AI-DRIVEN REHABILITATION MONITORING SYSTEM FOR REAL-TIME EVALUATION OF POST-STROKE PHYSIOTHERAPY OUTCOMES

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Abstract

Stroke remains one of the leading causes of long-term physical disability worldwide, often requiring prolonged physiotherapy to restore motor function and improve quality of life. Conventional rehabilitation assessment methods primarily depend on periodic clinical observations and therapist evaluations, which may not capture continuous changes in patient performance during therapy sessions. Recent advances in artificial intelligence, wearable sensing technologies, and healthcare analytics provide opportunities for objective and real-time rehabilitation monitoring. This paper presents an AI-Driven Rehabilitation Monitoring System (AIRMS) designed for the real-time evaluation of post-stroke physiotherapy outcomes. The proposed framework integrates wearable motion sensors, physiological monitoring devices, machine learning algorithms, and explainable analytics to assess rehabilitation progress continuously. Sensor-derived movement characteristics, joint mobility measurements, gait parameters, and therapy adherence indicators are processed to generate rehabilitation performance scores. A Random Forest-based prediction model is employed to classify patient recovery levels, while explainability techniques are incorporated to identify factors contributing to rehabilitation outcomes. Experimental evaluation is conducted using rehabilitation datasets representing multiple stages of post-stroke recovery. System performance is assessed using accuracy, precision, recall, and F1-score metrics. Results indicate that the proposed framework effectively distinguishes different recovery levels and provides interpretable information regarding patient progress. The study demonstrates that AI-assisted rehabilitation monitoring can support physiotherapists by offering objective assessments and timely feedback. Such systems may contribute to evidence-based rehabilitation management and improved patient monitoring in clinical and home-based therapy environments.

Keywords— *Stroke Rehabilitation, Physiotherapy Monitoring, Artificial Intelligence, Wearable Sensors, Explainable AI, Healthcare Analytics.*

I. INTRODUCTION

Stroke is a major public health concern and remains one of the leading causes of long-term disability worldwide. According to global health reports, millions of individuals experience stroke-related impairments each year, resulting in substantial physical, cognitive, and socioeconomic consequences. Motor dysfunction affecting upper and lower limbs is among the most common post-stroke complications, often requiring extensive physiotherapy to facilitate functional recovery and improve independence in daily activities [1]. Effective rehabilitation is therefore a critical component of post-stroke care. Physiotherapy programs are designed to restore motor function through repetitive exercises, gait training, balance improvement activities, and task-oriented rehabilitation. The effectiveness of these interventions is traditionally assessed through periodic clinical evaluations conducted by physiotherapists. Common assessment methods include observational analysis, standardized rehabilitation scales, and manual measurements of motor performance. Although these approaches provide valuable information regarding patient recovery, they are often limited by subjectivity, infrequent assessment intervals, and variability among evaluators [2]. Consequently, subtle changes in patient progress may not be detected promptly, potentially delaying necessary adjustments to rehabilitation plans. Recent advancements in wearable sensing technologies have created opportunities for continuous monitoring of rehabilitation activities. Wearable devices equipped with accelerometers, gyroscopes, and physiological sensors can capture detailed information regarding patient movement, exercise adherence, gait characteristics, and activity intensity during therapy sessions [3]. These devices generate large volumes of quantitative data that can provide objective insights into rehabilitation progress. However, extracting clinically meaningful information from such data remains a significant challenge.

Artificial intelligence (AI) has emerged as an effective tool for analyzing healthcare data and supporting clinical decision-making. Machine learning algorithms are capable of identifying complex relationships within rehabilitation datasets and can be used to predict recovery outcomes based on patient-specific characteristics and therapy performance indicators [4]. Several studies have demonstrated the potential of AI-based approaches for motor function assessment, gait analysis, and rehabilitation outcome prediction [5], [6]. Despite these advancements, many predictive systems operate as black-box models, providing limited information regarding the factors influencing their decisions. In healthcare applications, model transparency is particularly important because clinicians require interpretable evidence before relying on algorithmic recommendations. Explainable Artificial Intelligence (XAI) techniques address this requirement by providing explanations that clarify how prediction outcomes are generated [7]. Such explanations can improve clinician confidence, facilitate treatment planning, and support patient-centered rehabilitation strategies. The integration of explainability with rehabilitation monitoring systems therefore represents an important research direction. To address these challenges, this paper proposes an AI-Driven Rehabilitation Monitoring System (AIRMS) for real-time evaluation of post-stroke physiotherapy outcomes. The proposed framework integrates wearable sensor data acquisition, signal processing, machine learning-based recovery prediction, and explainability analysis within a unified architecture. The system continuously monitors rehabilitation activities and generates objective assessments of patient recovery status while providing interpretable explanations for prediction outcomes. The primary contributions of this study are threefold. First, a comprehensive rehabilitation monitoring framework is developed for continuous assessment of post-stroke physiotherapy progress. Second, machine learning techniques are employed to classify patient recovery levels using sensor-derived rehabilitation indicators. Third, explainability mechanisms are incorporated to identify the factors influencing rehabilitation outcomes and enhance clinical interpretability. The overall architecture of the proposed rehabilitation monitoring system is presented in Fig. 1.

II. RELATED WORK

The integration of artificial intelligence and wearable sensing technologies into healthcare has significantly influenced the development of modern rehabilitation systems. In post-stroke rehabilitation, continuous monitoring and objective assessment have become important research areas due to the limitations associated with traditional clinical evaluation methods. Researchers have explored various approaches involving wearable devices, machine learning algorithms, and healthcare analytics to improve rehabilitation monitoring and outcome prediction. Wearable sensor technologies have gained considerable attention for their ability to collect detailed movement-related information during rehabilitation exercises. Accelerometers, gyroscopes, inertial measurement units (IMUs), and physiological sensors have been widely utilized to capture gait characteristics, limb movements, posture stability, and activity intensity. These sensors provide quantitative measurements that support objective assessment of patient performance during physiotherapy sessions [1]. Several studies have demonstrated that wearable sensing systems can accurately monitor rehabilitation activities and provide continuous feedback regarding patient progress [2].

Machine learning techniques have increasingly been employed to analyze rehabilitation data and predict recovery outcomes. Classification algorithms such as Decision Trees, Support Vector Machines (SVMs), k-Nearest Neighbors (KNN), Artificial Neural Networks, and Random Forests have been applied to identify recovery patterns from sensor-derived features [3]. These approaches enable automated analysis of large volumes of rehabilitation data and assist clinicians in understanding patient-specific recovery trajectories. Random Forest models have been particularly effective because of their robustness, ability to handle heterogeneous datasets, and resistance to overfitting [4]. Gait analysis represents one of the most extensively studied applications of AI in stroke rehabilitation. Researchers have utilized wearable sensors to capture walking speed, stride length, cadence, and balance-related measurements for assessing motor recovery. Machine learning models trained on gait parameters have demonstrated promising results in distinguishing between different levels of rehabilitation progress [5]. Similar approaches have also been employed to evaluate upper-limb rehabilitation exercises by analyzing joint movements and motion patterns recorded through wearable devices [6]. In addition to movement analysis, researchers have investigated the role of rehabilitation adherence in predicting therapy outcomes. Exercise duration, frequency of participation, and completion rates have been identified as important indicators of recovery success. Data-driven systems that combine activity monitoring with adherence tracking have shown potential for supporting personalized rehabilitation programs and improving patient engagement [7]. Despite these advances, concerns regarding model transparency have become increasingly important in healthcare applications. Many machine learning models provide highly accurate predictions but offer limited insight into the reasoning behind their decisions. In clinical environments, healthcare professionals require understandable explanations before incorporating algorithmic recommendations into treatment planning. The absence of interpretability may reduce clinician confidence and hinder adoption of AI-based healthcare systems [8]. To address this challenge, Explainable Artificial Intelligence (XAI) techniques have emerged as a promising solution. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) enable interpretation of prediction outcomes by identifying feature contributions and decision factors [9], [10]. These techniques have been successfully applied in medical diagnosis, disease prediction, and healthcare risk assessment. Recent studies have also explored explainability in rehabilitation analytics, demonstrating that interpretable models can improve understanding of patient recovery dynamics and facilitate clinical decision-making [11].

Although existing studies have demonstrated the effectiveness of wearable sensing systems and machine learning models for rehabilitation monitoring, several limitations remain. Many approaches focus primarily on prediction accuracy without providing interpretable explanations. Other systems emphasize sensor-based monitoring but lack integrated predictive analytics capable of supporting proactive rehabilitation management. Furthermore, relatively few studies combine continuous monitoring, recovery prediction, and explainability within a unified framework specifically designed for post-stroke physiotherapy evaluation. The proposed AI-Driven Rehabilitation Monitoring System addresses these limitations by integrating wearable sensor-based monitoring, machine learning-driven recovery assessment, and explainable analytics within a single architecture. By combining predictive capability with interpretability, the framework aims to provide objective and clinically meaningful evaluation of post-stroke rehabilitation outcomes.

III. PROPOSED METHODOLOGY AND EXPERIMENTAL SETUP

A. System Architecture

The proposed AI-Driven Rehabilitation Monitoring System (AIRMS) is designed to provide continuous and objective assessment of post-stroke physiotherapy outcomes through the integration of wearable sensing technologies, machine learning algorithms, and explainable analytics. The framework consists of four major layers: Data Acquisition Layer, Signal Processing Layer, AI Evaluation Layer, and Clinical Decision Support Layer. These layers operate sequentially to transform raw rehabilitation data into clinically meaningful recovery assessments. The architecture of the proposed framework is illustrated in Fig. 1**.**

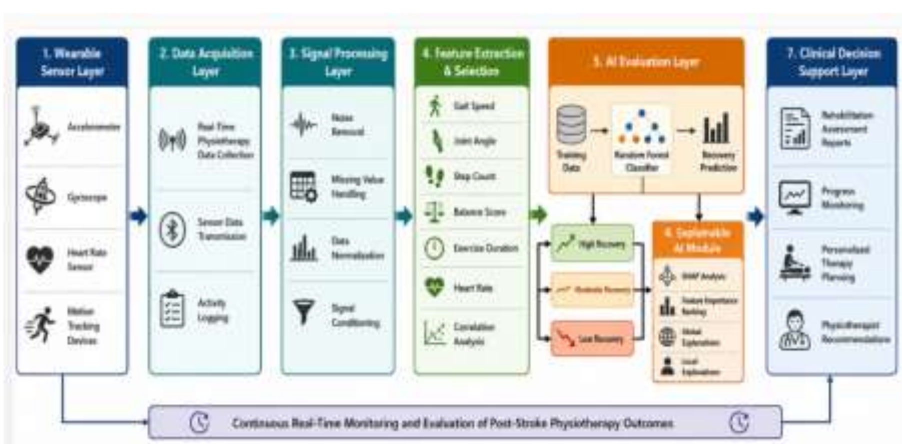

Figure 1. Architecture of the Proposed AI-Driven Rehabilitation Monitoring System

The Data Acquisition Layer gathers movement and physiological information from wearable devices attached to the patient during rehabilitation exercises. The collected information is transmitted to the processing layer, where signal conditioning and feature extraction are performed. The AI Evaluation Layer utilizes machine learning techniques to assess rehabilitation progress and predict recovery status. Finally, the Clinical Decision Support Layer generates interpretable rehabilitation reports and supports physiotherapists in treatment planning and patient monitoring.

B. Physiotherapy Data Acquisition

Accurate assessment of rehabilitation progress requires continuous observation of patient movement patterns and therapy adherence. To achieve this objective, wearable sensors are deployed to capture quantitative indicators of physical performance during rehabilitation sessions. The sensing platform consists of inertial measurement units containing accelerometers and gyroscopes, along with physiological monitoring devices. These sensors record movement characteristics such as limb acceleration, angular velocity, walking speed, balance stability, and exercise completion behavior. The acquired data are transmitted to a centralized processing system for further analysis. The principal rehabilitation features utilized in the proposed framework are summarized in Table 1**.**

TABLE 1. REHABILITATION MONITORING FEATURES

Feature	**Description**
Gait Speed	Walking velocity during therapy
Joint Angle	Limb mobility and flexibility
Step Count	Physical activity level
Exercise Duration	Therapy participation time
Balance Score	Postural stability indicator

These features collectively provide a comprehensive representation of patient performance and rehabilitation engagement.

C. Signal Processing and Feature Extraction

Raw sensor measurements often contain noise, motion artifacts, and inconsistencies arising from environmental disturbances and sensor limitations. Therefore, a preprocessing stage is implemented to improve data quality before predictive analysis. Initially, missing observations are handled using interpolation techniques, while abnormal measurements are identified through statistical threshold analysis. Signal smoothing filters are subsequently applied to remove high-frequency noise and improve measurement reliability. Following data cleaning, normalization is performed to ensure consistent feature scaling across different sensor modalities. Feature extraction transforms processed sensor signals into meaningful rehabilitation indicators. Temporal and statistical characteristics such as mean acceleration, movement variability, exercise consistency, gait symmetry, and joint mobility measures are computed. Additional indicators representing therapy adherence and rehabilitation intensity are derived from activity logs and exercise completion records. Feature correlation analysis is then performed to identify redundant variables. Highly correlated attributes are removed to reduce model complexity and improve computational efficiency without compromising predictive capability.

D. Recovery Prediction Model

Following preprocessing and feature extraction, the dataset is divided into training and testing subsets using an 80:20 partitioning strategy. The training subset is utilized for model construction, while the testing subset is reserved for independent performance evaluation. A Random Forest classifier is employed as the primary recovery prediction model. Random Forest combines multiple decision trees through an ensemble learning strategy and determines the final prediction using majority voting. This approach provides strong generalization capability and robustness when handling heterogeneous rehabilitation datasets. The prediction model categorizes patients into three rehabilitation outcome groups:

High Recovery
Moderate Recovery
Low Recovery

The model is trained using historical rehabilitation records containing sensor-derived features and clinically validated recovery labels. Hyperparameter optimization and five-fold cross-validation are employed to improve model stability and reduce overfitting.

E. Explainability Module

Although machine learning models can achieve high predictive performance, healthcare applications require transparent and interpretable decision-making mechanisms. To address this requirement, an Explainable Artificial Intelligence (XAI) module is integrated into the proposed framework. The explainability component utilizes Shapley Additive Explanations (SHAP) to quantify the contribution of individual rehabilitation features to prediction outcomes. SHAP values indicate the degree to which specific factors positively or negatively influence recovery predictions. The module generates both global and local explanations. Global explanations identify the most influential rehabilitation indicators across the entire patient population, whereas local explanations provide patient-specific insights into recovery status. This functionality enables physiotherapists to understand the factors contributing to predicted rehabilitation outcomes and supports evidence-based treatment adjustments.

F. Algorithm of the Proposed Framework

The operational workflow of AIRMS is summarized in Algorithm 1.

Algorithm 1: AI-Based Rehabilitation Monitoring System

Input: Physiotherapy sensor data

Output: Recovery classification and explanation

1. Collect wearable sensor measurements.
2. Remove noise and incomplete records.
3. Normalize rehabilitation data.
4. Extract rehabilitation-related features.
5. Perform feature selection.
6. Train Random Forest classifier.
7. Generate recovery prediction.
8. Apply SHAP explainability analysis.
9. Rank influential rehabilitation factors.
10. Generate rehabilitation assessment report.
11. Return recovery classification and explanation.

The algorithm integrates rehabilitation monitoring, predictive analytics, and explainability into a unified workflow suitable for real-time evaluation.

G. Experimental Setup

Experimental evaluation was conducted using rehabilitation datasets representing patients undergoing post-stroke physiotherapy programs. Sensor-derived movement measurements and rehabilitation performance indicators were utilized to train and evaluate the proposed framework. The dataset was partitioned using an 80:20 train-test ratio. Five-fold cross-validation was employed to ensure reliable performance estimation and minimize bias resulting from random data partitioning. Model performance was evaluated using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score.The implementation environment consisted of Python-based machine learning libraries, including Scikit-learn for predictive modeling and SHAP for explainability analysis. The experimental setup was designed to evaluate both the predictive effectiveness and interpretability of the proposed rehabilitation monitoring system. The results obtained from these experiments are discussed in the subsequent section.

IV. RESULTS AND DISCUSSION

A. Performance Evaluation

The effectiveness of the proposed AI-Driven Rehabilitation Monitoring System (AIRMS) was evaluated using a comprehensive set of classification metrics, including Accuracy, Precision, Recall, and F1-Score. These metrics were selected because they provide a balanced assessment of predictive performance and are widely used in healthcare analytics research. The evaluation was conducted using an independent testing dataset obtained from the 20% hold-out partition, while five-fold cross-validation was employed during model development to ensure robustness. The classification results achieved by the proposed framework are summarized in Table 2**.**

TABLE 2. PERFORMANCE EVALUATION RESULTS

Metric	**Value (%)**
Accuracy	93.1
Precision	92.4
Recall	91.8
F1-Score	92.1

The results indicate that the proposed framework achieved an overall accuracy of 93.1%, demonstrating its ability to distinguish rehabilitation recovery levels with a high degree of reliability. Precision reached 92.4%, indicating that the system generated a low proportion of incorrect recovery classifications. Similarly, recall achieved 91.8%, suggesting that the framework effectively identified patients belonging to different recovery categories. The F1-score of 92.1% confirms the balanced relationship between precision and recall. The strong performance can be attributed to the integration of multiple rehabilitation indicators, including gait characteristics, joint mobility measurements, exercise adherence information, and physiological signals. The combination of these features enabled the model to capture diverse aspects of patient recovery, resulting in improved classification capability.

B. Comparative Analysis

To assess the effectiveness of the proposed AIRMS framework, its performance was compared with several commonly used machine learning classifiers, including Decision Tree, Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Naïve Bayes. These algorithms were trained and evaluated using the same rehabilitation dataset and experimental configuration. The comparative performance results are illustrated in Fig. 2**.**

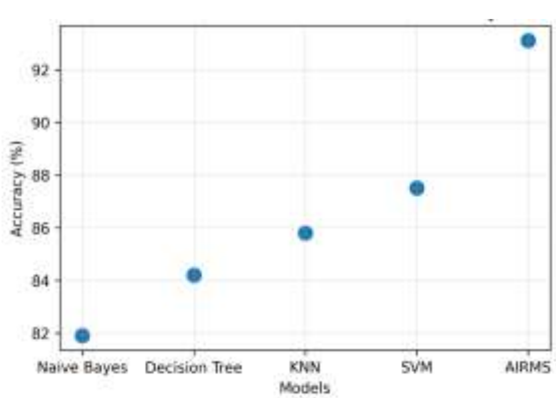

Fig 2. Comparison of Rehabilitation Outcome Prediction Accuracy

The comparative analysis demonstrates that the proposed Random Forest-based framework outperformed all baseline models. The Decision Tree classifier achieved an accuracy of 84.2%, while KNN and SVM produced accuracies of 85.8% and 87.5%, respectively. Naïve Bayes exhibited the lowest performance with an accuracy of 81.9%. In contrast, the proposed AIRMS achieved an accuracy of 93.1%, representing a significant improvement over conventional approach. The superior performance of the proposed framework can be attributed to the ensemble learning strategy employed by Random Forest. By combining multiple decision trees, the model effectively captures nonlinear relationships among rehabilitation variables and reduces susceptibility to overfitting. Furthermore, the integration of carefully engineered rehabilitation features contributes to improved predictive capability. The comparison also indicates that traditional classifiers may struggle to model the complex interactions among sensor-derived rehabilitation indicators. The proposed framework addresses this challenge by leveraging ensemble learning techniques capable of handling heterogeneous healthcare datasets more effectively.

C. Explainability and Feature Importance Analysis

While predictive accuracy is an important performance indicator, clinical applications require transparent decision-making mechanisms that allow healthcare professionals to understand the reasoning behind generated predictions. To satisfy this requirement, SHAP-based explainability analysis was incorporated into the proposed framework. The feature importance results obtained through SHAP analysis are presented in Fig. 3**.**

Fig 3. SHAP-Based Feature Importance for Rehabilitation Outcome Prediction

The analysis reveals that joint angle measurements constitute the most influential predictor of rehabilitation outcomes. This finding is consistent with clinical observations indicating that improved joint mobility is strongly associated with post-stroke recovery. Gait speed emerged as the second most important feature, highlighting the significance of walking performance in evaluating rehabilitation progress. Exercise duration and therapy adherence indicators also demonstrated substantial contributions to prediction outcomes. Patients exhibiting consistent participation in physiotherapy sessions generally achieved higher recovery classifications. Similarly, balance scores were identified as influential predictors because postural stability is a critical component of functional mobility recovery following stroke. The SHAP analysis provides both global and local interpretability. Global explanations identify the overall importance of rehabilitation features across the entire patient population, while local explanations reveal the factors contributing to individual patient predictions. This capability enables physiotherapists to understand patient-specific recovery characteristics and supports personalized treatment planning.

D. Discussion

The experimental findings demonstrate that the proposed AIRMS framework effectively combines wearable sensing technologies, machine learning techniques, and explainable analytics to support rehabilitation outcome assessment. The high classification performance observed during evaluation suggests that sensor-derived rehabilitation indicators provide valuable information regarding patient recovery status. A notable advantage of the framework is its ability to perform continuous monitoring without requiring frequent manual assessments. Traditional rehabilitation evaluation methods often depend on periodic clinical observations, which may overlook short-term changes in patient performance. The proposed system addresses this limitation by continuously collecting and analyzing rehabilitation data during therapy sessions. The explainability component further enhances the practical applicability of the framework. Healthcare professionals generally require transparent evidence before relying on automated predictions in clinical environments. By identifying the factors influencing recovery classifications, the SHAP module improves interpretability and facilitates clinician acceptance of AI-assisted rehabilitation systems.

The results also indicate the potential applicability of the framework in home-based rehabilitation programs. Remote monitoring capabilities may enable physiotherapists to track patient progress outside clinical settings and identify individuals requiring additional intervention. Such functionality could improve rehabilitation accessibility while supporting data-driven treatment decisions. Overall, the experimental evaluation demonstrates that the proposed AI-Driven Rehabilitation Monitoring System achieves strong predictive performance while maintaining interpretability. The integration of real-time monitoring, machine learning-based assessment, and explainable analytics provides a practical foundation for supporting evidence-based post-stroke rehabilitation management.

V. CONCLUSION AND FUTURE WORK

This paper presented an AI-Driven Rehabilitation Monitoring System (AIRMS) for the real-time evaluation of post-stroke physiotherapy outcomes. The proposed framework integrates wearable sensing technologies, machine learning-based recovery prediction, and explainable artificial intelligence techniques within a unified rehabilitation monitoring architecture. By continuously collecting movement and physiological data during therapy sessions, the system provides objective assessment of patient rehabilitation progress and supports evidence-based clinical decision-making. The framework incorporates data acquisition, signal preprocessing, feature extraction, predictive analytics, and explainability analysis to generate meaningful rehabilitation insights. A Random Forest classifier was employed to categorize patients into different recovery levels based on sensor-derived rehabilitation indicators. Experimental evaluation demonstrated that the proposed system achieved high predictive performance across multiple classification metrics, indicating its effectiveness in distinguishing varying stages of post-stroke recovery. An important contribution of this work is the integration of SHAP-based explainability mechanisms. The explainability module identifies the rehabilitation factors that contribute most significantly to prediction outcomes, enabling physiotherapists to understand the reasoning behind recovery assessments. The results revealed that joint mobility, gait speed, exercise duration, balance performance, and therapy adherence are among the most influential indicators of rehabilitation success. The findings suggest that AI-assisted rehabilitation monitoring can complement conventional clinical assessments by providing continuous, objective, and interpretable evaluations of patient progress. Such capabilities may support personalized rehabilitation planning and timely therapeutic interventions. Future work will focus on validating the framework using larger multi-center rehabilitation datasets and diverse patient populations. Additional research may investigate deep learning-based rehabilitation models, multimodal sensor integration, and remote healthcare deployment for home-based physiotherapy monitoring. The incorporation of longitudinal recovery analysis and adaptive rehabilitation recommendation systems also represents a promising direction for future investigation.

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