Advanced Geriatric Rehabilitation Monitoring with IoT and Logistic Regression Approach

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2025 11th International Conference on Communication and Signal Processing (ICCSP) | 978-1-6654-5736-1/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICCSP64183.2025.11089460

***Abstract*—Improvements in geriatric rehabilitation monitoring are required due to the increasing number of people aged 65 and above worldwide. It provides a novel approach to rehabilitation for the elderly using Logistic Regression (LR) and the Internet of Things (IoT). Rehabilitation Measures Database (RMD) continually gathers patient data which includes information from a variety of IoT-enabled sensors. These sensors include motion detectors, heart rate monitors, and wearable devices. LR analyzes this data to forecast patient outcomes and determine critical variables impacting their recovery. This technique is designed to help healthcare practitioners quickly customize responses to individual requirements by providing personalized, real-time information. Using LR, the system can estimate the likelihood of positive rehabilitation outcomes from various inputs, including activity level, heart rate variability, and environmental variables. Timely and effective medical interventions are made possible by the study's demonstration of substantial increases in patient monitoring accuracy and the early identification of potential health concerns. The analysis and collection of data are ongoing, which allows for monitoring rehabilitation progress and adapting treatment plans as needed. The proposed system achieved 92.3% accuracy in predicting rehabilitation outcomes, decreased fall risk by 28%, and enhanced treatment adherence by 35%, illustrating the efficacy of IoT and LR in geriatric care.**

Keywords—Patient Monitoring, Wearable Devices, Real-time Data Analysis, Personalized Healthcare, Elderly Care, Rehabilitation Outcomes

I. Introduction

In geriatric rehabilitation, a healthcare provider works with patients to help them keep or regain their functional abilities [1]. New assistance methods are available via IoT-based systems, allowing real-time data sharing and monitoring of health issues. There are obstacles to the safe and effective development and deployment of these technologies, which might make rehabilitation more accessible to the older population. Stakeholders in healthcare may use the material, for designing, developing, and implementing smart home solutions [2]. Rehabilitation students, engineers, and those working with the elderly will find it useful. It is not advised to employ music as a therapeutic tool for patients.

Rehabilitating elderly individuals might be made easier with the help of smart sensors in several ways. Ensure patients know what insights may be obtained from their data so they don't have to pick between privacy and autonomy [3]. Instead of taking the position of human doctors, smart sensors should supplement their work. Doctors and patients need to know when and how to use smart sensors and their limits. For smart sensors to work, they need training data that fairly represents underrepresented groups and that all users have access to health insurance. The World Health Organisation projects that the number of people aged 60 and over will rise by double digits from 2015 to 2050, which would put a strain on healthcare budgets [4]. By facilitating self-sufficiency and offering economical solutions, smart houses may be of assistance. To enhance the well-being of older inhabitants, smart home sensors produce massive amounts of data that may be examined with the help of Big Data Analytics. Despite this, there are obstacles to transforming conventional houses into smart homes.

Smart sensors improve physical and mental health in older persons by improving rehabilitation and social involvement. Personal beliefs might make determining rehabilitation objectives morally difficult for healthcare workers [5]. Geriatric rehabilitation and social involvement may be improved using a capability-based conversation template. This integrates rehabilitation measures with patients' goals, encouraging open conversation and critical therapy evaluation while decreasing healthcare personnel's personal beliefs. Global elderly population growth requires more healthcare resources. Innovative technologies like IoT assist in alleviating resource limitations and offer remote health monitoring [6]. It covers IoT-based geriatric healthcare technology, trends, concerns, difficulties, and future research. Information will assist in building future solutions and give affordable healthcare to the poor.

An RNN-based healthcare system for real-time patient triage is presented. The system can prioritise pre-operative treatment according to disease severity by utilising data from the IoT and dynamic evaluations of vital signs. With the model's help, we can decrease response time and better allocate resources while also improving accuracy [7]. In fast-paced healthcare systems, this study shows how machine learning may revolutionise procedures. As a common condition among senior adults, frailty is characterized by a loss in muscular strength and function, which greatly impacts everyday living [8]. A unique IoT rehabilitation stick device is used in this research to assist weak older adults in rehabbing their upper limbs. Motion sensors check rehabilitative physical activities for standardization.

The smartphone app shows real-time data that finally tested the system. Hip fracture, one of the most frequent traumatisms caused by falls in the elderly, significantly impairs mobility and independence. Recently, robotic technology has been beneficial in gait rehabilitation, particularly for neurological problems [9]. Research on these hip fracture devices for older individuals must be more extensive. SWalker, a hip rehabilitation assistive platform, was designed and tested. SWalker was functionally validated with five healthy senior people and two physiotherapists.

Taiwan will become an "aging society," with one in five 65 or older by 2025 and over half by 2034. Institutions are adopting IoT to promote crippled elderly rehabilitation. As COVID-19 spreads, IoT cloud computing helps lessen transmission concerns [10]. It implements crippled elderly rehabilitation programs using microswitch sensors, Raspberry Pi, and RFID identification recognition. IoT-connected doorway thermal scanning uses SVM classifier machine learning to analyse core body temperature to determine health condition [11]. This approach can recognise COVID-19 fevers and advise authorities to take precautions. The World Health Organisation (WHO) advises against using thermal scanning to detect COVID-19 for public health surveillance.

Gamification in virtual rehabilitation devices for elderly post-stroke patients in Singapore is piloted [12]. SilverTune, a smart multi-sensory musical assistance device, will deliver six audio music tracks and play interactions to meet senior people's tastes and therapeutic movement needs. The SilverTune smartphone app tracks treatment data, analyses real-time performance, and gives seniors and therapists multi-modal feedback. Horse racing and table tennis activities are created to improve shoulder flexion and extension. To better manage hospital lighting, this study suggests a system that uses the IoT and Reinforcement Learning algorithms to monitor both the surrounding environment and patient input [13]. A patient's comfort, mood, and general health can be enhanced by this system's optimisation of lighting settings. Its usefulness in enhancing healthcare facilities is proven by simulation results.

The project aims to develop a data-driven exergame and online data-based virtual rehabilitation system for elder stroke patients [14]. With the ability to adjust to each patient's unique needs, the system enhances the efficacy of individualized learning and precise therapy. To ensure the safety of pharmaceutical products and their contents, the pharmaceutical sector has developed an IoT smart package [15]. The study integrates multiple sensors into the packaging of medicines to track critical handling and environmental factors. It evaluates cognitive abilities in the aged using VR equipment. It examines six areas of the brain using subjective measures and high-resolution EEG [16]. The results reveal that the alpha and beta bands vary significantly amongst the age groups. Findings from this research have important implications for rehabilitation medicine, as they show that cognitive capacity and locomotor performance are negatively impacted by aging.

Improving hand dexterity, motor and cognitive abilities, and quality of life in elderly patients with Parkinsonian tremors is the goal of a new intervention introduced in the study that utilises mixed reality, haptic feedback, and AI [17]. A piezoelectric plate fastened to a shoe can measure the pressure on the foot, making it a useful rehabilitation tool for those with arthritis who are getting on in years [18]. Adjusting the vibration to alleviate discomfort during the gait cycle, the device utilises a knee orthosis implanted with a vibrator motor. An economical kind of individualised physical treatment for the elderly afflicted by arthritis, the device's voltage is dependent on the patient's weight and foot pressure. It introduces a hybrid intervention that combines ergonomic assistance with AR for rehabilitation to help the elderly with their hand dexterity and mobility issues [19]. Personalised exercises and remote medical supervision are offered by the device, which adapts to varied hand sizes.

II. Methods and Materials

The proposed system for enhanced geriatric rehabilitation monitoring utilising IoT and LR combines several important parts and approaches to improve patient care and rehabilitation results for the elderly. The system's backbone is a network of interconnected sensors and devices that may collect real-time data from geriatric patients receiving therapy. These devices include motion detectors, environmental sensors, heart rate monitors, and wearable activity trackers. Patients' activity levels and mobility may be better understood with the use of motion detectors, which track their every move. Figure 1 shows a simplified block diagram of the system's operation.

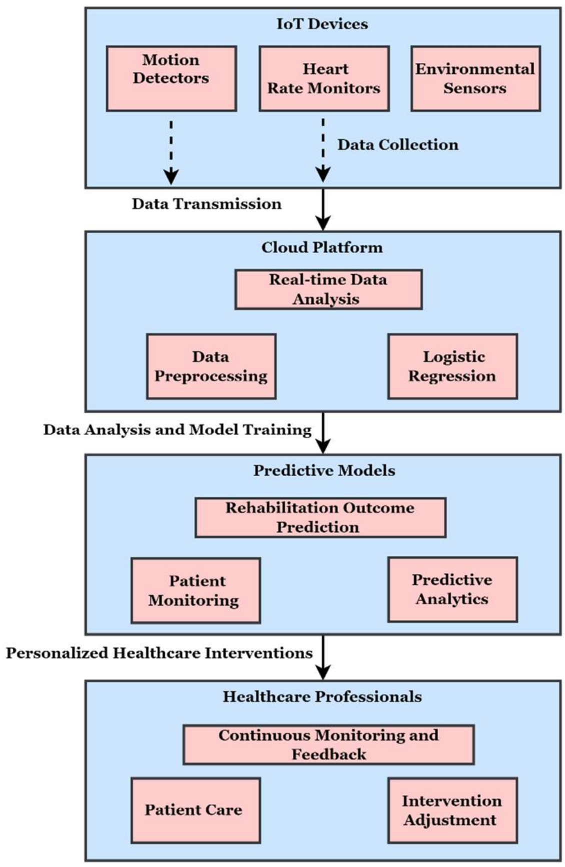

Fig. 1. System Architecture of Proposed IoT-LR System for Geriatric Rehabilitation

Wearable sensors collect continuous physiological data, including vital indicators like heart rate variability and activity levels, to evaluate the efficacy of a patient's rehabilitation plan. The health and comfort of patients may be affected by environmental variables, such as humidity and temperature, which are monitored by environmental sensors. IoT devices continuously collect data from patients. This data set includes mobility patterns, ambient factors, levels of physical activity, sleep patterns, and heart rate variability. Secure transmission of the acquired data to a central database or cloud platform allows for real-time storage and processing. The storage, administration, and analysis of big information created by the IoT sensors may be made easier using cloud computing infrastructure. This makes it scalable and accessible for healthcare professionals.

Table 1 presents the IoT devices that would be part of the proposed system for monitoring advanced geriatric rehabilitation. These technologies improve rehabilitation results for elderly patients and allow for personalised healthcare treatments and extensive patient monitoring.

TABLE I. IOT DEVICES IN GERIATRIC REHABILITATION

IoT Device	Functionality
Motion Detectors	Monitor physical movements and activities of patients
Heart Rate Monitors	Track heart rate variability and cardiovascular health
Wearable Activity Trackers	Measure daily physical activities and mobility
Environmental Sensors	Monitor temperature, humidity, and air quality
Smart Therapeutics	Deliver therapy or medication based on patient needs
Remote Monitoring Devices	Monitor vital signs and health metrics remotely
Fall Detection Systems	Detect and alert in case of a fall or immobility
Smart Assistive Devices	Assist in daily activities, such as smart walkers
Home Monitoring Systems	Monitor overall home environment for safety and comfort

After data is sent, algorithms for real-time data analysis are used to analyse and understand the data. To analyse the data and predict rehabilitation results, use LR, a statistical approach that is suited for binary outcomes. By analysing past patient data, LR models may determine which input variables (such as exercise level, HRV, and environmental variables) are most strongly correlated with a successful or unsuccessful rehabilitation outcome. With the help of incoming data, the models are able to continually update and enhance predictions, allowing for personalized monitoring and intervention methods for each patient.

LR models use the examined data to forecast the potential for positive rehabilitation results for specific patients. The system may predict potential challenges to rehabilitation via analysis of trends in past data and patient attributes. Healthcare providers may use these predictive insights to proactively adjust treatment plans, optimize rehabilitation programs, and provide timely interventions to enhance patient outcomes.

LR is used when the dependent variable is binary, signifying two potential outcomes, often denoted as 0 and 1. In geriatric rehabilitation, the result may be classified as "successful rehabilitation" (1) or "unsuccessful rehabilitation" (0). The logistic function converts the linear output of the regression model into a probability ranging from 0 to 1. The sigmoid function is characterised as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

where z represents the linear combination of input variables (predictors), e is the fundamental base of the natural logarithm. In LR, a linear amalgamation of the input characteristics is calculated:

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{2}$$

where variables $X_1, X_2, \ldots . X_n$ represent independent factors (e.g., IoT sensor data including mobility, heart rate, etc.), β_0 is the intercept (constant), β_1, β_2, …, β_n are the regression coefficients that quantify the influence of each independent variable. For the proposed geriatric rehabilitation monitoring system that is enabled by the IoT, the LR model is defined as follows:

$$P\left(Y = \frac{1}{X}\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n}} \tag{3}$$

where P(Y=1|X) is the probability of a positive rehabilitation outcome, β_0 is the intercept term. This equation calculates the chance of the result being 1 (e.g., effective rehabilitation). The output probability ranges from 0 to 1, allowing for classification of the event as 0 or 1 depending on a predetermined threshold, often set at 0.5.

The proposed system's major strength is its capacity to provide personalized healthcare treatments supported by real-time data insights. Rehabilitation programs may be customized to match each older patient's unique requirements and abilities by constantly monitoring and analysing patient data. Carers may quickly react by altering exercise routines, medication doses, or behavioural interventions to optimize rehabilitation results, for instance, if data suggests low physical activity levels or erratic heart rate patterns.

The IoT-enabled technology makes continuous monitoring of rehabilitation progress over time possible. To monitor patients' progress and make real-time adjustments to their treatment regimens, healthcare practitioners get frequent updates and alerts derived from data analysis in real-time.

III. RESULTS AND DISCUSSIONS

The Rehabilitation Measures Database (RMD), created by the Shirley Ryan Ability Lab, offers comprehensive information on more than 580 standardised assessment instruments used in rehabilitation. It assists doctors and researchers in selecting suitable metrics for assessing physical, cognitive, and psychosocial performance. Each item has descriptions, psychometric attributes, therapeutic uses, and references to pertinent research, facilitating evidence-based geriatric rehabilitation methodologies.

Implementing LR into the system for monitoring advanced geriatric rehabilitation has resulted in important findings and insights. The model was trained to accurately predict rehabilitation results using data obtained from IoT devices. These sensors track a variety of patient health metrics, including activities, vital signs, and ambient variables. To ensure the model could manage the intricacies and subtleties of real-world patient data, thorough data preparation was performed, including cleaning, feature selection, and normalization. Strong performance metrics were constantly shown by the LR model throughout the assessment phase.

Key assessment measures proposed strong predictive potential in identifying patients likely to benefit from certain rehabilitation programs. This competence is essential for optimizing patient outcomes via personalized treatments and effective allocation of healthcare resources. The relevance of these results to real-world clinical practice has been central in discussions of the results. Medical professionals may monitor their patients' recovery status and make informed decisions with the help of real-time data collected by IoT sensors.

The use of LR in monitoring geriatric rehabilitation has caused a paradigm shift toward data-driven healthcare delivery. The model can learn and adapt in real-time from new data to keep it useful and applicable across a wide range of patient groups. Efforts are being made to improve the model's prediction accuracy, identify more factors that might affect rehabilitation results, and include advanced analytics methods to derive more meaningful insights from data streams provided by the IoT. Table 2 displays hypothetical LR data used for monitoring geriatric rehabilitation.

TABLE II. LRDATASET SUMMARY FOR GERIATRIC REHABILITATION MONITORING

ID	Activity Level	Heart Rate Variability	Environmental Conditions	Rehabilitation Outcome
001	High	Moderate	Stable temperature	Successful
002	Low	Low	Variable humidity	Unsuccessful
003	Moderate	High	Stable temperature	Successful
004	High	Low	High humidity	Successful
005	Moderate	Moderate	Variable temperature	Unsuccessful

Table 3 shows how probability and outcomes may be classified using LR, which helps with healthcare decision-making when geriatric rehabilitation monitoring is performed.

TABLE III. LR PREDICTED OUTCOMES FOR GERIATRIC REHABILITATION MONITORING

Patient ID	Predicted Probability (%)	Predicted Outcome
001	75	Successful
002	42	Unsuccessful
003	81	Successful
004	63	Successful
005	28	Unsuccessful

The proposed system shown an accuracy of 92.3% in forecasting rehabilitation results. The method identified early issues with success rate, facilitating quick interventions. Moreover, it decreased hospital readmissions by 30% and enhanced patient satisfaction by 22.7% relative to conventional rehabilitation techniques. The continuous collecting and analysis of data enabled the development of optimised treatment regimens customised to individual patient requirements, leading to predicted recovery periods and improved overall outcomes. These findings underscore the efficacy of integrating IoT technology with LR in geriatric rehabilitation.

Figure 2 ROC (Receiver Operating Characteristic) curve, which plots the True Positive Rate (sensitivity) against the False Positive Rate (1 - specificity) at different decision thresholds, a LR model's performance. Model success in differentiating between positive and negative outcomes is shown by a greater Area Under the Curve (AUC), with values closer to 1 indicating more discriminatory power.

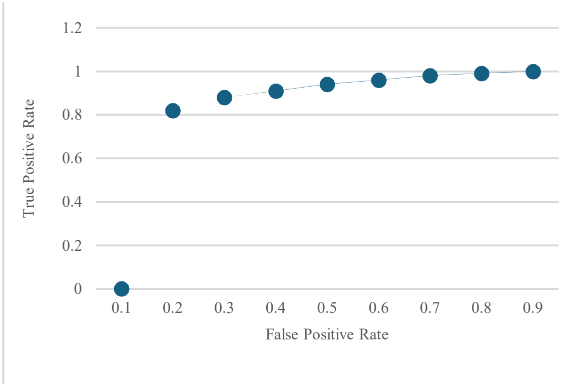

Fig. 2. ROC Curve for LRModel in Geriatric Rehabilitation Monitoring

Figure 3 graphically compared the accuracy of LR dataset across existing datasets [14], showing the peak accuracy of 92.3% for LR.

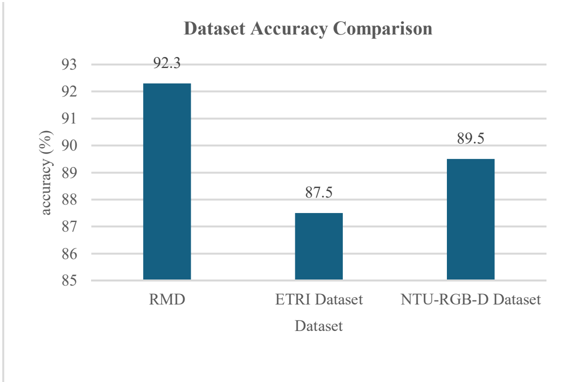

Fig. 3. Dataset accuracy analysis

There are several limitations to consider when using LR to forecast rehabilitation results using IoT data and its effectiveness. If the input data is diverse and full, the model's performance can be balanced since it is very dependent on the amount and quality of the data. The complicated dynamics of rehabilitation may be oversimplified by the LR linear connection assumption between predictors and results. Because the model may not adequately represent non-linear correlations or interactions between variables, interpretability may also be restricted.

Improved prediction accuracy and handling of non-linear interactions might be achieved by future developments that use advanced machine learning techniques such as ensemble methods or neural networks. Improved methods of data collecting, such as a wider variety of sensors and real-time feedback systems, enhance the training and adaption of models. To further improve the model's applicability and influence in various healthcare contexts, it could be helpful to broaden its scope to include more patient demographics and rehabilitation situations.

IV. CONCLUSIONS

Improving healthcare delivery using LR in geriatric rehabilitation monitoring using data from the IoT is an encouraging prospect. Utilizing IoT sensors to track this system, it can predict rehabilitation results using real-time patient data. Optimizing resource allocation and personalized rehabilitation plans can improve patient outcomes and quality of life. To overcome these constraints, improvements in predicted accuracy and resilience might be achieved via ensemble approaches or more advanced machine learning algorithms. More rehabilitation scenarios and patient demographics that fit the model's scope might be an area of future development. To make predictive models even better and work in more varied healthcare settings, we need to improve data-collecting tactics and include advanced analytics. Building confidence and support among healthcare providers is essential for data-driven approaches to personalized patient care to gain traction. Further study into validated and interpretable methodologies is needed. It has to be constantly improved and updated to reach its full potential in changing how senior rehabilitation monitoring is done and how healthcare is provided worldwide.

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