

Evaluation of Random Forest and LSTM for IMU-Based Wrist Movement Classification with sEMG Monitoring

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Abstract

Post-stroke motor impairment can limit wrist function and motivates rehabilitation systems that acquire movement and muscle-activity information. This study evaluates Random Forest (RF) and Long Short-Term Memory (LSTM) for five-class wrist-movement classification using six-channel inertial measurement unit (IMU) data, while surface electromyography (sEMG) is used for RMS-based muscle-activity monitoring. Two healthy male participants, both 22 years old, completed right-wrist recordings of REST, flexion, extension, radial deviation, and ulnar deviation, with 10 trials per movement, 20 s per trial, and five repetitions per trial. IMU signals sampled at 200 Hz were segmented using 50-sample windows with a 25-sample step, producing 30 statistical features per window. Under a held-out-trial protocol, RF achieved 87.71% accuracy and a macro F1-score of 0.877, whereas LSTM achieved 97.93% accuracy and a macro F1-score of 0.979. sEMG RMS was mapped to LOW and NORMAL states and combined with the movement class to determine assistance. The real-time system used RF with Python, MQTT, ESP32, OpenRB-150, and two Dynamixel MX-28AT actuators. Bench testing produced tracking RMSE values of 10.69° for flexion-extension and 7.28° for radial-ulnar motion, with zero overshoot.

Keywords: inertial measurement unit (IMU), Random Forest, Long Short-Term Memory (LSTM), surface electromyography (sEMG), wrist rehabilitation

INTRODUCTION

Stroke is a neurological disorder that can cause long-term motor impairment and reduce a person's ability to perform daily activities independently. Upper-extremity impairment is one of the common consequences of stroke, particularly affecting the shoulder, elbow, hand, and wrist. Repetitive and task-oriented rehabilitation is therefore important to support motor recovery. In recent years, robotic and sensor-based rehabilitation systems have been developed to provide more structured and measurable training while simultaneously acquiring information related to user movement and physiological activity (Fareh et al., 2023; Hays et al., 2023; Munoz-Novoa et al., 2022).

Surface electromyography (sEMG) and inertial measurement units (IMUs) are two sensing modalities that can provide complementary information in rehabilitation systems. sEMG records electrical activity generated by muscle activation and has been widely applied in human-machine interfaces, rehabilitation, and robotic control (Di Nardo et al., 2022; Song et al., 2023). Meanwhile, IMUs provide acceleration and angular-velocity information that can be used to characterize upper-extremity movement. Previous studies have demonstrated the potential of IMU data for upper-extremity motion analysis and activity recognition (J. Li et al., 2024; M. Li et al., 2023). In the present study, these sensors are assigned different functions: IMU data are used as the primary input for wrist-movement classification, whereas sEMG is processed using root mean square (RMS) to provide an operational indication of muscle-activity state.

The integration of sensors, microcontrollers, wireless communication, and real-time monitoring has also been demonstrated in various embedded systems. Siskandar and Kusumah (2019) developed an aquaponic monitoring and control device integrating multiple sensors, automation, and web-based control. Siskandar, Fadhil, et al. (2020) implemented an Internet of Things-based automatic monitoring and control system, while Siskandar, Indrawan, et al. (2020) demonstrated embedded image processing and automated actuation in a fruit-sorting machine. Integrated monitoring and automation were subsequently reported by Siskandar, Santosa, et al. (2022) and Siskandar, Wiyoto, et al. (2022). More recently, Siskandar, Mandang, et al. (2023a) developed a wireless sensor-reading monitoring architecture integrating multiple sensors with embedded processing devices. Collectively, these studies demonstrate that sensing, embedded processing, communication, monitoring, and control can be integrated within modular system architectures.

Machine-learning methods can extend such sensor systems by transforming time-series measurements into interpretable movement information. Random Forest (RF) is suitable for classification using statistical feature vectors, whereas Long Short-Term Memory (LSTM) networks are designed to learn temporal relationships in sequential data. Previous studies have shown the use of machine-learning approaches for inertial-sensor-based activity recognition and wrist-related movement analysis (Gomaa & Khamis, 2023; M. Li et al., 2023). However, model evaluation must also consider the data-splitting strategy because overlapping windows originating from the same recording may cause information leakage when distributed across training and testing sets (Rehman et al., 2024).

In addition to sensor monitoring and classification, the output of the sensing system must be connected to an actuator-control architecture when assistance is required. Siskandar, Mandang, et al. (2025) demonstrated the integration of microcontroller-based control, wireless command transmission, and robotic actuation in an agricultural robotic platform, while Siskandar, Novianty, et al. (2025) reported a remotely controlled soil-loosening robot incorporating microcontroller-based control and camera-assisted monitoring. Although the application domains differ from wrist rehabilitation, both studies illustrate modular communication and actuator-control architectures in which command information is processed before being translated into robotic motion. In rehabilitation applications, this integration requires additional considerations because actuator operation involves interaction with the human body and therefore requires appropriate motion limits, torque limits, and safety mechanisms.

Previous studies have investigated sEMG- and IMU-based rehabilitation, movement recognition, and robotic assistance. Bonilla et al. (2023) developed an exoskeleton rehabilitation system based on EMG gesture classification, while Hamid and Utomo (2025) integrated EMG, motion sensors, and machine learning in an upper-extremity exoskeleton system. Nevertheless, further investigation is needed to compare RF and LSTM using the same IMU-based wrist-movement dataset under a held-out-trial evaluation protocol while separating the role of IMU as the movement-information source from sEMG as the muscle-activity indicator. Therefore, this study evaluates RF and LSTM for five-class wrist-movement classification using IMU data, employs RMS-based sEMG monitoring to determine LOW and NORMAL muscle-activity states, and integrates the resulting information into a real-time assistance system using Python, MQTT, ESP32, OpenRB-150, and Dynamixel MX-28AT actuators.

METHODS

This study was conducted through sequential stages comprising participant data acquisition, IMU and sEMG signal processing, wrist-movement classification, muscle-activity monitoring, real-time system integration, and actuator bench testing. IMU data were used for movement classification and internal kinematic analysis, whereas sEMG was used as an RMS-based operational

indicator of muscle activity. The outputs of both sensing pathways were integrated into an assistance-decision mechanism that controlled the OpenRB-150 and Dynamixel MX-28AT actuators.

System Architecture

The proposed system integrates sensing, data acquisition, wireless communication, real-time processing, and actuator control. An ESP32 microcontroller (Espressif Systems, 2026) was used as the main acquisition unit for the IMU and sEMG sensors. Similar embedded architectures integrating sensors, microcontrollers, communication modules, and monitoring interfaces have been implemented in previous studies. Siskandar, Fadhil, et al. (2020) developed an IoT-based monitoring and control system using a microcontroller and an Android interface, while Siskandar, Santosa, et al. (2022) implemented integrated monitoring and automation in the INSMoaf greenhouse system. Microcontroller-based sensor integration in a light-detection and solar-tracking system was also reported by Siskandar, Mandang, et al. (2023b). These studies demonstrate the feasibility of combining sensor acquisition, embedded processing, monitoring, and control within a unified system architecture.

In the present system, the IMU provides three-axis accelerometer and three-axis gyroscope measurements, while the sEMG sensor provides muscle-activity signals. Sensor data are acquired by the ESP32 and transmitted to a host computer for processing and visualization. Internet-based and wireless sensor-monitoring architectures have also been demonstrated by Siskandar, Wiyoto, et al. (2022) and Siskandar, Mandang, et al. (2023a), in which sensor information was acquired by embedded devices and transferred to a monitoring system. Optical-sensor data acquisition for water-turbidity measurement was further demonstrated by Siskandar, Wiyoto, et al. (2023), providing another example of sensor readings being converted into interpretable monitoring information. MQTT was used as the communication protocol between the ESP32 and the Python-based application (Banks & Gupta, 2014). The overall processing and assistance-decision architecture of the proposed system is illustrated in Figure 1.

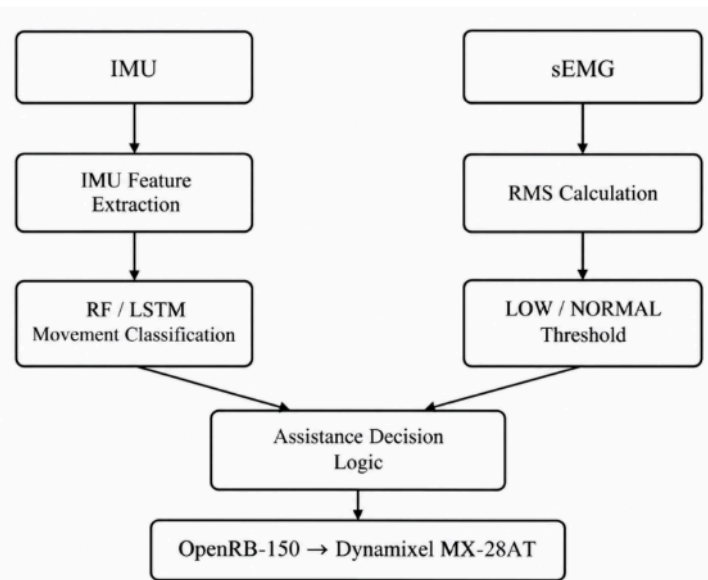


Figure 1. Integration architecture separating IMU-based movement classification and sEMG-based muscle-activity monitoring.

As shown in Figure 1, IMU and sEMG data are processed through separate pathways. IMU data are used for feature extraction and wrist-movement classification using RF or LSTM, whereas the sEMG signal is processed using RMS and an operational threshold to determine LOW or NORMAL muscle-activity states. The outputs of both pathways are subsequently combined in the assistance-decision logic. When assistance is required, a command is transmitted to the OpenRB-150

to control the corresponding Dynamixel MX-28AT actuator. The main hardware components and their respective functions are summarized in Table 1.

Table 1. Main hardware components and their functions.

Component	Main function
ESP32	Sensor acquisition, initial processing, Wi-Fi/MQTT communication, and UART communication with OpenRB-150.
Gravity analog sEMG sensor	Acquisition of muscle electrical activity for RMS-based LOW/NORMAL monitoring.
ICG-20660L IMU	Three-axis acceleration and three-axis angular-velocity acquisition (ax, ay, az, gx, gy, gz).
OpenRB-150	Interface and controller for the Dynamixel actuators.
2 × Dynamixel MX-28AT	Actuation of the FE and RU axes.
Power system	12 V actuator supply with voltage regulation for the electronic subsystems.

The physical arrangement and interconnection of the main hardware components used in the wrist rehabilitation prototype are shown in Figure 2.

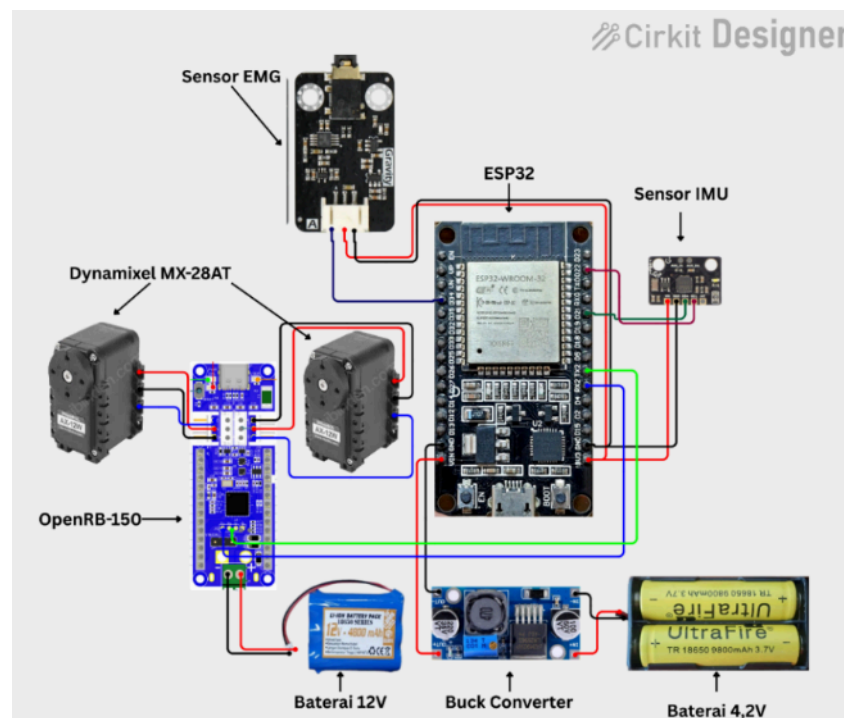


Figure 2. Hardware arrangement used in the wrist rehabilitation prototype.

As shown in Figure 2, the ESP32 is connected to the IMU and sEMG sensors for data acquisition and communicates with the OpenRB-150, which controls the Dynamixel actuators used for the FE and RU axes.

Participants and Experimental Protocol

Two healthy male participants contributed participant-specific datasets. Restu was 22 years old and Alwi was 22 years old; both recordings used the right wrist. Because both participants were healthy and had no history of stroke reported for this study, affected/non-affected limb terminology was not applicable. Each participant performed five conditions—REST, flexion, extension, radial

deviation, and ulnar deviation—with 10 trials per condition. Each trial lasted approximately 20 s and contained five repetitions, yielding 50 trials per participant. The two participant datasets were kept distinct rather than pooled as evidence of inter-subject generalisation. Classification and the internal FE analysis used the Alwi dataset, whereas the internal RU analysis used the Restu dataset, consistent with the final report. Accordingly, all reported model results are participant-specific held-out-trial results.

Signal Acquisition, Segmentation, and IMU Features

Both IMU and sEMG signals were acquired at 200 Hz. This rate reflects the configured acquisition setting of the integrated ESP32 system; it was not selected to capture the complete spectral bandwidth of surface EMG. In the final analysis, sEMG is not used for MNF, MDF, movement classification, or angle regression, and no conclusions are drawn about frequency-domain sEMG feature importance. Instead, sEMG is reduced to the time-domain RMS measure used for the LOW/NORMAL operational state. At 200 Hz, a 50-sample window corresponds to 250 ms and the 25-sample step to 125 ms. For movement classification, the IMU provides six channels (ax, ay, az, gx, gy, gz). From each channel, mean, standard deviation, minimum, maximum, and range are computed, producing 30 features per window. The 200 Hz configuration necessarily excludes sEMG spectral content above the 100 Hz Nyquist frequency; therefore, the present findings should not be generalised to spectral sEMG analysis, and a higher sampling rate would be required if frequency-domain EMG features were introduced in future work.

The RF classifier operated on the 30 features of each individual window. LSTM was used as a temporal comparison model and processed ordered window sequences. Training, validation, and testing were separated by trial so that all windows originating from one trial remained in a single partition. This held-out-trial strategy reduces leakage between highly similar overlapping windows. The complete real-time hardware and assistance workflow, from device initialization to actuator control and adaptive stopping, is illustrated in Figure 3.

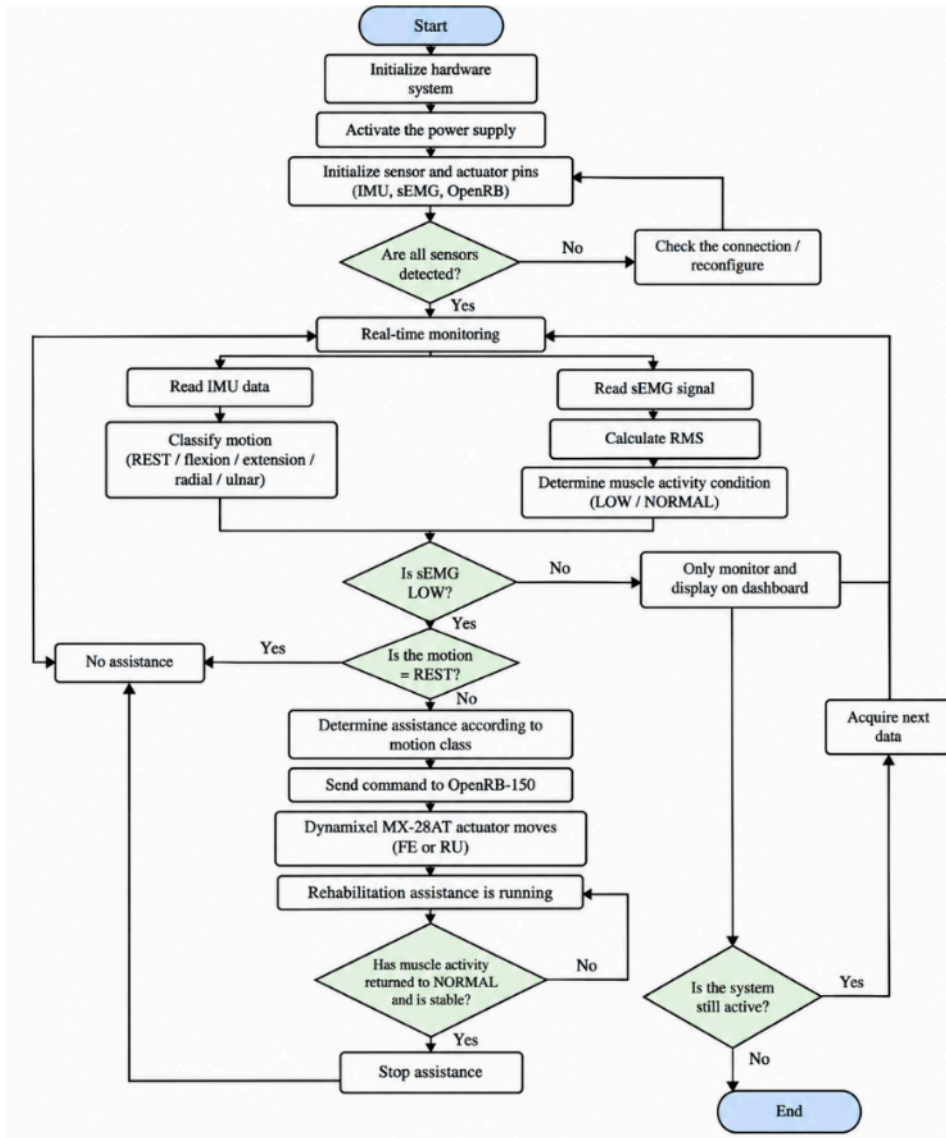


Figure 3. Real-time hardware and assistance workflow used in the integrated system.

sEMG Activity Monitoring and Assistance Logic

The sEMG signal was processed using the root mean square (RMS) as an operational time-domain indicator of muscle activity. RMS is commonly used to represent the amplitude of sEMG signals within an observation window (Di Nardo et al., 2022). The RMS value of the sEMG signal was calculated using Equation (1), where x_i represents the sEMG sample value and N represents the number of samples within the observation window.

$$RMS = \sqrt{\left(\frac{1}{N}\right) \sum_{i=1}^N x_i^2} \quad (1)$$

The calculated RMS value was compared with an adjustable operational threshold. Values below the threshold were labelled LOW, whereas values equal to or above the threshold were labelled NORMAL. These states are used solely for operational decision making and are not interpreted as clinical measurements of muscle strength. The assistance decision rule combining the movement class and sEMG activity state is summarized in Table 2.

Table 2. Assistance decision logic

Movement class	sEMG state	System response
REST	LOW or NORMAL	No assistance

Flexion / Extension	LOW	Assist FE axis
Radial / Ulnar	LOW	Assist RU axis
Any active movement	NORMAL	No assistance / adaptive stop

Based on Table 2, assistance is provided only when a non-REST movement is detected together with a LOW sEMG state. A stable return to NORMAL during assistance triggers adaptive stop and cancels the remaining repetitions. Target FE/RU angles and repetition counts are configured through the dashboard rather than estimated as real-time control references from the IMU.

Internal IMU Kinematic Analysis

In addition to classification, IMU signals were analysed to obtain internal kinematic estimates on the two wrist axes. FE used a Kalman-based fusion of accelerometer orientation and gyroscope angular velocity, while RU used relative gyroscope-derived yaw after bias and drift correction. This analysis was retained only to examine internal consistency of the IMU processing chain. The resulting angles were not used as the real-time position references for the actuators; target FE/RU angles and repetition counts were entered through the dashboard. Because no independent goniometer or joint encoder served as ground truth for the IMU estimates, these metrics cannot establish clinical angular accuracy or the adequacy of proportional assistance.

Internal consistency was quantified using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and Pearson correlation coefficient. R^2 , RMSE, and MAE are commonly used regression metrics for evaluating agreement and prediction error between reference and estimated values (Chicco et al., 2021). The metrics were calculated using Equations (2)-(4), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (2)$$

$$RMSE = \sqrt{\left(\frac{1}{N}\right) \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (3)$$

$$MAE = \left(\frac{1}{N}\right) \sum_{i=1}^N |y_i - \hat{y}_i| \quad (4)$$

Real-Time Implementation and Bench Testing

The real-time application was implemented in Python using FastAPI (FastAPI, 2026), while machine-learning processing used scikit-learn (Pedregosa et al., 2011) for the RF pipeline and PyTorch (Paszke et al., 2019) for LSTM evaluation. Communication between the ESP32 and host computer used MQTT (Banks & Gupta, 2014). The final online classifier was the RF model loaded from a saved model file together with its feature list. The dashboard displayed device connection status, movement prediction, confidence, sEMG RMS/activity state, target FE/RU angles, repetition count, and actuator status. The target angles and repetitions were operator-set parameters and were not derived from the internal IMU angle analysis. Siskandar, Mandang, et al. (2025) and Siskandar, Novianty, et al. (2025) provide related examples of microcontroller-based robotic control with wireless command transmission and remote monitoring. In the present system, actuator commands are relayed through the OpenRB-150 to the Dynamixel servos, following the controller and actuator specifications provided by ROBOTIS (2026a, 2026b).

Bench testing was performed with two MX-28AT actuators without a hand or human limb attached to the mechanism. Tracking performance was quantified using RMSE, MAE, 10–90% rise time, overshoot, and 5% settling time. These tests characterise only the unloaded mechanical and servo response. They do not reproduce human joint impedance, participant-specific range of motion,

biological torque requirements, interface compliance, discomfort, or safety constraints; consequently, bench tracking is not treated as evidence of human-exoskeleton performance or clinical readiness. The principal experimental parameters, signal-processing configuration, participant characteristics, and real-time implementation settings are summarized in Table 3.

Table 3. Experimental and system configuration.

Item	Configuration
Sampling	200 Hz for IMU and sEMG
IMU channels	ax, ay, az, gx, gy, gz
Segmentation	50-sample window; 25-sample step; 50% overlap
IMU features	Mean, standard deviation, minimum, maximum, range $\times$ 6 channels = 30 features
Classification	RF and LSTM; REST, flexion, extension, radial, ulnar
Data split	Held-out trial; all windows from a trial remain in one partition
sEMG monitoring	RMS compared with an adjustable LOW/NORMAL threshold
Real-time model	RF integrated with Python/FastAPI, MQTT, ESP32, OpenRB-150, and Dynamixel
Actuator test	Bench test only; no human limb attached
Participants	2 healthy males, both 22 years old; right wrist used; affected/non-affected limb not applicable
Movement protocol	REST, flexion, extension, radial, ulnar; 10 trials per movement; $\sim$ 20 s per trial; 5 repetitions per trial
Dataset relationship	Participant-specific datasets; classification and FE internal analysis: Alwi; RU internal analysis: Restu; no inter-subject claim
200 Hz rationale	Configured integrated acquisition rate; sEMG used for time-domain RMS only, not spectral MNF/MDF or sEMG-based regression

RESULTS AND DISCUSSION

IMU Signal Processing and Classification

The six IMU channels exhibited repeatable changes during wrist movements. A representative flexion trial is shown in Figure 4. The accelerometer channels reflect changes in acceleration and orientation, while the gyroscope channels reflect angular velocity. These patterns form the basis for windowing and statistical feature extraction.

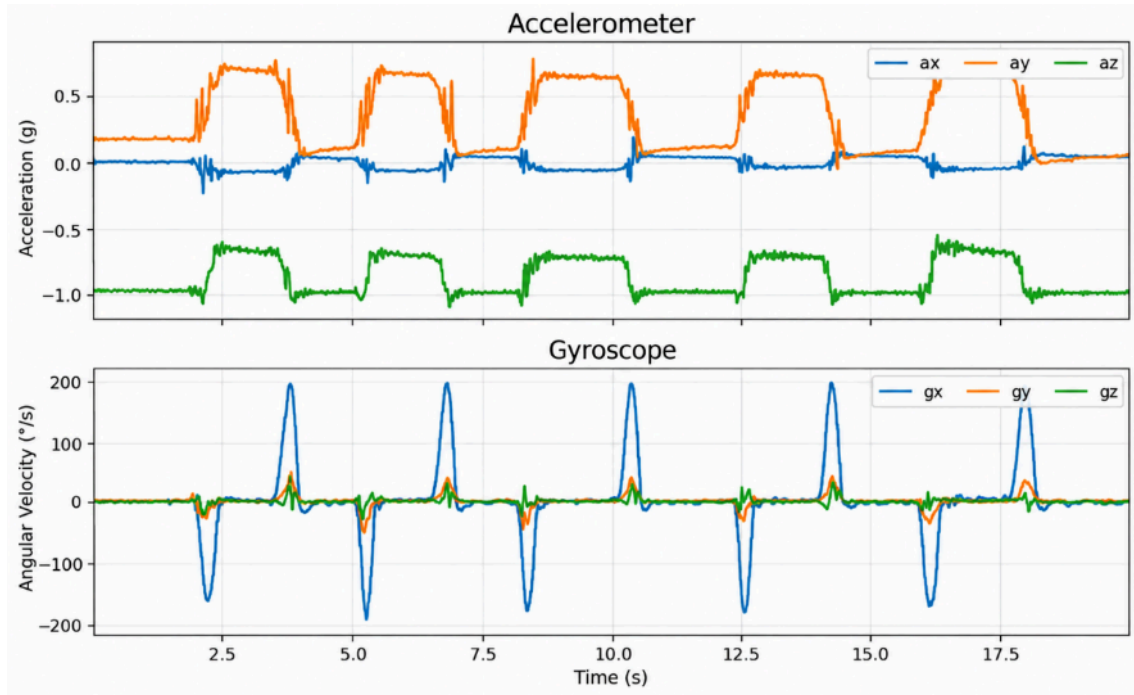


Figure 4. Representative accelerometer and gyroscope signals during one flexion trial.

The overall classification performance of RF and LSTM on the held-out-trial IMU test set is summarized in Table 4.

Table 4. RF and LSTM performance on the held-out-trial IMU test set.

Model	Accuracy (%)	Macro precision	Macro recall	Macro F1-score
Random Forest	87.71	0.901	0.877	0.877
LSTM	97.93	0.980	0.979	0.979

As shown in Table 4, LSTM achieved the higher overall performance, improving accuracy by 10.22 percentage points and increasing the macro F1-score from 0.877 to 0.979. The confusion matrices in Figure 5 show that RF errors were concentrated in several movement pairs: flexion was predicted as extension in 101 windows and radial movement was predicted as extension in 49 windows. LSTM produced substantially fewer errors, with its largest confusions consisting of 8 extension sequences predicted as radial and 7 flexion sequences predicted as radial.

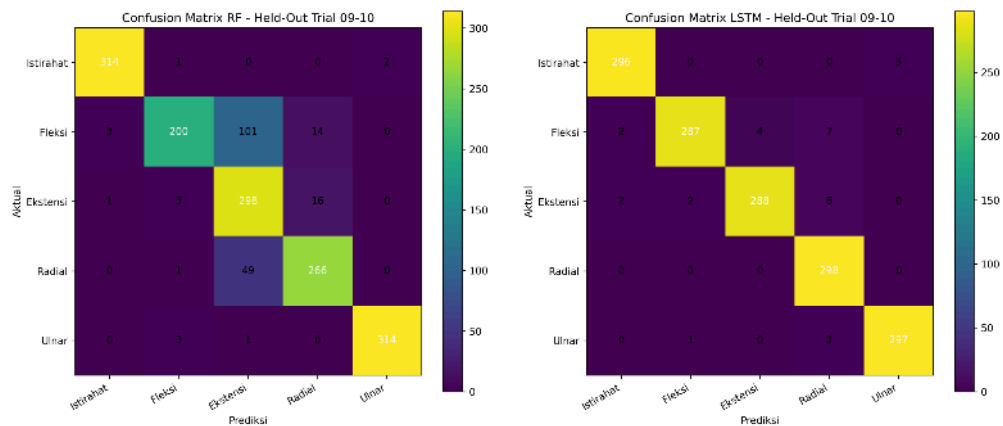


Figure 5. Confusion matrices for Random Forest (left) and LSTM (right) on the held-out-trial test set.

Internal IMU Kinematic Consistency

Internal kinematic consistency was evaluated for the flexion–extension (FE) and radial–ulnar (RU) axes using R^2 , RMSE, MAE, and Pearson correlation. The results of the internal IMU kinematic analysis for both axes are presented in Table 5

Table 5. Internal IMU kinematic-analysis results.

Axis	Dataset	R^2	RMSE (°)	MAE (°)	Pearson r
Flexion–extension	Alwi	0.986	2.817	1.519	0.993
Radial–ulnar	Restu	0.954	4.936	4.275	0.994

Based on Table 5, the FE axis produced lower RMSE and MAE values than the RU axis, while both axes showed high positive Pearson correlations. However, these results should be interpreted as internal agreement within the IMU processing pipeline. The FE and RU results were obtained from different participant-specific datasets and were not validated against a single independent external reference. Therefore, Table 5 does not represent an integrated two-DOF accuracy evaluation.

sEMG Monitoring and Real-Time Dashboard

RMS-based sEMG monitoring produced the two operational states required by the assistance logic. When RMS was below the configured threshold, the dashboard reported LOW; values at or above the threshold were reported as NORMAL. The status was combined with the IMU-derived movement class before any assistance command was issued. The real-time dashboard used to display connection status, movement prediction, sEMG activity state, target angles, repetitions, and actuator status is shown in Figure 6.

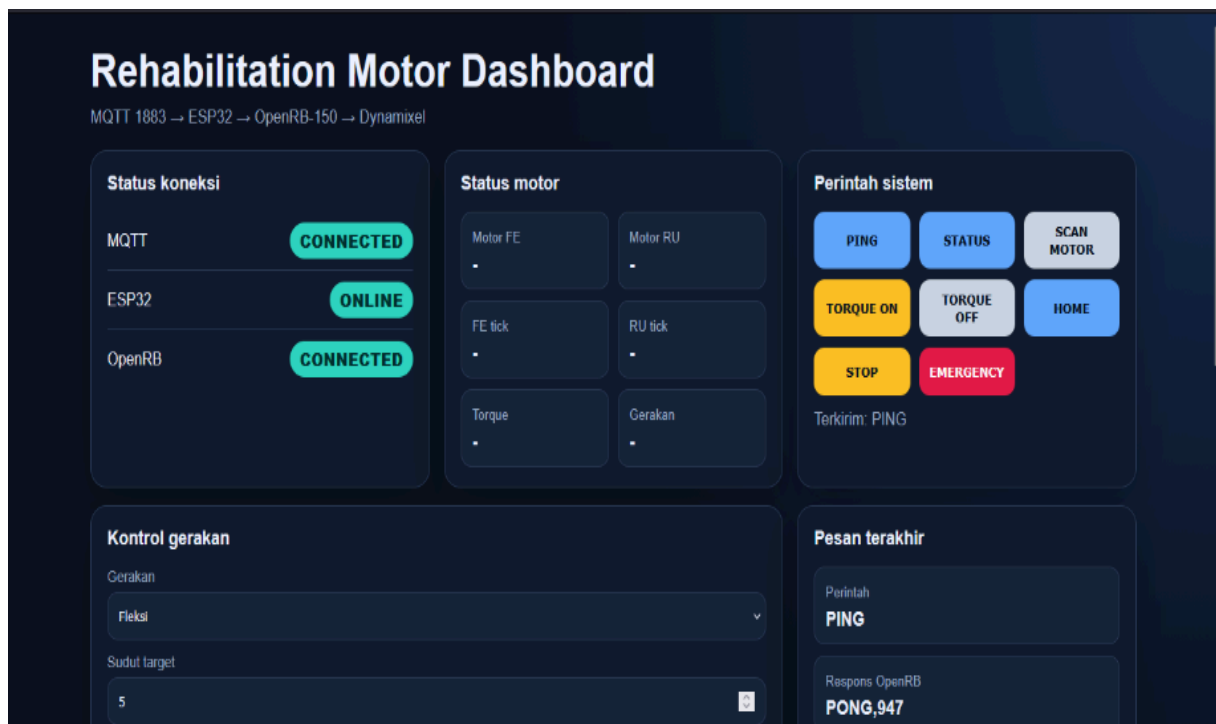


Figure 6. Real-time dashboard showing connection status, movement prediction, confidence, sEMG RMS/activity state, target angles, repetitions, and actuator status.

As shown in Figure 6, the dashboard provides the information required to monitor the sensing, classification, assistance-decision, and actuator-control stages during system operation. The final real-time implementation used RF for movement classification, whereas LSTM was retained as the higher-performing offline comparison model. This choice kept the online pipeline aligned with the implemented RF model file while preserving the RF–LSTM comparison in the evaluation stage.

Actuator Bench Tracking

To evaluate the mechanical response of the rehabilitation prototype, bench testing was performed on the two Dynamixel MX-28AT actuators assigned to the flexion-extension (FE) and radial-ulnar (RU) axes. The test focused on the ability of each actuator to follow the commanded position under unloaded conditions. Tracking performance was assessed using RMSE, MAE, rise time, overshoot, and settling time. The resulting bench-tracking performance of both actuators is summarized in Table 6.

Table 6. Bench tracking performance of the two Dynamixel actuators.

Axis	RMSE (°)	MAE (°)	Rise time (s)	Overshoot (%)	Settling time (s)
FE	10.69	4.12	1.15	0.0	1.66
RU	7.28	2.43	0.94	0.0	1.30

Based on Table 6, the RU axis demonstrated better tracking performance than the FE axis, with lower RMSE and MAE values as well as shorter rise and settling times. The RU axis achieved an RMSE of 7.28° and an MAE of 2.43°, whereas the FE axis produced an RMSE of 10.69° and an MAE of 4.12°. The RU axis also reached a rise time of 0.94 s and a settling time of 1.30 s, compared with 1.15 s and 1.66 s for the FE axis, respectively. Neither axis exhibited overshoot during the bench test. To further illustrate the tracking behaviour, the reference and measured actuator responses for the FE and RU axes are presented in Figure 7.

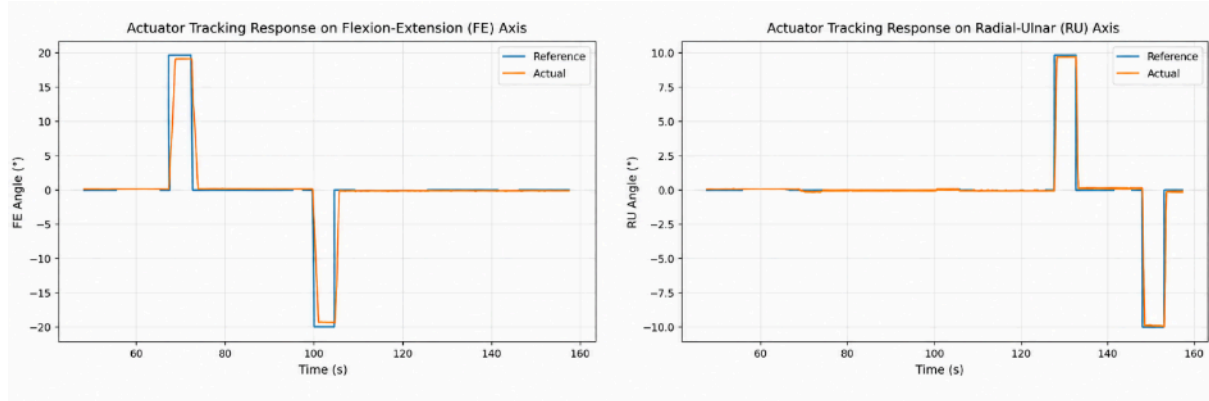


Figure 7. Bench tracking response on the flexion–extension axis (left) and radial–ulnar axis (right).

Temporal Modelling and Held-Out-Trial Classification

The central classification result is the consistent advantage of LSTM over RF under the held-out-trial protocol. RF decides from one 30-feature window at a time, whereas LSTM can use temporal relationships across ordered windows. The 97.93% LSTM accuracy and 0.979 macro F1-score therefore indicate that temporal context provides useful information for separating movement classes beyond the statistics available in an isolated window. This interpretation is consistent with prior IMU-based deep-learning work in upper-extremity activity recognition (M. Li et al., 2023).

The held-out-trial design is important when interpreting the result. Because overlapping windows from the same trial are kept in the same partition, neighbouring windows cannot leak from training into testing. The reported performance therefore reflects generalization to unseen trials within the evaluated participant-specific data, not to previously unseen users. This data-partitioning consideration is consistent with recommendations to avoid information leakage in wearable-sensor evaluation (Rehman et al., 2024).

Separation of IMU and sEMG Roles

A key design decision in the updated system is that movement class and muscle-activity state are obtained from different sensors. IMU is used for movement recognition because it directly measures motion through acceleration and angular velocity, while sEMG is used only to monitor

activity amplitude. This avoids attributing five-class movement information or wrist angle directly to one sEMG channel. The separation is consistent with rehabilitation approaches that combine physiological and motion-related information before assistance is delivered (Bonilla et al., 2023; Hamid & Utomo, 2025; Song et al., 2023).

The LOW/NORMAL labels should be interpreted only as operational states. sEMG amplitude is affected by electrode placement, skin condition, motion artefact, and inter-user variability, so the threshold requires session-specific calibration before broader use. The 200 Hz acquisition rate is also a limitation if the signal is later used for frequency-domain EMG analysis because components above 100 Hz cannot be represented. In this revised study, that limitation is contained by using only RMS amplitude for LOW/NORMAL monitoring; no MNF, MDF, sEMG-based movement classification, or sEMG-based angle regression is reported. Therefore, conclusions about the relative importance of spectral EMG features are intentionally omitted.

Interpretation of the Internal Kinematic Results

The internal kinematic metrics are numerically high, particularly the R^2 and Pearson values, but they must not be interpreted as clinically meaningful angular accuracy. The reference and estimate are derived from the same IMU data stream, so the analysis demonstrates internal consistency rather than agreement with an independent physical reference. No predefined clinical or application-oriented angular-error requirement was used in this study, and the IMU-derived angles were not used as actuator set-points in the real-time assistance loop. Therefore, the reported RMSE and MAE cannot be classified as acceptable or unacceptable for proportional exoskeleton assistance. Such a claim would require validation against an independent goniometer or joint encoder, followed by a predefined accuracy requirement linked to the intended human-interaction task.

Real-Time Assistance and Actuator Response

The real-time architecture combines movement prediction with the sEMG state before commanding assistance. LOW alone does not move the actuator: the system also requires a non-REST movement class, after which assistance is mapped to FE or RU. A stable NORMAL state can stop the remaining repetitions. This rule-based fusion reduces the risk of treating low muscle activity as sufficient evidence of a desired movement.

Bench tracking showed zero overshoot on both axes, but FE tracking error was larger than RU. These results demonstrate the response of the unloaded actuator-controller mechanism only. They do not account for human joint impedance, participant-specific range of motion, torque demand, soft-tissue compliance, mechanical-interface fit, discomfort, or interaction safety. Accordingly, the tracking RMSE values cannot be interpreted as human-exoskeleton positioning accuracy, and the absence of overshoot on the bench does not establish clinical safety. Human-in-the-loop evaluation would first require validated angular limits, current/torque limiting, mechanical end stops, emergency-stop behaviour, communication-loss shutdown, individualized ROM settings, and an appropriate supervised safety protocol.

Limitations

Several limitations constrain the scope of the findings. First, only two healthy 22-year-old male participants contributed participant-specific datasets, both using the right wrist, and the classification evaluation is held-out trial rather than inter-subject. The results therefore quantify generalisation to unseen trials within the available participant data and do not establish performance on a new user, a stroke population, or an affected limb. Second, the 200 Hz acquisition rate was a configured system setting and does not cover the full spectral bandwidth of sEMG; the present study limits its sEMG analysis to RMS amplitude and makes no spectral-feature claims. Third, the FE and RU internal kinematic analyses use different participant datasets and no independent ground truth. Fourth, LOW/NORMAL thresholds remain session dependent. Finally, actuator results were obtained only on an unloaded bench and cannot establish human-interaction safety, comfort, clinical effectiveness, or readiness for patient use.

CONCLUSION

This study updated the rehabilitation-system evaluation around the final system architecture: IMU data are used for five-class wrist-movement recognition, whereas sEMG is used for LOW/NORMAL muscle-activity monitoring. With six IMU channels represented by 30 statistical features per window, RF achieved 87.71% accuracy and a macro F1-score of 0.877, while LSTM achieved 97.93% accuracy and a macro F1-score of 0.979 under held-out-trial evaluation. The higher LSTM performance confirms the value of temporal context for the evaluated dataset.

Internal IMU kinematic analysis produced R^2 values of 0.986 for FE and 0.954 for RU, but these results represent internal processing consistency rather than absolute angular accuracy. The real-time implementation used RF with Python, MQTT, ESP32, OpenRB-150, and Dynamixel MX-28AT actuators. Bench tracking produced RMSE values of 10.69° on FE and 7.28° on RU with zero overshoot on both axes.

Future work should evaluate RF and LSTM on a larger and more diverse cohort using an inter-subject protocol, document sEMG threshold calibration across sessions, and validate IMU kinematics against an independent goniometer or encoder. If frequency-domain sEMG features are introduced, acquisition should be redesigned with a higher sampling rate and bandwidth appropriate to spectral EMG analysis. Human-in-the-loop testing should only follow verification of torque/current limits, individualized angular limits, mechanical stops, emergency-stop behaviour, communication-loss handling, and supervised safety procedures.

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