Journal of Electronics and Informatics(ISSN: 2582-3825)
www.irojournals.com/iroei/

Low-Cost AI-Based Wearable Rehabilitation Monitoring System for Upper-Limb Stroke Patients

Anisha N.[1], Ushus S Kumar[2*]

[1]Research Scholar, [2]Associate Professor, Department of Biomedical Engineering,

SRM Institute of Science and Technology, Ramapuram Campus, Chennai.

E-mail: [1]an7867@srmist.edu.in, [2*]ushusj@srmist.edu.in

Abstract

The low cost wearble monitoring framework for the automatic evaluation of exercises for stroke recovery of the upper limb with special attention to discrimination between the intended and compensatory motion of the elbow joint is designed. The monitoring framework utilizes a 9 degrees-of-freedom IMU combined with the ESP32-based data acquisition and transmission device to obtain the motion of the forearm at 100 Hz. The signals are processed using the fourth order Butterworth filter, orientation estimation by Madgwick algorithm, quaternion representation, fixed window segmentation, and features extraction. A stacked 128- and 64-unit LSTM network is used to identify the characteristics of movements for the four classes of correct elbow flexion, correct elbow extension, compensatory flexion, and compensatory extension. The proposed system obtains an accuracy of 93.25%, precision of 93.3%, recall of 93.25%, F1-Score of 93.2%, and an AUC-ROC macro average of 0.822. Processing time and communication time are estimated at 312 ms, and the estimated cost for wearable hardware is USD 27.40. The system combines movement classification and correction feedback and offers an efficient system for inexpensive rehabilitation monitoring.

Keywords: Stroke Rehabilitation, 9-DOF IMU, Compensatory Movement Detection, LSTM-Based Classification, Quaternion Orientation Estimation, Wearable Motion Monitoring, Real-Time Rehabilitation.

*** Corresponding Author**

Journal of Electronics and Informatics,December 2026, Volume 8, Issue 4, Pages 389-403
DOI:https://doi.org/10.36548/jei.2026.4.006
Extended version of article received from **6th International Conference on Smart Innovations in Engineering Technology (ICSIET 2026)**
Received: 19.08.2026, received in revised form: 17.09.2026, accepted: 01.10.2026, published: 14.10.2026
© 2026 Inventive Research Organization. This is an open access article under the Creative Commons Attribution-NonCommercial International (CC BY-NC 4.0) License

1. Introduction

Strokes are one of the causes of disability and can lead to prolonged disabilities of the motor function of the upper limbs [13]. Successful rehabilitation involves repetitive and properly executed therapeutic exercise; but conventional rehabilitation usually relies on clinical therapy sessions that might not allow continuous assessment of the exercise at home. This situation results to a need for monitoring systems that will be able to assess the exercise objectively outside the clinic.

Wearable Inertial Measurement Units (IMUs) offer an efficient and affordable method of recording upper limb movement using measurements of acceleration, angular velocity, and magnetic fields. In conjunction with machine learning, IMU data can be analyzed to identify patterns of movement and assist in rehabilitation analysis. Movement recognition by itself is not sufficient to ensure that an exercise is executed properly, as compensatory movements might happen during what seem like equivalent upper-limb movements. Recognizing intended movements from compensatory ones is necessary to ensure valuable corrective feedback is provided.

A research on a low-cost AI-driven wearable-based monitoring system for upper-limb rehabilitation post-stroke is presented here, with a focus on elbow flexion and extension. A combination of 9-DOF IMU and ESP32-based processing and transmission modules is used to acquire motion data. These signals are filtered, oriented, segmented based on windowing, and then their time and frequency domain features are extracted to classify with the research LSTM model. Four types of movements have been taken into consideration: elbow flexion (correct), elbow extension (correct), elbow flexion (compensatory), and elbow extension (compensatory). Feasibility analysis of the proposed wearable framework has been done by measuring classification accuracy, ROC-AUC, processing latency, and cost of hardware components.

2. Related Works

2.1 Wearable IMU-Based Rehabilitation Monitoring

Wearable inertial sensors have been explored for the objective quantification of upper limb impairment after stroke. Oubre et al. [1] proposed a wearable sensor-based system, which uses inertial sensors attached to the wrist and sternum region to quantify upper limb impairment

based on voluntary movement. Okita et al. [2] explored wearable sensor-based assessment of movement quality and considered smoothness of movements as a metric for assessment at home for rehabilitation purposes. Pohl et al. [3] made use of IMUs to classify functional vs. non-functional usage of the arm after stroke, whereas Subash et al. [4] have made comparisons between different methods for quantifying upper limb usage from inertial sensors.Pavan, Nagashree, and Praveen Kumar Reddy proposed Neuroflex, a wearable neuromuscular rehabilitation system integrating soft robotics and real-time monitoring [14].

2.2 Machine Learning for Rehabilitation Movement Analysis

ML and DL techniques have been used in understanding wearables' motion signals. In particular, Parnandi et al. [5] proposed a deep learning pipeline for measuring rehabilitation training, which showed how automated motion analysis can be done. Li et al. [7] used deep learning for monitoring upper-extremity task practice with wearable sensors. Also, Hwang et al. [8] developed an inertial signal model for analyzing the efficiency of stroke rehabilitation, and Oh et al. [9] studied activity recognition using deep learning in hemiparetic stroke patients with wearables and data augmentation.

2.3 Movement Quality and Compensatory-Movement Detection

Recognition of movement alone might not be enough to tell if the rehabilitation exercises have been done correctly. In Das et al. [6], the authors studied the idea of supervised classification in order to detect compensatory movement strategies. In Seo et al. [10], the use of wearable sensors to monitor task quality of upper limb exercises for stroke patients at home was explored. Further research into detecting and quantifying compensatory movements with wearables and machine learning was conducted by Ding et al. [11]. It is clear from all these papers that differentiating planned and compensatory movements is crucial for proper feedback delivery.Harish et al. investigated gyroscope-based hand-gesture recognition using ANOVA for feature discrimination [15], highlighting the role of inertial features in movement classification.

2.4 IMU-Based Functional Assessment and Research Gap

In Zhou et al. [12], the use of IMU based wearable technology and deep learning approach for evaluation of upper-extremity functional score was explored, highlighting the possibilities of temporal learning to extract clinical information from movement data. So far, several studies have been done on wearable movement tracking, activity recognition, movement

quality evaluation, and compensatory movement detection. But all these elements are seen as different components. A comprehensive framework including low-cost inertial sensing, signal processing, movement representation using features, temporal classification, and instant feedback is still applicable.

The proposed work addresses this requirement through a low-cost wearable architecture integrating a 9-DOF IMU, ESP32 based processing, LSTM-based movement classification, and corrective feedback. This framework also differentiates between the intention to move the elbow and compensation movements to the computational delay and cost of hardware for wearable deployment.

3. Proposed Methodology

3.1 Overall System Architecture and Wearable Data Acquisition

The proposed rehabilitation monitoring system comprises four stages, which include wearable sensors, acquisition and preprocessing of signals, movement classification using the LSTM algorithm, and feedback generation. The processing steps are shown in Figure 1. The architecture is expected to capture upper limb motion, map the acquired inertial data into movement features, classify the executed rehabilitation movement and generate feedback based on the movement features.

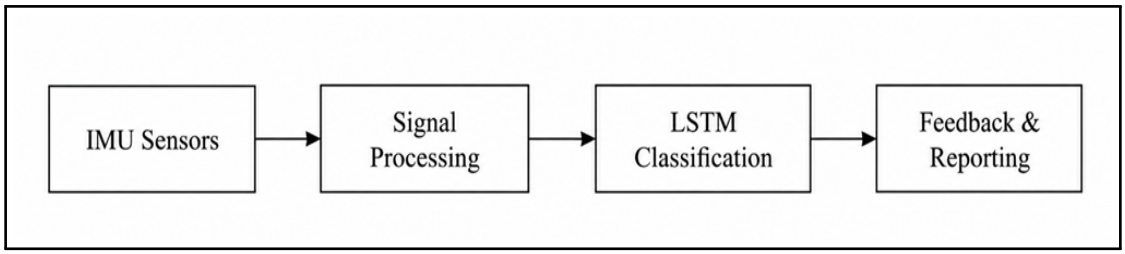


Figure 1. Overall architecture of the proposed wearable rehabilitation monitoring system

A low-cost 9-DOF inertial measurement unit (IMU) is positioned on the forearm to capture motion associated with elbow rehabilitation exercises. The sensor provides three-axis linear acceleration, three-axis angular velocity, and three-axis magnetic-field measurements. Data acquisition is performed at a sampling frequency of 100 Hz using an ESP32-based processing and communication unit. The ESP32 provides local sensor interfacing and Bluetooth Low Energy (BLE) communication for wireless transmission.

The acquired inertial data are passed to the signal processing phase, where filtering, orientation estimation, motion segmentation, and feature extraction are performed. The generated motion representation is then passed to the proposed LSTM classifier in order to classify whether the motion is proper rehabilitation or compensation motion. The predicted motion class is then passed to the feedback and reporting phase for exercise tracking and feedback generation.

3.2 Dataset Description and Motion Data Preparation

A low-cost 9-DOF inertial measurement unit (IMU) is positioned on the forearm to capture motion associated with elbow rehabilitation exercises. The sensor provides three-axis linear acceleration, three-axis angular velocity, and three-axis magnetic-field measurements. Data acquisition is performed at a sampling frequency of 100 Hz using an ESP32-based processing and communication unit. The ESP32 provides local sensor interfacing and Bluetooth Low Energy (BLE) communication for wireless transmission.

The acquired inertial data are passed to the signal processing phase, where filtering, orientation estimation, motion segmentation, and feature extraction are performed. The generated motion representation is then passed to the proposed LSTM classifier in order to classify whether the motion is proper rehabilitation or compensation motion. The predicted motion class is then passed to the feedback and reporting phase for exercise tracking and feedback generation.

The effectiveness of the designed monitoring framework for rehabilitation is evaluated on the ARM data set as described by Gomez-Arrunategui et al. [16]. The data set contains inertial measurements recorded using wearable sensors for the tracking of upper-limb movements after a stroke and includes measurements of 12 individuals with stroke. The measurements of acceleration and angular velocity serve as the key motions for the current analysis.

All the recordings are then partitioned into analysis segments of predetermined time duration prior to any signal processing and feature extraction. Four types of movements are taken into account in this particular study: correct elbow flexion, correct elbow extension, compensatory elbow flexion, and compensatory elbow extension. In the evaluation stage, the testing data consists of 2,000 segmented movements, 500 per movement type.

The distribution of samples per class in the confusion matrix corresponds to the 500 samples belonging to each of the four classes, 469 being correct flexion, 471 being correct

extension, 459 being compensatory flexion, and 466 being compensatory extension are present in the diagonal positions in the confusion matrix, whereas the rest 135 samples are placed in off-diagonal locations. These figures serve as a basis for further analysis of the samples per class. The segmented samples have been further subdivided into three categories of training, validation, and testing with 70%, 15%, and 15% samples respectively.

3.3 Signal Preprocessing and Motion Segmentation

The collected inertial signals are preprocessed in order to minimize any high-frequency disturbances and get a reliable estimate of the upper limb motion. In order to filter out the collected signals, a 4th-order Butterworth filter with a cut-off frequency of 20 Hz is used. Orientation estimation is then done using the Madgwick method for the filtered signals in order to avoid any drift. Quaternion representation is used to describe the estimated orientation. The signal properties post-processing is shown in Fig. 2. After processing, the continuous signals are then segmented into 2.5-s windows with 50% overlap. With a sampling rate of 100 Hz, each window will have 250 data points. This overlapping segmentation results in fixed-duration segments without losing the continuity of the data points at the adjacent time windows. The segment is then passed to the feature extraction process to obtain the movement representation required by the LSTM classifier.

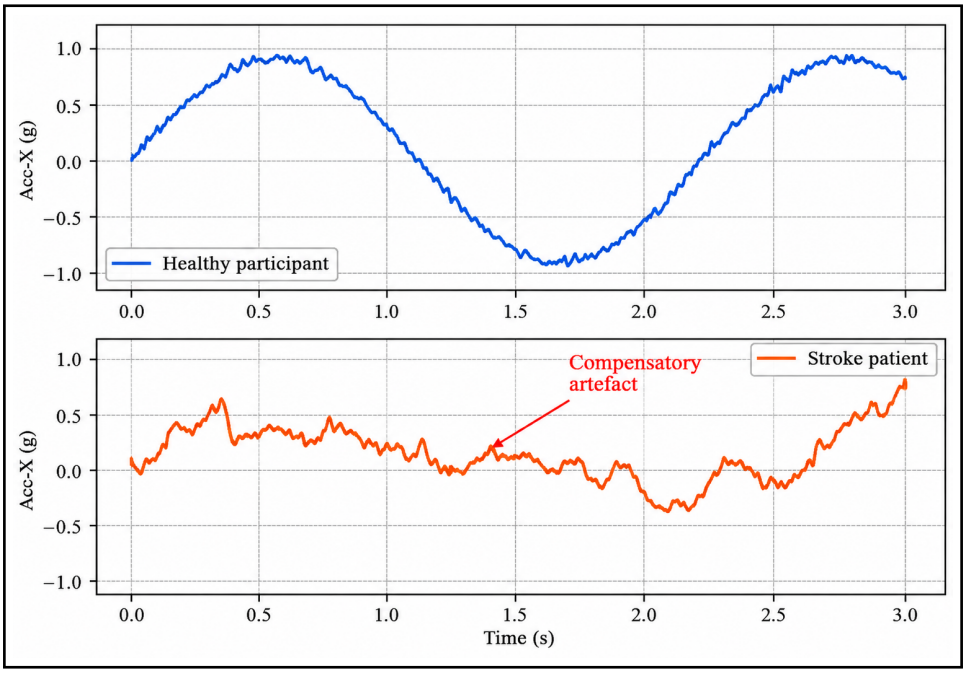


Figure 2. Representative preprocessed IMU signals for movement analysis

3.4 Feature Extraction and Feature Selection

The segmented inertial signals are encoded into an efficient set of features to describe the temporal and frequency characteristics of arm gestures. A total number of 63 window-based features are generated from the available IMU sensors. The time domain features include mean, standard deviation, root mean square, kurtosis, skewness, zero crossing rate, and signal magnitude area. The frequency domain features are computed through the Fast Fourier Transform (FFT) method and are comprised of spectral entropy, dominant frequency, and spectral centroid.

The extracted descriptors describe complementary properties regarding the magnitude, variation, distribution, temporal activation, and frequency properties of the signal. These properties are fused together to create the movement representation passed on to the classification stage based on LSTM. This representation retains the necessary movement properties to discriminate between the intended and compensatory elbow movements.

3.5 Machine-Learning-Based Movement Classification

This movement representation is further analyzed through an LSTM neural network to differentiate between intentional and compensatory upper limb movements. The LSTM model is chosen due to the presence of temporal dependencies in the rehabilitation movements which might not be effectively captured using independent windowed observations. The ability of LSTM to model sequences will enable movement features from sequential observations to be considered during movement classification. This is especially useful when differentiating correct movements from compensatory movements which might have similar elbow trajectories but different movement sequences.

The proposed network architecture comprises of two LSTM layers with 128 and 64 neurons each, respectively. While the first LSTM layer gets input as the representation of sequential movements derived from segmentation of the IMU dataset, the second LSTM layer transforms the learned sequence representation into a compact feature state that can be used for classification purposes. To avoid the problem of relying too much on individual features learned in the recurrent representation phase, dropout with a probability of 0.3 is added between this phase and the output phase of the network.

The predicted class with the maximum Softmax value from the predictions is the identified

movement pattern, which will be then sent to the feedback unit. The correct movements are stored for exercise monitoring, while the compensatory movements are kept for triggering the appropriate corrective feedback. Thus, the classification process has been directly associated with the intended use in rehabilitation monitoring.

3.6 Feedback Generation and Experimental Evaluation

The classification results are combined with the feedback module to facilitate instant interpretation of rehabilitation performance. In case a compensatory motion is recognized, the system provides visual and audio feedback indicating what kind of correction is needed. As an illustration, a corrective feedback message like “shoulder lowering” may be created in response to a recognized unwanted compensatory behavior. After each session of exercises, the system will create a summary consisting of repetition number, classification rate, and movement quality data.

For quantitative analysis, accuracy, precision, recall, F1 score, and AUC-ROC metrics are employed to evaluate the classification models. For the purpose of preserving class distribution within each subset, a stratified splitting technique is adopted. According to the original experiment, 70% of the dataset is training, while 15% for validation and testing respectively.

3.7 Computational Latency and Deployment Analysis

The deployment analysis evaluates the computational and communication aspects involved with the proposed wearable pipeline for monitoring. These processing steps involve signal preprocessing, feature calculation, LSTM inference, and BLE communication. These processing steps are considered in the context of understanding the computational needs of the system under resource-constrained wearable settings.

The computational environment has been modeled using signal core, 240 MHz processor having 512 KB RAM. The LSTM inference time is considered in the restricted computation environment while BLE transmission part is defined as per the communication environment. The computation and communication times obtained from the above are used for estimating the computational load of the proposed framework.

Latency analysis is based on computations and communications that occur once the 2.5-s analysis segment is generated. 2.5 s is the duration of the observation window for

movement-segment generation, while the computation times are related to further computations; thus, the two factors are considered separately in the deployment analysis.

4. Results and Discussion

4.1 Overall Classification Performance

Performance of the proposed LSTM network is shown in Table 1. The LSTM network shows consistent classification performance with respect to four types of movements, where there is not much fluctuation in the distribution of predictions made and the actual distribution of classes. It can be concluded from the above findings that the temporal feature learned through segmented data is efficient for differentiation.

Table 1. Classification performance of the proposed LSTM model

Evaluation measure	**Proposed LSTM (%)**
Accuracy	93.25
Precision	93.3
Recall	93.25
F1-Score	93.2
Macro-Average AUC-ROC	0.822

The classification results are further analyzed using the confusion matrix and ROC analysis in the following sections. The confusion matrix gives the distribution of errors in the respective classes, and ROC analysis tests discrimination ability at varying decision thresholds.

4.2 Class-Wise Classification Analysis

Class prediction distribution of the presented LSTM algorithm is illustrated in Figure 3. The matrix observed that there is a predominance of diagonal behavior, meaning that classes have been successfully separated from each other in the case of intended and compensatory arm movements. The class of correct extension has the most pronounced diagonal pattern, whereas the class of compensatory flexion demonstrates a higher dispersion of errors. It can be seen that the incorrectly classified examples are evenly spread among different combinations of

movements.

Such errors are mostly attributed to the motion categories with similar inertia characteristics. The performance of the right and the compensatory execution can yield a similar pattern of acceleration and angular velocity at certain stages of an elbow movement, particularly when the compensatory execution is performed during the same stage as the motion itself. The confusion comes from the timing variation of the pattern extraction, and not just from the gross size of the motion. This off-diagonal response pattern indicates that the LSTM network has learnt a discriminative feature related to time but is still sensitive to the overlapping of motion categories.

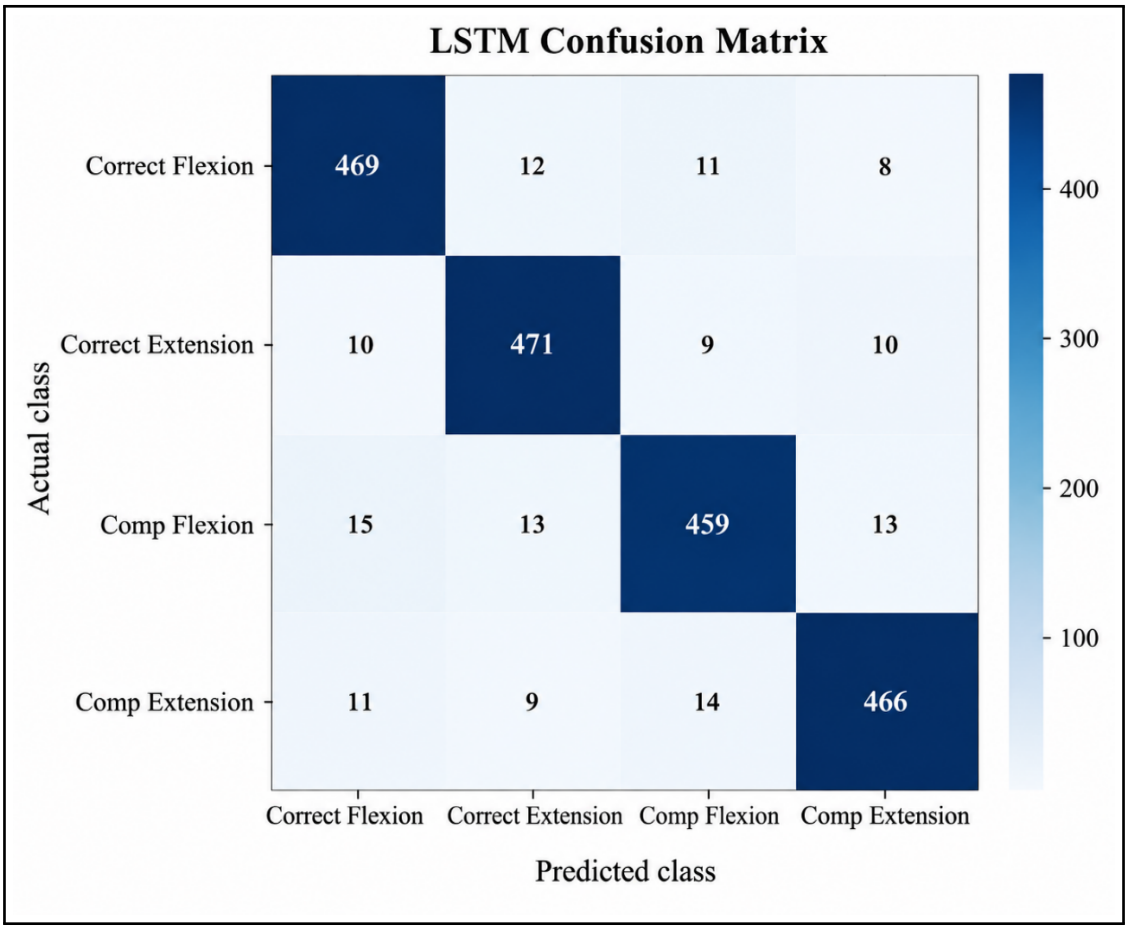


Figure 3. Confusion matrix of the LSTM-based movement classification

4.3 ROC-AUC Analysis

Figure 4 shows the ROC analysis of the proposed LSTM model. The ROC curves show the discriminatory ability of the proposed model by showing the correlation between the true

positive rate and the false positive rate for various classification levels. The ROC curves have been kept near the upper left corner, which signifies the good separation of the movement's categories.

The AUC values associated with each class display similar discriminative ability for all four classes. The small range of AUC values per class suggests that the model does not show much degradation for any one class of movement. This is crucial in rehabilitation since correct as well as compensatory movements must be differentiated.

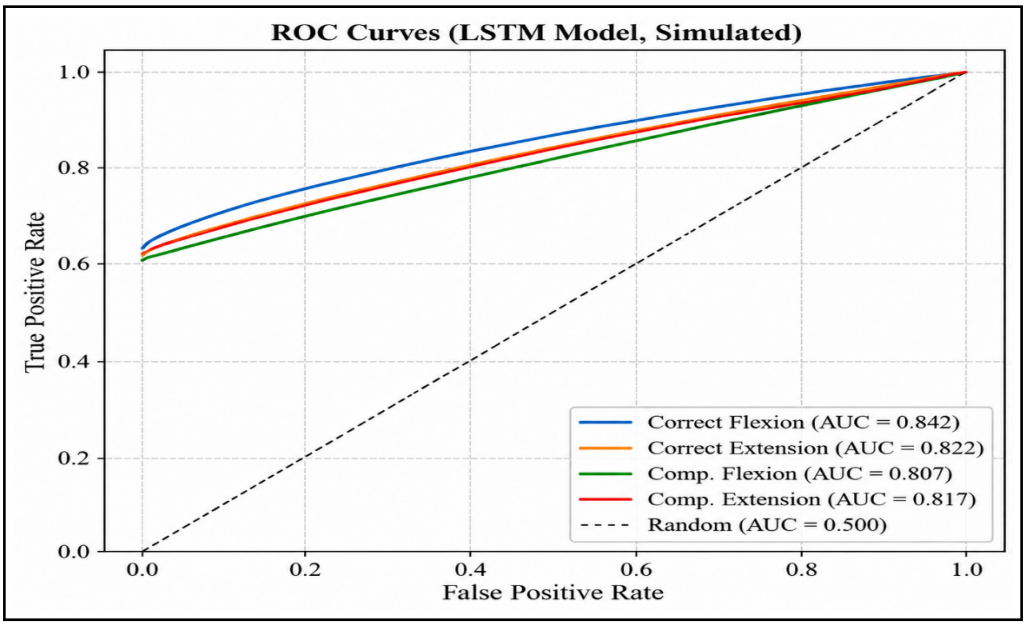


Figure 4. ROC curves of the proposed LSTM model for four-class Movement Classification

4.4 Real-Time Latency Analysis

The computational and communication constraints for the designed wearable device are described in Table 2. This processing model includes signal acquisition, pre-processing with FFT calculations, LSTM calculation, and BLE communication. The analysis of processing components shows that the classification part imposes little processing constraint compared to the whole processing algorithm, ensuring that the proposed movement recognition process can be performed on resource-constrained wearable computing devices.

The reported values should be considered as a calculated estimate of the processing time profile rather than as a hardware measurement in the end-to-end processing chain due to the use of a virtual processing environment of a single-core 240 MHz and a specification-driven

implementation of the BLE part. In turn, the acquisition time corresponds to the signal portion considered during latency calculations, while the 2.5 s window mentioned in the methodology corresponds to the movement observation period needed for the feature generation process.

Overall, the latency perspective, it appears possible to integrate signal processing, LSTM prediction, and wireless communication into one computational pipeline. But it is necessary to validate the results on the actual wearable device in order to obtain the latency of the system working in actual operating conditions.

Table 2. Estimated computational and communication time of the proposed system

Component	**LSTM (ms)**
Acquisition Window	250
Preprocessing + FFT	18
Classifier Inference	29
BLE Transmission	15
Total Latency	312

5. Conclusion and Future Work

The proposed wearable rehabilitation framework includes inertial motion sensing, signal processing, feature representation, and LSTM-based temporal classification for the automatic monitoring of upper-limb stroke rehabilitation. The proposed system is designed to discriminate between the desired elbow movements and the compensatory movements to provide instant correction in real time while exercising. Combining wearable sensing with embedded computing and wireless communication enables a compact solution for continuous monitoring in rehabilitation apart from the traditional supervised training sessions. The evaluation demonstrates the feasibility of the proposed approach in classifying and monitoring the movements in real time in a low-cost wearable framework. In future, the system will be tested using actual patient data to account for variations due to spasticity, tremor, fatigue, and sensor positioning. Future work will focus on expanding the framework to cover more rehabilitation exercises, efficient LSTM

inference on the embedded platform, and usability testing by involving clinicians to provide real-world feasibility.

References

[1] Oubre, Brandon, Jean-Francois Daneault, Hee-Tae Jung, Kallie Whritenour, Jose Garcia Vivas Miranda, Joonwoo Park, Taekyeong Ryu, Yangsoo Kim, and Sunghoon Ivan Lee. "Estimating upper-limb impairment level in stroke survivors using wearable inertial sensors and a minimally-burdensome motor task." IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2020, vol. 28, no. 3: 601-611.

[2] Okita, Shusuke, Diogo Schwerz De Lucena, Vicky Chan, and David J. Reinkensmeyer. "Measuring movement quality of the stroke-impaired upper extremity with a wearable sensor: toward a smoothness metric for home rehabilitation exercise programs." In 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), IEEE, 2021, 6691-6694.

[3] Pohl, Johannes, Alain Ryser, Janne Marieke Veerbeek, Geert Verheyden, Julia Elisabeth Vogt, Andreas Rüdiger Luft, and Chris Awai Easthope. "Classification of functional and non-functional arm use by inertial measurement units in individuals with upper limb impairment after stroke." Frontiers in physiology, 2022, vol. 13: 952757.

[4] Subash, Tanya, Ann David, StephenSukumaran ReetaJanetSurekha, Sankaralingam Gayathri, Selvaraj Samuelkamaleshkumar, Henry Prakash Magimairaj, Nebojsa Malesevic et al. "Comparing algorithms for assessing upper limb use with inertial measurement units." Frontiers in Physiology, 2022, vol. 13: 1023589.

[5] Parnandi, Avinash, Aakash Kaku, Anita Venkatesan, Natasha Pandit, Audre Wirtanen, Haresh Rajamohan, Kannan Venkataramanan, Dawn Nilsen, Carlos Fernandez-Granda, and Heidi Schambra. "PrimSeq: A deep learning-based pipeline to quantitate rehabilitation training." PLOS Digital Health, 2022, vol. 1, no. 6: e0000044.

[6] Das, Neha, Satoshi Endo, Sabrina Patel, Carmen Krewer, and Sandra Hirche. "Online detection of compensatory strategies in human movement with supervised classification: a pilot study." Frontiers in Neurorobotics, 2023, vol. 17: 1155826.

[7] Li, Mingqi, Gabrielle Scronce, Christian Finetto, Kristen Coupland, Matthew Zhong, Melanie E. Lambert, Adam Baker, Feng Luo, and Na Jin Seo. "Application of deep learning algorithm to monitor upper extremity task practice." Sensors, 2023, vol. 23, no. 13: 6110.

[8] Hwang, Yi-Ting, Yu-Qian Tung, Chun-Shu Chen, and Bor-Shing Lin. "B-spline modeling of inertial measurements for evaluating stroke rehabilitation effectiveness." IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2023, vol. 31: 4008-4016.

[9] Oh, Youngmin, Sol-A. Choi, Yumi Shin, Yeonwoo Jeong, Jongkuk Lim, and Sujin Kim. "Investigating activity recognition for hemiparetic stroke patients using wearable sensors: A deep learning approach with data augmentation." Sensors, 2023, vol. 24, no. 1: 210.

[10] Seo, Na Jin, Kristen Coupland, Christian Finetto, and Gabrielle Scronce. "Wearable sensor to monitor quality of upper limb task practice for stroke survivors at home." Sensors, 2024, vol. 24, no. 2: 554.

[11] Ding, Kangjia, Jiping Wang, Xiaojun Wang, Linfu Zhou, Daxi Xiong, and Liquan Guo. "System for detection and quantitative evaluation of compensatory movement in post-stroke patients based on wearable sensor and machine learning algorithm." IEEE Sensors Journal, 2024, vol. 24, no. 14: 22830-22842.

[12] Zhou, Weinan, Diyang Fu, Zhiyu Duan, Jiping Wang, Linfu Zhou, and Liquan Guo. "Achieving precision assessment of functional clinical scores for upper extremity using IMU-Based wearable devices and deep learning methods." Journal of NeuroEngineering and Rehabilitation, 2025, vol. 22, no. 1: 84.

[13] World Health Organization, “The top 10 causes of death,” WHO, Geneva, Switzerland, 2020. Available: https://www.who.int/

[14] Pavan, Nagashree, and Praveen Kumar Reddy. 2026. “Neuroflex: A Real-Time, Wearable Neuro-Muscular Rehabilitation System Using Soft Robotics”. Journal of Electronics and Informatics 8 (4): 317-29.

[15] Harish, Neela, Deepa S., Uma Loganathan, Kavitha J., and Praveen Kumar. 2026. “Wearable Gyroscope-Based Motion Tracking and Hand Gesture Recognition Using ANOVA for Feature Discrimination”. Journal of Innovative Image Processing 8 (4): 1393-1412.

[16] Gomez-Arrunategui JP, Eng JJ, Hodgson AJ. Monitoring Arm Movements Post-Stroke for Applications in Rehabilitation and Home Settings. IEEE Trans Neural System Rehabil Engineering. 2022, 30:2312-2321. Available: https://pubmed.ncbi.nlm.nih.gov/35947559/