MJSAT 6 (1) 35-40

MJSAT

Malaysian Journal of Science
and
Advanced Technology

journal homepage: https://mjsat.com.my/

Correlation and ANOVA-Based Validation of IoT-Derived Motion Metrics in Post-Stroke Hand Rehabilitation

Md Sariful Islam[1], Ahmad Anwar Zainuddin*[1], Ainul Hani Binti Mohd Manoj[1], Siti Maisarah Binti Abdul Aziz[1], Siti Aishah Binti Abdul Aziz[1], and Nurul Farah Hanim Muhamad Nasir[1]

[1] *Kulliyyah of Information and Communication Technology, IIUM, Gombak, Selangor, Malaysia.*

KEYWORDS

Correlation analysis
Stroke rehabilitation
IoT
Remote monitoring
Clinical assessment

ARTICLE HISTORY

Received 23 February 2026
Received in revised form
6 March 2026
Accepted 10 March 2026
Available online 27 March 2026

ABSTRACT

Reliance on intermittent and subjective clinical assessment in stroke rehabilitation has remained a persistent weakness with limited information on daily recovery progress and it has impeded access to patients in the remote or underserved regions. To overcome this, the paper proposes RIoTv2, which is a system that can monitor motor activity in an objective and continuous manner. The vision-based system employed in the solution is that of MediaPipe Pose to extract 4D skeletal arm motion values using regular webcam when doing important key hand rehabilitation exercises, including Hand Strengthening and Hand Opposition. The algorithmic method of kinematic measurements (velocity, smoothness, range of motion, repetition accuracy) was conducted in a quasi-experimental study of 200 post-stroke patients. These RIoTv2 measurements were correlated with and compared to Fugl-Meyer Assessment (FMA) and Barthel Index (BI) scores under different degrees of impairment with the help of correlation analysis and ANOVA. This system was seen to be accurate in most cases (largely over 75 percent), which corresponds to pragmatic clinical limits (the error rate is often not far below 25 to 30 percent) with normalized kinematic errors of about 7 to 20 percent and FMA thresholds of remote monitoring literature. The RIoTv2 system is an efficient device that can be used as a remote-monitoring platform offering healthcare providers with objective and real-time information to use in personalized therapy and intervention. The critical social repercussion comprises the development of health equity by providing cost-effective and administrable technology to break geographic and economic boundaries, improving patient agency amid home-based care, and improving a more transparent and data-based paradigm on the care of post-stroke patients.

1. INTRODUCTION

Stroke is a major disability because that is currently a leading cause of long-term disability, and upper-limb impairment is a major cause of lower independence[1]. Traditional rehabilitation evaluation is based on the periodical clinical scales such as Fugl-Meyer Assessment (FMA) and Barthel Index (BI), which are subjective and do not reflect the dynamics of recovery [2]. Rehabilitation Internet of Things version 2 (RIoTv2) framework tackles this loophole by tracking motion with vision based on MediaPipe Pose, which creates objective kinematic information. Nonetheless, these metrics based on IoT must be statistically proven to be clinically valid vis-a-vis gold-standard measurements. In this research, the correlations between the main kinematic measures (velocity, smoothness, range of motion, repetition accuracy) and clinical scores will be performed, and further ANOVA analysis of the measures at different levels of impairment severity will be performed to prove the IoT measures as valid digital biomarkers of post-stroke hand rehabilitation[2].

A high percentage of the stroke survivors have upper-limb

*Corresponding author:
E-mail address: Ahmad Anwar Zainuddin < anwarzain@iium.edu.my >.
https://doi.org/10.56532/mjsat.v6i1.752
2785-8901/

impairment, and the prevalence rate lies between 35 percent in the acute stages (SAFE score 8 or below) to 55-80 percent in chronic/acute stages, which tends to persist in the long run and impair the efficiency of activities of daily living including self-care, food, dressing. This movement disorder, which presents as paresis, spasticity, restricted range of motion and poor coordination, is a leading source of disability, reduces the quality of life and places excessive socio-economic burdens on patients, families and systems of healthcare especially in underserved or remote locations where the benefits of regular clinic-based care are not easily available[3].

Conventional measures such as the Fugl-Meyer Assessment (FMA) and Barthel Index (BI) are the gold standards of motor impairment and functional independence assessment, although they possess significant limitations, including infrequent testing (not measuring daily changes), subjectivity (reliance on a clinician and inter-rater reliability) and time-intensive and restricted to a clinic, and do not capture performance (in the real world, patient remains unobserved) or the subtle kinematic alteration of recovery dynamics[4].

More recent developments in vision-based telerehabilitation have filled these gaps with low-cost markerless mechanical techniques such as Kinetc cameras or Mediapipes as objective kinematic trackers of the upper-limb movement. Such methods generate digital biomarkers (e.g. smoothness as a proxy of neuromuscular control) with webcam information, allowing home based, continuous measurement. Although they promise gross movements and show good correlations with FMA in a few of their validations, many systems are still at prototype levels, do not have large-scale clinical cohort studies, and have difficulty with fine motor tasks, particularly with moderate-to-severe impairments because of monocular occlusions and landmark instability[5].

The prototype discussed in this paper, RIoTv2, builds on top of the previous prototype, RIoTv1, but adds capabilities to track pose, and count repetitions, along with other capabilities implemented in MediaPipe, namely skeletal tracking and the computation of clinically relevant kinematic metrics to assess rehabilitation. RIoTv2 framework is based on those advances to present a cost-effective, scalable solution: MediaPipe Pose-based 4D skeletal tracking through a standard web camera and during a specific exercise: MediaPipe Hand Strengthening - gross motor and MediaPipe Hand Opposition - fine motor[6]. It yields validated advanced (velocity, smoothness, ROM, repetition accuracy) and rigorously compares it to FMA/BI both through correlation and severity-stratified ANOVA, a quasi-experimental study of 200 post-stroke patients validated it. RIoTv2 can be applied and converted into equitable, data-driven telerehabilitation via establishing them as valid digital biomarkers, especially the smoothness that serves gross recovery, crosses geographic/economic barriers, and justifies personalized interventions performed at home. Early investigation of these RIOT works has been described in [6], [7], [8], [9], [10], [11] papers providing foundational insights into their development and applications.

This paper is structured in the following way. The introduction and the motivation of the research is presented in section 1. Section 2 is the review of related literature. Section 3 states the materials and resources involved in the research. The suggested methodology is described in Section 4. The experimental findings and analysis are provided at Section 5. Section 6 addresses the results and gives recommendations. Lastly, Section 7 brings a conclusion to the paper.

2. LITERATURE REVIEW

Stroke is still among the major causes of permanent motor impairment globally, and dysfunction of upper limbs is the greatest inhibitor of the independence of activities of daily living. The assessment of conventional rehabilitation mostly uses standardized clinical scales including the Fugl Meyer Assessment (FMA) and Barthel Index (BI)[12], [13]. Since these instruments are clinically valid and have been extensively used, they rely on factor of therapist observation and only periodic assessment, which adds subjectivity and is unable to measure recovery dynamics over time. As a result, subtle day to day motor changes or changes might go unnoticed, which prevents timely therapeutic changes.

To overcome these challenges, the use of digital health technologies and Internet of Things (IoT)-based rehabilitation systems as objective and remote patient monitoring have been investigated in recent studies. The techniques of wearable sensors using inertial measurement devices (IMUs), accelerator and electromyography (EMG) have been seen to measure kinematic features like velocity, tremor and smoothness of movement[14]. Though such techniques are capable of large time resolutions, most of them need costly equipment, periodic calibration, and patient cooperation that can make them prohibitively expensive and possibly less scalable in home-based rehabilitation[15].

Motion capture systems that utilize a vision-based system have become a cheaper option. The development of computer vision allows tracing skeletal movements without the use of a marker (skeletal tracking with normal cameras), eliminating the need to carry equipment on the body[16]. Google, in its MediaPipe frameworks, offers pose estimation and hand landmark detection in real-time, which makes them useful in tele-rehabilitation use[17]. Previous research has demonstrated that joint trajectories derived in vision can estimate clinical monitoring and allow automatic repetitions counting and range-of-motion. Numerous of these systems are however still in prototype stage, and they have had little clinical validation, small cohort size or are limited to simple measures like repetition frequencies without additional biomechanical analysis[18].

Movement smoothness, speed profiles and the consistency of the trajectory are also identified in recent literature as promising digital biomarkers of neurological recovery. Jerk-based and acceleration-variance measures of smoothness have been closely linked with neuromuscular control and motor relearning. However, little has been done to statistically confirm such kinematic signs in comparison to gold-standard clinical scales in large, as well as severity-stratified group. Additionally, monocular vision systems still face fine motor processing difficulties as they cannot adequately address the problems of occlusion, landmark instability, or finger overlap and hence their accuracy in gross motor tracking is decreased relative to the accuracy level in gross motor tracking[19].

Thus, although there has been an increasing interest in using the IoT technology in rehabilitation, there is still the research gap in creating scalable and low-cost systems, (i) that obtain multi-dimensional kinematic metrics, (ii) that are validated against standard clinical measures, and (iii) that are reliable across different levels of impairment. This gap is filled by one proposed in the present study, namely addition of the framework called RIoTv2 that enables the integration of skeletal tracking and velocity, smoothness, range-of-motion, and repetition-accuracy measures and then subjects them to correlation and ANOVA versus standardized clinical scores. The combination of continuous digital monitoring and statistical validation of the system would form clinically meaningful digital biomarkers of post-stroke hand rehabilitation.

3. MATERIALS AND RESOURCES

This study utilized a clinical cohort, technological infrastructure, and validated instruments. The participant cohort consisted of 200 post-stroke patients from Putrajaya Hospital. Data acquisition used standard laptops with integrated 1080p webcams. The core technical resources were the RIoTv2 framework and Google's MediaPipe Pose library for skeletal tracking. Analysis was performed using Python (NumPy, Pandas, SciPy). Clinical validation employed the Fugl-Meyer Assessment (FMA) and Barthel Index (BI). Ethical approval was granted by the Ministry of Health Malaysia Medical Research & Ethics Committee (MREC Ref: 24-02136-NJQ).

3.1 Study Design and Data Collection

Table 1. RIoTv1 vs RIoTv2

Feature	RIoTv1	RIoTv2
Tracking Model	Basic pose estimation	MediaPipe skeletal tracking
Motion Metrics	Repetition count only	Velocity, Smoothness, ROM, Accuracy
Clinical Validation	Prototype-level	Correlation + ANOVA
Patient Cohort	Pilot (<30)	Clinical (n = 200)
Severity Stratification	Not included	Mild / Moderate / Severe
Digital Biomarkers	Not established	Smoothness-based indicator

Table 1 presents the comparison of RIoTv1 and RIoTv2 where improvements are made greatly on a system. Whereas RIoTv1 only manages to do basic pose tracking and repetition counting on small pilot studies, RIoTv2 fuses MediaPipe skeletal tracking and superior motion metrics such as velocity, smoothness, ROM, and accuracy. Clinical validation, severity stratification, and digital biomarkers are also present in RIoTv2 as it will allow clinically reliable, personalized, and data-driven rehabilitation assessment with a larger clinical group.

4. METHODS

4.1 Maintaining the Integrity of the Specifications

A quantitative, quasi-experimental design was employed. Each participant performed one-minute sessions of Hand Strengthening (fist open-close) and Hand Opposition (finger-to-thumb sequencing). The RIoTv2 system recorded these sessions via webcam, while a clinical therapist simultaneously scored the performance using FMA and BI sub-scores. Participants consisted of 200 post-stroke individuals (age: 45–75 years) with varying levels of upper-limb impairment. Based on baseline Fugl-Meyer Assessment (FMA) scores, 78 participants were categorized as Mild impairment, 69 as Moderate, and 53 as Severe.

4.2 Kinematic Feature Extraction

Four important measures of the raw Media Pipe skeletal coordinates were algorithmically computed per session:

(1) Movement Velocity (angular displacement of the wrist joint over time),
(2) Gesture Smoothness (division of acceleration variance),
(3) Range of Motion (ROM) (maximum angular displacement at the wrist),
(4) Repetition Accuracy (number of full and correctly completed movement cycles).

4.3 Statistical Analysis: Correlation Analysis

The r coefficient was used to measure the linear relationships between each of the metrics of kinematics and the corresponding clinical score (Pearson, 2016). Severity-Stratified Analysis: Participants were categorized to Mild impairment, Moderate impairment and Severe impairment according to their initial manual scores. A one-way Analysis of Variance (ANOVA) was used to see the significant difference among these three groups in system accuracy (absolute error) with regards to both HS and HO tasks. The level of significance was established at $\alpha = 0.05$.

5. FINDING AND ANALYSIS

5.1 Summary of Correlation Trends

The statistical evidence confirmed a significant positive relation between the IoT-measured kinematic indices and the clinical scale of assessment scores and the strength of correlation differed significantly across tasks. This relationship is well illustrated in a grouped bar chart (Figure 1) that summarizes the correlation coefficients (r) of each of the kinematic measures to the Fugl-Meyer Assessment (FMA) score of both the Hand Strengthening (HS) and Hand Opposition (HO) tasks

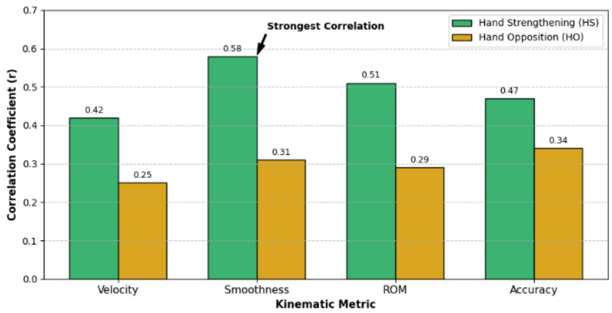

Fig. 1. Summary of correlation coefficients between IoT-derived kinematic metrics and FMA scores for Hand Strengthening (HS) and Hand Opposition (HO) tasks

As noted in the chart, the ratio of movement smoothness is the most interrelated measure during the gross motor HS task, and the correlation is generally lower in the fine motor HO task.

5.2 Key Interpretive Result

The most salient finding was that movement smoothness demonstrated the strongest association with clinical motor function for the gross motor Hand Strengthening task. This confirms its utility as a primary digital biomarker for tracking recovery. As illustrated, correlations for the fine motor Hand Opposition task were notably weaker across all metrics.

5.3 Severity-Dependent Performance

ANOVA demonstrated that the level of impairment of a patient had a statistically significant impact on the accuracy of both tasks in the system (HS: $p<0.001$; HO: $p=0.020$). The post-hoc analysis also established that the error in measurement was minimal in patients with mild impairment then high in moderate and severe.

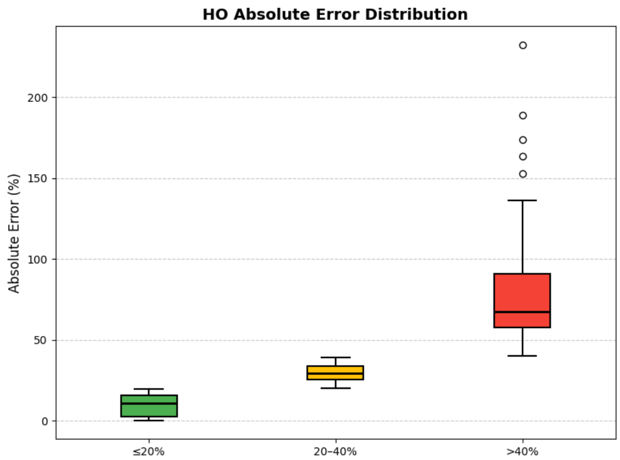

Fig. 2. HS Absolute Error Distribution

The plot (Fig. 2) of the absolute error (percentage) in the RIoTv2 system in absolute error (percentage) during the Hand Strengthening (HS, gross motor) task under the conditions of mild/lowest errors, moderate and severe/highest errors revealed that the absolute error (percentage) is evenly spread across all the conditions. In mild impairment, median errors are relatively low and stable (10% tight, interquartile), in the middle range, they grow to acceptable levels (30, wider spread), and in severe cases, they get to quite high levels (55, even higher). This physical trend graphically demonstrates the statistically significant ANOVA value ($p<0.001$) and post-hoc value, indicating the consistency of good performance on gross motor tasks in less severe impairment and severe impairment whereby errors tend to be below pragmatic acceptability rates (e.g., less than 2530) of the severity.

Figure 3 shows the distribution of absolute error (%) for the Hand Opposition (HO, fine motor) task across the same impairment severity groups. Errors are low in mild impairment (median ≈10–15%, narrow range), rise to ≈30–35% in moderate cases, but escalate dramatically in severe impairment (median ≈70–80%, very wide interquartile range, long whiskers, and multiple outliers exceeding 150%). These distributions align with the ANOVA significance ($p=0.020$) and underscore monocular MediaPipe limitations—such as landmark flickering, disappearance, and occlusions during

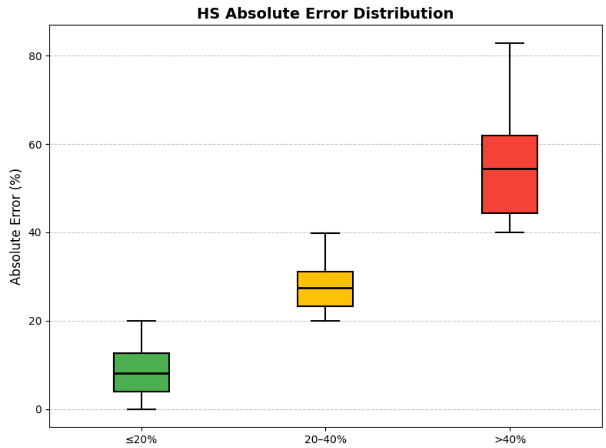

Fig. 3. HO Absolute Error Distribution

finger-to-thumb sequencing—making fine motor tracking less reliable in moderate-to-severe cases, where errors frequently exceed practical clinical thresholds.

5.4 Overall Validation Outcome

In remote rehabilitation monitoring, a variation of error to 20-30 percent of the range is a common number in the previous tele-assessment research because of inconsistency in the unsupervised home-based data gathering condition and the sensor specifications. The RIoTv2 system displayed good results in this clinically pragmatic rage of tolerance, with the two rehabilitation activities showing over 75% detection accuracy of movements in the entire group of participants.

5.5 Technical Error Analysis for Fine Motor Tasks

The comparatively weaker correlations observed during the Hand Opposition (HO) task were further investigated through a technical analysis of the skeletal tracking output generated by the MediaPipe framework. Unlike the gross motor Hand Strengthening (HS) exercise, the HO task involves sequential fingertip-to-thumb contact, which introduces several vision-based tracking challenges in monocular camera systems.

Frame-by-frame inspection revealed intermittent instability in distal finger landmarks (particularly landmarks 8, 12, 16, and 20 representing index to little fingertips). During finger-to-thumb opposition, partial self-occlusion frequently occurred when the thumb overlapped the distal phalanges, causing temporary landmark disappearance or spatial jitter. This resulted in high-frequency positional noise in the extracted coordinate data.

Consequently, the computed kinematic parameters such as movement smoothness and repetition accuracy exhibited variance inflation due to discontinuities in angular displacement trajectories. These tracking inconsistencies were more prominent in participants with moderate-to-severe motor impairment, where compensatory movements and tremor further degraded landmark stability.

This finding highlights a known limitation of monocular vision-based hand tracking for fine motor rehabilitation tasks, where millimetre-level motion accuracy is required for reliable digital biomarker generation.

6. Discussions and Recommendations

Smoothness and FMA have a high correlation, which confirms that smoothness is a powerful digital biomarker of gross motor recovery, which is an indication of an efficient neuromuscular control. The correlations of the HO task were significantly lower, which demonstrates a limitation of the present study since they were measured using monocular vision that might have been a reason to underuse the method because of occlusions and landmark estimation errors. Most importantly, the results of the ANOVA prove that the severity of impairment is a significant confounding factor; the more impaired a system is, the worse is the accuracy of that system. This requires sensitivity-based use of such tools.

This significant correlation between smoothness and FMA in gross task is consistent with previous findings that smoothness is a delicate kinematic analogue of motor recovery following stroke that frequently demonstrates moderate to also strong associations (r -0.48 to -0.70) among impairment adjustments and functional enhancements in reaching/pointing movements. This goes in favor of the value of RIoTv2 which is a low-cost, objective, remote tool in mild-moderate cases when the boxplot distributions indicated errors that were pragmatically low (<2530%), consistent with normalized kinematic errors about 720 percent and FMA-UE MDC/MCID thresholds of about 820 percent, subscale in telerehabilitation literature. Monocular limitations however are reflected in weaker performances by HO, severe-group escalation, monocular limitations that are also recorded in MediaPipe validations in clinical experiments, where the accuracy of monocular performance is lower in occluded/fine tasks, than in gross activities. The relationship between telerehabilitation and severity is reflected by the fact that remote monitoring of more impaired patients continues to deteriorate as a result of tremor, compensatory mechanisms and less control. These findings highlight the importance of context-aware application: RIoTv2 is the best to detect the gross motor weakness in mild impairment, promote equity in the understaffed regions, and necessitates improvement to perform small tasks, or the severe ones to deliver clinical utility and value to withhold soft.

Recommendations:

(1) Algorithmic Refinement: Future work must improve fine-motor tracking, potentially via higher-resolution hand models or sensor fusion.

(2) Personalized Calibration: Developing calibration routines tailored to an individual's specific movement patterns (e.g., tremor) could mitigate errors in severe cases.

(3) Longitudinal Validation: These cross-sectional correlations should be tested in longitudinal studies to confirm the metrics can predict recovery trajectories.

7. Conclusion

The study provides statistical support of the fact that kinematic values obtained using the IoT, especially the movement smoothness, are significantly correlated with the existing clinical measurements of post-stroke hand rehabilitation. The combination of correlation analysis and severity-stratified ANOVA provides a subtle validation system. It supports the high potential of the RIoTv2 system as a goal-oriented monitoring aid to patients with mild-to-moderate impairment, gross motor activities, in particular. Closing the gap between continuous motion data and clinical interpretation, this work helps build ultimate, data-driven rehabilitation interventions, and presents a clear outline of the steps that are needed to improve further the analysis of fine motions and use severe cases of impairment in future.

It is established in this work that RIoTv2, with low-cost webcam-based MediaPipe tracking and advanced kinematic measurements, provides a low-cost alternative to more conventional clinic-bound testing, especially in the gross motor recovery where smoothness as a strong digital biomarker (as a moderate-to-strong correlation $r \approx 0.48070$) has been identified. The gradual increase in error with severity of impairment (observable in boxplots and ANOVA) reflects the issue of telerehabilitation, where fine motor reliability is constrained by monocular limitations (occlusions, landmark instability) in cases of moderate-severe impairment- however, errors in the pragmatic range (2530) are acceptable in cases of relatively mild impairment, with normalized kinematic errors (s -720) and FMA-UE minimal detectable change (MDC -720) or minimal clinically RIoTv2 achieves health equity, geographic/economic geographic disparities in underserved regions (e.g., rural Malaysia), patient autonomy in recovery at home and facilitates personalized, intervention-adaptive care by facilitating remote real-time objective data collection. Future developments (e.g. sensor fusion, depth enhancement) may extrapolate usefulness to fine tasks and severe impairment performance, which will benefit a more comprehensive, data-driven paradigm in the field of post-stroke telerehabilitation.

Acknowledgement

This work was supported by the Ministry of Higher Education (MOHE), Malaysia, under the Fundamental Research Grant Scheme (FRGS23-307-0916). The authors also thank the National Medical Research Register (NMRR) for their support and access to research facilities under NMRR ID-24-02136-NJQ, which were vital to the successful completion of this study.

References

[1] L. A. Ingram, A. A. Butler, M. A. Brodie, S. R. Lord, and S. C. Gandevia, "Quantifying upper limb motor impairment in chronic stroke: A physiological profiling approach," Journal of Applied Physiology, vol. 131, no. 3, pp. 949–965, Sep. 2021, doi: https://doi.org/10.1152/japplphysiol.00078.2021.

[2] D. T. H. Nguyen and D. T. T. Trinh, "Correlation of the Fugl Meyer assessment, Motricity Index and Barthel Index scales in the assessment of rehabilitation in post-stroke patients," MedPharmRes, vol. 7, no. 4, pp. 1–10, Dec. 2023, doi: https://doi.org/10.32895/UMP.MPR.7.4.1.

[3] C. D. Rocha, I. Carneiro, M. Torres, H. P. Oliveira, E. J. Solteiro Pires, and M. F. Silva, "Post-stroke upper limb rehabilitation: clinical practices, compensatory movements, assessment, and trends," Progress in Biomedical Engineering, vol. 7, no. 4, Oct. 2025, doi: https://doi.org/10.1088/2516-1091/adeb1e.

[4] D. T. H. Nguyen and D. T. T. Trinh, "Correlation of the Fugl Meyer assessment, Motricity Index and Barthel Index scales in the assessment of rehabilitation in post-stroke patients," MedPharmRes, vol. 7, no. 4, pp. 1–10, Dec. 2023, doi: https://doi.org/10.32895/ump.mpr.7.4.1.

[5] K. Hou, M. M. R. Khan, and M. H. Rahman, "An Accessible AI-Assisted Rehabilitation System for Guided Upper Limb Therapy," Sensors (Basel)., vol. 25, no. 19, Oct. 2025, doi: https://doi.org/10.3390/s25196239.

[6] N. H. M. Dhuzuki et al., "Design and Implementation of a Deep Learning-Based Hand Gesture Recognition System for Rehabilitation Internet-of-Things (RIoT) Environments Using MediaPipe," IIUM Engineering Journal, vol. 26, no. 1, pp. 353–372, 2025, doi: https://doi.org/10.31436/IIUMEJ.V26I1.3455.

[7] M. S. Islam et al., "Advanced Rehabilitation IoT (RIoT) System Utilizing IMAGy MEMS Sensors and Deep Learning for Hand Gesture Recognition," 2025 International Conference on Electrical Engineering and Informatics (ICEEI), pp. 1–4, Nov. 2025, doi: https://doi.org/10.1109/ICEEI68459.2025.11331189.

[8] M. S. Islam et al., "AI and RIoT for Rehabilitation: Advancing Hand Gesture Recognition and Voice Assistance," pp. 439–453, 2026, doi: https://doi.org/10.1007/978-3-032-00232-7_28.

[9] A. A. Zainuddin, M. S. Islam, D. Handayani, S. I. Kamarudin, M. I. Mohd Tamrin, and A. F. Misman, "Tolerance-Based Evaluation of a Shariah-Compliant Rehabilitation IoT Framework for Post-Stroke Hand Gesture Monitoring," 2025 8th International Conference on Information and Communications Technology (ICOIACT), pp. 232–237, Dec. 2025, doi: https://doi.org/10.1109/ICOIACT67584.2025.11345020.

[10] A. A. Zainuddin, N. H. M. Dhuzuki, A. A. Puzi, M. N. Johar, and M. Yazid, "Calibrating Hand Gesture Recognition for Stroke Rehabilitation Internet-of-Things (RIOT) Using MediaPipe in Smart Healthcare Systems," International Journal of Advanced Computer Science and Applications, vol. 15, no. 7, pp. 568–583, Jul. 2024, doi: https://doi.org/10.14569/IJACSA.2024.0150756.

[11] N. H. M. Dhuzuki, A. A. Zainuddin, S. I. Kamarudin, D. Handayani, K. Subramaniam, and M. I. M. Tamrin, "Web-Based Medical Information System for Stroke Rehabilitation Internet-of-Things (RIOT) Patients: A Prototype," 6th IEEE International Conference on Artificial Intelligence in Engineering and Technology, IICAIET 2024, pp. 326–330, 2024, doi: https://doi.org/10.1109/IICAIET62352.2024.10729958.

[12] D. J. Gladstone, C. J. Danells, and S. E. Black, "The Fugl-Meyer Assessment of Motor Recovery after Stroke: A Critical Review of Its Measurement Properties," Neurorehabilitation and Neural Repair, vol. 16, no. 3, pp. 232–240, 2002, doi: https://doi.org/10.1177/154596802401105171.

[13] D. T. H. Nguyen and D. T. T. Trinh, "Correlation of the Fugl Meyer assessment, Motricity Index and Barthel Index scales in the assessment of rehabilitation in post-stroke patients," MedPharmRes, vol. 7, no. 4, pp. 1–10, Dec. 2023, doi: https://doi.org/10.32895/ump.mpr.7.4.1.

[14] M. Rana and V. Mittal, "Wearable Sensors for Real-Time Kinematics Analysis in Sports: A Review," IEEE Sensors Journal, vol. 21, no. 2, pp. 1187–1207, Jan. 2021, doi: https://doi.org/10.1109/JSEN.2020.3019016.

[15] R. De Fazio, V. M. Mastronardi, M. De Vittorio, and P. Visconti, "Wearable Sensors and Smart Devices to Monitor Rehabilitation Parameters and Sports Performance: An Overview," Sensors (Basel)., vol. 23, no. 4, Feb. 2023, doi: https://doi.org/10.3390/s23041856.

[16] D. S. Y. Vun, R. Bowers, and A. McGarry, "Vision-based motion capture for the gait analysis of neurodegenerative diseases: A review," Gait & Posture, vol. 112, pp. 95–107, Jul. 2024, doi: https://doi.org/10.1016/j.gaitpost.2024.04.029.

[17] "MediaPipe Hands: On-device Real-time Hand Tracking - Consensus." Accessed: Feb. 27, 2026. [Online]. Available: https://consensus.app/papers/mediapipe-hands-ondevice-realtime-hand-tracking-zhang-bazarevsky/6526b10aff0452039f78bc323b196be4/

[18] Q. Shi, H. Zhang, L. Dong, Q. Lei, and T. Hsiao, "Vision skeleton trajectory based motion assessment system for healthcare rehabilitation," The Journal of Engineering, vol. 2020, no. 9, pp. 805–808, Sep. 2020, doi: https://doi.org/10.1049/joe.2019.1316.

[19] G. Kwakkel et al., "Standardized measurement of sensorimotor recovery in stroke trials: Consensus-based core recommendations from the Stroke Recovery and Rehabilitation Roundtable," International Journal of Stroke, vol. 12, no. 5, pp. 451–461, Jul. 2017, doi: https://doi.org/10.1177/1747493017711813.