2, pp. 281–289, 2001.

[7] S. Y. Mounis and N. Z. Azlan, "Assist-as-needed control strategies for upper limb rehabilitation therapy: A review," *Jurnal Mekanikal*, vol. 42, pp. 57–74, Oct. 2019.

[8] N. R. Saini and A. L. Gurvendra, "Stroke-related risk factors: A review," *Asian Pacific J. Health Sci.*, vol. 9, no. 3, pp. 102–107, Apr. 2022, doi: 10.21276/apjhs.2022.9.3.21.

[9] H. E. Bays, P. R. Taub, E. Epstein, E. D. Michos, R. A. Ferraro, A. L. Bailey, H. M. Kelli, K. C. Ferdinand, M. R. Echols, H. Weintraub, J. Bostrom, H. M. Johnson, K. K. Hoppe, M. D. Shapiro, C. A. German, S. S. Virani, A. Hussain, C. M. Ballantyne, A. M. Agha, and P. P. Toth, "Ten things to know about ten cardiovascular disease risk factors," *Amer. J. Preventive Cardiol.*, vol. 5, Mar. 2021, Art. no. 100149, doi: 10.1016/j.ajpc.2021.100149.

[10] R. K. Upadhyay, "Chronic non-communicable diseases: Risk factors, disease burden, mortalities and control," *Acta Sci. Med. Sci.*, vol. 6, no. 4, pp. 153–170, Apr. 2022, doi: 10.31080/asms.2022.06.1227.

[11] W.-W. Chang, S.-Z. Fei, N. Pan, Y.-S. Yao, and Y.-L. Jin, "Incident stroke and its influencing factors in patients with type 2 diabetes mellitus and/or hypertension: A prospective cohort study," *Frontiers Cardiovascular Med.*, vol. 9, pp. 1–10, Feb. 2022, doi: 10.3389/fcvm.2022.770025.

[12] M. P. Malcolm, C. Massie, and M. Thaut, "Rhythmic auditory-motor entrainment improves hemiparetic arm kinematics during reaching movements: A pilot study," *Topics Stroke Rehabil.*, vol. 16, no. 1, pp. 69–79, Jan. 2009, doi: 10.1310/tsr1601-69.

[13] S. J. Housman, K. M. Scott, and D. J. Reinkensmeyer, "A randomized controlled trial of gravity-supported, computer-enhanced arm exercise for individuals with severe hemiparesis," *Neurorehabilitation Neural Repair*, vol. 23, no. 5, pp. 505–514, Jun. 2009.

[14] I. M. Khairuddin, S. N. Sidek, H. M. Yusof, K. Baarath, and A. P. P. A. Majeed, "Assistive-as-Needed strategy for upper-limb robotic systems: An initial survey," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 260, no. 1, 2017, Art. no. 012027, doi: 10.1088/1757-899X/260/1/012027.

[15] C. Wang, L. Peng, Z.-G. Hou, J. Li, T. Zhang, and J. Zhao, "Quantitative assessment of upper-limb motor function for post-stroke rehabilitation based on motor synergy analysis and multi-modality fusion," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 943–952, Apr. 2020, doi: 10.1109/TNSRE.2020.2978273.

[16] M. Błaszczyszyn, A. Szczęsna, M. Konieczny, P. Pakosz, S. Balko, and Z. Borysiuk, "Quantitative assessment of upper limb movement in post-stroke adults for identification of sensitive measures in reaching and lifting activities," *J. Clin. Med.*, vol. 12, no. 9, p. 3333, May 2023, doi: 10.3390/jcm12093333.

[17] I. Boukhennoufa, X. Zhai, K. D. McDonald-Maier, V. Utti, and J. Jackson, "Improving the activity recognition using GMAF and transfer learning in post-stroke rehabilitation assessment," in *Proc. IEEE 19th World Symp. Appl. Mach. Intell. Informat. (SAMI)*, Jan. 2021, pp. 391–397, doi: 10.1109/SAMI50585.2021.9378670.

[18] X. Li, H. Zeng, Y. Li, and A. Song, "Quantitative assessment via multi-domain fusion of muscle synergy associated with upper-limb motor function for stroke rehabilitation," *IEEE Trans. Biomed. Eng.*, vol. 71, no. 5, pp. 1430–1441, May 2024, doi: 10.1109/TBME.2023.3339634.

[19] I. Bisio, C. Garibotto, M. Hamedani, F. Lavagetto, V. Prada, A. Schenone, and A. Sciarrone, "Towards IoT-based eHealth services: A smart prototype system for home rehabilitation," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2019, pp. 1–6, doi: 10.1109/GLOBECOM38437.2019.9013194.

[20] M. Weiss and C. Daniele, "Hand rehabilitation assessment system using leap motion controller," *AI Soc.*, vol. 35, Sep. 2019, Art. no. 0123456789, doi: 10.1007/s00146-019-00925-8.

[21] M. Ma, B. J. Meyer, L. Lin, R. Proffitt, and M. Skubic, "VicoVR-based wireless daily activity recognition and assessment system for stroke rehabilitation," in *Proc. IEEE Int. Conf. Bioinform. Biomed.*, Dec. 2018, pp. 1117–1121.

[22] Z. Moore, C. Sifferman, S. Tullis, M. Ma, R. Proffitt, and M. Skubic, "Depth sensor-based in-home daily activity recognition and assessment system for stroke rehabilitation," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Nov. 2019, pp. 1051–1056, doi: 10.1109/BIBM47256.2019.8983376.

[23] C. Li, L. Cheng, H. Yang, Y. Zou, and F. Huang, "An automatic rehabilitation assessment system for hand function based on leap motion and ensemble learning," *Cybern. Syst.*, vol. 52, no. 1, pp. 3–25, Jan. 2020, doi: 10.1080/01969722.2020.1827798.

[24] S. Chen, X. Lin, J. Fu, Y. Qian, Z. Chen, Z. Huang, Q. Liu, X. Lu, and J. Jia, "Prediction of the hand function part of the Fugl-Meyer scale after stroke using an automatic quantitative assessment system," *Brain-X*, vol. 1, no. 3, Sep. 2023, Art. no. e26, doi: 10.1002/brx2.26.

[25] J. Kim, H. Kim, and J. Kim, "Quantitative assessment test for upper-limb motor function by using EMG and kinematic analysis in the practice of occupational therapy," in *Proc. 39th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, Jul. 2017, pp. 1158–1161, doi: 10.1109/EMBC.2017.8037035.

[26] R. J. Adams, M. D. Lichter, A. Ellington, M. White, K. Armstead, J. T. Patrie, and P. T. Diamond, "Virtual activities of daily living for recovery of upper extremity motor function," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 1, pp. 252–260, Jan. 2018, doi: 10.1109/TNSRE.2017.2771272.

[27] K. O. Thielbar, K. M. Triandafilou, H. C. Fischer, J. M. O'Toole, M. L. Corrigan, J. M. Ochoa, M. E. Stoykov, and D. G. Kamper, "Benefits of using a voice and EMG-driven actuated glove to support occupational therapy for stroke survivors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 3, pp. 297–306, Mar. 2017, doi: 10.1109/TNSRE.2016.2569070.

[28] Z. Hussain, N. Zainul Azlan, and A. Z. B. Yusof, "Human hand motion analysis during different eating activities," *Appl. Bionics Biomech.*, vol. 2018, no. 1, 2018, Art. no. 8567648, doi: 10.1155/2018/8567648.

[29] S. V. Duff, A. Miller, L. Quinn, G. Youdan, L. Bishop, H. Ruthrauff, and E. Wade, "Quantifying intra- and interlimb use during unimanual and bimanual tasks in persons with hemiparesis post-stroke," *J. NeuroEng. Rehabil.*, vol. 19, no. 1, pp. 1–10, Dec. 2022, doi: 10.1186/s12984-022-01020-8.

[30] Y.-W. Chen, K.-Y. Li, C.-H. Lin, P.-H. Hung, H.-T. Lai, and C.-Y. Wu, "The effect of sequential combination of mirror therapy and robot-assisted therapy on motor function, daily function, and self-efficacy after stroke," *Sci. Rep.*, vol. 13, no. 1, pp. 1–10, Oct. 2023, doi: 10.1038/s41598-023-43981-3.

[31] E. Marques-Sule, A. Arnal-Gómez, G. Buitrago-Jiménez, L. Suso-Martí, F. Cuenca-Martínez, and G. V. Espí-López, "Effectiveness of nintendo wii and physical therapy in functionality, balance, and daily activities in chronic stroke patients," *J. Amer. Med. Directors Assoc.*, vol. 22, no. 5, pp. 1073–1080, May 2021, doi: 10.1016/j.jamda.2021.01.076.

[32] R. Singh, D. Kumar, and B. B. Sagar, "Valuation of significant difference between various agile methods using one way ANOVA," in *Proc. 9th Int. Conf. Rel., Infocom Technol. Optim. Trends Future Directions (ICRITO)*, Sep. 2021, pp. 1–5, doi: 10.1109/ICRITO51393.2021.9596099.

[33] C. Wu, Y. Yan, Q. Cao, F. Fei, D. Yang, X. Lu, B. Xu, H. Zeng, and A. Song, "SEMG measurement position and feature optimization strategy for gesture recognition based on ANOVA and neural networks," *IEEE Access*, vol. 8, pp. 56290–56299, 2020, doi: 10.1109/ACCESS.2020.2982405.

[34] H. Harb, A. Makhoul, S. Tawbi, and R. Couturier, "Comparison of different data aggregation techniques in distributed sensor networks," *IEEE Access*, vol. 5, pp. 4250–4263, 2017, doi: 10.1109/ACCESS.2017.2681207.

[35] G. Varas-Diaz, L. Kannan, and T. Bhatt, "Effect of mental fatigue on postural sway in healthy older adults and stroke populations," *Brain Sci.*, vol. 10, no. 6, pp. 1–17, Jun. 2020, doi: 10.3390/brainsci10060388.

[36] R. M. Mehmood, R. Du, and H. J. Lee, "Special section on advances of multisensory services and technologies for healthcare in smart cities optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," *Optim. Feature Selection Deep Learn. Ensembles Method Motion Recognit. From Hum. Brain EEG Sensors*, vol. 5, pp. 14797–14806, Aug. 2017.

[37] E. Taub, K. McCulloch, G. Uswatte, and D. M. Morris, "Motor activity log (MAL) manual," Therapy Res. Group, Amer. Acad. Neurology, Tech. Rep., 2011, pp. 1–18, doi: 10.1212/01.wnl.0000238164.90657.c2.

[38] Y.-W. Chen, W.-C. Chiang, C.-L. Chang, S.-M. Lo, and C.-Y. Wu, "Comparative effects of EMG-driven robot-assisted therapy versus task-oriented training on motor and daily function in patients with stroke: A randomized cross-over trial," *J. NeuroEng. Rehabil.*, vol. 19, no. 1, pp. 1–9, Dec. 2022, doi: 10.1186/s12984-021-00961-w.

[39] P. Chen, T.-W. Liu, M. M. Y. Tse, C. K. Y. Lai, J. Tsoh, and S. S. M. Ng, "The predictive role of hand section of Fugl-Meyer assessment and motor activity log in action research arm test in people with stroke," *Frontiers Neurol.*, vol. 13, pp. 1–10, Jul. 2022, doi: 10.3389/fneur.2022.926130.

[40] S. M. dos Anjos, V. W. Mark, C. M. Rodriguez, D. M. Morris, J. E. Crago, D. K. King, G. Uswatte, and E. Taub, "Reliability and validity of the lower extremity motor activity log for measuring real-world leg use in adults with multiple sclerosis," *Arch. Phys. Med. Rehabil.*, vol. 102, no. 4, pp. 626–632, Apr. 2021, doi: 10.1016/j.apmr.2020.10.125.

[41] A. McDermott. *Motor Activity Log (MAL)*. Stroke Engine. Accessed: Nov. 14, 2024. [Online]. Available: https://strokengine.ca/en/assessments/motor-activity-log-mal/

[42] A. S. Sadun, J. Jalani, and J. A. Sukor, "Force sensing resistor (FSR): A brief overview and the low-cost sensor for active compliance control," *Proc. SPIE*, vol. 10011, Jul. 2016, Art. no. 1001112, doi: 10.1117/12.2242950.

[43] A. Moschetti, L. Fiorini, D. Esposito, P. Dario, and F. Cavallo, "Recognition of daily gestures with wearable inertial rings and bracelets," *Sensors*, vol. 16, no. 8, p. 1341, Aug. 2016, doi: 10.3390/s16081341.

[44] M. Scattolini, A. Tigrini, F. Verdini, G. Iadarola, S. Spinsante, S. Fioretti, L. Burattini, and A. Mengarelli, "Leveraging inertial information from a single IMU for human daily activity recognition," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Jun. 2024, pp. 1–6, doi: 10.1109/MEMEA60663.2024.10596886.

[45] S. Moccia, S. Solbiati, M. Khornegah, F. F. Bossi, and E. G. Caiani, "Automated classification of hand gestures using a wristband and machine learning for possible application in pill intake monitoring," *Comput. Methods Programs Biomed.*, vol. 219, Jun. 2022, Art. no. 106753, doi: 10.1016/j.cmpb.2022.106753.

[46] I. Arora, J. Gambhir, and T. Kaur, "Data normalisation-based solar irradiance forecasting using artificial neural networks," *Arabian J. Sci. Eng.*, vol. 46, no. 2, pp. 1333–1343, Feb. 2021, doi: 10.1007/s13369-020-05140-y.

[47] S. Kim, K. H. Kim, B. Min, J. Lim, and K. Lee, "Generation of synthetic density log data using deep learning algorithm at the golden field in Alberta, Canada," *Geofluids*, vol. 2020, pp. 1–26, Jan. 2020, doi: 10.1155/2020/5387183.

[48] F. Porciuncula, A. V. Roto, D. Kumar, I. Davis, S. Roy, C. J. Walsh, and L. N. Awad, "Wearable movement sensors for rehabilitation: A focused review of technological and clinical advances," *PM R*, vol. 10, no. 9, pp. S220–S232, Sep. 2018, doi: 10.1016/j.pmrj.2018.06.013.

[49] P. Picerno, P. Caliandro, C. Iacovelli, C. Simbolotti, M. Crabolu, D. Pani, G. Vannozzi, and A. Cereatti, "Assessing reach-to-grasp movements in the stroke unit: Validity of an inertial sensor-based approach," in *Converging Clinical and Engineering Research on Neurorehabilitation III*, vol. 21. Cham, Switzerland: Springer, 2019, doi: 10.1007/978-3-030-01845-0_122.

[50] T. S. Rehabil, "Real-world affected upper limb activity in chronic stroke: An examination of potential modifying factors," vol. 22, no. 1, pp. 26–33, 2016, doi: 10.1179/1074935714Z.0000000040.

MOHD AZRI BIN ABD MUTALIB received the B.Eng. degree in electrical engineering from Universiti Malaysia Pahang, in 2008, and the M.Sc. degree in mechatronics engineering from the International Islamic University Malaysia, in 2020, where he is currently pursuing the Ph.D. degree. He is an Engineer at the Machine Design Section, Machinery Technology Centre, SIRIM Berhad. His research interests include robot aided neurorehabilitation, exoskeletal robotics, nonlinear control, and mechatronics.

NORSINNIRA ZAINUL AZLAN (Member, IEEE) received the bachelor's degree (Hons.) in mechatronics engineering from International Islamic University Malaysia (IIUM), in 2003, and the master's and Ph.D. degrees in mechanical and control engineering from Tokyo Institute of Technology, Japan. She is currently a Lecturer with IIUM. Her research interests include nonlinear control, upper limb rehabilitation robots, artificial prosthetic hands, and robot manipulators and automations.

NOR MOHD HAZIQ NORSAHPERI received the B.Eng. and M.Sc. degrees in mechatronics engineering from International Islamic University Malaysia (IIUM), in 2015 and 2017, respectively, and the Ph.D. degree in electrical engineering from Universiti Teknologi Malaysia, in 2020. He is currently a Senior Lecturer with the Department of Electrical and Electronic Engineering, Universiti Putra Malaysia (UPM). His research interests include nonlinear control, robotics, and artificial intelligence.

IBRAHIM HAFIZU HASSAN received the B.Sc. degree in mechanical engineering from Bayero University, Kano, Nigeria, in 2005, and the M.Sc. degree in mechatronics engineering from International Islamic University Malaysia, where he is currently pursuing the Ph.D. degree in mechatronics engineering. His research interests include rehabilitation robot, modeling of nonlinear systems, control systems, AI and machine learning, and deep learning.