MACHINE LEARNING-BASED PREDICTION OF FUNCTIONAL RECOVERY IN STROKE PATIENTS USING PHYSIOTHERAPY AND CLINICAL ASSESSMENT DATA

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Abstract - Stroke rehabilitation aims to restore functional independence and improve quality of life through structured physiotherapy interventions. Accurate prediction of functional recovery outcomes is important for rehabilitation planning, resource allocation, and personalized treatment design. Traditional recovery assessment methods rely primarily on periodic clinical evaluations, which may not fully utilize the information available from physiotherapy records and patient-specific clinical characteristics. Recent developments in machine learning have enabled the analysis of complex rehabilitation datasets and the identification of patterns associated with recovery progression. This paper presents a machine learning-based framework for predicting functional recovery in stroke patients using physiotherapy and clinical assessment data. The proposed framework integrates data preprocessing, feature engineering, predictive modeling, and explainability analysis to support rehabilitation outcome prediction. Physiotherapy indicators, demographic characteristics, mobility assessments, balance scores, motor function measurements, and clinical evaluation records are utilized as predictive variables. A Random Forest classifier is employed to classify patients into different recovery categories based on observed rehabilitation outcomes. To improve interpretability, Shapley Additive Explanations (SHAP) are incorporated to identify the factors contributing to prediction results. Experimental evaluation is conducted using stroke rehabilitation datasets containing physiotherapy and clinical assessment records. Model performance is assessed using accuracy, precision, recall, and F1-score metrics. Results indicate that the proposed framework effectively predicts functional recovery outcomes while providing interpretable explanations regarding influential rehabilitation factors. The findings demonstrate the potential of machine learning-assisted rehabilitation analytics for supporting evidence-based clinical decision-making and individualized rehabilitation planning.

Keywords— *Stroke Rehabilitation, Functional Recovery Prediction, Machine Learning, Physiotherapy Analytics, Clinical Assessment, Explainable Artificial Intelligence*.

I. INTRODUCTION

Stroke is one of the leading causes of long-term disability worldwide and represents a major challenge for healthcare systems. Although advances in acute stroke management have improved survival rates, many patients continue to experience motor impairments, reduced mobility, and limitations in performing daily activities. Functional recovery following stroke depends on multiple factors, including the severity of neurological damage, patient characteristics, rehabilitation intensity, and clinical management strategies [1]. Consequently, accurate assessment and prediction of rehabilitation outcomes are essential for designing effective treatment plans and optimizing resource utilization.

Physiotherapy plays a central role in post-stroke rehabilitation by promoting motor recovery, improving balance, enhancing gait performance, and increasing functional independence. Rehabilitation programs typically involve structured exercises targeting muscle strength, coordination, mobility, and task-specific motor skills. Clinical assessment tools such as the Functional Independence Measure (FIM), Fugl-Meyer Assessment (FMA), Berg Balance Scale (BBS), and gait evaluation scores are commonly used to quantify patient progress and monitor recovery status [2]. These assessment instruments provide valuable information regarding rehabilitation outcomes; however, their interpretation often depends on clinician experience and periodic evaluations. Predicting functional recovery remains a complex task because rehabilitation outcomes are influenced by numerous interacting clinical and physiological factors. Traditional statistical approaches have been employed to identify predictors of recovery, but their ability to model nonlinear relationships among rehabilitation variables is often limited [3]. As rehabilitation datasets continue to expand in size and complexity, there is increasing interest in applying data-driven methods capable of extracting meaningful patterns from clinical and physiotherapy records.

Machine learning techniques have demonstrated considerable potential in healthcare analytics and outcome prediction. These approaches can analyze large datasets, identify hidden relationships among variables, and generate predictive models capable of supporting clinical decision-making [4]. In stroke rehabilitation, machine learning algorithms have been applied to predict motor recovery, estimate functional outcomes, and classify rehabilitation progress using clinical assessment scores and patient-specific characteristics [5]. Such models may assist healthcare professionals in identifying patients who require intensive interventions and in developing individualized rehabilitation programs. Despite the growing use of machine learning in healthcare, concerns regarding model interpretability remain significant. Many predictive algorithms function as black-box systems that provide limited information about the factors contributing to prediction outcomes. In rehabilitation settings, clinicians require transparent and interpretable evidence before incorporating predictive recommendations into treatment planning. Explainable Artificial Intelligence (XAI) techniques have emerged as a promising solution by providing insights into feature contributions and decision mechanisms [6].

The integration of machine learning and explainability offers an opportunity to develop predictive systems that are both accurate and clinically interpretable. Such systems can support rehabilitation professionals by identifying the factors most strongly associated with recovery outcomes while maintaining transparency in decision-making processes. This paper proposes a Machine Learning-Based Functional Recovery Prediction Framework for stroke patients using physiotherapy and clinical assessment data. The framework integrates data preprocessing, feature engineering, predictive modeling, and explainability analysis within a unified architecture. Clinical variables and physiotherapy indicators are utilized to predict recovery outcomes and identify influential rehabilitation factors. The overall architecture of the proposed recovery prediction framework is illustrated in Fig. 1.The primary contributions of this study are threefold. First, a comprehensive prediction framework is developed using clinical and physiotherapy assessment records. Second, a machine learning model is employed to classify functional recovery outcomes. Third, explainability mechanisms are incorporated to improve transparency and facilitate clinical interpretation of prediction results.

II. RELATED WORK

Stroke rehabilitation has been an active area of research due to the increasing need for effective strategies that improve functional recovery and quality of life among stroke survivors. Accurate prediction of rehabilitation outcomes is particularly important because it assists clinicians in establishing realistic treatment goals, optimizing therapy plans, and allocating rehabilitation resources efficiently. Over the past decade, advances in healthcare analytics, machine learning, and rehabilitation informatics have contributed to the development of predictive models for assessing recovery potential in stroke patients. Traditional approaches to rehabilitation outcome prediction have primarily relied on statistical methods and clinical observations. Clinical assessment scales such as the Functional Independence Measure (FIM), Fugl-Meyer Assessment (FMA), Barthel Index, and Berg Balance Scale have been extensively used to evaluate motor recovery and functional independence following stroke [1]. Several studies have reported significant associations between these assessment scores and long-term rehabilitation outcomes. Although such approaches provide valuable clinical insights, their predictive capabilities may be limited when dealing with complex interactions among multiple rehabilitation variables.

Machine learning techniques have increasingly been applied to overcome these limitations. By analyzing large volumes of rehabilitation data, machine learning models can identify hidden relationships that may not be readily observable through conventional statistical analysis. Researchers have employed various algorithms, including Decision Trees, Support Vector Machines (SVMs), Artificial Neural Networks, Random Forests, and Gradient Boosting methods for rehabilitation outcome prediction [2]. These techniques have demonstrated promising performance in identifying patients likely to achieve favorable functional recovery. Several studies have investigated the use of clinical assessment data as predictors of rehabilitation outcomes. Fugl-Meyer scores, balance measurements, muscle strength assessments, and gait performance indicators have been identified as significant predictors of post-stroke recovery [3]. Researchers have reported that combining multiple clinical indicators generally improves predictive accuracy compared with relying on a single assessment measure. Consequently, multidimensional rehabilitation datasets have become increasingly important for predictive modeling applications. Physiotherapy-related variables have also received considerable attention in rehabilitation analytics. Therapy intensity, session frequency, exercise duration, and patient adherence to rehabilitation programs are recognized as important determinants of recovery success [4]. Studies examining physiotherapy participation have shown that consistent engagement in rehabilitation activities is associated with improved motor function and greater independence in daily living tasks. The incorporation of physiotherapy variables into predictive models therefore provides a more comprehensive representation of rehabilitation progress.

The growing availability of electronic health records and rehabilitation databases has further accelerated the application of machine learning in healthcare. Researchers have developed predictive systems capable of estimating discharge outcomes, mobility recovery, and long-term functional independence using patient demographic information, clinical characteristics, and rehabilitation assessments [5]. Among various machine learning approaches, Random Forest models have demonstrated strong performance due to their ability to handle heterogeneous datasets and nonlinear feature interactions while maintaining robustness against overfitting [6].Despite these advancements, interpretability remains a significant concern in healthcare applications. Many high-performing machine learning algorithms operate as black-box systems that provide limited insight into the factors influencing prediction outcomes. Clinical practitioners often require understandable explanations before integrating predictive recommendations into rehabilitation planning. Consequently, the lack of transparency may hinder the practical adoption of machine learning-based decision support systems [7].

Explainable Artificial Intelligence (XAI) techniques have emerged as an important solution to this challenge. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) provide mechanisms for interpreting model predictions by quantifying feature contributions [8], [9]. Recent healthcare studies have demonstrated that explainable models improve clinician trust and facilitate understanding of complex prediction outcomes. In rehabilitation research, explainability techniques have been utilized to identify the clinical and physiological factors most strongly associated with recovery progression [10].Although previous studies have demonstrated the value of machine learning for rehabilitation outcome prediction, several limitations remain. Many investigations focus primarily on predictive performance without providing sufficient interpretability. Other studies rely exclusively on clinical assessments while neglecting physiotherapy-related variables that may significantly influence recovery outcomes. Furthermore, relatively few frameworks integrate clinical assessment data, physiotherapy indicators, machine learning prediction, and explainability analysis within a unified architecture. To address these limitations, the proposed framework combines physiotherapy records, clinical assessment measures, predictive analytics, and explainable artificial intelligence to support functional recovery prediction in stroke patients. By integrating prediction accuracy with interpretability, the framework aims to provide clinically meaningful insights that can assist rehabilitation professionals in evidence-based decision-making.

III. PROPOSED METHODOLOGY AND EXPERIMENTAL SETUP

A. Framework Architecture

The proposed framework is designed to predict functional recovery outcomes in stroke patients using physiotherapy records and clinical assessment data. The framework integrates data acquisition, preprocessing, feature engineering, predictive modeling, and explainability analysis within a unified architecture. By combining rehabilitation-related variables with machine learning techniques, the framework aims to support objective recovery assessment and assist clinicians in rehabilitation planning. The overall architecture of the proposed framework is illustrated in Fig. 1**.**

Fig 1. Architecture of the Proposed Functional Recovery Prediction Framework

The framework consists of four major components. The first component collects patient demographic information, physiotherapy records, and clinical assessment measurements. The second component performs data preprocessing and feature extraction to improve data quality and prepare the dataset for predictive modeling. The third component employs a machine learning model to predict functional recovery outcomes. Finally, the explainability module identifies the factors contributing to prediction results and provides interpretable insights for rehabilitation professionals.

B. Dataset Description

The dataset used in this study consists of physiotherapy and clinical assessment records obtained from stroke rehabilitation programs. Each patient record contains demographic information, rehabilitation participation indicators, and standardized clinical assessment scores commonly used in stroke recovery evaluation. Clinical assessments provide objective measurements of motor impairment, mobility, balance performance, and functional independence. Physiotherapy-related variables describe the intensity and consistency of rehabilitation participation. These features collectively represent patient recovery characteristics and rehabilitation progress. The primary features utilized for functional recovery prediction are summarized in Table 1.

TABLE 1. CLINICAL AND PHYSIOTHERAPY FEATURES USED FOR RECOVERY PREDICTION

Feature	Description
Age	Patient age
Stroke Type	Ischemic or hemorrhagic stroke
FIM Score	Functional independence level
Fugl-Meyer Score	Motor function assessment
Berg Balance Score	Balance performance
Gait Assessment Score	Walking ability evaluation
Physiotherapy Sessions	Number of therapy sessions
Muscle Strength Score	Limb strength measurement

The target variable represents recovery status and is categorized into three outcome groups:

High Recovery

Moderate Recovery
Low Recovery
These categories are determined using clinically validated rehabilitation outcome criteria.

C. Data Preprocessing and Feature Engineering

Rehabilitation datasets frequently contain incomplete observations, inconsistencies, and measurement variations that may affect prediction performance. Therefore, data preprocessing is performed before model development. Initially, missing values are identified and handled using appropriate imputation techniques. Numerical attributes are replaced using mean-value imputation, while categorical variables are processed using mode substitution. Duplicate records and inconsistent entries are removed to improve dataset reliability. Following data cleaning, feature normalization is performed to eliminate scale differences among clinical measurements. Standardization ensures that variables with larger numerical ranges do not dominate the learning process. Categorical attributes such as stroke type are transformed into numerical representations using label encoding techniques. Feature engineering is subsequently applied to derive meaningful rehabilitation indicators. Composite rehabilitation measures are generated by combining multiple assessment scores and physiotherapy participation variables. Correlation analysis is performed to identify redundant features and reduce multicollinearity. Features exhibiting high redundancy are removed to improve computational efficiency and model stability. The resulting dataset provides a balanced representation of clinical status, physiotherapy engagement, and rehabilitation performance.

D. Functional Recovery Prediction Model

Following preprocessing, the dataset is divided into training and testing subsets using an 80:20 partitioning strategy. The training subset is utilized for model development, while the testing subset is reserved for independent performance evaluation. A Random Forest classifier is selected as the primary prediction model because of its ability to manage heterogeneous healthcare datasets and capture nonlinear relationships among rehabilitation variables. The model constructs multiple decision trees using bootstrap sampling and random feature selection. The final recovery classification is determined through majority voting across all trees. The model predicts one of three recovery outcomes:

High Recovery
Moderate Recovery
Low Recovery
Hyperparameter tuning and five-fold cross-validation are employed during training to improve generalization performance and reduce overfitting. This strategy enhances model reliability when applied to unseen patient records.

E. Explainability Analysis

Interpretability is an important requirement in healthcare decision support systems because clinicians must understand the factors influencing prediction outcomes. To improve transparency, the proposed framework incorporates an explainability module based on Shapley Additive Explanations (SHAP). SHAP assigns contribution scores to individual features according to their influence on prediction outcomes. Positive contributions indicate factors associated with improved recovery, whereas negative contributions identify variables linked to lower recovery potential. The explainability module provides both global and local interpretations. Global explanations identify the most influential recovery predictors across the entire dataset. Local explanations describe the factors responsible for individual patient predictions. This capability assists rehabilitation specialists in understanding recovery patterns and supports evidence-based clinical decision-making.

F. Algorithm of the Proposed Framework

The operational procedure of the proposed recovery prediction framework is summarized in Algorithm 1.

Algorithm 1. Functional Recovery Prediction Framework
Input: Clinical and physiotherapy dataset

Output: Recovery prediction and explanation

1. Acquire patient rehabilitation records.
2. Remove incomplete and duplicate data.
3. Normalize clinical assessment variables.
4. Encode categorical features.
5. Extract rehabilitation-related features.
6. Split dataset into training and testing subsets.
7. Train Random Forest classifier.
8. Generate functional recovery prediction.
9. Apply SHAP explainability analysis.
10. Rank influential rehabilitation factors.
11. Generate explanation report.
12. Return recovery classification and feature contributions.

The algorithm integrates predictive analytics and explainability to provide both recovery estimates and clinically interpretable insights.

G. Experimental Setup

Experimental evaluation was conducted using stroke rehabilitation datasets containing physiotherapy records and clinical assessment measurements. The dataset was divided into training and testing subsets using an 80:20 ratio. Five-fold cross-validation was employed to improve the robustness of performance estimation and reduce the influence of random data partitioning. The framework was implemented using Python-based machine learning libraries. Model performance was evaluated using four widely adopted classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of prediction effectiveness and classification reliability. The experimental setup was designed to evaluate both predictive performance and interpretability. The results obtained from the proposed framework are discussed in the subsequent section.

IV. RESULTS AND DISCUSSION

A. Performance Evaluation

The proposed machine learning-based framework was evaluated using an independent testing dataset to assess its ability to predict functional recovery outcomes in stroke patients. Performance was measured using four commonly adopted classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive evaluation of classification effectiveness and are widely used in healthcare analytics research.The prediction performance achieved by the proposed framework is summarized in Table 2**.**

TABLE 2. PERFORMANCE EVALUATION RESULTS

Metric	**Value (%)**
Accuracy	92.7
Precision	91.9
Recall	91.3

F1-Score	91.6

The results indicate that the proposed framework achieved an overall classification accuracy of 92.7%, demonstrating strong capability in distinguishing among different functional recovery levels. Precision reached 91.9%, indicating that the model generated a relatively low number of incorrect recovery classifications. Recall achieved 91.3%, suggesting that the framework effectively identified patients belonging to each recovery category. The F1-score of 91.6% further confirms the balanced predictive performance of the model. The high classification performance can be attributed to the integration of multiple clinical and physiotherapy variables. Functional assessment scores, balance measurements, gait indicators, muscle strength evaluations, and rehabilitation participation records collectively provide a comprehensive representation of patient recovery status. The inclusion of both clinical and therapy-related features enables the model to capture complex recovery patterns that may not be apparent through individual assessments alone.

B. Comparative Analysis

To evaluate the effectiveness of the proposed framework, its performance was compared with several widely used machine learning algorithms, including Decision Tree, k-Nearest Neighbors (KNN), Naïve Bayes, and Support Vector Machine (SVM). All models were trained and evaluated using identical datasets and experimental conditions to ensure a fair comparison. The comparative results are illustrated in Fig. 2**.**

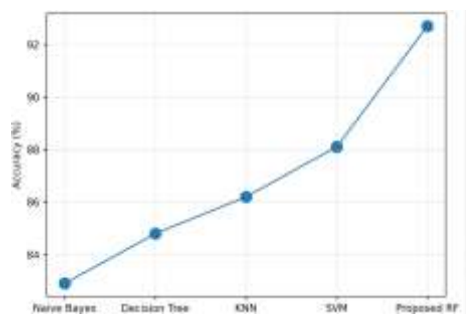

Fig 2. Comparison of Functional Recovery Prediction Accuracy Across Machine Learning Models

The comparison demonstrates that the proposed Random Forest-based framework achieved the highest classification accuracy among all evaluated methods. The Decision Tree classifier obtained an accuracy of 84.8%, while KNN achieved 86.2%. The SVM model produced an accuracy of 88.1%, whereas Naïve Bayes exhibited the lowest performance at 82.9%. In contrast, the proposed framework achieved an accuracy of 92.7%.The superior performance of the proposed model can be attributed to the ensemble learning mechanism of Random Forest. By combining multiple decision trees, the model effectively captures nonlinear relationships among rehabilitation variables while reducing the risk of overfitting. This characteristic is particularly important in healthcare datasets where interactions among clinical measurements and rehabilitation indicators are often complex. Furthermore, the inclusion of physiotherapy participation information contributes significantly to prediction accuracy. While clinical assessment scores provide information regarding patient condition, physiotherapy-related variables offer additional insights into rehabilitation engagement and treatment response. The combination of these complementary data sources improves overall predictive capability.

C. Feature Importance Analysis

Although predictive performance is essential, rehabilitation professionals require interpretable information regarding the factors influencing recovery outcomes. Therefore, SHAP-based explainability analysis was performed to identify the relative importance of clinical and physiotherapy variables. The feature importance analysis is presented in Fig. 3**.**

Figure 3. SHAP-Based Importance of Clinical and Physiotherapy Features

The SHAP results indicate that the Functional Independence Measure (FIM) score is the most influential predictor of functional recovery. This finding is consistent with clinical practice because FIM directly measures a patient's ability to perform activities of daily living independently. Higher FIM scores are generally associated with improved rehabilitation outcomes. The Fugl-Meyer Assessment score emerged as the second most important feature. Since this assessment evaluates motor impairment and movement capability, its strong contribution to prediction outcomes is expected. Berg Balance Scale scores also demonstrated substantial influence, highlighting the importance of balance performance in post-stroke recovery.

Gait assessment scores and physiotherapy session frequency were identified as additional influential predictors. Patients demonstrating better walking ability and greater participation in rehabilitation programs were more likely to achieve favorable recovery outcomes. Muscle strength measurements also contributed significantly, reflecting the role of physical function restoration in rehabilitation success. The explainability analysis provides both population-level and patient-specific insights. Global explanations identify the most influential recovery factors across the dataset, while local explanations enable clinicians to understand the reasons underlying individual patient predictions. This capability improves transparency and supports informed rehabilitation planning.

D. Discussion

The experimental results demonstrate that the proposed framework effectively combines machine learning techniques with clinical and physiotherapy data to predict functional recovery outcomes in stroke patients. The achieved accuracy of 92.7% indicates that rehabilitation assessment records contain sufficient information to support reliable outcome prediction. A notable finding is the importance of combining physiotherapy participation indicators with conventional clinical assessments. While measures such as FIM and Fugl-Meyer scores remain strong predictors of recovery, rehabilitation engagement variables provide complementary information regarding treatment adherence and therapy effectiveness. This observation supports the use of multidimensional rehabilitation datasets for predictive modeling. The comparative analysis further demonstrates the advantages of ensemble learning approaches in rehabilitation analytics. Random Forest consistently outperformed conventional classifiers, suggesting that ensemble models are better suited for handling heterogeneous rehabilitation datasets characterized by nonlinear relationships among variables. The SHAP-based explainability component represents another important contribution of the framework. In healthcare environments, clinicians require understandable explanations before incorporating predictive recommendations into decision-making processes. By identifying the factors responsible for recovery predictions, the explainability module enhances transparency and facilitates clinical interpretation. Overall, the results indicate that the proposed framework provides a practical approach for predicting functional recovery outcomes while maintaining interpretability. Such capabilities may support individualized rehabilitation planning, early identification of patients requiring additional intervention, and evidence-based management of stroke rehabilitation programs.

V. CONCLUSION AND FUTURE WORK

This paper presented a machine learning-based framework for predicting functional recovery in stroke patients using physiotherapy and clinical assessment data. The proposed framework integrates data preprocessing, feature engineering, predictive modeling, and explainability analysis to support rehabilitation outcome prediction. By utilizing clinical assessment measures such as the Functional Independence Measure, Fugl-Meyer Assessment, Berg Balance Scale, gait evaluation scores, and physiotherapy participation indicators, the framework provides a comprehensive representation of patient recovery status. A Random Forest classifier was employed to predict recovery outcomes and classify patients into different functional recovery categories. Experimental evaluation demonstrated strong predictive performance across multiple classification metrics, indicating that the proposed framework can effectively identify recovery patterns from rehabilitation datasets. The results further showed that combining clinical assessment variables with physiotherapy-related indicators improves prediction accuracy compared with relying solely on conventional clinical measures. An important contribution of this work is the incorporation of SHAP-based explainability analysis. The explainability module identifies the factors contributing to prediction outcomes and provides interpretable information regarding recovery determinants. The analysis revealed that functional independence, motor assessment scores, balance performance, gait characteristics, and physiotherapy participation are among the most influential predictors of rehabilitation success. These insights may assist clinicians in understanding patient recovery trajectories and support evidence-based rehabilitation planning. The findings suggest that machine learning techniques can serve as useful tools for rehabilitation outcome prediction while maintaining clinical interpretability. Future work will focus on validating the proposed framework using larger multi-center rehabilitation datasets and more diverse patient populations. Additional investigations may explore deep learning approaches, longitudinal recovery prediction models, and the integration of electronic health record data to further improve predictive performance and clinical applicability. The incorporation of real-time rehabilitation monitoring and personalized therapy recommendation mechanisms also represents a promising direction for future research.

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